Tourist experiences recommender system based on wearable devices data

Doctoral Thesis

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Abstract

Background

The collection of physiological data from people has been facilitated due to the mass use of cheap wearable devices. Although the accuracy is low compared to specialized healthcare devices, these can be widely applied in other contexts. This research proposes the architecture for a tourist experiences recommender system (TERS) based on the user's emotional states who wear these devices. The issue lies in detecting emotion from Heart Rate (HR) measurements obtained from these wearables. Unlike most state-of-the-art studies, which have elicited emotions in controlled experiments and with high-accuracy sensors, this research's challenge consisted of emotion recognition (ER) in the everyday context of users based on the gathering of HR data.

Furthermore, an objective was to generate the tourist recommendation considering the emotional state of the device wearer. The method used comprises three main phases: The first was the collection of HR measurements and labeling emotions through mobile applications. The second was emotional detection using deep learning algorithms. The final phase was the design and validation of the TERS-ER. In this way, a dataset of HR measurements labeled with emotions was obtained as results. Among the different algorithms tested for ER, the hybrid model of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks had promising results. Moreover, concerning TERS, Collaborative Filtering (CF) using CNN showed better performance.

Aims

This project proposes a tourist experiences recommender system based on emotion detection from wearable device data. The specific objectives are:

- Analyze the historical behavior of the physiological data of wearable devices users to find emotional patterns.

- Define the emotion recognition component based on physiological data collected before the tourist experience.
- Design the context-aware recommender system according to the user's profile, emotional data, and the tourist experience portfolio.
- Validate the recommender system through a case study of experiences for a tourist destination.

Method

This research defined the phases of generating the conceptual base and developing the architecture of a Tourist Experiences Recommendation System based on Emotion Recognition (TERS-ER). Initially, the state-of-art analysis presented the trends, theoretical background, and algorithmic approaches to identify guidelines for designing an emotion-aware tourist RS.

The TERS-ER purpose was to previously detect the user's emotional state who wore a wearable for a significant time. Based on the predominant emotion of this user, the recommender generated a list of Tourist Experiences (TE). The general process of the method involved three phases: HR measurements and emotion labeling, detection of emotional states, and TERS-ER design and validation.

Results

The main results were: (i) A scientometric review of Tourist Recommender Systems based on Emotion Recognition (ER). (ii) An application for ER based on shallow machine learning algorithms to extract the features of physiological signals in the time and frequency domain. The experimental results on the AMIGOS dataset showed that the proposed DCNN method achieved better accuracy in the classification of emotional states compared to that obtained initially by the authors of this dataset. (iii) A MyEmotionBand mobile application to collect the affective dataset. (iv) A Heart Rate (HR) dataset of the experiment participants of this study. (v) A time series synchronization algorithm for labeling emotions in HR instances called a sliding and adjustable window. (vi) Two implementations for affective detection and the recommender engine of the TERS-ER architecture. In the validation results, we found that the recommender had a better performance in the models developed of Collaborative Filtering using Convolutional Neural Networks (CF-CNN) and Content-Based Filtering (CBF), in contrast to the Matrix Factoring algorithms.

Conclusions

A system for TE recommendation based on emotional recognition with data from low-cost wearable devices called TERS-ER was presented. This recommender generates the TE most relevant to the user's preferences, location, and felt emotion in a period before the visit. The TERS-ER architecture was made up of two main subsystems. The first ER integrated the data collection from the experiment participants, preprocessing, Emotional Segments (ES) analysis of HR instances, balancing the emotion classes, and affective detection using DNN models. To this end, an algorithm was designed to label emotions in HR instances called a sliding and adjustable window. Also, an ES algorithm was developed for the predominant affective state, parameterized by the amount and time between the labeled instances.

The second TERS was implemented with the dataset management components and the recommender engine. The TERS engine integrated a user similarity algorithm, selecting candidate users from the ontology based on the profile and contextual data of the wearable user. Also, two approaches to Content-Based Filtering (CBF) and Collaborative Filtering (CF) based on CNN were designed to generate the top-N list of Tourist Experiences (TE) recommendations.

Keywords:

Recommender system, emotion detection, tourist experiences, heart rate, wearable, deep neural network.

Resumen

Antecedentes

La recopilación de datos fisiológicos de personas se ha visto facilitada debido al uso masivo de dispositivos wearable baratos. Aunque la precisión es baja en comparación con los dispositivos médicos especializados, estos pueden aplicarse ampliamente en otros contextos. Esta investigación propone la arquitectura de un sistema de recomendación de experiencias turísticas (TERS) basado en los estados emocionales de los usuarios que usan estos dispositivos. El problema radica en detectar la emoción a partir de las mediciones de Frecuencia Cardíaca (HR) obtenidas de estos dispositivos wearable. A diferencia de la mayoría de los estudios de estado del arte, que han provocado emociones en experimentos controlados y con sensores de alta precisión, el desafío de esta investigación consistió en el reconocimiento de emociones (ER) en el contexto cotidiano de los usuarios basado en la recopilación de datos de HR.

Además, un objetivo fue generar la recomendación turística considerando el estado emocional del usuario del dispositivo. El método utilizado consta de tres fases principales: La primera fue la recolección de medidas de HR y etiquetado de emociones a través de aplicaciones móviles. El segundo fue la detección emocional mediante algoritmos de aprendizaje profundo. La fase final fue el diseño y validación del TERS-ER. De esta manera, se obtuvo como resultados un conjunto de datos de medidas de HR etiquetadas con emociones. Entre los diferentes algoritmos probados para ER, el modelo híbrido de Redes Neuronales Convolucionales (CNN) y redes de Memoria a Largo y Corto Plazo (LSTM) tuvo resultados prometedores. Además, en cuanto a TERS, el Filtrado Colaborativo (CF) con CNN mostró un mejor rendimiento.

Objetivos

Este proyecto propone un sistema de recomendación de experiencias turísticas basado en la detección de emociones con datos de dispositivos wearable. Los objetivos específicos son:

- Analizar el comportamiento histórico de los datos fisiológicos de los usuarios de dispositivos wearable para encontrar patrones emocionales.
- Definir el componente de reconocimiento de emociones en función de los datos fisiológicos recopilados antes de la experiencia turística.
- Diseñar el sistema de recomendación contextual de acuerdo con el perfil del usuario, los datos emocionales y el portafolio de experiencias turísticas.
- Validar el sistema de recomendación a través de un estudio de caso de experiencias para un destino turístico.

Métodos

Esta investigación definió las fases de generación de la base conceptual y desarrollo de la arquitectura de un Sistema de Recomendación de Experiencias Turísticas basado en el Reconocimiento de Emociones (TERS-ER). Inicialmente, el análisis del estado del arte presentó las tendencias, los antecedentes teóricos y los enfoques algorítmicos para identificar las pautas para diseñar un sistema de recomendación turística consciente de las emociones.

El propósito de TERS-ER fue detectar previamente el estado emocional del usuario que usó un wearable durante un tiempo significativo. A partir de la emoción predominante de este usuario, el recomendador generó una lista de Experiencias Turísticas (TE). El proceso general del método involucró tres fases: mediciones de HR y etiquetado de emociones, detección de estados emocionales, diseño y validación de TERS-ER.

Resultados

Los principales resultados fueron: (i) Una revisión cienciométrica de Sistemas de Recomendación Turística basados en el Reconocimiento de Emociones (ER). (ii) Una aplicación para el ER basada en algoritmos de aprendizaje automático superficial para extraer las características de las señales fisiológicas, en el dominio del tiempo y la frecuencia. Los resultados experimentales sobre el dataset AMIGOS, muestran que el método propuesto DCNN logró una mejor exactitud de la clasificación de los estados emocionales, en comparación con la originalmente obtenida por los autores de este dataset. (iii) Una aplicación móvil MyEmotionBand para la recolección del dataset afectivo. (iv) Un dataset de Ritmo cardíaco (HR) de los participantes del experimento de este estudio. (v) Un algoritmo de sincronización de series de tiempo para etiquetar las emociones en las instancias HR denominado ventana deslizante y ajustable. (vi) Dos implementaciones para la detección afectiva y el motor del recomendador de la arquitectura TERS-ER. En los resultados de la validación, encontramos que el recomendador tuvo un mejor desempeño en los modelos desarrollados de Filtrado Colaborativo usando Redes Neuronales Convolucionales (CF-CNN) y Filtrado Basado en Contenido (CBF), en contraste con los algoritmos de Factorización Matriz.

Conclusiones

Se presentó un sistema de recomendación de TE basado en el reconocimiento emocional con datos de dispositivos wearable de bajo costo llamado TERS-ER. Este recomendador genera el TE más relevante a las preferencias, ubicación y emoción sentida del usuario en un período previo a la visita. La arquitectura TERS-ER estaba compuesta por dos subsistemas principales. El primer ER integró la recopilación de datos de los participantes del experimento, el preprocesamiento, el análisis de segmentos emocionales (ES) de instancias de recursos humanos, el equilibrio de las clases de emociones y la detección afectiva mediante modelos DNN. Con este fin, se diseñó un algoritmo para etiquetar las emociones en instancias de recursos humanos llamado ventana deslizante y ajustable. Además, se desarrolló un algoritmo ES para el estado afectivo predominante, parametrizado por la cantidad y el tiempo entre las instancias etiquetadas.

El segundo TERS se implementó con los componentes de administración de conjuntos de datos y el motor de recomendación. El motor TERS integró un algoritmo de similitud de usuarios, selección de los usuarios candidatos de la ontología en función del perfil y los datos contextuales del usuario del wearable. Además, se diseñaron dos enfoques de filtrado basado en contenido (CBF) y filtrado colaborativo (CF) basado en una CNN para generar la lista de las N-principales recomendaciones de experiencias turísticas (TE).

Palabras Clave:

Sistema recomendador, detección de emociones, experiencias turística, ritmo cardíaco, wearable, redes neuronales profundas.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This doctoral thesis outlines an original scientific contribution both in computer science and in the domain of tourism. A TERS-ER model of three phases articulated the proposed research objectives were developed. The first is preprocessing Heart Rate (HR) measurements and emotional labels. The second is emotion detection, and the third is the Tourism Experiences Recommender System based on Emotion Recognition (TERS). Besides the scientific publications that validated the original contributions of this research. The TERS-ER modules using the APIs of Keras, SciKitLearn, Python Surprise were implemented. For data collection, an experiment was designed with 18 participants. Each participant wore a low-cost wearable (Xiaomi Mi Band 3 or 4). The third-party application to record HR pulses and the My Emotion Band (in-house) application to register emotions were installed on their mobile device. However, unlike the experiments in other related studies, this research was conducted outside a laboratory setting. According to the temporal perspective, this research focused on the preliminary tourism phase, where the user who wore a low-cost wearable plans their tourist experience next.

This document shows the following sections: Chapter 2 establishes the relationship of the scientific literature of recommendation systems in the tourism domain based on emotion. Chapter 3 describes the emotion detection model based on physiological signals using the AMIGOS multimodal dataset. Then, chapter 4 explains the architecture model of a TERS-ER using data from low-cost wearable devices. Chapter 5 evaluates the performance of deep neural network models for emotion detection and tourist destination recommendation. Finally, chapter 6 presents the conclusions, contributions, and future work.

1.1 Problem Statement

When somebody wonders about which tourist experience is most convenient, the person contemplates as a response the consideration of the following factors: travel agencies, suggestions from third parties, economic plans, or the desire to know new places (novelty). However, a convenient factor that should be taken into account is the emotional state that the person has presented before consuming the tourist experience. Then the question arises: How is a person's emotional state determined? In addition, according to this emotional state, which is the tourist experience most convenient?

In recent years the development and use of wearable technology have increased; for example, CCS Insight forecasts that by 2021 technology companies will produce about 185 million wearable devices (such as a smartwatch, wristband, cameras, hearable, footwear, eyewear, and jewelry) [2]. A wearable device is worn on the body and functions as a small computer with detection, processing, storage, and communication capabilities [3]. These devices are equipped with sensors to capture the user's physiological data (heart rate, blood pressure, electrodermal activity, among others) and data about the user's environment (location, time, and weather). The collection and processing of these data have become a major technological and scientific challenge [4], with broad applicability for improving the user experience in the domain of tourism. On the other hand, consideration should be given to the systematic exploration of wearable devices best suited to specific situations and applications for the context of daily life [5].

Concerning the dimension of the tourist attraction, the Recommendation Systems (RS) are an essential tool before visiting the tourist destination. Research on the management of the tourism industry highlights the importance of this type of device for ER, such as the improvement of the Tourist Experiences (TE) through the personalization of the services [6, 7], where the tourist's expectation is analyzed in three phases (before, during and after the tourist visit) for different dimensions or tourist activities. The emergence of sensors and wearable devices as mechanisms for the acquisition of physiological data of people in their daily lives [8] has made possible the research in affective patterns recognition for the improvement of the user experiences in diverse contexts. In the same way, the World Tourism Organization recognizes that in the market of the increasingly competitive tourist destination, the tourist attractions are more inclined towards the emotional benefits than the physical features and price of the destination [9].

During the last two decades, MIT's affective computing research group has aroused great interest in scientific and academic communities that seek to improve the human emotional experience with technology [10]. Some challenges focus on deepening machine learning and deep algorithms to ensure that the Emotion Recognition (ER) system has high precision and robustness in the processing of physiological data [11]. The emotional computational models [12] have been applied to the recognition of the affective state through physiological measures. It is based on a specific emotion model, for instance, the evaluation of valence dimension from unpleasant to pleasant and arousal dimension from low to high [13].

Besides, the recommendation of the TE may be influenced by the dynamic and subjective nature of the emotions of a user when performing an activity [14]. Consequently, it is necessary to build and dispose of datasets with physiological data coming from wearable devices, to diagnose the emotional states of diverse user profiles, at different times, in the distinct contexts of daily life, and over some time. Once trained and tested, these types of datasets would be the entry to the recommender system, which would lessen the problem of cold start [15, 16].

In this sense, RS are software tools that suggest items that interest a particular user. These are classified in RS: content-based, collaborative filtering, knowledge-based, and demographic [17]. For the tourism domain, demographic information is combined with the context data to guide the recommendation process; this approach is related to the methodology of the Context-Aware RS (CARS) [18, 19]. Emotions are an important contextual element and in the investigations consulted, evidence the need to reduce complexity in algorithms, propose architectures, frameworks [20] and, approaches to facilitate the development, implementation, and evaluation of CARS [17].

There are antecedents of tourist RS that use collaborative filtering techniques to determine tourist satisfaction during or after their visit [16]. Other content-based RS analyzes user preferences and experiences previously made [21]. Knowledge-based RS through large datasets, created from hotel information or tourism infrastructure, make the respective proposals [18]. However, concerning wearable devices in the context of tourism, few documents were found in the bibliometric study (see Chapter 2). From the physiological data of people in their daily life, the emotions can be recognized, and an opportunity and one scientific challenge are detected.

According to Buhalis [6] and Kim [22], tourist expectations are analyzed in three phases from a temporal perspective. Anticipation phase to the trip's decision and in the user's daily life. Experiential phase during the tourist experience and finally reflective phase of the travel experience. However, how satisfying is the consumption of a tourist experience for a person? It largely depends on the destination's decision. However, the emotional state that the person manifested before their visit is rarely taken into account. This research focused on the preliminary phase of the visit, which detects people's affective state as a contextual factor of a recommender.

The gaps we found to address this study were.

- Gap 1: Considering that from a wearable device, we can obtain user profile data and HR measurements, and unlike controlled experiments, the challenge arises: in a person's everyday environment, how to discover hidden patterns in the physiological data obtained from a low-cost wearable?

- Gap 2. Regarding the assignment of emotions to HR measurements: How to assign a person's emotion to a set of HR time series? Moreover, How do we differentiate the intensity and duration of an emotional state in the HR time series?

- Gap 3. Furthermore, based on the emotional state of the wearable user: how to recommend suitable tourist experiences?

Therefore, the following research question arises:

How to design a tourist experiences recommender system based on the user's emotional state who wears a low-cost wearable in a period before the tourist visit?

The hypothesis of this research is: One system recommends tourist experiences based on the user's emotional state who wears a low-cost wearable, based on this device's heart rate measurements.

1.2 Objectives

1.2.1 General Objective

Propose a tourist experiences recommender system based on emotion detection from wearable device data.

1.2.2 Specific Objectives

- Analyze the historical behavior of the physiological data of wearable devices users to find emotional patterns.

- Define the emotion recognition component based on physiological data collected before the tourist experience.

- Design the context-aware recommender system according to the user's profile, emotional data, and the tourist experience portfolio.

- Validate the recommender system through a case study of experiences for a tourist destination.

Chapter 2

State of the art

Recommendation systems have surpassed the overload of irrelevant information by considering users' preferences and emotional states in the fields of tourism, health, e-commerce, and entertainment. This chapter reviews the principal recommendation approach documents found in scientific databases (Elsevier's Scopus and Clarivate Web of Science) through a scientometric analysis in ScientoPy. Research publications related to the recommenders of emotion-based tourism cover the last two decades. The review highlights the collection, processing, and feature extraction of data from sensors and wearables to detect emotions. The study proposes the thematic categories of recommendation systems, emotion recognition, wearable technology, and machine learning. This chapter also presents the evolution, trend analysis, theoretical background, and algorithmic approaches used to implement recommenders. Finally, the discussion section provides guidelines to design emotion-sensitive tourist recommenders.

2.1 Introduction

Nowadays, people find varied information about service portfolios (for instance, books, videos, and tourist attractions) to choose the most relevant to their personal needs. Although many times, the choice of a service or product does not generate the expected results. For this reason, Recommender Systems (RS) are valuable tools that provide adequate and contextualized items to the users' preferences. Emotion Recognition (ER) [23–25] and sentiment analysis [26–28] are vital contextual factors to improve user satisfaction and accuracy in tourist recommendations. So the user's affective context has been inferred from social network reviews [29–31]. Emotion detection, based on the physiological signals collected from wearable devices, has been used to customize the user's context [32–34].

As a result, RS implementation is considered an interdisciplinary field of research that involves data collection, information preprocessing, the definition of Machine Learning (ML) approaches, and specification of recommendation services [26, 35, 36]. Such as the recommenders of movies [37, 38, 31], music [34, 30, 39], tourist attractions [40–44], and medical care [45–47].

In recent years, the development and use of wearable technology have increased [48–50]. In particular, CCS Insight predicted that by 2021 technology companies will produce around 185 million wearable devices (such as a smartwatch, bracelet, cameras, audible devices, footwear, glasses, and jewelry) [2]. A wearable device is worn on the body. It has computational capabilities to detect, process, store, and communicate data [51, 52]. They are also equipped with sensors to capture physiological data [39, 53, 54] and data about the user's environment [55, 56]. Therefore, this data collection and processing have become a tremendous technological challenge to improve the user experience using the ER [32, 33, 1, 34].

Consequently, the purpose of this study is to provide both an overview and an understanding of the theoretical background, approaches, models, and methods for the implementation of ER-based tourism recommender systems. This document presents a scientometric review that covers the analysis of research documents published from 2000 to 2019. Section 2.2 details the materials and methods used in the preprocessing and analysis of bibliographic datasets. Sections 2.3 to 2.6 comprise the four main categories around the classification of recommender systems, emotional detection based on wearable sensors data and proposed machine learning approaches. Besides, Section 2.7 presents the thematic clusters associated with recommendation systems, tourism, and emotions. Finally, sections 2.8 and 2.9 summarize the main findings and conclusions found in this work.

2.2 Materials and Methods

This section describes the bibliographic dataset gathering, the preprocessing, and the review methodology applied in the scientometric analysis.

2.2.1 Dataset Collection

Initially, a specialized search of scientific papers from the Clarivate Web of Science and Elsevier's Scopus platforms was performed. These bibliographic databases contain information on high-quality multidisciplinary research published in scientific journals of meaningful global impact and allowed the consolidation of a dataset to contribute to this study. The search string was "(((recommender OR recommendation) AND system) AND (tourist OR tourism OR emotion OR physiological OR affective OR wearable)). The first part of the string refers to the recommender systems, and the second part mentions the recognition of emotions. The information was extracted from the bibliographic platforms on July 15, 2020, filters were applied to the search chain by subject (Computer Science, medicine, engineering, business, telecommunications, artificial intelligence, psychology, multidisciplinary and tourism) and by years (2001 to 2020) A representative dataset of 1829 documents was obtained, corresponding to 33.6% from WoS and the remaining from Scopus (see Table 2.1).

Table 2.1 Filters applied to the search string of WoS and Scopus dataset.

Filter	**Scopus**	**WoS**	**Documents**
By years: Limit-to	2001 to 2020	2001 to 2020	(4308, 1623)
By subject area: Limit-to	Computer Science, Medicine, Engineering, Psychology, and Business.	Computer Science Information Systems, Artificial Intelligence, Engineering, Tourism, Telecommunications, and, Psychology.	(3637, 570)
By subject area: Exclude	Mathematics, Social Sciences, Decision Sciences, Biochemistry, Nursing, Health, among others.	-	(2030, 570)
By document type: Exclude	Exclude Short Survey, Note, Editorial, and Letter.	-	(2016, 570)
By language: Limit-to	English	English	(1861, 551)
By keywords: Exclude	Human, article, priority journal, female, review, male, adult, adolescent, among others.	-	(1303, 551)
By source title: Exclude	Advanced Materials Research, Information Japan, Applied Mechanics, among others.	-	(1278, 551)

The bibliographic dataset preprocessing was generated with the ScientoPy tool [57]. Table 2.2 shows a summary of the preprocessing of the duplicate documents that were removed from the consolidated Scopus and WoS dataset. Additionally, it displays the bibliographic dataset statistical information filtered by type of documents (conference papers, articles, reviews, proceedings papers, and articles in press) and duplicates records in the DOI match. In particular, the first column of information describes the input dataset. The second column specifies the number of published documents and the number of papers resulting from the duplicate filter. Finally, the third column shows the relative percentages before and after the filter.

Table 2.2 Preprocess brief with ScientoPy for the dataset obtained.

Information	Number	Percentage
Total loaded documents	1829	
Omitted documents by type	200	10.9%
Total documents after omitted documents removed	1629	
Loaded documents from WoS	547	33.6%
Loaded documents from Scopus	1082	66.4%
Duplication removal statics:		
Duplicated papers found	180	11.0%
Removed duplicated papers from WoS		
Removed duplicated papers from Scopus	180	16.6%
Total papers after remove duplicates	1449	
Papers from WoS	547	37.8%
Papers from Scopus	902	62.2%

2.2.2 Review Methodology

The research field was systematically determined as following the scientometric review methodology [58]:

- First, the subject of the review was searched for in the Scopus and WoS databases. The search string was designed according to the research topic of recommendation systems in the tourism domain based on recognizing emotions from wearable device physiological data.

- Secondly, the scientometric tool ScientoPy [57] was used, which pre-processed these two bibliographic databases' files. In this way, several clusters were determined, and the categories related to the research topic were formed. Moreover, the lead authors' first 1000 keywords were chosen from this dataset consisting of 1449 documents. Then, the most relevant author keywords from this list were analyzed to consolidate 16 categories (recommender system, tourism, emotion recognition, machine learning, social media, user modeling, collaborative filtering, mobile application, context, personalization, sentiment analysis, wearable, healthcare, ontology, affective computing, and physiological signal). Later, the categories displayed in the graphics cluster the similar author keywords that belong to the same topic (such as words in plural/singular, acronyms, classes, or category types). For instance, the RS topics include the keywords (recommender system, recommendation system, recommendation, recommendation systems, recommendations, and others), and the deep learning topic includes the keywords (convolutional neural networks, convolutional neural network, CNN, deep neural network, LSTM, and others).

- Third, it shows the statistical graphs of the bar and parametric trend analysis constructed with the indicators of Average Documents per Year (ADY) and Percentage of Documents in Recent Years (PDLY) [57]. It is interesting to highlight the rise of the RS and tourism as transversal and thematic axes. Figure 2.1 shows the trend bar graph of the main categories and highlights in the orange bar the documents published in the last four years in sentiment analysis, wearable devices, physiological signals, and use of ML algorithms in the ER. Furthermore, it includes the value of PDLY (2016 -2019). Similarly, the trend analysis in Figure 2.2 uses the ADY and PDLY indicators to describe the behavior of the strongly related themes to RS-based research. The graph on the left shows the evolution of the S curve of technology or category calculated by the number of documents accumulated per year (logarithmic scale). It represents the initial evolution, the period of growth, and the boom of the publication of documents related to research topics. While the parametric scatter graph located on the right side visualizes the growth of publications in recent years (2016 -2019). New themes have emerged to support tourism RS development, such as sentiment analysis, wearable devices, social networks, and ML algorithms. The thematic axes of ER, affective computing, and collaborative filtering are of great interest to recommenders.

- Fourth, the analysis of research trends belonging to these clusters was carried out with the WoSViewer (Section 2.7) and ScientoPy tools, which determined that the boom in the publication of the documents in these clusters began in 2016. Figures 2.1 and 2.2 show the peak of 2016, especially in the clusters of collaborative filtering, wearables, physiological signals, sentiment analysis, healthcare, affective computing, and social networks. The topics mentioned are included in sections 2.3 to 2.6. In each section, reference is made concerning the most relevant documents to RS, ER, wearable technology, and ML.

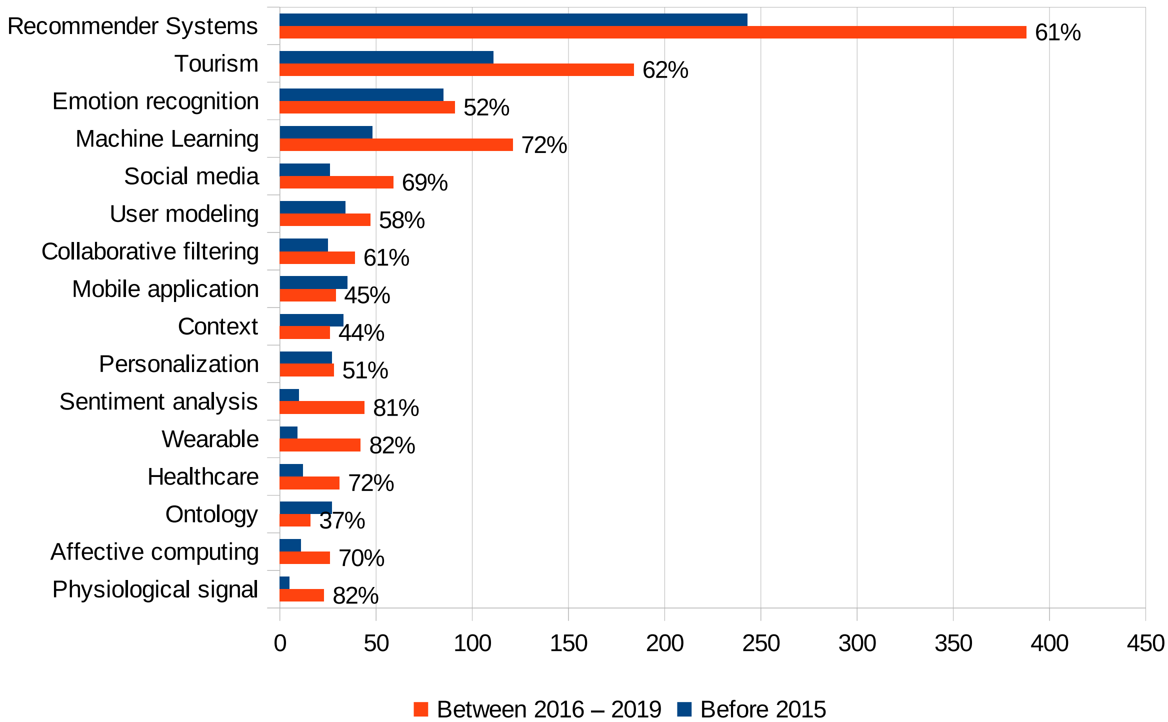


Fig. 2.1 Research topics related to RS, tourism, and ER between 2001 and 2019.

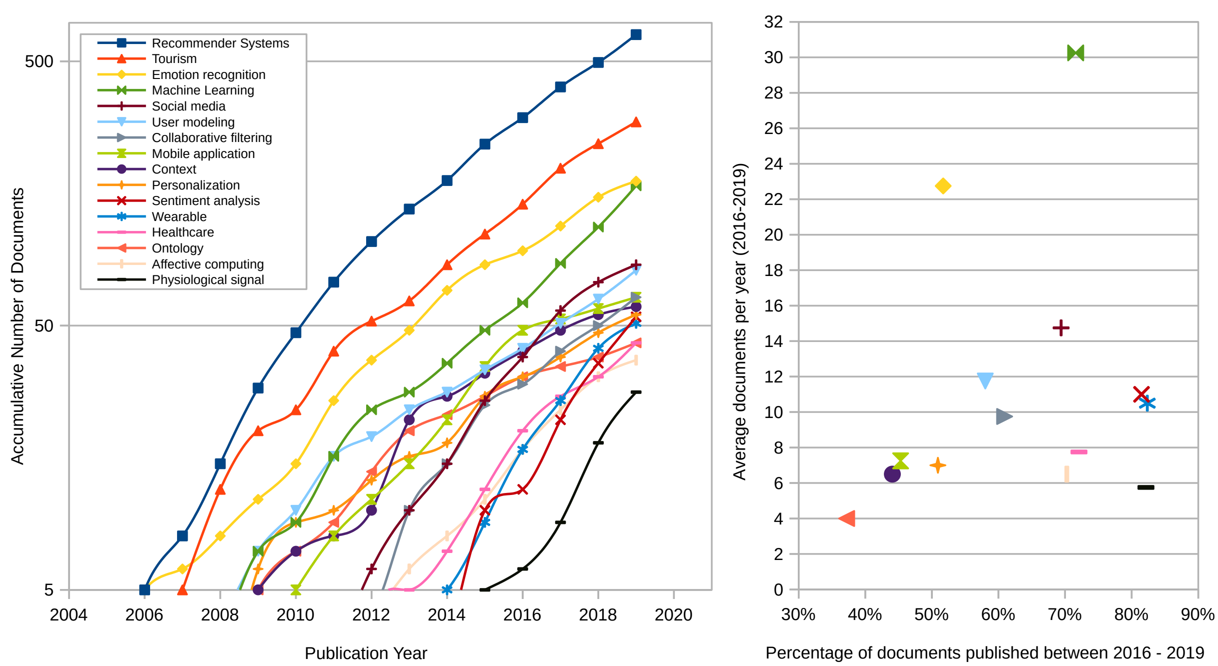


Fig. 2.2 Top applications and technologies in tourist recommender systems research.

2.3 Recommender Systems

RS are software tools and techniques that provide suggestions for items that are likely to be of interest to a determinate user. The documents cited in this section are related to recommendations for tourism, videos, music, content-based filtering, and collaborative filtering (see Figure 2.3). Although the search spanned the last two decades, most of the papers related in this section have been published in the last five years and have the highest PDLY. The RS landscape has been diverse regarding developing research prototypes that integrate Web technologies, mobile computing, and social networks in tourism [59–61]. Furthermore, RS approaches have evolved concerning the application, the business model, the user profile, the techniques, and the algorithms implemented.

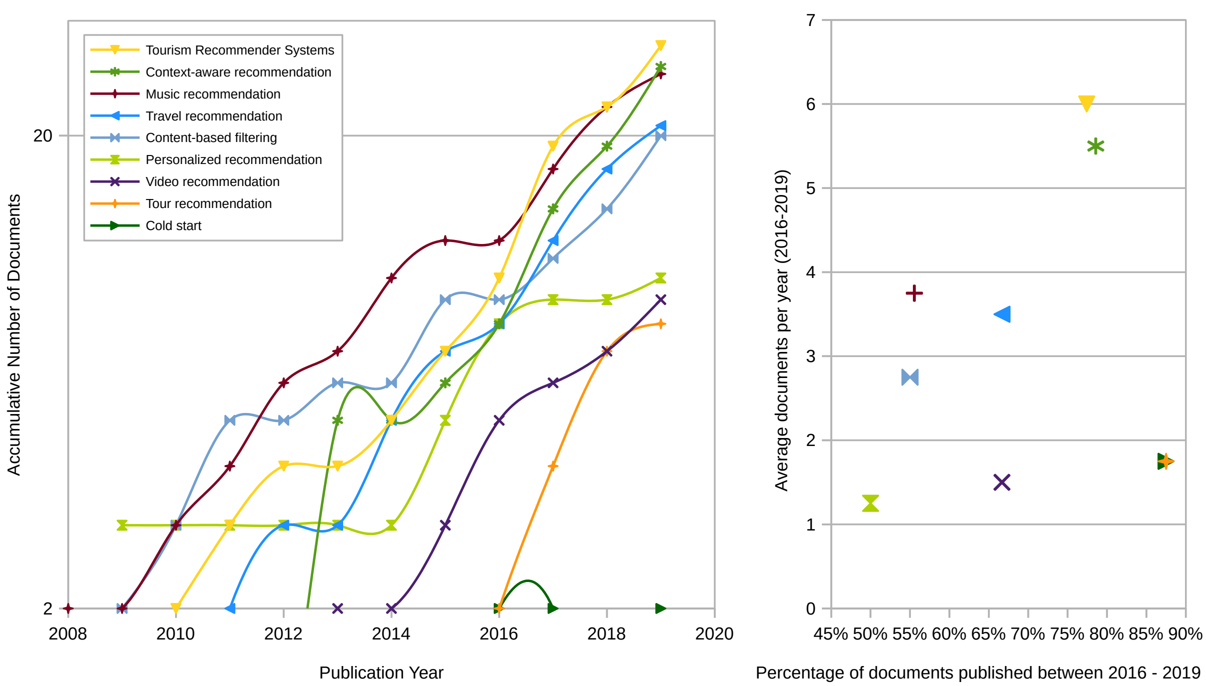


Fig. 2.3 Trends of approaches, frameworks, and applications in RS research.

The RS architecture integrates data collection, preprocessing, prediction models, and recommendation services [26, 35, 36]. The papers referenced in Table 2.3 describe the functionality and application of the stages of the recommendation process. Moreover, the preprocessing stage extracts the relationship between the user, the item, and the contextual features represented in a data model (vector or tensor matrix). The prediction stage then generates a relevant list of items calculated with algorithms and recommendation models based on similarity. Finally, the recommender specifies the services related to the users' interests, such as listing the most innovative items and adapted to the users' demand.

2.3.1 Content-Based Filtering

A typical recommendation approach shares a mechanism to describe the detailed features of items that may be of special suitable to a user [17]. Based on the representation of these items, a user preference profile is built. Through an ML algorithm, it compares the item features with the user's profile and generates the recommendation list. The item similarity is calculated based on the attributes associated with the compared items. For example, in a music recommender, a user rates a relaxation song with a high estimate, then the system learns to suggest other songs of the same emotional state. The song features can describe both structured data (song title, singer name, music genre, year of release, and emotional state) and unstructured data (user comments and song description).

Some studies have used the Cosine Similarity (CS) metric [62, 28, 63] to determine the similarity of the items represented in the n-dimensional space vectors (for example, a matrix of similarity between songs and emotional state). In contrast, the Euclidean Distance (ED) [64–67] was used to measure the actual distance between the elements and the user's profile. The implementation of recommenders based on content emerges as an alternative to personalize the multimedia, tourist, and entertainment content available on the Web. Emotions have aroused intense interest in the design of user preference models. For example, the influence of affective metadata on image rating performance using the Support Vector Machine (SVM) algorithm [68]. The definition of the travel profiles based on a multiple regression model of Points of Interest (POI) images implicitly extracted the user preferences [64].

Due to the semantic ambiguity of unstructured data, Probabilistic Latent Semantic Analysis (PLSA) techniques have been proposed for tourist attraction image annotation and ontological representation of user profile data [69–71]. Also, [72, 73] described a tourism approach based on social relationships and user preference profiles to calculate the POI similarity. A hybrid approach in [29] compared the Rocchio algorithm for customizing required queries in the classification of candidate POI with the k-Nearest Neighbors (kNN) weighted classifier query builder.

Although content-based approaches have limitations for predicting novel items, they have datasets that enrich domain knowledge and avoid cold start problems [74]. To overcome the problems of prediction accuracy, some researchers have proposed hybrid approaches. In particular, [75] presented a framework of mobile tourist services based on the semantic relationship of the agreement of words and frequency of terms to determine the item's similarity to recommend. The architecture of a content-based and semantic-conscious RS [76] described the components from a computational perspective. It introduced a cleaning user-profile method and overcame the magic barrier problem by detecting the semantic similarity between the item and the profile. Besides, it used a filtering component to generate the recommendation list appropriate to the user's preferences.

2.3.2 Collaborative Filtering

Unlike content-based filtering, Collaborative Filtering (CF) automatically learns the relationship of items, extracts their features, and discovers new interest items to users [74]. CF methods generate user-specific item recommendations based on rating patterns from multiple users who share similar preferences [17]. The data sources indicate the behaviors and interests that users have had in the past concerning the products. These can be implicit (for instance, tourist attraction reviews, review history, and search patterns) and explicit (for example, scaling from 1 to 5 to quantify liking for a tourist site). The ratings recorded by users are related to the dataset elements and form a two-dimensional matrix. CF recommendation models calculate similarity weights between users and items [77].

User-Based Collaborative Filtering (UBCF), also known as Neighborhood-based, establishes a target user's neighborhood by analyzing historical behavior and preferences to find the best similarity between the items of other users similar to those that the target user liked [38, 37, 30, 78]. In comparison, Items Based Collaborative Filtering (IBCF) predicts the rating of a new item and weights the ratings of the item set by the similarity of the target user behavior [39, 30]. The CF approaches used Pearson's Correlation Coefficient (PCC) [38, 29, 36, 78–80] and CS [26, 81, 30, 35] metrics to generate a list of product recommendations of interest to the target user.

The recommenders, faced with the problem of cold start and the scarcity of user behavior data, have implemented mining and affective computing techniques to obtain implicit information [36, 26, 82, 38]. In personalization of tourist attractions and multimedia content, CF hybrid models merged the emotions of user comments, contextual data, and explicit's ratings available on online social networks [83, 72, 29, 84]. Tourist destination recommenders used CF review extraction methods to refine user preferences and article reputation [26, 73].

In contrast to CF algorithms, model-based approaches are categorized into factoring machine, matrix factoring, and ML algorithms. These models are scalable and handle sparse data [17, 77]. The Factorization Machine (FM) is a general-purpose regression method that models the interaction between contextual variables [17]. Some recommenders implemented the Stochastic Gradient Descent (SGD) algorithm with regularization hyperparameters to optimize the FMs of affective factors and tourist attractions features [85, 82, 86]. Additionally, Matrix Factorization (MF) is a model of latent factors represented in a three-dimensional grade cube denoted by users, items, and values of the contextual dimension [17, 77, 26, 87, 88].

Furthermore, the Singular Value Decomposition (SVD) algorithm transforms the original rating matrix $R = users * items$ into a matrix of users with latent features $U = users * latentfactors$. Then, it calculates the transpose of the original rating matrix $RT = items * users$ and generates a matrix of items with latent features $RT = items * latentfactors$. Lastly, the prediction function for a specific user rating is given by $R = U * MT$ [77, 36, 89]. Simultaneously,The SVD ++ algorithm is a specific variant of SVD that handles both implicit and explicit interactions [17, 77]. Some studies [90] modified the SVD ++ model by merging user sentiment and tourist destinations temporal influence in the POI recommendation. Also, [91] used the emotion label weighting as a tensor value of the High-Order Singular Value Decomposition (HOSVD) method to consider the preference and interest in movies suggestion.

Recently, the research challenge of developing recommendation models with a contextualized approach arises to overcome users' limitations in terms of geographic coverage and social interaction [74]. Most recommender architectures are hybrid because they combine various approaches with IBCF and UBCF [92]. In particular, [93] proposed a tourist system that matches the user's location with the top-k recommendations through a linear distance for the contents and the CS for the relationship between the user profiles. Also, [94] developed an approach to extract information from users' preferences of a website, established the similarity of users, and generated a tourist attraction with the Slope One algorithm. Considering the problem of cold start and the scarcity of the CF algorithms' information, [95] developed an architecture of a deep neural network based on an MF of latent features of the project developers, their tasks, and their relationships.

2.3.3 Knowledge-Based

A knowledge-based recommender (KB) consolidates data on user preferences, restrictions, and needs essential for item suggestions [96, 97]. Knowledge-based systems satisfy user preferences using knowledge bases that associate item features with user requirements [98–100]. KB recommender [73] compared user requirements with candidate travel destinations by assigning a score to each dimension (location, tourist profile, type of attraction, transportation costs) and a weighted average to predict the rating. Online social networks provide information related to the profile, location, and feelings of users for the construction of ontologies that have been used in the monitoring of emotional health [101]. However, the recommendation performance depends on the knowledge base, and its implementation is costly due to the quality of the information [102].

2.3.4 Tourist Context

This section details the RS categories of the tourism context. Although the search spanned the last two decades, most of the mentioned papers in this section have been published in the last five years and have the highest PDLY. Travel planning and e-tourism documents are closely related to emerging topics of tourist trip design problems, POI, travel, and smart tourism (see Figure 2.4).

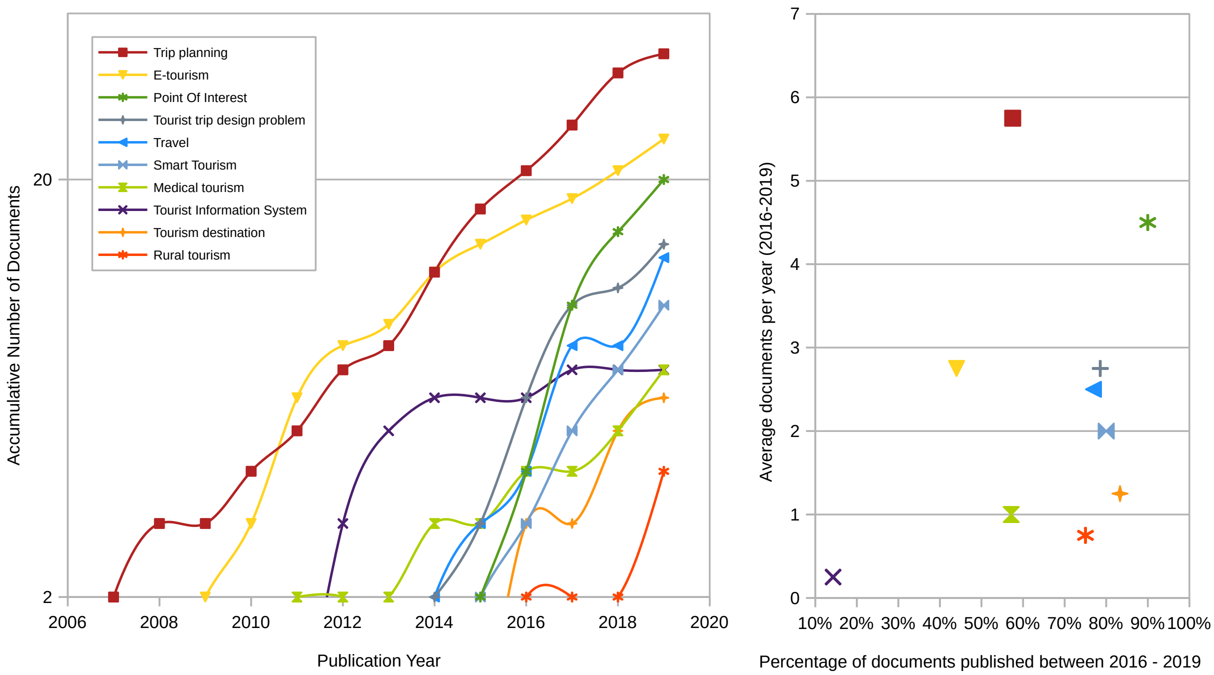


Fig. 2.4 The domain of the top applications in tourist recommenders.

In the tourism sector, experiences are the main product and directly impact receptive tourist satisfaction [6, 22]. For this, stakeholders prepare the tourist destination to have positive experiences in the social and physical context [103, 104, 43]. One experience is inherently personal and can involve an individual on different rational, emotional, sensory, physical, and spiritual levels [105]. Smart tourism transformed information services to support the design of personalized tourism experiences in a ubiquitous context [98, 106, 44]. Therefore, a recommender as technology tools provides valuable suggestions on tourist attractions tailored to personal preferences and restrictions.

Precisely, in a smart tourism ecosystem [107, 98], wearable device sensory technology can be considered the enabling layer that supplies the context factors and user data. Meanwhile, the recommender displays the suggested contents about the tourist experience and is part of the facilitation layer. Therefore, mobile tourism [108, 106, 109–111] is an emerging field that combines various ubiquitous devices, technologies, and services necessary to provide well-being to tourists in the destination. Indeed, the heterogeneous data extracted in a smart city favor the design of tourism behavior models based on travel routes' digital patterns [112] and cultural heritage routes[113] with a user theme similarity model and a mean-shift clustering algorithm for visitor location.

Location-based tourism recommenders [40, 83, 41, 42] have used mobile devices' technological capabilities to provide information to the user about POI near their geographical position. Specifically, [114] developed a recommender based on a clustering algorithm to discover user preferences and visualize the most novel POI on a cartesian coordinates map. [115] proposed a context-sensitive itinerary recommender based on a routing algorithm that used the user's social information, popularity, and distance from the POI. Furthermore, mobile communications and social media allowed users to share ratings and experiences related to POI comments based on their preferences [116–118, 35].

The tourist trip design problem [119–121, 41, 122, 123, 63] has involved implementing tourist route planning to meet the trip's expectations, the novelties in the destination, and the visitor's satisfaction. For instance, the routing model based on metaheuristics made it possible to search for POI located on the journey routes [124, 125]. According to the user's preferences and context, the recommender based on Dijkstra's algorithm [123] constructed short tourist trips within a feasible time frame. While [126] proposed a POI recommender based on MF algorithms and an enriched cultural typology.

The trip planning of itineraries to tourist places has incorporated the user's relevance, location, and travel time between POI [127–129]. Some travel recommendation methods [130–132] generated a list of POI that matched the user's preferences obtained from geotagged photographs and comments from tourist experiences posted on social media. Hybrid location-based recommenders considered dynamic user interaction to suggest custom POI using an intelligent swarm algorithm [78] and a hybrid selection scoring algorithm [133].

On the other hand, the destination recommenders have guided the tourists in the trip purpose, adapting their personal needs and preferences [119]. Some researchers have extracted user sentiment trends toward preferred items by analyzing the social media reviews. Also, they have addressed data scarcity limitations in the recommendation process [90, 26, 73].

The researchers have boosted the visitors' motivation towards medical and rural tourism. Recently, rural tourism offered exciting challenges for developing the RS frameworks for these tourist experiences [134]. Some studies [135, 85] proposed methods for the extraction of geographic features from rural tourism attractions. Medical tourism recommenders have supported users' health care and medical attention while traveling [136]. For instance, the health-conscious ubiquitous context approach used visitor physiological sensor data [137]. Moreover, the social trust-based approach developed an ontology for medical tourism services [100].

It is worth highlighting the interest of researchers in integrating the contextual factor of emotions into RS approaches to provide tourists with novel experiences that satisfy their travel motivations and expectations.

2.3.5 Context-Aware

In recent years, contextual information has been significant in describing current user behavior, scenarios, and mobile recommenders' application domain [138–140, 106]. Contextual information can involve various contexts related to user features, technological resources, and physical conditions [17, 77, 141]. The first involves user interaction on social media, mood, experiences, and preferences. The second describes the communication and computing capabilities of the user's ubiquitous devices. The last one specifies using the sensors to measure the climate, the weather, and the recommendation's location. For the above, some studies proposed a multi contextual perspective of mobile tourism RS by integrating users' location with environmental, temporal, and social factors to generate more effective predictions [142–144, 110, 145].

Unlike traditional recommendation approaches, the Context-Aware Recommender System (CARS) added contextual information to the multidimensional classification prediction function $user * item * context \longrightarrow rating$ [17]. The three CARS categories that adapted the user's contextual information in a prediction model are pre-filtering, post-filtering, and contextual modeling [17, 77]. In pre-filtering, preference data is selected according to the context before algorithms calculate predictions [44]. In post-filtering, context is used to filter recommendations once predictions have been calculated with a traditional approach [44]. In contrast, contextual models incorporate contextual data directly into the prediction model.

Some studies [37, 146] demonstrated better results in the suggestion of movies by incorporating contextual dimensions of the emotional [147] to the context-sensitive algorithms (items, users and User Interface, UI), Differential Relaxation Context (DCR), and Differential Context Weighting (DCW). Similarly, [38] used a hybrid CF approach based on mood, the fusion of preferences, and users' ratings with similar interests. While [89] adopted multiclass classification algorithms (Decision Tree - DT, Random Forest - RF and SVM) to predict interactive emotional states. Furthermore, musical CARS investigations [30, 39] have used CF approaches to extract emotional labels from songs associated with users' physiological states. Also, they implemented neural network models for the representation of the users' musical sequences [148].

Semantic Web techniques have enabled recommenders to add reasoning ability to context information. Ontologies semantically describe the concepts for modeling the features of user profiles, preferences, and items [99, 100]. The personalized recommenders of tourist activities are based on ontologies built from various data sources (travel motivations, user opinions, geographic information, ratings, among others) [149]. Particularly [80] proposed a travel RS based on the contextual information of emotions [150] extracted from social networks with semantic analysis techniques. Additionally, [151] proposed a cultural hybrid RS of personalized itineraries based on social networks' activities, the linked open data, and the physical context. For this, it implemented the semantic-based match algorithm for the user's profile.

Also, POI recommenders have implemented mining techniques to identify contextual user preferences in social media reviews. [133] generated the candidate POI with the Adaptive KNN and Social Pertinent Trust Walker (SPTW) algorithms. Then, it displayed the recommendations with the Hybrid Selection Score (HSS) method. Another study [78] incorporated pre-filtering user preferences and a CF algorithm based on its proximity. On the other hand, [88] proposed the Largest Deviation technique to estimate the selective, parsimonious, and most relevant context of user preferences when rating POI items.

Compared to traditional RS frameworks, the majority of CARS research demonstrated better performance on prediction results when implementing sentiment analysis and opinion mining techniques [152]. Besides, some studies described RS architectures in various tourist settings. [153] presented a POI itinerary recommender architecture sensitive to the user's physical and social context. It used semantic similarity algorithms based on a graph for the extraction and filtering of the multimedia content of LinkedGeoData. Likewise, [154] designed a travel itinerary recommender based on dimension trees of contextual features, an inferential tourist guide engine, and a recommendation engine. [155] proposed a recommender of cultural routes based on the geotagged photo content, the temporal context, and the geographical location. For this, it used a thematic model based on the PLSA of POI and visitors.

The analysis of user behavior is very relevant to design tourist RS frameworks with personalized services and applications. [112] proposed an ontological framework for predicting temporal events based on tracking tourist behavior changes. It stored contextual information in a data lake repository and implemented neural network algorithms to group tourists and classifier their road trip satisfaction level. On the other hand, [156] designed a mobile system to detect danger sources in the tourist destination. The system integrated the risk analysis component of technological, socio-political, and natural situations to generate recommendations for a safe trip.

2.3.6 Emotion-Based

Affective computational models are increasingly efficient in generating personalized recommendations by detecting the user's emotions. Understanding and predicting user behavior is vital to an affect-sensitive recommendation system. Emotions are closely related to people's physical features and are considered a relevant contextual factor in the recommendations [68, 65, 157, 158]. Some studies [159, 160] designed user models based on personality traits and emotional states. These models comprise a conceptual level composed of profile data, physiological measures, contextual data, and subjective user attributes. In contrast, the specific domain level defines the connection between emotional states and affective elicitation attributes that can influence the recommendation process.

The emotional information of users can be obtained with explicit and implicit methods and in a non-intrusive way. [82] integrated long-term mood into the prediction model, and fashion product recommendations improved in contrast to short-term emotion. [86] presented a recommendation system sensitive to affect that infers the emotional features [147] of multimedia content. It used a cluster-based Latent Bias Model (LBM) to predict the probability that a user would click on images taking into account emotional context, mobile behavior, and social closeness.

The exponential growth of content on online social networks has made it possible to identify user affective features to improve the recommendation quality. Emotional data is restricted by the scarcity and noise of user reviews. However, emotional information extraction avoids negative posts with the probability of increasing precision in the prediction [102]. [35] developed an affect-sensitive RS with an emotion lexicon [147] extracted from the reviews of the social networks of location and generated a list of POI [120]. Also, [36] designed a recommender based on the fusion of social, emotional and rating information to maximize the probability of the user's selection behavior.

Some emotion-sensitive RS approaches use social information to prompt users to provide implicit feedback on an item rating. [92] presented an algorithm that extracts emotional information from a social network digital element rating. Then, it used the user satisfaction scale to generate a list of neighbors based on the similarity of emotions. In addition to the product rating, both the textual emotion analysis that detects affective polarization and the extraction of the labels (user preferences and intrinsic attributes of the product) favor user satisfaction when purchasing products [81, 91, 79]. [161] defined emotional contagion and user satisfaction in a group recommender that suggests sequences of items obtained with emotion decay and mood assimilation that impact future items satisfaction.

Emotion-sensitive RS architectures improve the user experience by implementing services adapted to the current emotional state. [162] developed a song recommender based on contextual data, current emotion, and musical preferences. It showed a better prediction when incorporating the emotions (happy, neutral, and sad) concerning the recommenders of similarity of content and feedback of the electroencephalogram signals. In particular, [163] designed a platform sensitive to emotions to improve people's productivity in smart offices. It proposed a module that recognizes the emotional context by obtaining data from sensors (temperature and humidity), detecting emotions (facial expression, voice and text analysis), and information from the Internet. Then, semantic rules were used in the task automation module.

2.3.7 Sentiment Analysis-Based

Social network emotion content is an indispensable source of data to determine a user's points of view concerning a product or service. Affective information can be extracted with sentiment analysis techniques to infer the user's emotional context [29–31]. Hybrid recommender approaches reduce the cold start problem using data from users posted on social media [26–28, 164, 165]. Opinion mining detects and extracts affective states subjectively expressed by users in reviews, texts, and documents shared on online social networks [96, 166, 101, 167]. Preprocessing can use many techniques such as tokenization and stemming that remove irrelevant data, divide text reviews into small parts (tokens), and classify them by the highest frequency into emotional polarity (positive, negative, or neutral) [91, 168].

Some studies have used emotion analysis to predict online product tastes and musical choices of users [36, 169]. The Word2Vec and fastText techniques generated the corpus of embeddings of words to suggest smartwatches [170] and the concatenation of specific information from the corpus of words grouped by sentiments [171]. The Term Frequency - Inverse Document Frequency (TF-IDF) technique was used to weigh the review features of tourist destinations [26, 62, 80], measure the relevance of POI tags [73], and the vector representation of social data [28, 67]. [90] identified the text clauses' polarity and calculated the trend value of tourist destinations' sentiment. [133] built a hybrid user preference algorithm based on a multi-criteria technique and used an affective lexicon. Then, analyzed reviews to determine the likelihood of a new POI feeling.

RS approaches based on data mining techniques take advantage of accessing large amounts of user comments shared on social media. Researchers highlight the relevance of incorporating rich text sources to discover emotional patterns using natural language processing techniques, opinion mining, and ML [152]. [172] proposed a structured music recommender in a content analyzer component that labels an emotion from a thesaurus and a user preferences model. Also, [173] specified a framework for analyzing of negative emotions disseminated on social networks. Then, it used a corpus for community detection of affective nodes defined with a frequency of word co-occurrence. Unlike previous techniques, [174] considered a multi-tag toxic comment classification approach with the Apache Spark Framework ML library. The results demonstrated better precision in word embeddings compared to a bag of words.

2.3.8 Evaluation of Recommender

The evaluation datasets were extracted from social networks and publicly shared databases. The data has an overview of recommended items, user preferences, and historical reviews from visitors. Depending on the experimental design, the algorithms can implement cross-validation techniques. Initially, the item review dataset is split into a significant percentage to train the recommender and the other to test the model's performance. Some studies used the k-fold Cross-Validation (CV) technique [69, 26, 82, 34, 33] to verify the precision of each fold of the comparative methods. On the other hand, the Leave-One-Out Cross-Validation (LOOCV) technique [26] eliminates each user's item that ensures the impartiality of the system to recommend items that were left out of the training data.

The challenge of providing high-quality recommendations involves using evaluation methods to extract value from the prediction from a technical and experimental POI [17, 77, 102]. In general, the recommendation and affective detection models according to the performance indicators used accuracy metrics (MAE and RMSE) [78], decision support metrics calculated in the confusion matrix (precision, recovery, and F1 score) [35, 30, 91, 78, 148, 170], and metrics with recognition of range (MRR and NDCG) [29].

- Accuracy: Measures the ratio of suggestions for relevant items compared to actual user ratings. Besides, it indicates the proximity of the results concerning the right recommendations [69, 86, 28, 89, 36, 175, 81, 171, 101, 176].

- Mean Absolute Error (MAE) and Root Mean Square Error (RMSE): Compare the predicted scores' closeness to the actual ones and estimate the mean model's prediction error. In particular, RMSE assesses all rating inaccuracies, while MAE measures the average magnitude of prediction errors. Some RS investigations implemented these metrics [26, 72, 28, 34, 167, 177, 178, 133, 87, 171].

- Precision: Determines the percentage of selected items relevant to the user's recommendation [35, 29, 129, 133]. In contrast, the Mean Average Precision (MAP) presents insight into how relevant the list of recommended items [39, 126].

- Area Under the Curve (AUC): Shows the relation between True Positive rates and False Positive rates. This metric is used as the recommender performance measure with a value close to 1 [38, 82, 35].

- Mean Reciprocal Rank (MRR): Identifies the first relevant item's location in the recommendation list. The elements relevant to the user must be located in the notable positions of the generated list [29, 126].

- Normalized Discounted Cumulative Gain (NDCG): Use a gain factor to consider the position in which each suggestion was relevant [29, 89].

- Hit rate: Represents the fraction of hits of the items in the recommendation list. Besides, it contains the preferred items associated with the current context of the user [35, 30, 133, 148].

Table 2.3 compares some recommender implementations that involved emotional data in the personalization of music, movies, tourist attractions, and online products. Initially, the recommended approaches were described previously (Content-based filtering CB, Knowledge-based KB, and Collaborative-Filtering CF). The data collection section lists the user model features and the datasets that provided the recommendation process's contextual factors. Then, the algorithms of the context-aware recommender system approaches were specified (pre-filtering PRE, post-filtering POS, contextual modeling CM, based on emotion EM, and SA sentiment analysis). Finally, in sections 2.3 and 2.6, the algorithms, similarity metrics (Sim), validation (Valid), and the performance results evaluation of the proposed recommendation models were synthesized. The symbol "✓" indicate that the research complies with the approaches and types of CARS, as corresponds to the above.

Table 2.3 Implementation of RS based on emotions in various contexts

Period	Research	Approach			Data Collection			CARS					Machine Learning			
		CB	KB	CF	Item	User Model	Dataset	PRF	POS	CM	EM	SA	Algorithms	Sim	Valid	Result
2010	Wang et. al. [38]			✓	Movie	Mood and preferences.	Moviepilot: 4.544.409 ratings, 105.137 users, and 25.058 movies.				✓		UBCF, Similarity Fusion (SF), and Rating Fusion (RF) based on KNN.	PCC	With other methods.	**AUC:** 0.71 UBCF, 0.72 SF, and 0.73 RF.
2013	Alhamid et. al. [39]			✓	Music and movies	Profile, HRV, and stress status.	Last.fm: 192 users, 2509 items, 15 contexts, and 11632 assignments.			✓	✓		CARS: User CS and IBCF.	CS	With other methods.	**MAP:** 0.25 CARS, 0.2 UBCF and 0.23 ItemRank.
	Tkalcic et. al. [65, 68]	✓		✓	Image	User personality.	LDOS PerAff-1 and Cohn-Kanade.					✓	SVM emotion classifier and UBCF.	ED	-	**Mean accuracy:** 0.77 SVM and 0.72 relevant content.
2015	Pliakos and Kotropoulos [69]	✓			POI	Profile, emotion and test imagen input.	Flickr images 150000.					✓	SVM images classifier, PLSA, and geo-cluster.	HD	5-fold CV with SVM.	**MAP:** 0.82 SVM, 0.92 max-PLS, and 0.86 TF-IDF.
2016	Zheng et. al. [146, 37]			✓	Movie	Emotional state (mood, dominant emotion, and end emotion).	LDOS - CoMoDa: 113 users, 1186 items, 2094 ratings, and 12 contexts.	✓		✓	✓		Context-aware: item, user, and UI Splitting. UBCF: DCR and DCW.	User context	5-fold CV.	**RMSE Splitting:** 0.94 all contexts, 0.95 emotions only, and 0.98 no emotions.
	Wu et. al. [86]	✓			Image	Emotion, mobile behavior pattern, and social closeness.	Flickr images and 16.952 people Twitter traces.				✓		Social friendship K-means, cluster-based LBM, SGD, LR, and SVM.	User cluster	With other methods.	**Accuracy:** 0.82 LBM, 0.71 LR, and 0.68 SVM.
	Christensen et. al. [72]	✓		✓	Tours	Individual profile and group profile.	1300 tours and 800 users.	✓				✓	KNN CF rating, demographic rating, and CB rating.	PCC	With other methods.	**MAE:** 0.55 CF, 0.45 CB, and, 0.4 Hybrid.
	Zheng et. al. [26]			✓	Tourism	Profiles of user preferences and item opinion.	312.896 Tongcheng reviews and 5.722 destinations.					✓	UBCF, IBCF, and TF-IDF (scenery, cost, traffic, infrastructure, lodging, and travel sentiments).	CS	LOOCV for the items. 5-fold CV.	**MAE and RMSE:** Hybrid CF: 0.63 and 0.97 TopicMF: 0.76 and 1.04.
2017	Piazza et. al. [82]			✓	Fashion product	Profile, mood (PANAS), and emotion (SAM).	337 users,64 products, and 1081 ratings.			✓	✓		Vector representation of the user, item, and context. FM and SGD.	User, item, and context	10-fold CV.	**AUC:** FM: 0.85 PANAS, 0.73 SAM, and 0.89 only ratings.
	Logesh et. al. [35]			✓	POI	User Emotion, location, and time.	TripAdvisor and Yelp: 48.253 POI, 33.576 users, and 738.995 ratings.	✓				✓	Emotion Induced UBCF and Emotion Induced IBCF.	CS	With other methods.	**Precision:** 0.74 UBCF, 0.66 IBCF, and 0.67 Hybrid.
2018	Zheng et. al. [90]			✓	Tourism	User preferences	312.896 Tongcheng reviews and 5.722 destinations.			✓		✓	Syn-ST SVD++ model:vsentiment tendency and temporal factors dynamic.	PCC	Latent factors vector (f=50).	**MAE and RMSE:** Syn-ST SVD++: 1.04 and 0.91 SVD++: 1.17 and 0.96.
	Arampatzis and Kalamatianos [29]	✓		✓	POI	Profile and positive and negative rated.	TREC Contextual Suggestion: 1.235.844 POI.	✓					Weighted kNN and Rated Rocchio.	PCC	With other methods.	**Precision and MRR:** Rrocchio: 0.47 and 0.68. WkNN: 0.46 and 0.66.
	Contratres et. al. [28]	✓			Product	Emotion and social networks profile.	12.172 Facebook and Twitter; reviews, 163 users, and 1758 documents.					✓	TF-IDF: vector space, SVM: emotions classifier, and NB: product category classifier.	CS	-	**Accuracy:** 0.8 SVM and 0.93 NB. **RMSE:** 1.22 RS.
2019	Qian et. al. [36]			✓	Song book	Social network, rating, and reviews (sentiment).	Watercress: 346.242 musical acts and 373.648 behavior of several books.					✓	UBCF: user-friendly collection, IBCF: user behavior history items, sentiment lexicon, and SVD.	PCC	With two methods.	**F-measure:** 0.55 UBCF, 0.56 IBCF, and 0.70 emotion- aware.
	Logesh et. al. [133]			✓	POI	Demographic, social, contextual, behavioral, and categorical.	TripAdvisor and Yelp: 48.253 POI, 33.576 users, and 738.995 ratings.	✓				✓	Fuzzy C-means: user. HSS: AKNN and SPTW. AbiPRS: Fuzzy-C-means.	User cluster	With other methods.	**Precision, MAE, and Hit rate:** HSS: 0.81, 0.63, and 81%. AbiPRS: 0.77, 0.73, and 76%.

2.4 Emotion Recognition

This section describes the diverse approaches supported by technology and emotional models to identify people's feelings. Although the search for the documents spanned the last two decades, most of the documents related in this section have been published in the last five years and have the highest PDLY (see Figure 2.5). Likewise, the ER based on physiological signals (see Table 2.4) has involved the knowledge of different areas that make it possible to develop emotional detection frameworks made up of [32, 33, 1, 34]:

- The experimental design definition enables collecting objective and subjective data from the participants exposed to stimuli in a controlled environment.
- The application of preprocessing techniques are used to reduce noise and artifacts of physiological signals.
- The extraction of relevant features applying statistical and mathematical models.
- The identification of ML algorithms for the detection of the emotional states of the participants.
- The application of performance metrics to validate and evaluate the prediction results.

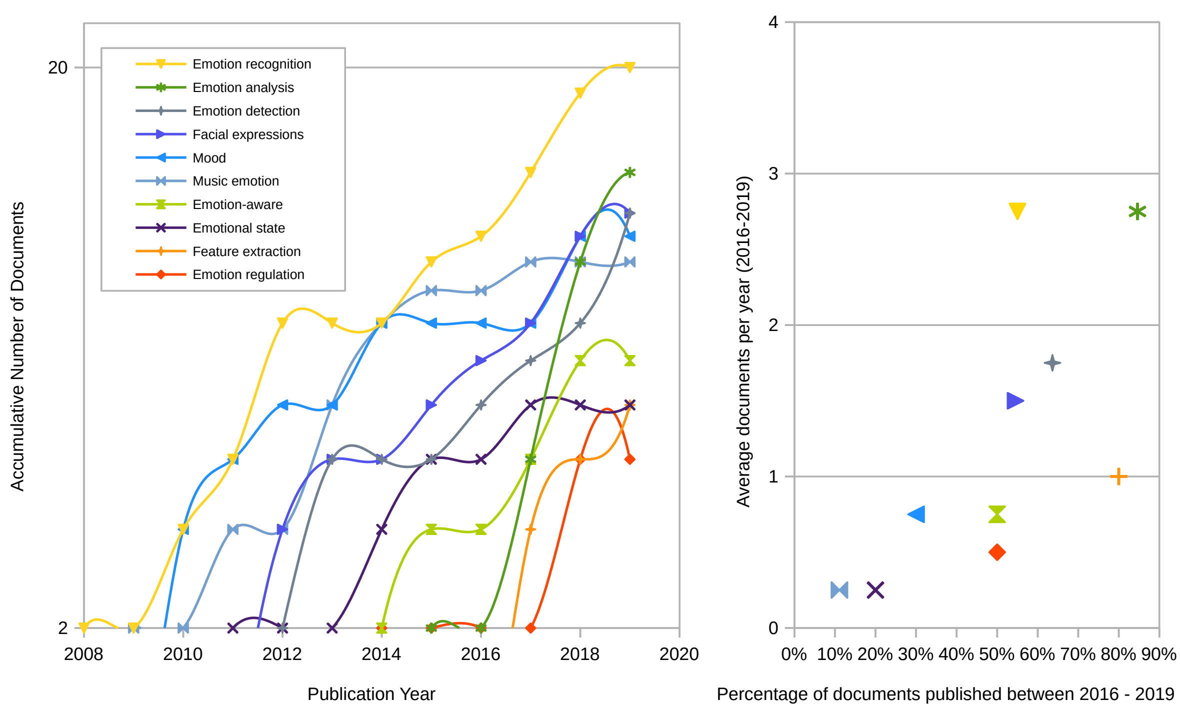


Fig. 2.5 Evolution and relevance of emotions in affective recognition.

In particular, [179] provided recommendations related to affective detection using a multimodal human-computer interaction system [180, 181]. These automated systems can recognize and interpret the emotional states of a person through physical and physiological measures. Physical conditions represent communicative signals such as facial expressions [182, 65, 183], speech detection [184, 66], body gestures [185, 66], and eye-tracking when viewing interactive content [186, 53]. Whereas the physiological measurements involve the recording of bodily variations such as the change in temperature and the increase in blood pressure [23–25]. Physiological information collected from wearable devices can be used as personalized multisensory emotional support in the user's context.

Emotion is a conscious and subjective experience associated with moods, physiological changes, and behavioral responses [187]. Affective states can be classified into a categorical model of emotions made up of basic emotions and a dimensional model of emotions represented in a coordinate map.

In the categorical model, human beings' primary emotions generate automatic and temporary reactions to stimuli in the environment, daily life events, physical activities, or personal memories [188]. Ekman [147] proposed six discrete categories of emotions (anger, disgust, fear, sadness, happiness, and surprise) associated with facial expressions. Emotions are related to physiological variations. For instance, the state of fear increases heart rate measurements and skin conductance compared to the state of disgust [187]. [150] developed the eight emotion wheel (anticipation, joy, trust, fear, surprise, sadness, disgust, and anger) and can lead to more complex emotions. Physiological measures are also vital indicators for detecting stress and emotions that a person feels [189, 190].

The dimensional model conceptualizes emotions in continuous data in the two-dimensional central affect space of arousal and valence [33]. In the arousal dimension, the Autonomic Nervous System (ANS) regulates the physiological changes of the human body, and the sympathetic nervous system responds to an emotional activation produced by a threatening or challenging situation [188]. Sympathetic activation increases electrodermal activity, respiratory and heart rates associated with "fight or flight" reactions [191]. These responses lead to the suppression of systems that are not essential for immediate survival. In contrast, the parasympathetic nervous system (PNS) keeps the body in a state of relaxation by decreasing physiological measurements' frequency. The valence dimension indicates the degree of pleasure and displeasure in response to emotional motivation [159].

Additionally, the multidimensional model incorporated arousal, valence, and dominance, the latter defining emotional experience (on a scale from low to high) [192, 175]. Essentially, Russell's circumflex model [193] has significantly influenced the studies proposed for ER (see Table 2.4). This model defines a two-dimensional circular structure that interrelates emotional states with discrete measurements on the axes of arousal (Low to High) and valence (Low to High). There is an inverse relationship between the quadrants emotions on the other side of the circle structure (HAHV quadrant: happy emotion with LALV quadrant: sad emotion and HALV quadrant: anger emotion with LAHV quadrant: calm emotion) [184]. Emotion-based recommenders adopted the multidimensional model for the statistical calculation of emotions, due to its complexity, [102] provided a mapping of the basics emotion to the multidimensional model.

2.4.1 Emotion measurements

Most of the studies utilized various stimuli to provoke the emotional states of the participants. Various methods have been described, including viewing video clips [194, 195, 185, 33, 175, 196, 177], images [68, 49, 181], listen to music [34, 30, 197, 198], read texts [53, 28], and doing physical activities [199, 200, 189]. Emotions can be assessed through subjective and objective methods.

In the first method, people record subjective measurements on Positive and Negative Affect Schedule (PANAS), and Self-Assessment Manikin (SAM) instruments [185, 82, 201]. During the process of eliciting emotional states, the user performs a self-analysis of what "he/she feels" and assigns the ratings to each of the SAM parameters (arousal, valence, or dominance) on a nine-point scale. Meanwhile, PANAS evaluates two 10-item scales (rating from 1: not at all to 5: very much) to estimate positive affect on the vertical axis and negative affect on the horizontal axis. Furthermore, valence and arousal dimensions are in a 45-degree rotation about these axes [202].

The second method employs sensors or wearable devices for the measurement of physiological signals. For instance, [34] defined a framework that recommends songs based on the variability of the heart rate of users, a music database classified into four categories based on the degree of arousal (0 extremely low HRV to 1 too high HRV) and in the degree of valence (1 very negative to 5 very positive). Similarly, [66] applied four domains of the emotional semantic space model (arousal, valence, sense of control, and ease of finding a goal) [193] to categorize user's affective states while interacted with a video game.

Alternatively, the consolidation of multimodal datasets has assisted the analysis of emotional stimuli with publicly available physiological data such as the Database for Emotion Analysis Using Physiological Signals (DEAP) [192], The International Affective Picture System (IAPS) [203], and Nencki Affective Picture System (NAPS) [204]. Specifically, DEAP [192] contains information on peripheral physiological signals, brain activity signals, levels of arousal, valence, and dominance, and the subjective rating of the emotions perceived by 32 participants during video viewing. Using DEAP, [196] proposed a music recommendation framework, and [175] developed an emotional model on users' behavior in an educational environment. Additionally, IAPS [203] and NAPS [204] have a repository of photographs with the arousal and valence scores registered in SAM.

In conclusion, these datasets have been used to design affective models for images classification [68, 49] and in the simulation of quantifiable emotional stimuli to obtain physiological data [49].

2.5 Wearable technology

There are multiple applications supported in sensors and wearable devices for the collection of user data. Mainly, this section includes the use of physiological sensors for the ER. Although the search for the documents spanned the last two decades, most of the documents related in this section have been published in the last five years and have the highest PDLY. Besides, Figure 2.6 shows the recent trend of wearable technology used in monitoring and tracking user activities.

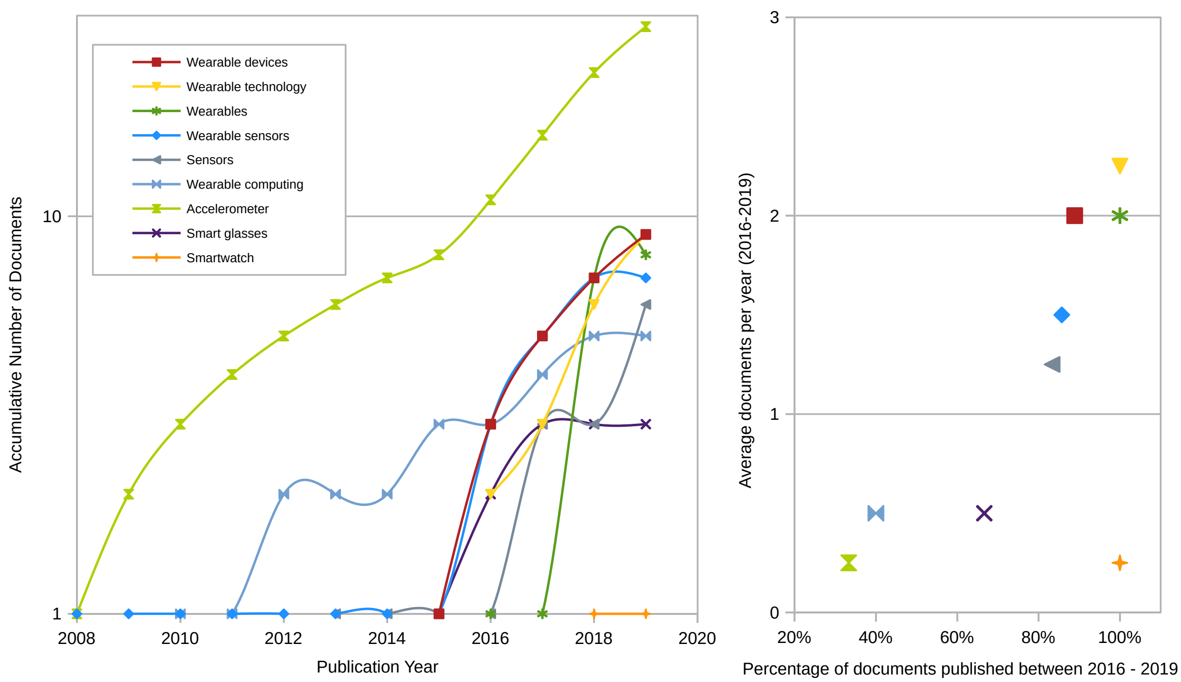


Fig. 2.6 Evolution and relevance of personalized applications using wearable devices.

The convergence of wearable devices and the Internet of Things (IoT) has had enormous potential as a source of data to provide personalized and contextualized services that operate on cloud computing, edge computing, and mobile computing platforms [48, 205, 49, 50]. Some studies [206, 197, 44, 111, 207] integrated Big Data and the multilayer modeling architectures for validating the data collected from sensors. These used edge computing and cloud computing for improving the performance and storage capacity of music and tourist attraction recommenders. Furthermore, [208] implemented a trusted IoT edge computing system for smart device recommender, and [170, 205] designed a corpus of reference phrases to recommend smartwatches to users.

Regarding the framework design using wearables, [209] proposed a generic sensor framework for personalizing medical care based on household monitoring of physiological measurements. Each sensor used a java component to store data records and manage access to the system. Also, [210] defined an IoT services framework with a semantic component for detecting falls and recognizing stress. Besides, it used a notifications component to generate statements resulting from health monitoring. On the other hand, a data model supported on wearable devices [211] identified the physiological conditions related to health in the context of tourism.

2.5.1 Devices

Wearable technology is an emerging trend that enables digital traces of people to provide contextualized and personalized information. The study of these digital life records has promoted recommenders development that positively affects people's lives [212, 213]. Such as the suggestion of activities based on timeline sequences [214, 215, 55], the sentiment analysis of registered users in health trackers' reviews [216]. Other studies also use physical activity and patient health history data to predict clinical diagnoses in healthcare [45–47, 217, 218, 210, 219, 220].

While the evolution of wearable and ubiquitous computing has enriched the construction of user models with data obtained from information systems, social networks, and the context of people's daily lives [207, 221–223]. Wearable device sensors collect individual data related to the user's behavior, physical and physiological states. Precisely, data modeling provides the knowledge of users essential in the design of personalized services oriented to favor well-being in health [224–226], the location of tourist activities [211], and travel by public transport [227].

In another way, wearable wristbands and smartphones have supported monitoring the user's activities in real-time with the data obtained by the accelerometer, proximity sensor, skin temperature (TEMP), and calorie consumption [51]. Some studies involved the identification of physical activities to improve user lifestyle [52, 55, 228]. Particularly [199, 229, 53, 230] detected the emotional activation using biosensors while users performed high-stress computing tasks and also to personalize musical preferences.

Eventually, augmented reality integration to smart glasses [231] has favored developing applications related to the personalization of real-time conversations [232], tourist activities guide [233], and specialized remote assistance [234, 235].

2.5.2 Sensors

Wearable devices incorporate various sensors to collect and process data to monitor human activities and affective detection [178, 217, 196]. Some studies have developed wearable prototypes to measure physiological signals based on emotional elicitation [199, 200], whose purpose is to improve the user experience [236, 33] and provide personalized emotional support in the educational field [23, 24].

Additionally, the users' physical activities have been monitored with inertial locomotion sensors such as the accelerometer, gyroscope, and magnetometer with mechanisms to collect data to monitor people's movement [55, 56, 237]. Also, used [51, 238, 52, 228] the data collected from inertial sensors to extract the features required in recognition of human activity.

2.5.2.1 Physiological

Affective states and physiological data are closely related to the elicitations that people perceive in daily life [191]. The following describes the detection of the emotional patterns extracted from the features of the physiological signals:

- The ANS directs the physiological responses associated with emotional ones derived from stimuli from the external environment or the human body's reactions [33].

- Physiological indicators are monitored through various sensors that measure cardiac and electrodermal activity [188, 191].

- The raw physiological data is processed by applying resampling and filters to reduce noise, detect the affective components in the signals captured within a time window [199].

- Manual or automatic feature extraction methods facilitate the detection of emotional states. Depending on the classifier's approach, statistical, frequency, and non-linear techniques can be used for the physiological segments [1, 196].
  Eventually, the analysis of the features in the time domain shows the change of affective patterns in a temporal sequence calculated by parametric methods such as the mean, minimum (min), maximum (max), variance (var), Standard Deviation

(SD) and mediate. Also, the Frequency Domain (DF) features are derived from the Fourier transform and the spectral density of power [239, 240].

The cardiac monitoring sensors capture the Heart Rate (HR) of the beats per minute and the time recording of the Intervals Between Beats (IBI) of the Heart Rate Variability (HRV) [39, 53, 241]. The emotions analysis stems from the feature extraction in time series and different rhythms of the Electrocardiogram (ECG) and Photoplethysmogram (PPG) signals. The ECG measures the heart muscle electrical activation, and the PPG measures the arterial volume through the skin [242, 229]. The time-domain parameters of the IBI established SD in RR intervals (SDNN), applying Levene's test and t-test to the data by gender [34]. Also, [39, 49] applied Root Mean Square of the Successive Differences and percentage of adjacent RR intervals with differing by more than 50 milliseconds (pNN50). It should be noted that the detection of the R peaks resulted in different features of the intervals between the peaks of the signals [199, 1, 178]. Regarding the spectral analysis of the HRV time series, [34] adopted the high-frequency band HF (0.15 - 0.4 Hz), low-frequency band LF (0.04 - 0.15 Hz), and very-low-frequency band VLF (0.003 - 0.04 Hz).

Additionally, Electrodermal Activity (EDA) or Galvanic Skin Response (GSR) signals were employed to measure the skin's electrical conductivity variations produced by the sweat glands. The features of Skin Conductance Response (SCR), Skin Conductance Level (SCL), and the detection of EDA peaks recorded the changes in the affective states of the people [200, 54, 53, 243]. While, in the EDA and HR signals [33], applied a moving window for the extraction of features, the Principal Component Analysis (PCA), and the selection of the features with a priority of weighting of the input variables (calculated with PCC, minimum redundancy maximum relevance and joint mutual information).

However, Electroencephalogram (EEG) signals calculate electrical variability in the brain using ionic current-voltage fluctuations within neurons [240]. The EEG features used operated in the delta (1-4 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (13-29 Hz), and gamma (30-47 Hz) frequency bands. The last three bands seem to differentiate the affective conditions better [32, 244, 33]. The original signals were pre-processed with downsampled techniques, and the bandpass filters extracted the artifacts and noise from the EEG [201]. Statistical methods and wavelet transformation [175, 240] supported the feature extraction process. Some studies found a strong relationship between the EEG and the musical categorization by emotions [244, 175], emotional states communication transmitted by movements, and people's sign language [185].

Table 2.4 consolidates some works on non-intrusive sensors for emotion recognition of participants (pt) based on physiological signals and EEG features. The experimental designs were focused on evaluating the performance of emotional estimators according to the measurement of emotions (Arousal A and Valence V), the stimuli for the participants' affective elicitation, subject (Sb), and the physiological responses collected with the sensors. Affective detection implies the adaptation of computational processes that have enabled the interpretation of emotions related to users within a specific application context [181]. EDA and HR signals displayed better accuracy to predict arousal [33], while EEG signals were more effective with valence. Also, [1] presented representative results to predict arousal with ECG signals and detect valence with GSR signals. The comparison of the classification algorithms [185, 34, 175, 196] allowed to validate the emotional detection performance.

Table 2.4 Emotion recognition based on data wearable devices.

Period	Research	Experiment data				Physiologic signals			Classifiers	
		Emotion	**Measuring**	**Elicitation**	**Sb**	**Device**	**Sensor**	**Features**	**Algorithm**	**Result**
2016	Matsubara et al. [53]	Emotional arousal.	A: 10 points scale.	Comic reading.	5	E4 Wristband and RED250	EDA, BVP, HR, TEMP, and pupil diameter.	SCL, SCR, and HR.	SVM	**Accuracy**: 0.58 A.
2017	Hassib et al. [185]	Amused, sad, angry, and neutral.	Emotions: Likert scale. AV: SAM 9 point scale.	FilmStim movie clips database.	10	Emotiv EPOC	EEG	Min, max, mean, median, and SD.	RF	**Accuracy**: 0.72 AV.
	Chiu and Ko [34]	Sleep, boredom, anxiety, and panic.	AV point scale.	15 song.	30	Gear live smartwatch	HRV	SDNN, pNN50, ULF, VLF, LF, and HF.	DT and LR. 5-fold CV.	**MAE**: DT: 0.82 A and 0.26 V. LR: 1.77 A and 0.32 V.
2018	Dabas et al. [175]	VA and dominance.	AV: SAM 9 point scale.	40 videos.	32	DEAP Dataset	EEG	Wavelet function and mean.	NB and SVM	**Accuracy**: 0.78 NB and 0.58 SVM of emotional states eight.
	Ayata et al. [196]	Four quadrants in VA dimension.	AV: SAM 9 point scale.	40 videos.	32	DEAP Dataset	GSR and PPG	Mean, min, max, var, SD, median, skewness, kurtosis, moment, 1 and 2 degree difference.	RF, SVM, and KNN. 10-fold CV.	**Accuracy**: RF: 0.72 A and 0.71 V.
	Mahmud et al. [199]	Stress	Emotion survey.	Exercise (cycling task).	43	SensoRing	EDA, HR, TEMP, and ACC	R-peaks, SRC, SCL. Mean RR and STD RR.	Signal processing.	**Correlation**: 0.9 Measured data from SensoRing with BITalino.
2019	Santamaria-Granados et al. [1]	Arousal and valence: Low and High.	AV: SAM 9 point scale.	16 short videos.	40	AMIGOS Dataset	ECG and GSR	R peaks and SCR peaks.	CNN	**Accuracy**: 0.76 A and V 0.73 in ECG and GSR signals.
2020	Dordevic et al. [33]	Arousal and valence.	V: SAM 9 point scale.	3D video contents.	18	EDA and ECG Electrodes Emotiv EPOC	HR, EDA, and EEG	HR: median, SD, and PCA. EDA: median, SD, and SCR. EEG: mean, median, and SD.	MLP and GRNN. 9-fold CV.	**RMSE**: MLP: 0.05 A and 0.024 V. GRNN: 0.12 A and 0.14 V. In HR and EDA signals.

2.6 Machine Learning

This section outlines the ML techniques and algorithms used to implement RS (see Table 2.3) and ER (see Table 2.4). Although the search for the documents spanned the last two decades, most of the documents associated in this section have been published in the last five years and have the highest PDLY. Figure 2.7 highlights the implementation of deep learning approaches for sentiment analysis and ER as an emerging issue.

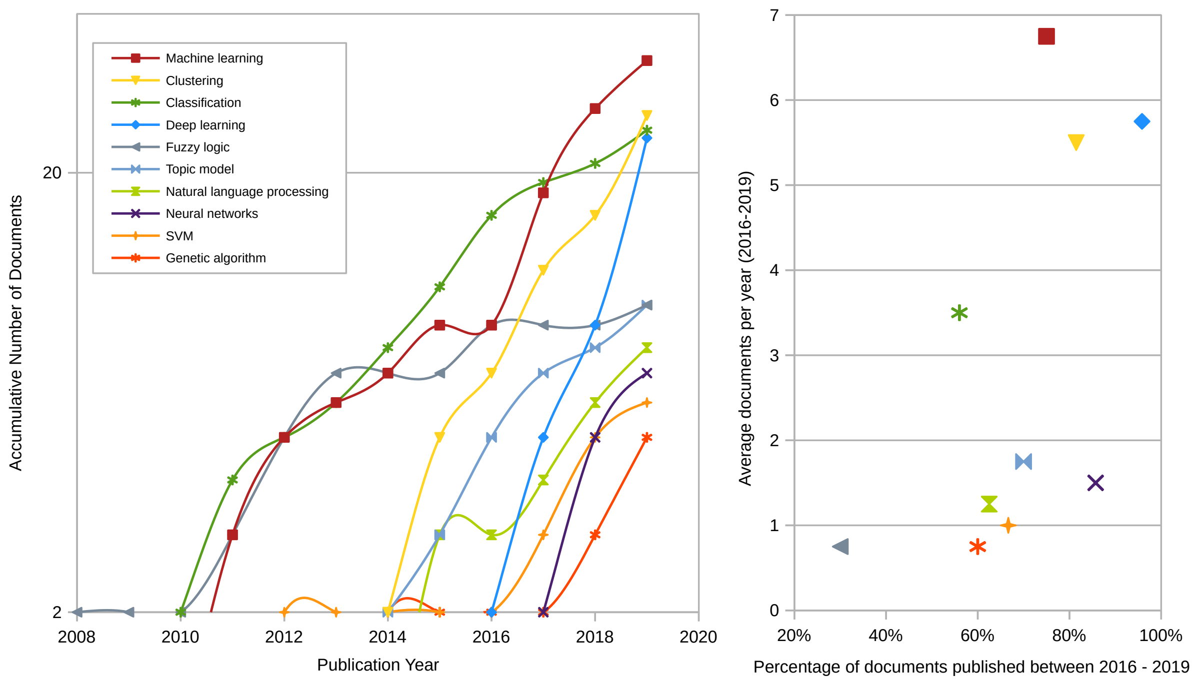


Fig. 2.7 The tends of machine learning approaches in the implementation of RS and ER.

2.6.1 Classification

In Section 2.3, research related to RS approaches to tourism is defined. The recommendation models used ML algorithms to validate and compare the performance of the classifiers of emotions, tourist attractions, and multimedia content (see Table 2.3). Some studies used KNN and SVM algorithms for POI classification [29, 133, 72] and image classification [65, 68, 86]. Moreover, [245] proposed an approach based on a decision tree that uses the users' predictions and historical interests to generate movie recommendations. Other studies used Linear Regression (LR) and neuronal network algorithms to classification trip profiles [64] and road trips [112].

The integration of wearable technology with ML approaches is being adopted to identify patterns that support personalized clinical diagnoses for health care systems [242] through kNN algorithms [217] and DT [246, 247, 218]. The users' lifestyle was supported in physical activity recommenders based on SVM algorithms, RF [248] [249, 51], kNN [237], and LR [52]. Some affective recognition studies based on data collected from sensors used decision rule classifiers, and DT required in the music recommendation [34, 200, 197]. In particular, the analysis of physiological signals [192], with the techniques of Naïve Bayes (NB), RF, and SVM, was applied in emotional detection [175, 196, 185, 53, 89].

On the other hand, a multimodal approach for collecting affective responses (facial movements, speech, and interactive activities in a video game) demonstrated greater efficiency with the use of multiple sensors in SVM and DT emotion classifiers [66]. The direct measurement of physiological signals from visual stimuli made it possible to design an estimator of emotional state based on the Artificial Neural Network (ANN) of Multilayer Perceptron (MLP) and Generalized Regression Neural Network (GRNN) [33]. Whereas [178] extracted the features of the peaks of the physiological signals (ECG and PPG), estimating the blood pressure with the ANN, SVM, and Least Absolute Shrinkage and Selection Operator (LASSO) regression models. Regarding affective recognition in the video analysis [177] used the SVM algorithm to classify the input hybrid features and the linear regression in the arousal detection.

2.6.2 Clustering

RS approaches have implemented clustering algorithms as an alternative to overcome data scarcity problems and reduce the response time of predictions [74]. The grouping of users based on the features extracted from the datasets of social networks has made it possible to detect the relationships between user interests, affective states, and the similarity of POI. Just like, the k-means and k-modes methods customized the grouping of users with standard profiles and common interests [83, 86, 129]. Besides, the fuzzy c-means algorithm used demographic and preference data to construct the behavior profile of user activities [133]. The hierarchical grouping algorithm has grouped the tourist destinations geotagged images based on Haversine Distance (HD) [69]. Another travel recommender [112] presented a tourist clustering based on preferred attractions, travel expenses, route features, ratings, and tourist sites reviews. To do this, it defined a neural network model to simplify user parameters on a two-dimensional map.

2.6.3 Deep learning

Recent studies used Deep Learning Networks (DLN) to construct recommendation models for automatic notifications, content classification, and pattern recognition [84, 167, 87].

DLN differ from ANN by the interconnection of multiple layers that handle various weights and trigger functions between the inputs and outputs of hidden layers. The deep architecture allows forward or backward propagation with adjustment of weights during feature learning and detection. Loss functions are used in classification or regression tasks to determine the difference between the labels predicted by the DLN and the actual labels in the dataset. Unlike ML, DLN models use unstructured data, reduce computational costs, and the performance scale is directly proportional to the data amount [250]. Considering the cold start problem and the scarcity of CF algorithms information, [95] developed a recommender based on a DLN and an MF of latent features to manage software projects.

Convolutional Neural Networks (CNN) are DLN used to identify patterns in input data segments that operate in one, two, or three dimensions. Unlike classical ML approaches, CNN uses filters to automatically extract features, reduce complexity, and overfit with pooling layers [198, 129]. The specific class classification process is supported in Fully Connected Layers (FCL). Particularly [238] managed CNN to extract features from geo-referenced images used to recognize human activities. Also, [1] proposed combining CNN and FCL models to extract affective features from physiological signals (ECG and GSR), surpassing traditional techniques precision. These models (CNN and FCL) extracted emotional features from multimedia text [168] and discriminatory features from optical flow images [177]. A hybrid CNN model [171] applied one-hot vectors in the prediction of sentiment polarity.

The Long Short-Term Memory (LSTM) approach is a version of the Recurrent Neural Network (RNN) that overcomes gradients' problems by remembering long-term sequential data, with its structure that includes inputs, outputs, and gates of forgetfulness regulated with the sigmoid function [250]. Specifically, [176] integrated the 3DCNN and LSTM algorithms to extract Spatio-temporal features in gesture detection. Some affective semantic analysis studies used the CNN and LSTM RNN algorithms in the classification of emotions from movie comments [31] and the detection of stress in psychological phrases [101]. Additionally, [67] proposed the CNN and LSTM algorithms to extract the contextual features of tourist attractions sentences. [170] applied the CNN and RNN techniques to predict the phrases related to the users' perception and intention to recommend smart wearable devices.

Especially, the integration of ML algorithms and chatbots has enormous potential for recommending tourist destinations. [251] designed a POI recommendation architecture based on decision trees to establish the profile of the user of a social network with the history of visits. Besides, [252] proposed an LSTM RNN model to detect the users' interests based on the history of preferences. The query chatbot provided travel options based on the detected profile.

Most studies showed better performance in emotion-sensitive RS when using DLN algorithms [171, 1, 31]. For instance, [162] customized an emotion-sensitive recommender using a DCNN to classify songs in a dataset based on user profile and history of preferences. It defined latent features and musical relationships with the weighted feature extraction algorithm based on an MF.

2.7 Clusters Mapping

This section analyzes the co-occurrence mapping to identify the themes related to RS and tourism transversal axes. For this purpose, the dataset preprocessed with SientoPy (which unifies Scopus and WoS) was used to generate a network map with the VOSViewer tool [253]. Initially, the author keyword co-occurrence map was created by setting up a thesaurus file to combine standard terms of technologies and algorithms to implement recommenders based on emotions. Also, 35 words unrelated to the theme described were filtered. The network map formed five clusters from the selection of 52 keywords, which were merged based on the co-occurrence links values. The merged network represents the thematics evolution over time (2000 to 2019), showing the most meaningful traces of the related research documents (see figure 2.8). Each point represents a node in the network, and the lines connecting the nodes are co-occurrence links. The five clusters show homogeneity with the thematic categories considered in the preceding sections.

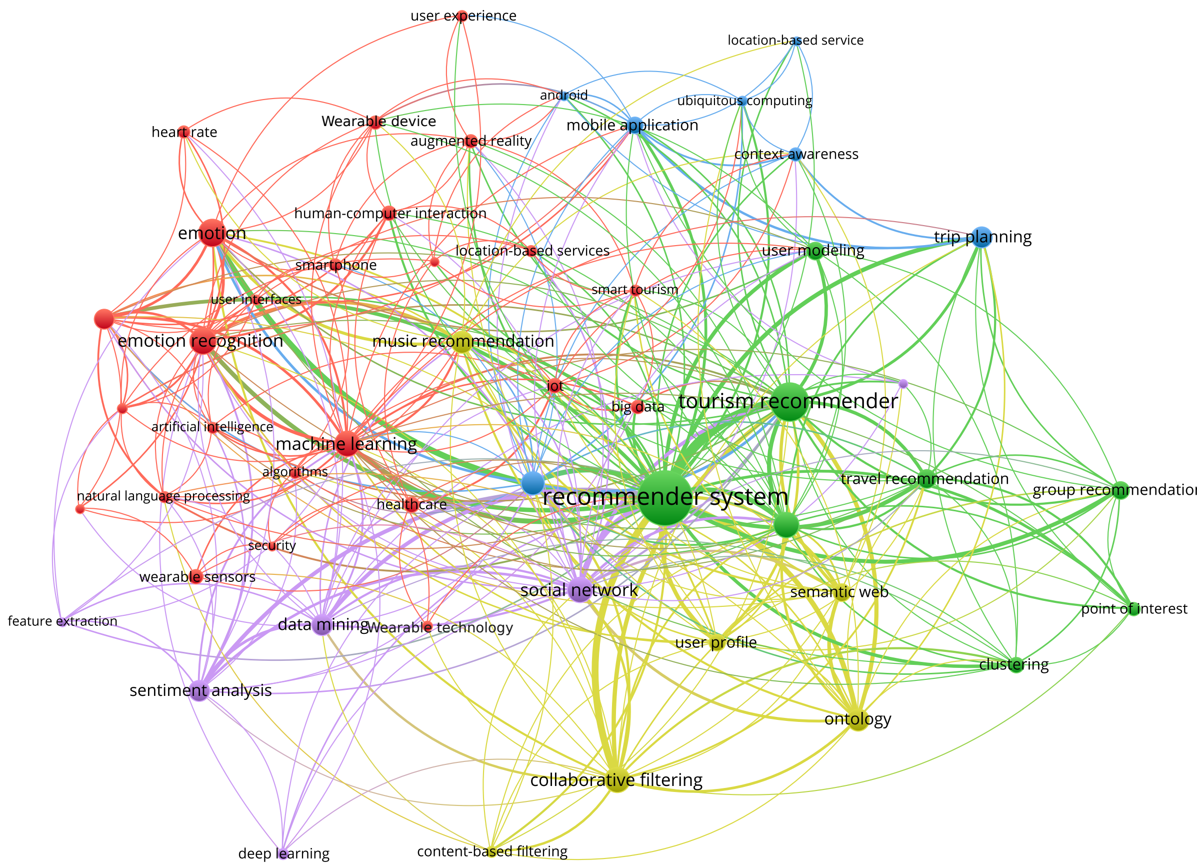


Fig. 2.8 It is a co-occurrence network mapping of author keywords related to the RS, tourism, ER, and ML. Also, it displays five color clusters made up of nodes identified by labels. The grouping of relevant documents defines the nodes' size and the lines between the nodes.

- The first red cluster focuses on implementing machine learning algorithms to recognize emotions based on physiological data from wearable devices [53, 34, 196, 199, 1, 33] and affective data of social networks [38, 65, 68, 37, 82]. The emerging IoT topic encourages collecting large datasets analyzed in big data architectures that support smart tourism applications [44, 111, 207] and health care recommenders [218, 47, 46, 210, 220].

- The second green cluster considers the implementation of on-line product recommender systems [38, 39, 65, 68, 37, 86, 82, 28, 36], tourism recommenders [72, 90, 26, 80, 130–132, 67], and user modeling using clustering algorithms [83, 129, 133]. The pop-up theme is oriented to the recommendation of interest points based on data from social networks [69, 35, 29, 133, 116–118].

- The third purple cluster emphasizes sentiment analysis using data mining algorithms to process and extract contextual features in social network datasets [96, 166, 101, 167, 62]. The emerging topic of deep learning applied to the recommendation based on emotions [168, 171, 1, 31, 101] is highlighted.

- The fourth yellow cluster establishes the relationship between collaborative filtering and semantic web techniques in the definition of user-profiles and the construction of the recommender systems ontologies [99, 100, 149, 101, 26, 73]. An emerging topic is content-based filtering, which integrates the knowledge base into the recommendation process [69–71, 64, 72, 73].

- The fifth blue cluster is oriented to implementing recommenders and context-sensitive mobile applications supported in the ubiquitous computing infrastructure [138–140, 106, 142–144, 110, 145]. It is worth highlighting the importance of the user's context in the planning of tourist trips [127–129, 63, 78, 123, 122].

2.8 Discussion

This chapter provides an overview of the background, algorithmic approaches, data models, and emerging technologies involved in sentiment analysis and emotional recognition. These guidelines for the design of tourist recommenders with affective contextual information are aimed at the academic and scientific community. The challenges identified are described below.

First, challenging the emotional context leads to improved user experience and accuracy of travel recommenders. Initially, Section 2.3 analyzes the dominance of RS architecture approaches, platforms, and components [35, 36, 69, 26]. Table 2.3 chronologically summarizes some studies on CARS with data sources, user models, algorithms, similarity metrics, and performance evaluation. It shows that most of the works used sentiment analysis techniques to extract the emotional context of the users' comments posted on social networks. However, the collection of physiological data with wearable devices for emotional recognition in tourism has been little explored. Also, rural tourism emerges as an area of interest in planning personalized trips to manage geographical, emotional, and environmental factors. Additionally, both wearable, IoT, and Big Data technologies are emerging in smart tourism to implement recommenders of positive and satisfactory tourism experiences [110, 111, 44, 111].

Second, the emotion recognition of section 2.4 describes the framework for the analysis of physiological signals, affective detection, and validation of the classifier's results. The relationship between physiological changes and emotional models was evidenced, emphasizing Russell's circumflex [193]. In particular, the measurement of the dimensions of arousal and valence in the face of short-term stimulus elicitation in a controlled laboratory environment. Additionally, Table 2.4 chronologically summarizes some studies with the experimental design of the collection of affective data, extraction of features from physiological signals, and prediction algorithms. As a result, the detection of arousal achieved similar or better accuracy than valence detection [33, 1, 196]. However, in the tourism domain, emotions are considered a relevant contextual factor in recommendation satisfaction. For this reason, there is the challenge of proposing well-defined experimental designs to obtain physiological data and measurements of emotions in everyday life.

Third, wearable technology and IoT environments have supported the infrastructure for data collection to personalize healthcare services [47, 46], music recommendations [206, 197], and suggestions of e-commerce products [208, 170]. In particular, section 2.5 related recent studies of emotion recognition based on data from physiological sensors (see table 2.4), recognition of human activity using inertial sensors [51, 238], and augmented reality applications supported on Smart devices Glasses [233, 234]. Besides, the investigations evidenced the correlation between emotions and data from the physiological sensors of Empatica E4 wristband devices (EDA and HR) [53], Gear live smartwatch [34] (HRV) and electrodes (ECG, GSR, and EDA) [1, 33]. Hence, in the tourism domain, wearable sensors' integration could improve the recommenders' prediction by defining a user model with various contextual factors.

Fourth, the ML approaches depicted in section 2.3 and section 2.6 were organized into classification, clustering, and Deep Learning Network (DLN) algorithms. First, the classification approaches in most of the studies described in Table 2.4 used classical ML algorithms based on feature extraction engineering (KNN, SVM, and RF). Besides, in the personalization of clinical diagnoses [217, 246], physical activities [248, 237], and multimodal approaches for affective prediction (MLP, ANN, and GRNN) [66, 178]. Table 2.3 also implemented classic ML algorithms to classify candidate films, images, travel profiles, and POI. Second, the clustering algorithms (k-means, k-modes, and Fuzzy-C-means) made it possible to design the users' preference models (see table 2.3). Third, unlike previous algorithms, DLNs lower computational costs and require large datasets. Recent studies (see table 2.3 and table 2.4) used CNN to extract affective features from physiological data [1], detect human activities in images [238], and analyze feelings in comments of tourist attractions [171, 101]. Consequently, the challenge arises to propose deep learning approaches to extract emotional pattern features from online social media datasets and multimodal physiological signals to improve the quality of tourist recommendation services.

Finally, future trends in recommendation platforms are oriented towards collaborative environments to support accessible tourism [254, 255] and POI recommenders based on the contextual data gathering of the user's lifelog [212, 213]. Besides, developers could propose real-time recommendation approaches that are more efficient and solve data scarcity problems using cloud computing, edge computing, big data, and IoT platforms [48, 49, 208, 256, 112].

2.9 Conclusion

This chapter presented a review of the literature related to emotion-sensitive RS in the tourism domain. The analysis carried out showed several heterogeneous data sources drawn from wearable devices, IoT, and social networks. The user profiles' definition contains explicit and implicit information collected from daily life records about emotional states, physiological signals measurements, geographical location, and tourist attractions reviews. This definition could be applied to behavior models and recommendations according to the user's preferences, based on recognizing emotions.

The scientometric review focused on analyzing technological research of the user emotion detection in the tourist recommenders framework. The architectures proposed in the RS investigations that develop efficient approaches to processing, data storage, and access to services in mobile or cloud computing environments were considered. In tourism, the need to develop personalized and innovative applications to help users suggest travel experiences is highlighted. User emotions are closely related to positive satisfaction with a recommendation. Therefore, the research challenge arises from integrating data from IoT sensors, wearable devices, smartphones (heart rate, EDA, and affective states) into the recommendation process.

Based on the analysis of the research works listed in Table 2.3, the following findings should be taken into account in the design of emotion-aware RS:

- User models are the starting point of research approaches and, based on contextual data, recommendation services are defined in various application domains. User models have evolved by delving into daily life data obtained from ubiquitous devices. Although in medical tourism, physiological measures have already been used for health care. The user models have not yet been enriched with the data recorded from the wearable devices intended to design personalized services according to the tourist's affective state.

- The tourist information sources come mainly from user reviews on social networks and openly available datasets. There is a limitation in using other sources to discover contextual patterns that enrich the data models. Furthermore, the restriction of heterogeneous information access on tourist behavior directly impacts the performance of the ML models.

- Approaches based on user emotions increased the predictive capacity of recommendation models by fusing contextual features and sentiment analysis. Also, the emotions polarity, POI ratings, and contextual factors infer behavior from user preferences. In most researches, affective states were taken into account for the recommendation process's implicit feedback.

Table 2.4 consolidates some research of emotion recognition with data from wearable devices useful in designing RS frameworks in the tourism domain. Affective sensing systems extract emotional patterns from non-intrusive sensor signals associated with heart activity, electrodermal activity, and brain variability. The research opportunity arises to deepen the relationship of affective with physiological changes and emotional models. The experiments carried out with physiological datasets reported better results in predicting emotions with deep learning algorithms.

There are research gaps focused on developing secure tourism recommenders with models for detecting danger sources to mitigate tourists' risks in the destination. Besides, the implementation of interest detection algorithms for travel planning, using chatbot applications and deep learning techniques. The recommenders require algorithms to determine affective similarity and detect the emotions resulting from tourist preferences and the construction of user-profiles based multimodal approaches that allow the extraction of emotional features from speech analysis, physiological measurements, and facial recognition.

Chapter 3

Emotion Detection Model Based on Physiological Signals

Recommender systems have been based on context and content, and now the technological challenge of making personalized recommendations based on the user's emotional state arises through physiological signals acquired from devices or sensors. This chapter outlines the deep learning approach using a Deep Convolutional Neural Network (DCNN) on a dataset of physiological signals (electrocardiogram and galvanic skin response), in this case, the AMIGOS dataset [257]. The emotion detection is done by correlating these physiological signals with the data of arousal and valence of this dataset to classify a person's affective state. Besides, an application for emotion recognition based on shallow machine learning algorithms is proposed to extract the features of physiological signals in the domain of time, frequency, and non-linear. This application uses a CNN for the automatic feature extraction of the physiological signals, and through fully connected network layers, the emotion prediction is made. The experimental results on the AMIGOS dataset show that the method proposed in this part achieves a better precision of the emotional states' classification compared to the initially gathered by the authors of this dataset.

For the above, we used CNN networks [258] in comparison with traditional machine learning algorithms, which are used as a framework for emotions detection (See Figure 3.1). The experimental tests for the classification of the emotional dimensions of arousal and valence were made with the AMIGOS dataset [257]. Then, in the preprocessing stage, we transformed the physiological signals with the QRS detection methods [259] for obtaining the RR intervals of the ECG. Likewise, the temporal series of the Skin Conductance Response (SCR) peaks of the GSR signals [260] were identified. A determining factor in the effectiveness of the emotion prediction is defined in the extraction and correlation of the features of the physiological signals ECG and GSR.

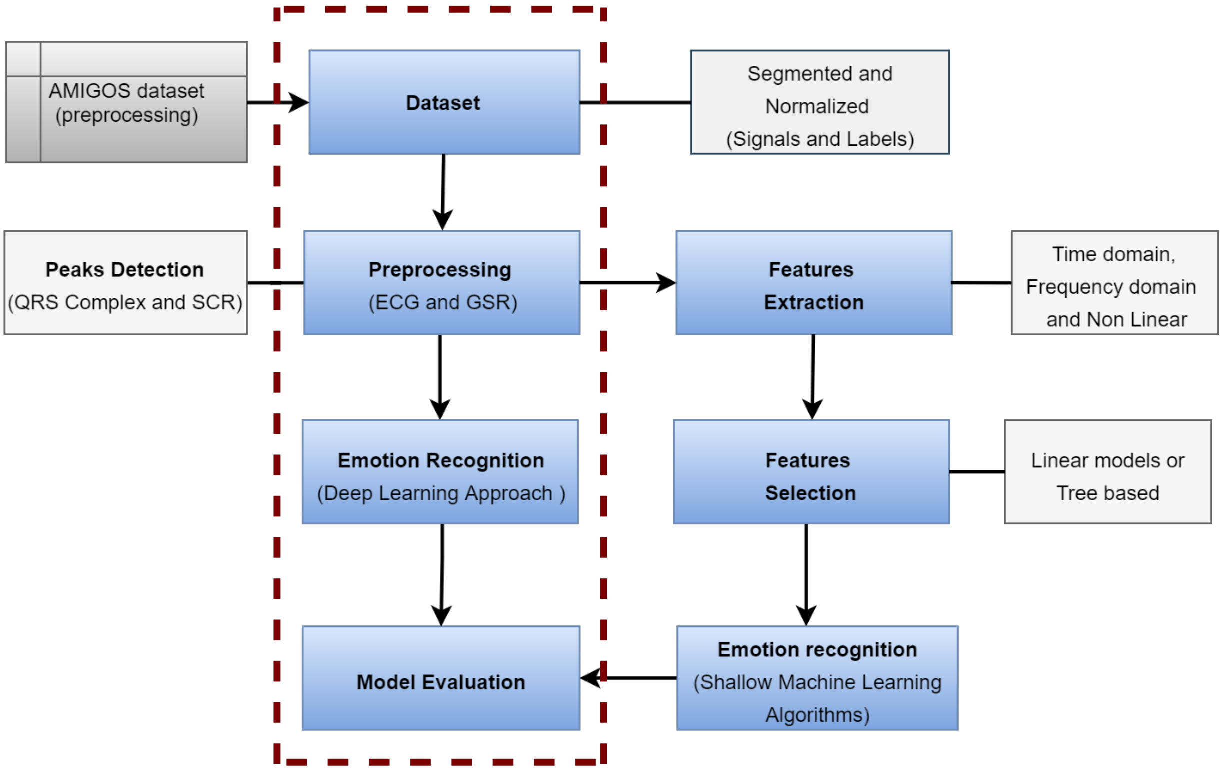


Fig. 3.1 Emotion recognition based on physiological signals with deep learning and shallow machine learning algorithms.

3.1 Related Work

This section presents researches on datasets for the multimodal emotions recognition and the affective states detection through physiological responses.

3.1.1 Multimodal Dataset

Affective states are subjective experiences classified in valence and arousal focuses [261]. The stimulus of valence focus is associated with pleasurable or unpleasant aspects, in contrast with arousal focus that induces the activation or deactivation of an emotion. Similarly, both focuses reflect the degree to which a person incorporates emotions into their conscious affective experience [262]. Some databases correlate the affective states with physiological signals [192, 263, 257], which are the result of emotions self-reported by people. The emotional categories are established in a circular structural model that contains basic emotions (for instance, excited, happy, relaxed, sad, and annoyed) to define the arousal and valence dimensions [264, 265].

Emotion is the degree to which a person reacts to changes in the context as a response to the elicitation that manifests itself in their affective states [266]. People use the senses to express the emotion experienced through gestures, speech, or physiological responses. The correlation between emotions and physiological data determines the multimodal affect recognition. The contents of images [267], movie clips [268] and music videos [192] have been used to induce emotions that users appraisal with explicit measurements [269], in order to verify the arousal and valence levels. On the other hand, emotions elicited by multimedia content are implicitly recognized using physiological and brain signals, enabling the consolidation of a multimodal affective dataset that compares the affective response of people [270].

Precisely, the dataset ASCERTAIN [271] induced the emotions through 36 movie clips that had a duration of 58 to 128 seconds, with the registration of physiological signals (ECG and GSR), EEG, and activity facial of 58 participants. AMIGOS dataset [257] detected the mood, affect, and personality of 40 participants with the registration of their EEG, ECG, and GSR signals, as a result of the stimulus caused during the viewing of short and long videos.

Abadi et al. [272] for the affect detection analyzed the physiological response of the ECG, Electrooculogram (EOG), and trapezius-Electromyogram (EMG), and contrasts the brain signals (EEG and Magnetoencephalogram) of 30 participants who watched 36 movie clips from 80 seconds and 40 segments of one-minute music videos that are part of the DEAP dataset [192]. In the emotional state's recognition of 32 participants, DEAP includes physiological signals (GSR, BVP, SKT, EOG, and EMG) and EEG. Similarly, the multimodal database MAHNOB-HCI [273] contains physiological signals (ECG, GSR, SKT, and Respiration), eye gaze, and EEG from 27 participants, who evaluated the emotion through various stimuli (20 videos, 14 short videos, and 28 images).

Both DEAP and MANNOB-HCI demonstrated better EEG effectiveness in predicting arousal and physiological signals obtained a better outcome with valence. AMIGOS had the same behavior with EEG signals, but unlike [192, 273], it obtained a better f1-score outcome with arousal. The physiological features in DECAF had a better arousal recognition in the movie clips and a better valence outcome in the music clips. In ASCERTAIN, the multimodal results (ECG and GSR) had a better performance than the EEG.

The works related to ER established the experimentation of the users with diverse stimuli and the influence of the emotions in their physiological behaviors. Therefore, a need arose to identify emotional patterns in the physiological features that improve the states' emotional detection. Moreover, section 3.2 describes the experiment with short videos of the AMIGOS affective dataset used for the ER with the ML approaches proposed in this survey.

3.1.2 Emotional States Detection

The publications related to the ER from physiological data aim to construct reliable models supported by techniques and ML algorithms to discover patterns of the emotional states that are hidden in the physiological signals. Various methodologies were explored for the data preprocessing, the extraction, and selection of physiological features, as stages prior to the emotion classification.

Some studies for the ER have implemented supervised classification approaches [274] such as k-Nearest Neighbor (k-NN) [275, 276], and Support Vector Machine (SVM) [263, 277]. The researchers defined keywords to validate the user's emotional responses through the valence and excitation model. The physiological signals are processed by sliding window technique [278], and the process of reducing the dimensionality of the features is based on the Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) techniques [277].

On the other hand, the Deep Learning approach applies non-linear transformations to physiological signals for the features detection of human emotional behavior. In this context, CNN [279] techniques have been used for the automatic extraction of SCR and BVP features, and 70 to 75% accuracy results have been obtained in the prediction of emotion (relaxation, anxiety, excitement, and fun). Other investigations validated the performance of affection models with deep learning using the multimodal DEAP database [280, 281]. They adopted a multiple-fusion-layer-based ensemble classifier of stacked autoencoder (MESAE) framework to extract the physiological features merged into an SAE network. The accuracy results in arousal and valence were 0.83 and 0.84, respectively.

Regarding semi-supervised learning methodologies, SAE was integrated with Deep Belief Network (DBN) using a Bayesian inference classification based decision fusion method [282], results of arousal were obtained in 73.1% and valence in 78.8%. Li et al. [283] defined a hybrid model composed of a CNN and a Recurrent Neural Network (RNN). As a requirement for the sequential processing in the CNN, the features were extracted, and the prediction was made in the Long Short-Term Memory (LSTM) unit of the RNN. This model obtained an accuracy of 74.1% for arousal and 72.1% for valence. The models based on CCN and DNN [284] showed better results in the affective classification when using the image domain of the EEG signals [285, 240].

The related works deal with the trend of deep learning for the ER related to heart disease, mental disorder, and stress. However, to validate the affective models, there is a limitation in the access to small physiological datasets [286], or there is a problem in obtaining correct data [258]. Therefore, it is necessary to publish repositories of physiological datasets to test the classification models used in the personalization of the services.

3.2 AMIGOS Dataset

The validation of the emotions classifier is done with A dataset for Mood, personality, and affect research on Individuals and GrOupS (AMIGOS) [257]. This dataset is the result of two experiments related to the multimodal study of emotional responses. In the first, 40 participants watched 16 short videos (duration < 250 seconds), in the second, 17 people individually and five groups of four participants watched four long videos (duration > 14 minutes). In both experiments, neurophysiological signals were captured from the subjects during the elicitation of emotion [268].

Electroencephalogram (EEG) signals were recorded using the Emotiv EPOC Neuroheadset containing 14 electrodes for AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 channels [240]. The physiological signals were recorded with the ECG Shimmer 2R5 platform from three electrodes for the Electrocardiogram (ECG right and ECG left channels) and two electrodes for the Galvanic Response of the Skin (GSR channel). The physiological data were preprocessed with a sampling frequency of 128 Hz.

The emotional levels of the participants were reported in a self-assessment (arousal, valence, dominance, liking, familiarity, and seven basic emotions) and an external annotation (arousal and valence). The five dimensions are measured on a scale of 1(low) to 9 (high) and, the basic emotions (neutral, disgust, happiness, surprise, anger, fear, and sadness) are binary values. Specifically, this study focuses on the experiment with the 16 short videos because a long video is more likely to elicit diverse emotional states according to the scenes presented. The emotion appraisal is determined by the changes that the subject can experience in the context. The experienced emotions can change through a process of regulating emotion, which determines the effects on human behavior [287].

The classification of the 16 short videos by quadrants of valence and arousal (high and low) was performed by [257] according to the elicitation of the emotion, for each participant, 94 clips were recorded according to the duration of each video (see Table 3.1). The first 20 seconds of each clip included five seconds from the beginning of the stimuli, then were generated non-overlapping intermediate segments of 20 seconds, excepting for the final clip.

In the current study, the emotional classification is defined as a low and high subjective scale for the valence and arousal dimensions. Figure 3.2 shows the distribution of the valence and arousal means of the self-assessing participants during the experiment; $40 * 16 = 640$

Table 3.1 Classification of the 16 short videos with the physiological signals instances that were recorded during the presentation of the stimuli of each subject [257].

Video	Instances	Duration	Quadrant	Film	Clips
10	12225	96	LAHV	August Rush	6
13	7229	57	LAHV	Love Actually	4
138	15610	122	LALV	The Thin Red Line	7
18	10575	83	LAHV	House of Flying Daggers	5
19	16106	126	LALV	Exorcist	8
20	8335	65	LALV	My girl	5
23	14265	112	LALV	My Bodyguard	7
30	9717	76	HALV	Silent Hill	5
31	19886	155	HALV	Prestige	9
34	8417	66	HALV	Pink Flamingos	5
36	8698	68	HALV	Black Swan	5
4	11621	91	HAHV	Airplane	6
5	14347	112	HAHV	When Harry Met Sally	7
58	8181	64	LAHV	Mr Beans Holiday	4
80	13047	102	HAHV	Love Actually	6
9	9630	75	HAHV	Hot Shots	5

instances are available. However, it is observed that videos 20 and 23 tend a neutral value of arousal. That is, the intensity of the emotion is not so marked. Therefore, using the k-means method, we defined the four clusters with the thresholds for the labels of arousal and valence [280]. Besides, Figure 3.3 depicts the clusters with a threshold of (5, 5) for the two or four classes of low or high emotion and were obtained with the K-means clustering method [274].

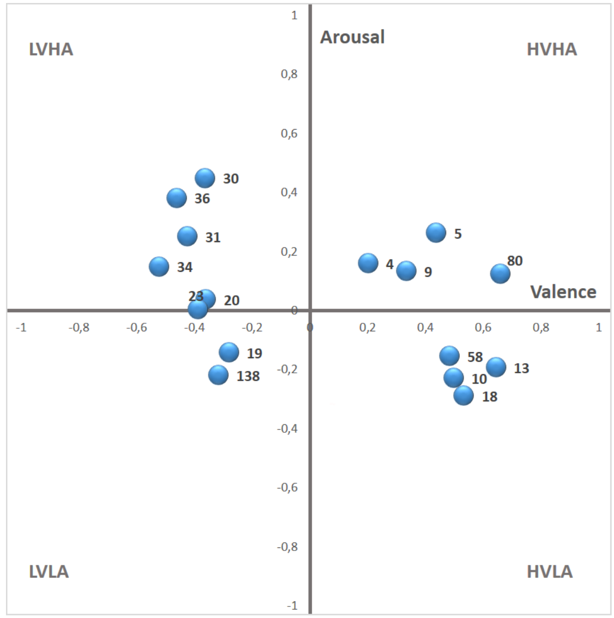


Fig. 3.2 Distribution of mean ratings of valence and arousal of self-assessment of the 16 short videos. Scale from -1 to 1.

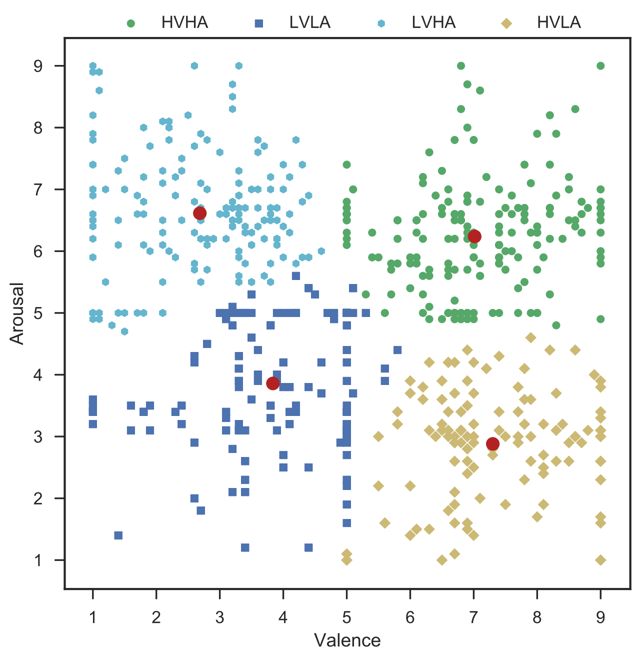


Fig. 3.3 Clustering of valence and arousal of self-assessment of the short videos. Scale from 1 to 9.

3.3 Proposed Method

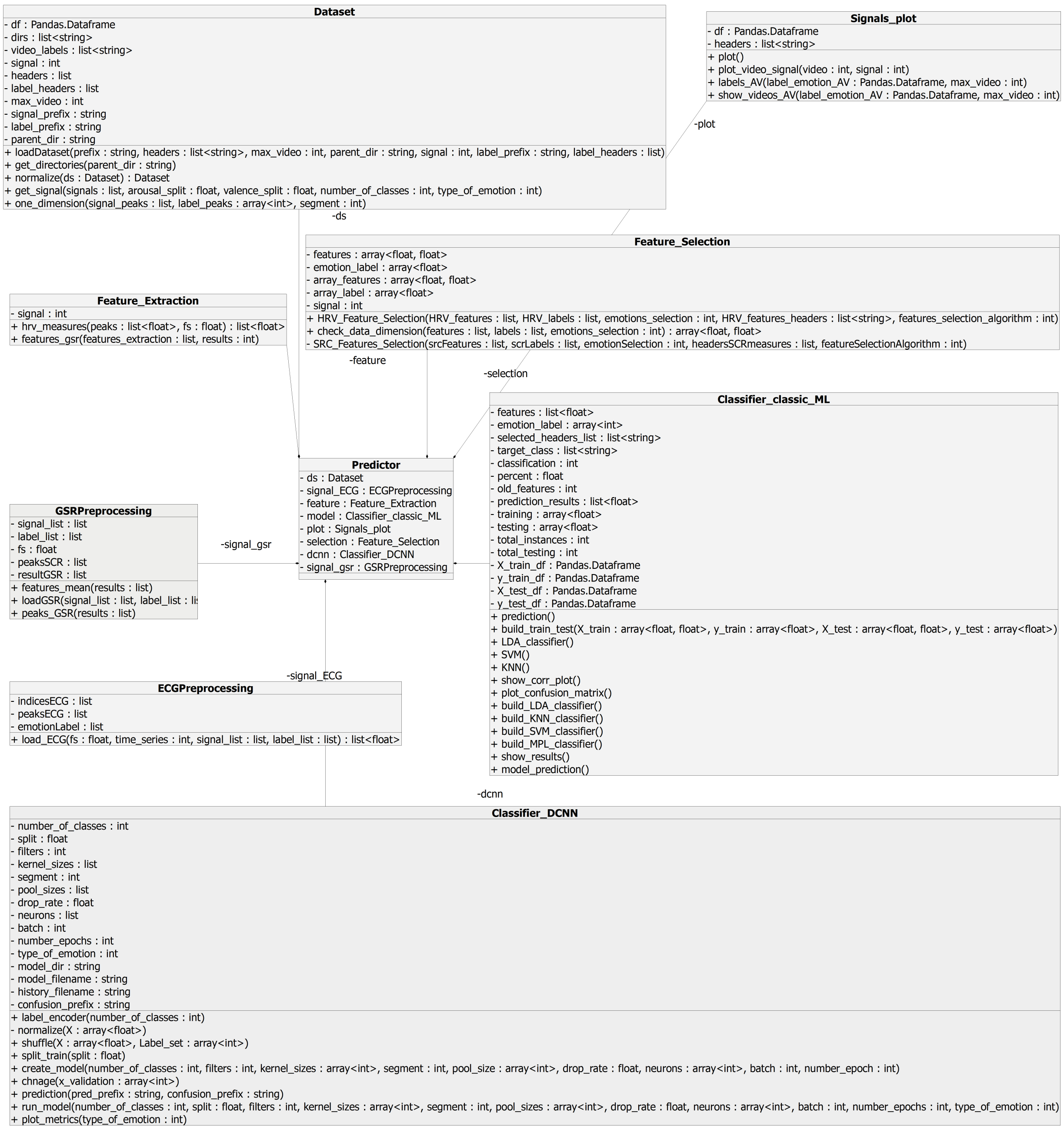


Fig. 3.4 Software components for the emotion recognition system, with a deep learning approach and classic machine learning algorithms.

Affective computing involves the design of machine learning models to discover physiological patterns of affective states from datasets. In this research, we propose validating supervised learning algorithms and Deep Learning for efficient emotion detection. Therefore, Figure 3.4

depicts the system with the components to load the dataset in a data frame as a requirement for the preprocessing of the ECG and GSR signals. Then, the feature extraction stage can be developed explicitly or implicitly. The first uses hand-crafted functions to obtain features in the time or frequency domain, selected with ML algorithms. The second, with deep learning, extracts automatic representations of the features. Finally, the models are trained and tested with algorithms from the two approaches.

3.3.1 Machine Learning

3.3.1.1 Data Preprocessing

As a previous step to the features extraction of the physiological signals, the detection of peaks of the ECG and GSR signals is performed because the emotions generate significant changes in these segments. The Heart Rate Variability (HRV) analysis is an emotion diagnostic tool to determine the beat-to-beat interval (RR interval) [259]. The values between a RR interval correspond to the time between two peaks R, calculated through a standard wave of the QRS complex. The ECG signal is transformed with the PanTomkins QRS detection algorithm proposed in [288]. The signal is filtered to reduce the noise with cutoff frequencies of 0.5 and 15 Hz and uses an adaptive threshold for the detection of the QRS complex (see Figure 3.5).

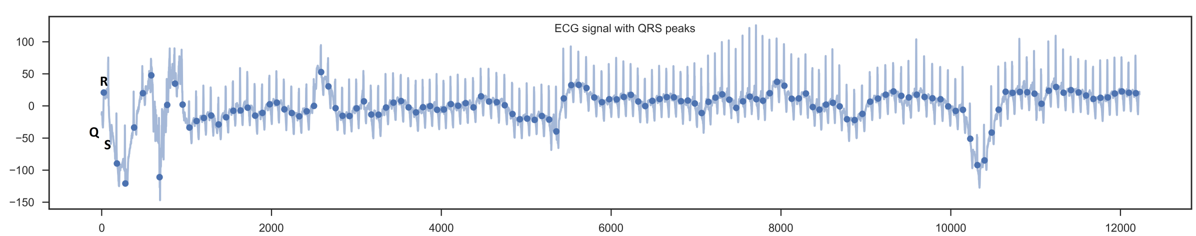


Fig. 3.5 Detection of RR interval in the ECG signal. AMIGOS Dataset [257], participant 1, video 10.

Similarly, the GSR signal is preprocessed using bandpass filters to reduce noise with cutoff frequencies of 0.05 and 19 Hz [289]. Then it is resampled with a digital phase filter of 10 Hz. During SCR peak detection, a standard method is used that identifies the max, min, and offset indexes of the signal GSR [290]. So, the threshold of the amplitude is determined, and the features between SCR peaks are calculated (see Figure 3.6).

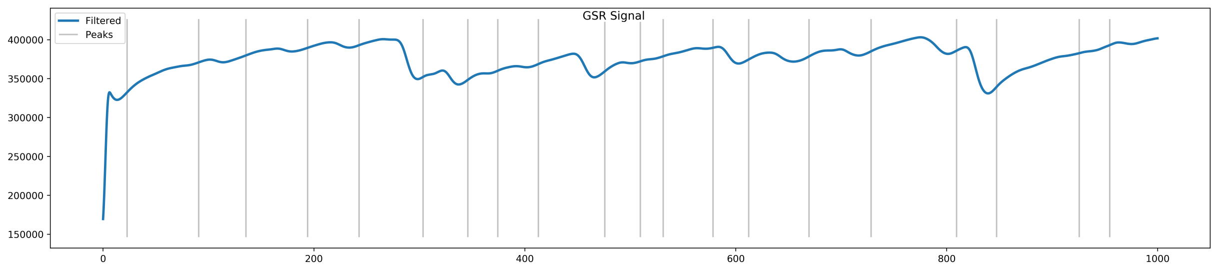


Fig. 3.6 Detection of peaks in the GSR signal. AMIGOS Dataset [257], participant 1, video 10.

3.3.1.2 Extraction and Selection of Features

The affect detection requires an adequate features extraction of the signals, which correlate with the emotional states recorded by the participants in the self-assessment. That is, the relationship between features and emotions determines the physiological reaction [291] and is taken as input to the predictor. Parametric measurements of the ECG signals in the time domain quantify the variability of interbeat intervals (IBI) measurements successive. The power distribution is determined in the frequency domain, and the unpredictability of a series IBI is quantified in the non-linear according to [292, 293].

GSR signals are extracted statistics in the time domain related to amplitude, rise time, decay time, latency, mean amplitude indexes, and SCR peak indexes. Because each GSR signal produces a set of measurements by the amount of detected SCR peaks, some measures of central tendency, dispersion variation, and distribution are applied.

In Table 3.2, the features generated from the peaks of the ECG and GSR signals are described.

Table 3.2 Notation of features extracted from ECG and GSR signals [293, 290].

Signal	Features group	Description of the extracted features
ECG	Time Domain (1 - 13)	meanNN, medianNN, standardDeviationNN, rmSSD, pnn50, pnn20, coeffVariationSD, medianADNN, coeffVariationNN, mCoeffVariationNN, shannonEntropy, HRVtriangular, and numArtifacts.
	Frequency Domain (14 - 24)	peakHF, hfTotalPowerRatio, normalizedHF, peakLF, lfhfRatio, lfTotalPowerRatio, normalizedLF, totalPower, ulfPeak, vhfPeak, and vlfPeak.
	Non Linear (25 - 33)	correlation dimension, entropy (SVD, HF, LF, VLF, and shannon), fractal dimension (higushi and petrosian), and fisher information.
GSR	Mean, standard deviation, max, min, kurtosis, and skew (34 - 87)	EDA at apex, SCR width, amplitude, decay time, half amplitude, half amplitude (index and indexpre), latency, and rise time.

After the process of extracting features, ML algorithms are used to filter the redundant features that can cause overfitting in the classification model [294].

3.3.2 Deep Convolutional Neural Network

Deep learning is an area of machine learning based on algorithms and techniques for modeling high-level abstractions in datasets [295], such as patterns recognition in images, text, or emotions. The learning levels take the results of the previous levels, which are transformed into insights, to train and validate the classification model.

The DCNN architecture proposed for the emotion detection system was adapted from the work of [296], with the Keras framework [297]. The DCNN involves a sequence of CNN layers and pooling layers to extract features from the physiological signals automatically. Fully connected layers are located in front of CNN, operate on all nodes, and predict the affective state.

In this study, CNN layers are considered fuzzy filters [298] that reduce noise and discover particular morphological patterns in the R peaks of the ECG signals and the SCR peaks of the GSR signals. Initially, the transformation implemented by the neuronal layers is parameterized by its weight w, since the neurons learn to discover the correct values (convolution kernel) without affecting the behavior of the other layers [299]. That is, in the 1D convolutional layer, the features vector of the physiological signals resulting from the transformation of the input data x is defined in equation 3.1.

$$x_i^l = f\left(\sum_j w_{ij}^l x_j^{l-1} + b_i^l\right) \tag{3.1}$$

Where x_j^{l-1} represents the input vector to the convolutional function, w_{ij}^l denotes the kernel weight between the i^{th} and j^{th} neurons of the layers l and $l-1$ respectively. b_i^l is the bias coefficient of the neuron i^{th} in the layer l and x_i^l indicates the output of the convolutional layer.

In the CNN and fully connected layers, the Rectified Linear Unit (ReLU) activation function is set, which handles a threshold of 0 for the negative values. This $ReLU(x)$ function is calculated as equation 3.2:

$$f(x) = max(0, x_i) \tag{3.2}$$

The max-pooling layers are alternated between the CNN layers to segment a convolutional region that can increase the robustness of the features and reduce the dimensionality of the physiological signals vector. As a regularization technique to decrease the overfitting in the neural network layers, the dropout with a value of 0.5 is added. The output layers of the fully connected network are configured with the softmax classifier, with the purpose that the hidden layers verify the probability of predicting the emotion.

During the supervised training, the loss is minimized with the Root Mean Square Propagation (RMSProp) [300] optimizer, since it adjusts the learning rate adaptively. Initially, the learning rate is set to 0.001. Once the model is executed, the knowledge base is consolidated between the vector of physiological features and the class vector. Then, to evaluate the emotion recognition, in the fully connected layer, the cross-entropy loss function is set, which determines the degree of correspondence of the target output vector y_i, with the predicted output vector c_j, as follows in equation 3.3:

$$E = \frac{1}{2}\sum_{j=1}^{N}(y_i - c_j)^2 \tag{3.3}$$

The emotion recognition model based on deep learning algorithms is shown in Figure 3.7.

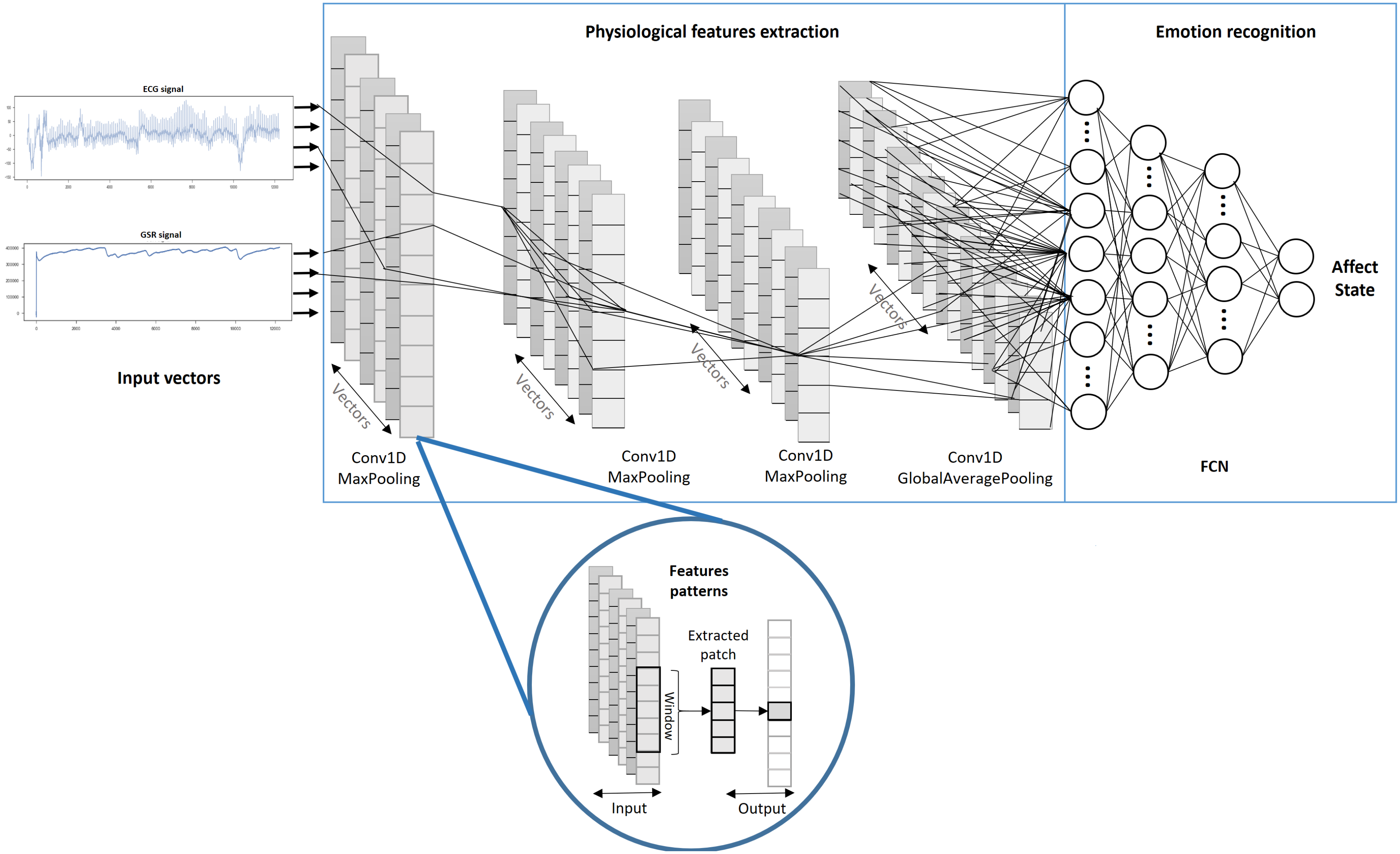


Fig. 3.7 An schema of emotion recognition process based in deep learning.

The structure is defined by an input layer that connects the vector of physiological features with the neurons of the first convolutional layer. Which, in turn, connects with three consecutive convolutional layers to extract the features of the ECG and GSR signals. Further, it is appreciated the transformation process of the input vectors in local patches inside a convolution window [299]. Each 1D CNN contains a sequence of temporal data to recognize local patterns, which can be learned from the morphology of the physiological signal. The functionality of the CNN layers is given by the convolution kernel that obtains the local patches, and the Max pooling extracts the windows from the feature vectors to generate the downsampling output vector.

The vector resulting from the physiological features extraction state is sent to the input neurons of the three FCN to perform the training and testing process of the model. The last FCN layer is used to predict the affective state.

3.4 Experimental Results

Emotion recognition models are tested through the AMIGOS dataset. In the first validation with the deep learning algorithms, the automatic extraction of the features is performed from the R peaks and SCR peaks. In contrast, with the instances of physiological signals that are loaded directly from the data frame to the convolutional layers.

The second experiment is based on some classic machine learning algorithms to extract, select and detect emotions. Each physiological signal comprises 640 instances $40 participants * 16 videos$, but at the time of consolidating the data frame, null values were found; therefore, it was reduced to 603 instances.

3.4.1 Emotion Detection with DCNN

During the experiment, the configuration parameters previously explained were defined for the training and testing of the deep learning model. Once the physiological signals have been preprocessed, a segment of the length of 200 R peaks is defined for the input vector of the ECG signal. For the GSR signal, it is specified as an input segment of 20 SCR peaks. The values of each vector were normalized with the calculation of the mean and the standard deviation of all the points of the signal segment. The sizes of the kernel and the filter of the CNN layers affect the features detection that is represented in a convolution vector.

For the ECG vector, the kernel size for the four convolutional layers is defined at 15, 10, 5, and 1. In the GSR vector, it was configured at 10, 3, 1, and 1. The max-poling sizes were defined in 5, 2, 2, and 2,1,1 respectively for the ECG and GSR signals. Kernel filter sizes were set to 256. The epochs number used to train the model was 200. Table 3.3 shows the accuracy results that were obtained for the best model during training and testing.

Table 3.3 The classification accuracy for the CNN model.

Physiological data		**Arousal**		**Valence**	
Signal	**Input lenght**	**Train Acc.**	**Test Acc.**	**Train Acc.**	**Test Acc.**
ECGL	200	0.83	0.82	0.75	0.71
ECGL-ECGR	200	0.83	0.76	0.79	0.75
ECGL	15000	0.82	0.82	0.66	0.72
GSR	15000	0.66	0.69	0.66	0.67
GSR	20	0.71	0.71	0.73	0.75

In the experimentation process, two types of input data segments were configured for each ECG signal. The first was transformed to 200 R peaks, and the second was normalized and segmented to 15.000 points. In the case of the ECGL signal, the results obtained for the arousal dimension were similar, although different processing techniques were applied, mainly in terms of dimensionality reduction.

Since the length of the segment of the ECGL signal is not significant, it is evident that the convolutional layers extract emotionally discriminatory features for the detection of arousal levels (low and high). The valence dimension obtained better results when the ECG signals were integrated (ECGL and ECGR) than when using only the ECGL signal. Similarly, for the GSR signal, regarding the type of segments used during the experiment, it can be seen that with the length of 20 SCR peaks, the valence levels (low and high) have a better performance.

3.4.2 DCNN vs. Shallow Machine Learning Algorithms

In this section, we compare the performance results in the prediction of the affective states obtained initially by the authors of the AMIGOS dataset [257], with the algorithms proposed in this study. Unlike CNN, the features of the physiological signals of the ECG and GSR were extracted manually, as explained in the section on extraction and selection of features. In most cases with machine algorithms, similar prediction results were obtained or a little higher than the previous study of [257].

Therefore, with DCNN, better performance in arousal recognition is achieved through the ECGL signals (see Table 3.4), in contrast to the GSR signal that shows better results in valence prediction (see Table 3.5).

Table 3.4 Performance comparison of DCNN with classical ML algorithms for ER based on ECG signals.

ECGL Classifier	**Arousal**		**Valence**	
	Accuracy	**F1-Score**	**Accuracy**	**F1-Score**
Naive Bayes [257]		0.59		0.57
Nearest Neighbors	0.69	0.66	0.58	0.57
Linear Discriminant Analysis	0.72	0.63	0.67	0.65
Linear Support Vector	0.68	0.60	0.61	0.55
Multi-Layer Perceptron	0.68	0.59	0.61	0.51
AdaBoost	0.70	0.66	0.61	0.58
Random Forest	0.68	0.67	0.59	0.59
DCNN	0.81	0.76	0.71	0.68

Table 3.5 Performance comparison of DCNN with classical ML algorithms for ER based on GSR signals.

GSR Classifier	**Arousal**		**Valence**	
	Accuracy	**F1-Score**	**Accuracy**	**F1-Score**
Naive Bayes [257]		0.54		0.53
Nearest Neighbors	0.68	0.64	0.69	0.68
Linear Discriminant Analysis	0.67	0.61	0.64	0.55
Linear Support Vector	0.69	0.56	0.68	0.55
Multi-Layer Perceptron	0.68	0.60	0.64	0.55
AdaBoost	0.64	0.59	0.66	0.65
Random Forest	0.58	0.58	0.64	0.64
DCNN	0.71	0.67	0.75	0.71

Considering the physiological data limitation of the AMIGOS dataset, it was proposed to validate the deep learning model with the data of the EEG and ECG signals. Each signal was segmented and normalized by 10,000 points. For the training, 90% of the data was used, and the rest for the testing, 965 instances were assigned to validate the model. Due to the size of the dataset, the processing of each epoch lasted 550 seconds. Compared to the other tests, the computational effort was increased to generate a more robust model. The categorical recognition of emotions was evaluated from 4 classes (HALV, HAHV, LALV, and LAHV).

The Figure 3.8 shows the exponential behavior of the accuracy during the training and testing for the 500 epochs. Similarly, in the Figure 3.9 the values of loss are displayed during the learning that is decreasing for each epoch. The confusion matrix shows the results of prediction for the four classes of arousal and valence, respectively (see Figure 3.10). The unification of the EEG and ECG signals ratifies the trend of the prediction results for arousal compared to valence because better results were obtained when the values of the labels were high. Possibly, by the participants' subjective evaluation in the self-assessment of the emotion elicitation during the experiments of the short videos.

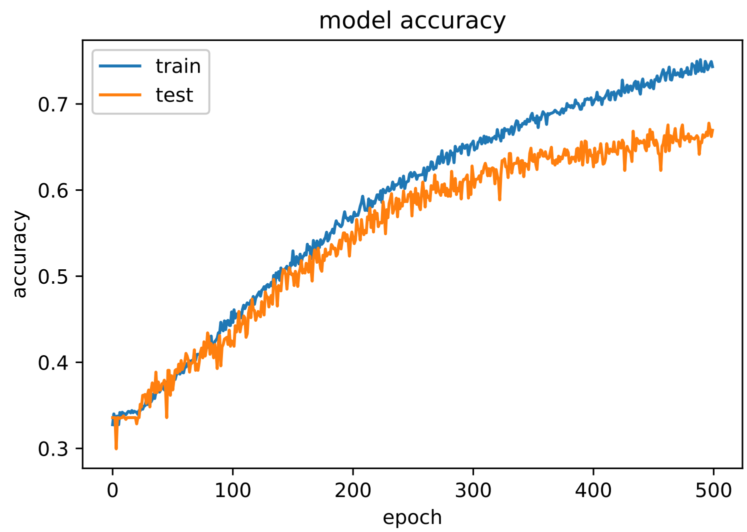


Fig. 3.8 Accuracy result for DCNN model using the EEG and ECG signals for the ER [257], participant 1, video 10.

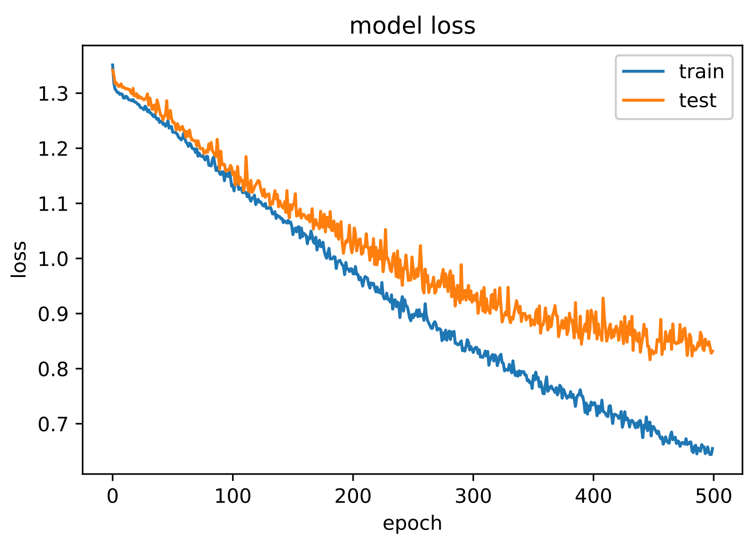


Fig. 3.9 Loss result for DCNN model using the EEG and ECG signals for the ER.

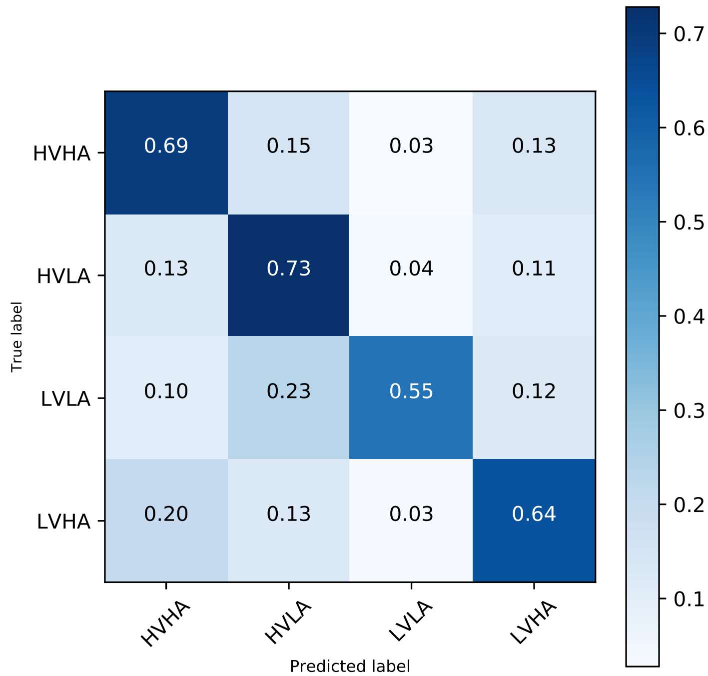


Fig. 3.10 Confusion matrix for the prediction of four emotion classes.

Table 3.6 shows the comparative results of studies similar to this research. In [286] describes a recognition method of arousal from ECG signals of various datasets represented in a common spectrum-temporal space to train a deep neural network. Derived from the results of the affect prediction with DECAF, it can conclude that the stimulus is an indispensable factor to induce emotion. Also, other studies for the arousal and valence detection used diverse EOG, EMG and, EEG signals from the DEAP dataset [282, 280, 284], and they got the same or better results than the reported in this work (see Table 3.3). Unlike AMIGOS, DEAP is one of the most explored datasets for ER since different ML models have been developed to automatically extract physiological features, features fusion, and classification of the affective states. Hence, the performance outcome of ER models is subject to the number of physiological signals, the stimuli selection to elicit emotion, the reliability of the emotional assessment labels (self-evaluation), and the participants' number in the experiment.

Table 3.6 Accuracy comparison with other datasets.

Research	**Dataset**	**Arousal**	**Valence**
DNN [286]	DEAP	0.64	
	MAHNOB	0.66	
	ASCERTAIN	0.7	
	DECAF movie	0.65	
	DECAF music	0.79	
SAE and DBN [282]	DEAP	0.73	0.78
MESAE [280]		0.84	0.83
CNN [284]		0.73	0.81
Our work (DCNN)	Amigos	0.76	0.75

Compared to the classic algorithms of ML, the CNN demonstrated a better performance in the emotion detection in physiological signals, despite being conceived for object recognition in images. The preprocessing of the peaks of the ECG and GSR signals as an entry vector to the CNN made possible the identification of morphological features suitable for the affective state prediction. The experimental results validated the proposed methods and improved the performance in the emotion classification for the AMIGOS Dataset.

Physiological datasets with many instances are optimal for the proposed experiments since these directly impact the emotion prediction; the greater the number of instances, the more influential the model. Consequently, several annotations of arousal and valence must be recorded since, when subjecting a participant to the stimulus of a short video, it can manifest different levels of emotion during of experiment.

The future work of this research consists of applying these computational models to data acquired with wearable devices to recognize emotion from physiological signals.

Chapter 4

TERS-ER

This part describes the architecture of a Tourist Experiences Recommender System based on Emotion Recognition (TERS-ER). TERS-ER's purpose was to previously detect the user's emotional state who uses a wearable for a significant time. Based on the predominant emotion of this user, the recommender generated a list of Tourist Experiences (TE). We had 18 participants who wore Xiaomi Mi Band devices with their respective mobile applications during the proposed experiment. Also, we collected two datasets: one Heart Rate (HR) from wearers of these devices and the other from their affective states using the myEmotionBand (MEB) mobile application. Then, we created an emotional dataset from HR time series preprocessing algorithms and affective detection based on Deep Neural Networks (DNN). Subsequently, we obtained the TE portfolio from the OntoToutra ontology, profiled the users, applied the prediction algorithms, and produced the recommendation list filtered by contextual features. Finally, the evaluation results among the different algorithms tested for ER showed that the hybrid Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks had promising results. Moreover, concerning TERS, Collaborative Filtering (CF) using CNN gave better performance.

4.1 Introduction

Internet of Things (IoT) technology enables the integration of wearable and mobile devices to gather historical data from users. Personalized services are designed based on this data to contribute to people's well-being and quality of life [301, 302]. Researchers, in recognition of emotional patterns, find the physiological data of people that is relevant in their daily lives. These devices become a ubiquitous source for providing this data [8]. Emotional detection can be applied in various contexts, including tourism, to improve the tourist experience at destinations [303, 19].

On the other hand, tourist expectations from a temporal perspective are analyzed in three phases: before, during, and after the tourist visit [6, 7]. This study focuses on the preliminary phase of the visit, which detects the affective condition of people as a contextual factor of a recommender system. To this end, the World Tourism Organization highlights that the tourism industry is more competitive when receptive tourists are more inclined to the emotional benefits than to the physical features and cost of the destination [9].

Preliminarily, the literature review was conducted to identify the components of the emotion-based tourism recommender frameworks [304]. This study showed the gap in integrating physiological data from wearable sensors to detect the affective condition of the user as a relevant contextual factor in the satisfaction of the recommendation. The analyzed approaches mainly considered sentiment analysis techniques to detect emotional states from the social networks reviews. Moreover, these models did not consider low-cost wearables to discover emotional patterns in the user's daily life.

In this review of the state-of-the-art, it was also found that there is a disparity of formats, emotional states, and physiological signals in the datasets. Wearables of a different range were also used, mainly medium and high-end. Most of these studies took biosignal measurements in controlled experiments [305–308, 304]. As wristbands evolve, they integrate more sensors and with better accuracy. The most common sensors measure heart rate (HR), Galvanic Skin Response (GSR), and temperature. In the context of tourism, the most common wearables are those that are affordable and non-intrusive. Therefore, in this study, the wearable Xiaomi Mi Band was chosen because it is cheap, includes basic physiological sensors, is comfortable, and is easy to use.

One of the research challenges of this study was detecting changes in people's emotional states in natural and uncontrolled conditions, using wearables with low accuracy in their measurements. To do this, we developed a mobile application to record emotions, independent of the HR record. As a result of this double registration, creating a time series synchronization algorithm called the adjustable and sliding window became necessary.

There are different types of emotions, and therefore their duration and intensity are varied. Norman's model [309] describes three levels of brain processing to explain the distinct emotional reactions that a person experiences: visceral, behavioral, and reflective. Each person interprets their emotional response according to their identity, culture, personality, and context. Therefore, the automatic detection of emotional states in a time series of physiological measurements became another challenge for this research. In this way, another algorithm was proposed to detect emotional states, known as Emotional Slicing (ES). This algorithm groups HR instances into a time slot to which it assigns an emotional label.

In the previous study of emotional detection on the AMIGOS dataset [310], Convolutional Neural Networks (CNN) [1] were used. Now, in this study, a hybrid Deep Learning (DL) algorithm from CNN and Long Short-Term Memory (LSTM) networks [311–313] was implemented for Emotion Recognition (ER) from the ES dataset.

Once the emotion was detected, the Tourist Experience Recommendation System based on the ER (TERS-ER) was developed as the last phase of this study. An interface was designed with the Tourist Traceability Ontology (OntoTouTra) [314] to get the contextual data.

In addition, for the TERS engine, two approaches to Content-Based Filtering (CBF) [315, 316] and Collaborative Filtering (CF) based on CNN [317, 302, 304] were designed to generate the top-N list of Tourist Experiences (TE) recommendations. The TERS engine integrated a user similarity algorithm, selecting candidate users from the ontology based on the profile and contextual data of the wearable user.

4.2 Literature Review

4.2.1 Background

Previously, the performance of some Shallow Machine Learning and Deep Learning algorithms for emotion detection [1], based on the AMIGOS public dataset [310], was compared. In conclusion, it was evidenced that the DCNN architecture showed a better performance in detecting Arousal (0.71 and 0.81) and Valence (0.75 and 0.71) using GSR and Electrocardiogram (ECG) signals (see Table 4.1). The AMIGOS dataset was collected in tests controlled in the laboratory, using 14 electrodes for the electroencephalogram (EEG), two for the ECG, and one for the GSR. These electrodes were placed on the body of each of the 40 participants. Emotions were elicited through 16 short videos of less than 250 s in length. The resulting dataset is a time series with features corresponding to the physiological signal measurements displayed on 17 channels. Moreover, as labels, it presents the annotations of Arousal, Valence, and dominance [193, 318].

Table 4.1 Performance of DCNN and shallow ML algorithms using AMIGOS dataset [1].

ER Classifier	GSR Signals				ECGL Signals			
	Arousal		Valence		Arousal		Valence	
	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score
Naive Bayes [310]		0.54		0.53		0.59		0.57
Nearest Neighbors	0.68	0.64	0.69	0.68	0.69	0.66	0.58	0.57
Linear Discriminant Analysis	0.67	0.61	0.64	0.55	0.72	0.63	0.67	0.65
Linear Support Vector	0.69	0.56	0.68	0.55	0.68	0.6	0.61	0.55
Multi-Layer Perceptron	0.68	0.6	0.64	0.55	0.68	0.59	0.61	0.51
AdaBoost	0.64	0.59	0.66	0.65	0.7	0.66	0.61	0.58
Random Forest	0.58	0.58	0.64	0.64	0.68	0.67	0.59	0.59
DCNN [1]	0.71	0.68	0.75	0.71	0.81	0.76	0.71	0.68

In recent years, wearables have entered the market in significant numbers and have increasingly incorporated sensors that measure physiological signals [304, 319]. The most common sensor present in this type of device is the Photoplethysmogram (PPG) [307, 196, 320, 321], which registers HR signals. The configuration of these devices has aroused scientific interest in detecting the emotional state of a person from these signals [307, 322, 308]. However, not all wearables have the same level of accuracy in getting the physiological signals [321]. There are devices ranges [305, 319]: Expensive devices with high accuracy sensors, principally used for healthcare purposes, for instance, include the Empatica E4 [306, 320, 308, 323]. Medium range devices with precise sensors have more extensive use, targeted to high-performance athletes, mainly for fitness and sports, and these include, for example, Garmin and Microsoft Band [5, 324, 305, 307]. Affordable devices for all audiences are used for general purposes, for instance, the Xiaomi Mi Band [305, 325–328].

The second stage of the research project [1] corresponds to the study proposed in this section, applied in the context of tourist recommendations outside the laboratory. The massification of low-cost devices made it possible to reach different contexts, including tourism. Of the three ranges of wearables, the low-cost ones have the highest probability of being used by people who want to have a tourist experience in a destination soon. Then a scientific challenge is created to take advantage of these wearables, which despite their low precision in the measurement of physiological signals, still generate a large amount of data that can be processed with data analytics to discover hidden patterns and trends.

Most of the studies described to the TERS design worked with traditional filtering classifiers such as Collaborative and Content-Based [304]. The second challenge of this study is to integrate the detection of people's emotional states into the recommender systems. It was traditionally recommended through the reviews of other tourists on lived experiences or based on the context and configuration of the tourist experience in a destination. Nevertheless, this study is intended to refine this type of recommendation according to a person's emotional state, either to counteract it for negative moods; or to maximize it for positive emotional states. The related work in [304] did not show previous studies regarding a TERS based on the emotional state of a person using HR signals from a low-cost wearable device.

The third challenge of this study is related to how to register the emotional state of a person. In experiments such as the consolidation of the AMIGOS [310] and DEAP [192] datasets, self-annotators and external annotators recorded perceived emotion using a Self-Assessment Manikin (SAM) questionnaire [318]. However, in the daily life context of a person, the researchers of this study developed a mobile application that recorded the mood of the wearable user at different times when he/she felt that an emotion elicitation was being presented. A new challenge arises: synchronizing the time series data of HR measurements with the recording of emotional elicitations. This is achieved by developing a new algorithm, which is the contribution of this study, the sliding and adjustable window algorithm.

4.2.2 Related Works

In this section, ER architectures and methods based on data from wearable devices are analyzed. On the other hand, TERS studies similar to the architecture proposed in this section are related, based on the previous research of [304].

4.2.2.1 Affective Detection

Studies have been developed on the detection of the emotional state in different contexts [196, 308], most of them in controlled environments and with sensors or specialized wearable devices. The number of participants involved in these types of experiments is around 20 people. Table 4.2 describes some research for affective detection according to the two-dimensional model of emotions by Arousal (A) and Valence (V) [193]. Also, the specification of the wearable device (physiological sensors and low-cost sensors) and the data collection method (dataset, experiment type, and participants) are given. The last three columns of Table 4.2 show the physiological signals, the emotion classification approach, and the best performance results of each study.

Table 4.2 Emotion detection studies based on physiological data from wearable devices.

Reseach	Wearable		Method			Emotion Detection		
	Technology	Low-Cost	Dataset	Experiment	Participants	Signal	Classifier	Accuracy
[196]	Electrodes	No	DEAP	Controlled	32	GSR and PPG: Covariance matrix	Random Forest	0.72 A and 0.71 V
[322]	Electrodes	No	DEAP	Controlled	32	EEG: Time domain	LERM	0,73 A and 0.74 V
[1]	Electrodes	No	AMIGOS	Controlled	40	GSR and ECG: SCR peak and R-peak	DCNN	A (0.71, 0.81) and V (0.75, 0.71)
[307]	Garmin Vívosmart 3	No	(own dataset created)	Controlled	17	PPG: IBI (Frequency and Time domain)	Bayesian DNN	F1 score: 0.7 V
[308]	Empatica E4	No	(own dataset created)	Controlled	20	PPG: HR	SVM	0.46: HVHA, HVLA, LVHA, LVLA
This study	Xiaomi mi band	Yes	(own dataset created)	Semi controlled	18	PPG: HR	1D CNN-LSTM	0.44: HVHA, HVLA, LVHA, LVLA

Meanwhile, Abdel et al. [322] described a method of extracting covariance matrices from EEG signals for the emotion classification using the Log-Euclidean Riemannian Metric (LERM). The study [196] proposed an ER framework by merging multiple physiological signals from the DEAP dataset. Also, they extracted time-domain features from GSR and PPG signals to assess AV detection. These attributes are provided as input to a music recommendation system.

Bulagang et al. [308] used the Empatica E4 device for the collection of HR data from 20 participants, a virtual reality viewer for the elicitation of emotions (emotional quadrants: HVHA, HVLA, LVHA, and LVLA) while the subjects visualized a stream of sixteen 360º videos, for 365 s. Accuracy performance is compared to three methods: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF).

The SAM questionnaire was adopted for the self-assessment of the emotions of 17 participants while watching a series of 24 short videos of affective induction [307]. Inter-Beat-Interval (IBI) features were processed to classify emotional valence using a Bayesian Deep Neural Network (DNN) model.

Deep Learning reduces the complexity of extracting features of traditional statistical techniques because, with manual extraction, the inconvenience of bias in data induction can arise [304]. Another drawback to take into account is the accuracy level of the sensors used. Researchers prefer specialized devices but recognize the need to build new datasets with enough instances, achieved through the use of cheap off-the-shelf wearable devices [307, 321].

Unlike the previously described methods for collecting physiological data and emotional labels [304] (see Table 4.2), this research proposes data collection methods in people's daily lives, processing, labeling, and emotional detection based on HR data from Xiaomi Mi Band devices.

4.2.2.2 Tourist Recommendation Systems

Habitually, Recommender Systems (RS) are becoming more relevant for the decision of the choice of tourist experiences by people [6, 7, 19, 329]. The large Online Travel Agencies (OTAs) incorporate the RS in their systems, and the competitive factor of the agency depends on its effectiveness in the recommendation. Typically RS engines base the prediction primarily on CF and CBF. Considering the maximum number of contextual variables contributes to the accuracy enhancement of the RS [302, 330, 303].

Table 4.3 Studies of recommendation systems based on emotions.

Research	Dataset	Algorithms	Similarity	Result
[26]	312,896 Tongcheng reviews and 5722 destinations	UBCF, IBCF, and TF-IDF (scenery, cost, infrastructure, accommodations, traffic, and travel sentiments)	CS	MAE and RMSE: Hybrid CF (0.63, 0.97) and TopicMF (0.76, 1.04)
[35]	TripAdvisor and Yelp: 48,253 POI, 33,576 users, and 738,995 ratings.	Emotion Induced UBCF and Emotion Induced IBCF	CS	Precision: 0.74 UBCF, 0.66 IBCF, and 0.67 Hybrid
[90]	312,896 Tongcheng reviews and 5722 destinations	Syn-ST SVD++ model: sentiment tendency and temporal factors dynamic	PCC	MAE and RMSE: Syn-ST SVD++ (1.04, 0.91)
[133]	TripAdvisor and Yelp: 48,253 POI, 33,576 users, and 738,995 ratings.	HSS (AKNN and SPTW) and AbiPRS (Fuzzy-C-means).	User cluster	Precision and MAE: HSS (0.81, 0.63) and AbiPRS (0.77, 0.73)
This study	OntoTouTra [314]: 1939 TE, 42,202 users, and 530,294 ratings	CF-CNN and CBF	CS	MAE and RMSE: CBF (0.15, 0.23) and CF-CNN (0.12, 0.16)

Preliminarily, in the analysis of the RS literature [304], related works were filtered, whose domain is tourism and that have used sentiment analysis as a contextual factor in the recommendation process (see Table 4.3). This table incorporates some studies with descriptions of datasets related to tourist destinations (reviews, users, and items), the RS approaches, the similarity metrics (similarity of cosine and Pearson's coefficient), and the performance evaluation outcomes.

Data from social networks promote emotion analysis and opinion mining from user reviews to determine TE preferences, as well as addressing issues related to a cold start and data scarcity in CF [26, 35]. Other studies [26, 90] proposed to involve the feelings of the trip as a relevant factor in the experience at the destination using the Term Frequency-Inverse Document Frequency (TF-IDF) technique in the emotion polarity. The studies [35, 133] involved the affective, temporal, and location features of users to improve the quality of the RS through a hybrid preference mining algorithm.

Furthermore, in other contexts such as entertainment, business, health care, and smart tourism, the contextual factors of emotions applying sentiment analysis techniques in the classification of reviews have been the subject of research [304]. The user models, based on contextual features extracted from social networks, established the similarity of the users' preferences of tourist destinations. Also, the application of the algorithms of SVM, KNN, DNN, CNN, and LSTM have been used for the automatic extraction of features and the classification of the mood [304, 1].

Unlike the sentiment analysis based on the explicit rating of the reviews in the recommendation processes, this study defines a TERS-ER architecture incorporating the contextual data of the users' emotions before the tourist visit. For this purpose, a knowledge base of tourist destinations from OntoTouTra [314] is obtained, and the TE are defined according to the AV quadrants. Subsequently, Deep Learning techniques are employed for extracting features and generating the top-N list of TE recommendations.

4.3 Materials and Methods

The general process of the methodology used is depicted in Figure 4.1, which comprises three phases: HR measurements and emotion labeling, detection of emotional states, and TERS-ER design and validation.

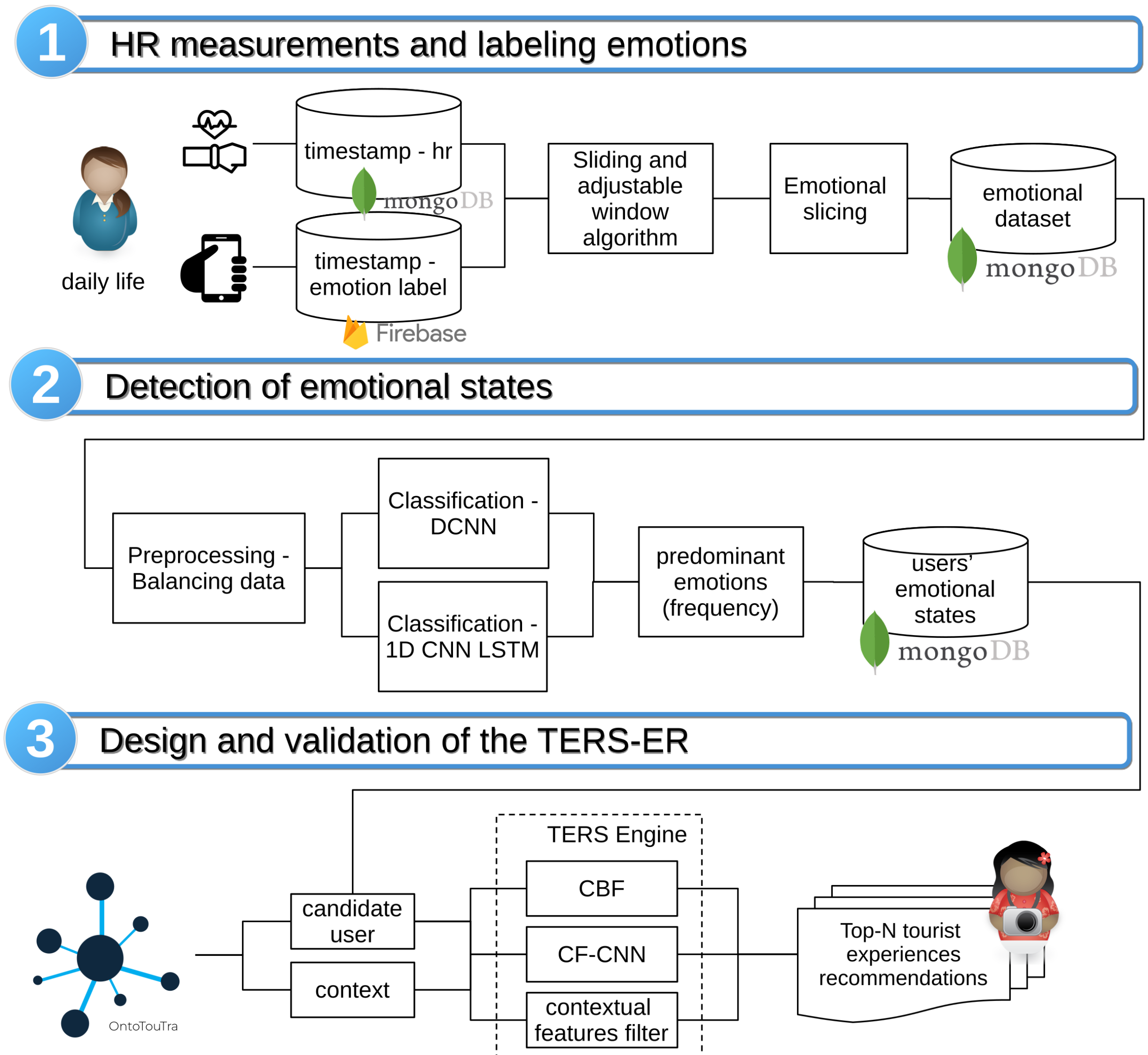


Fig. 4.1 Method overview.

4.3.1 HR Measurement and Labeling Emotions

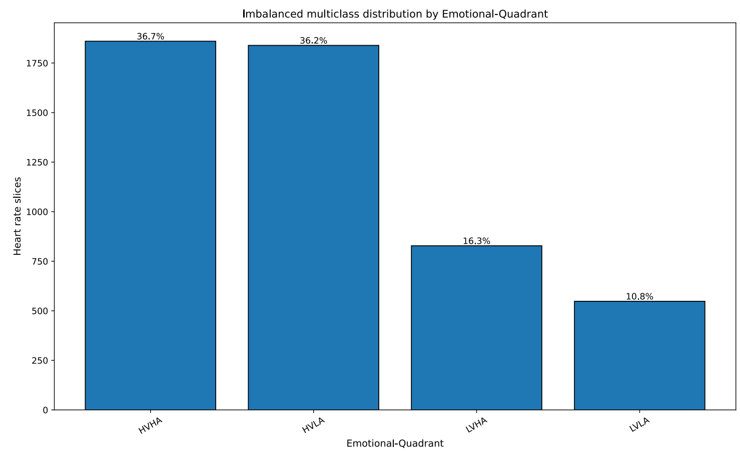
The purpose of this phase was to create an emotional dataset. This dataset is a time series of HR measurements tagged with the emotion felt by the wearable user. The HR register is an objective response to the elicitation of the perceived stimulus in the context, while the emotion register is a subjective response.

As in the similar experiments described in Section 4.2.2.1, a group of 18 participants was formed, nine men and nine women, whose ages ranged from 18 to 44 years. However, unlike the related work experiments, the study was carried out in contexts outside a laboratory, in the participants' daily lives. However, three group sessions of controlled elicitation of emotions were programmed to verify the correct recording of the measurements. Each participant was given a Xiaomi Mi Band wristband, and two applications were installed on their mobile device: Master For mi Band (MFB) [331] and MyEmotionBand (MEB). The first app recorded heart rate measurements. The second app was developed in this study to record the person's emotional states, activities, and location. Before starting the experiment, a group of healthcare professionals assessed the physical and emotional state of the participants. Once the group of participants knew the purpose and procedure of the investigation, they signed the consent for participation. The duration of the experiment was eleven weeks. Short videos were projected for the three group sessions: 19, 19, and 11 videos, respectively. These videos were chosen from the FilmStim repository [332] according to the emotional elicitation of the four AV quadrants [193].

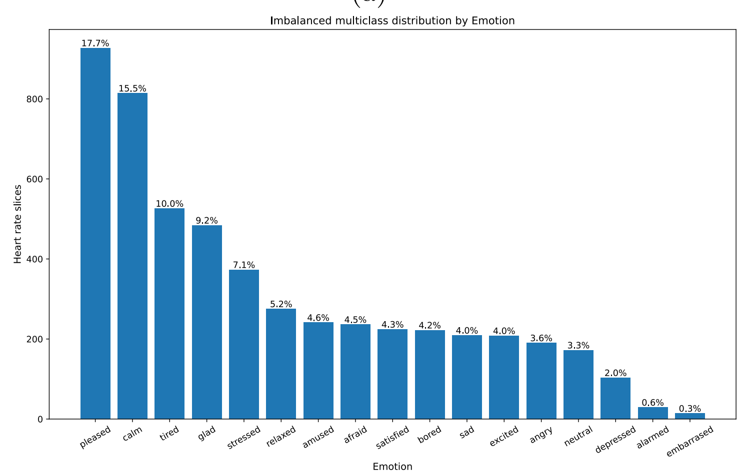
As a result of registering HR measurements, a dataset was created in MongoDB, and from registering the labels, another dataset was created in Firebase. Later, both datasets were synchronized so that the time series coincided with labeling the HR measurements with emotions. For this, Algorithm 1 was developed. Then it was necessary to determine the duration of emotional states [309] using Algorithm 2. Once both algorithms were executed, the emotional dataset was created.

4.3.2 Detection of Emotional States

In IoT environments, the collection of user datasets can lead to multi-class imbalance, which affects the efficiency and performance of the prediction models. The consolidated dataset in this study presented an unequal distribution in the emotion classes (see Figure 4.2b) because the participants showed different affective behaviors in their contexts. Likewise, the participants were predisposed to the affective states of pleased, calm, tired, and glad. In contrast to the lower emotional classes of HR records (embarrassed, alarmed, and depressed). In Figure 4.2a, this same distribution was confirmed for the positive emotion quadrants (HVHA and HVLA) compared to the negative emotion quadrants (LVHA, LVLA).



(a)



(b)

Fig. 4.2 Physiological dataset with a distribution of classes: (**a**) by emotional quadrants; (**b**) by affective states.

For this purpose, some studies have used heuristic sampling methods and oversampling techniques for the Multi-class Imbalanced Classification (MIC) using neural networks [333–335]. These sampling techniques are based on the nearest neighbor rule of the feature space of each class [335, 336]. For the above, the data balancing component sizes the dataset and adjusts the label names by quadrants or emotional states. It also uses class balancing methods to evaluate the performance of affective detection models. That is, the dataset is transformed with the ES instance interpolation methods in the minority classes [337] with the Synthetic Minority Oversampling Technique approaches with K-means (K-SMOTE) [338, 335] and TomekLinks (TL) [336]. Subsequently, the combined techniques (K-SMOTE + TL) and oversampling (K-SMOTE) were implemented separately to process the dataset in training [337].

Once the emotional dataset had been balanced, a CNN and LSTM networks hybrid model was used to detect emotion. This model was chosen because it better classified the shallow algorithms' emotional quadrants (happy, calm, sad, and angry).

An algorithm was designed to determine the predominant emotional state that defined the frequency of the emotion felt by the participants. The results of the execution of this algorithm were stored in a MongoDB collection.

4.3.3 Design and Validation

This phase corresponds to the moment that the wearable device user plans their next TE. The emotional dataset has already been collected, and the predominant emotion of the user has been calculated. So, a TERS is needed that recommends TE according to the person's emotional state, context, and profile. Therefore, as input sources, the TERS needs the emotional dataset, and concerning the other two requirements, a knowledge base in tourism is used. For this study, OntoTouTra was used.

Initially, similar features were selected among users of the tourist review dataset. To know the profiles of the participants of the experiment, they, in advance, completed a survey with their profile data and TE preferences. With the data from these profiles, similar users were filtered using NLP techniques applied to the username in the ontology to determine its gender. Features of the ontology such as country, ratings, TE, and location were also extracted. The location was compared with the geographic coordinates obtained in the emotional dataset. Then, the similarity was calculated using the Cosine Similarity (CS) metric. In this way, the candidate users were obtained from OntoTouTra.

Two approaches were developed for the TERS engine: A CBF method that determines the similarity between tourist destinations and the other CF-CNN method to relate user preferences. These classification methods processed the filtered information from the destination dataset and extracted the most relevant TE items for the recommendation process. Finally, the list of recommended TE was generated based on the target user's profile, preferences, context, and emotions.

The following categories of TE [339–341] were established:

- Adventure: defines experiences of risky activities such as scuba diving, waterskiing, horse riding, and canoeing.
- Ecological: relates experiences of contact with nature such as hiking, ecological walks, and bicycle tours.
- Entertainment: involves experiences of fun attractions such as movie theaters, theme parks, live music, and sports shows.

- Family: promotes experiences of strengthening relationships between parents and children through attractions on the beach, in the pool, family and children's games.

- Fitness: promotes wellness experiences and physical activities such as aerobics, gym routine, personal training, and dance.

- Heritage / Culture: promotes experiences of authentic activities such as visits to museums, archaeological sites, and typical food festivals.

- Romantic: involves couples' romance experiences such as themed dinners, fun in nightclubs and bars.

- Relaxation: involves health care experiences and relaxation activities such as spa, hydrotherapy, sauna, yoga, among others.

The distribution analysis of affective states showed a high rate of participants who registered positive emotions in contrast to negative ones (see Figure 4.2a). This study assumed that the TE recommendations that people seek are strongly related to increased satisfaction and improving their experiences at destinations [6, 7, 19]. For this reason, if the detected emotion was negative (sad: LVLA quadrant or anger: LVHA quadrant) or positive (happy: HVHA or calm: HVLA emotional quadrant), the recommender emphasizes positive emotions and mitigates negative ones. For instance, the suggestion for a person who was stressed is the relaxation experience. At the same time, the recommendation for someone calm may be the ecological experience. In this sense, the relationship of emotions with the categories of TE was:

- Happy (HVHA) or sad (LVLA): encourages adventure, family, romantic, and heritage/culture experiences.

- Calm (HVLA) or angry (LVHA): promotes ecological, entertainment, fitness, and relaxation experiences.

4.4 System Architecture

This section describes the operational and structural levels of detail of the TERS-ER architecture. For this purpose, the functional modules, data models, user profiles, and services represented in the context diagrams, containers, components, and classes were identified [342]. Also, according to the IoT architecture [313, 302], the TERS-ER layers are (see Figure 4.3):

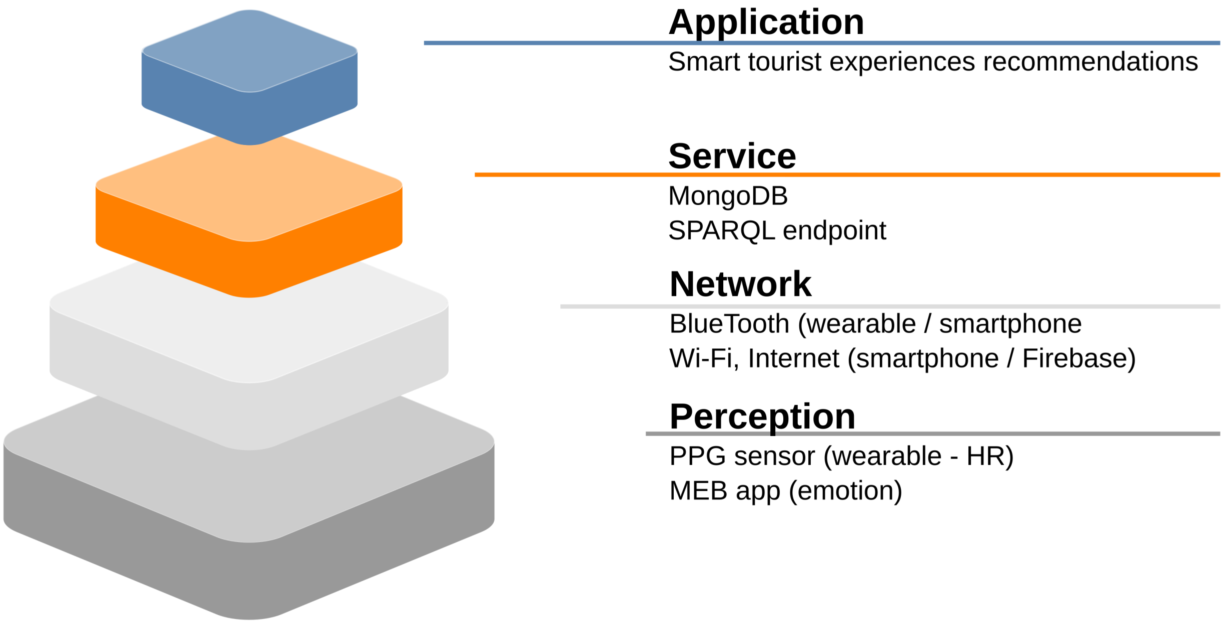


Fig. 4.3 IoT architecture

- The perception layer: It is responsible for collecting HR data using the PPG sensor of the wearable and the emotion and context data from the MEB app installed on smartphones
- The network layer: Transfers HR measurement data using the Bluetooth connection between the wearable and the mobile device. In addition, the smartphone using mobile networks for transferring the emotion and location data of the MyEmotionBand app to the Firebase cloud.
- The service layer: Provides the connections to the Firebase cloud to get the emotion data, the MongoDB server to obtain the HR collections, and the SPARQL endpoint server to retrieve the tourism knowledge base. These datasets are then pre-processed and filtered for the TERS-ER subsystems.
- The application layer: Manages an intelligent RS that displays TE suggestions according to the user's preferences and contextual factors.

4.4.1 System Context

How satisfying is a particular tourist experience for a person? It depends mainly on the reason for the tourist visit. Often a person looks for options according to information from travel agencies, suggestions from friends, cost of the plans, or the desire to know new destinations. However, the emotional burden that the person manifested before the visit is seldom taken into account. Specifically, to understand the emotional state in a period before the tourist visit, wearable devices are an exciting alternative for capturing physiological and context data. In this way, with the processing of these data, the user's emotions can be recognized and therefore recommend the appropriate tourist experiences to their affective state. The research question arises: How to design a TERS based on the wearable users' emotional state in the preliminary visit phase?

Before the visit that can measure in days or weeks, a person in their daily life uses the wristband and mobile devices to record physiological and affective data. In this scenario (see Figure 4.4), a user, depending on the activity type, (for instance, working, watching movies, resting, traveling, driving, among others) can experience an emotional change caused by various stimuli from the context. Then, through mobile applications, the user can measure HR and record the emotion perceived at that moment (happy, content, sad, calm, angry, and stressed). Afterward, the data from the objective and subjective measurements are processed and analyzed by machine learning (ML) algorithms that detect the person's affective state.

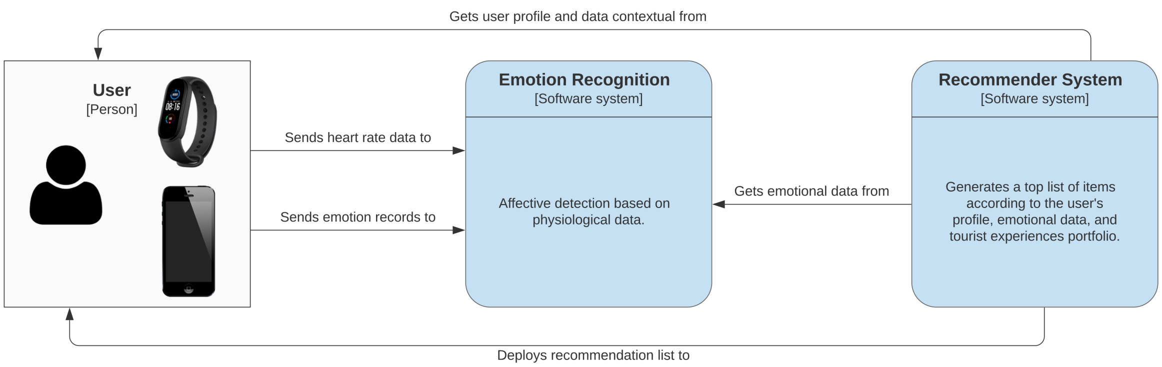


Fig. 4.4 Scenario and context.

The recommender system uses the user's profile (gender and tourist preferences), emotional data, location, and TE portfolio as input items to display destination suggestions. The recommendation list is created from similarity metrics and ML algorithms. Subsequently, the user checks the recommendations of TE according to their emotional state, profile, and preferences.

4.4.2 TERS-ER Architecture

The TERS-ER architecture has two main subsystems. The first is the ER built with the following components: data collection, preprocessing, ES analysis, emotion class balancing, and affective detection using DNN models. The second is TERS, which is implemented with the dataset management components and the recommender engine. This recommender generates the most relevant TE according to the preferences, location, and user emotion in a period before the tourist visit.

4.4.3 Technological Container Communication

In this section, Figure 4.5 depicts the distribution of the technological infrastructure functionalities and the interaction in the TERS-ER subsystems. The following outlines the high-level implementation of the software architecture:

- The users in their context use the Xiaomi Mi Band wristband and the MFB mobile application [331] to store HR data in an SQLite database. In turn, the emotion, activity, and location data is recorded in the MyEmotionBand (MEB) mobile application.
- A real-time database that stores the JSON files of the MEB application in the Firebase cloud.
- An application that manages the connection to the Firebase and MongoDB databases. Also, it handles the collections gathered from wearable and mobile devices.
- A MongoDB database to store collections of HR, emotions, and user profiles.
- An application for ER that generates an affective detection dataset.
- A dataset of the TE portfolio is consulted from the SPARQL endpoint server. This dataset was acquired from the Ontology of Tourist Traceability (OntoTouTra) proposed in [314].
- A recommender engine that processes MongoDB data collections and TE datasets. It then analyzes and displays a list of tourist recommendations.

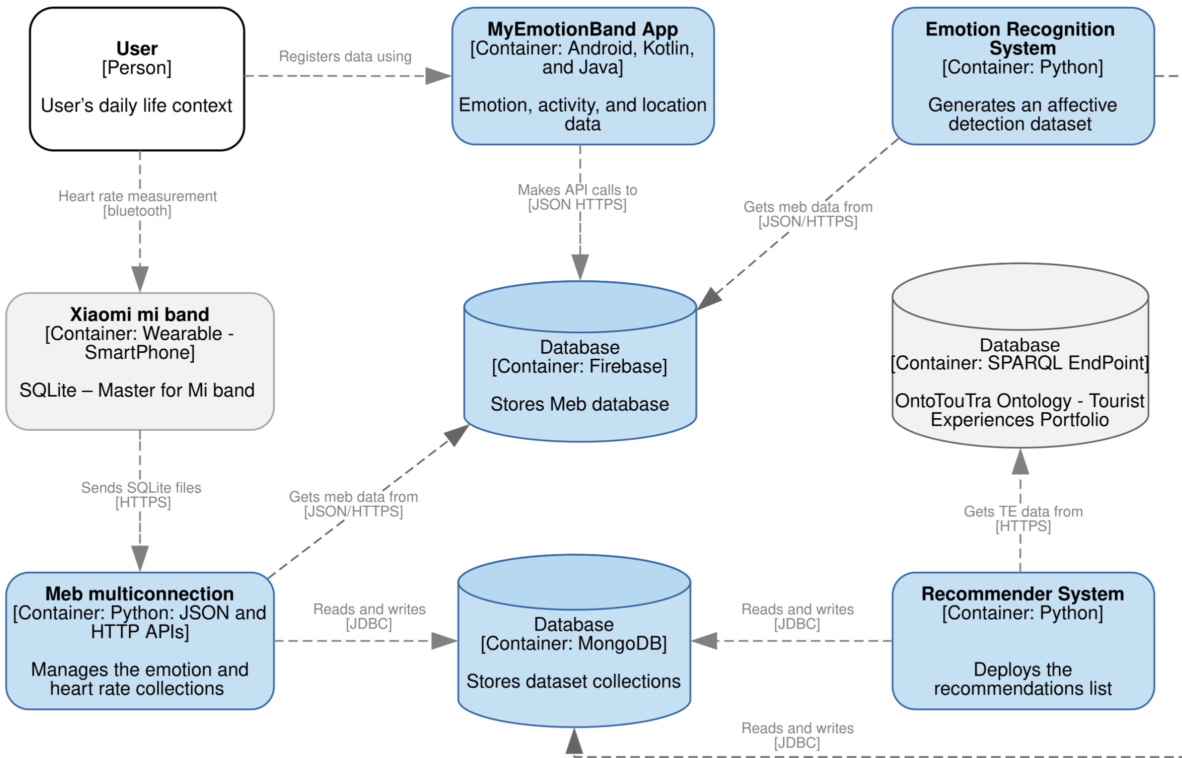


Fig. 4.5 Containers of technological infrastructure.

4.4.4 Implementation of functional components

The architecture of the TERS-RS model (see figure 4.6) portrays the procedure for collecting affective and physiological data in the daily lives of users (see section 4.3.1). These datasets are required by the emotion recognition and recommendation system containers. The software components are indicated below:

- Authentication to Firebase was achieved with the Kotlin Android SDK to store data collected by users with the MEB mobile application in the Cloud Firestore database.
- The connection to the Cloud Firestore service was performed with the Python SDK library to obtain the JSON files stored in the Firebase database.
- The connection to the MongoDB server was programmed with the Python library. This database server allowed the storage and administration of the data collections required by the TERS-ER.

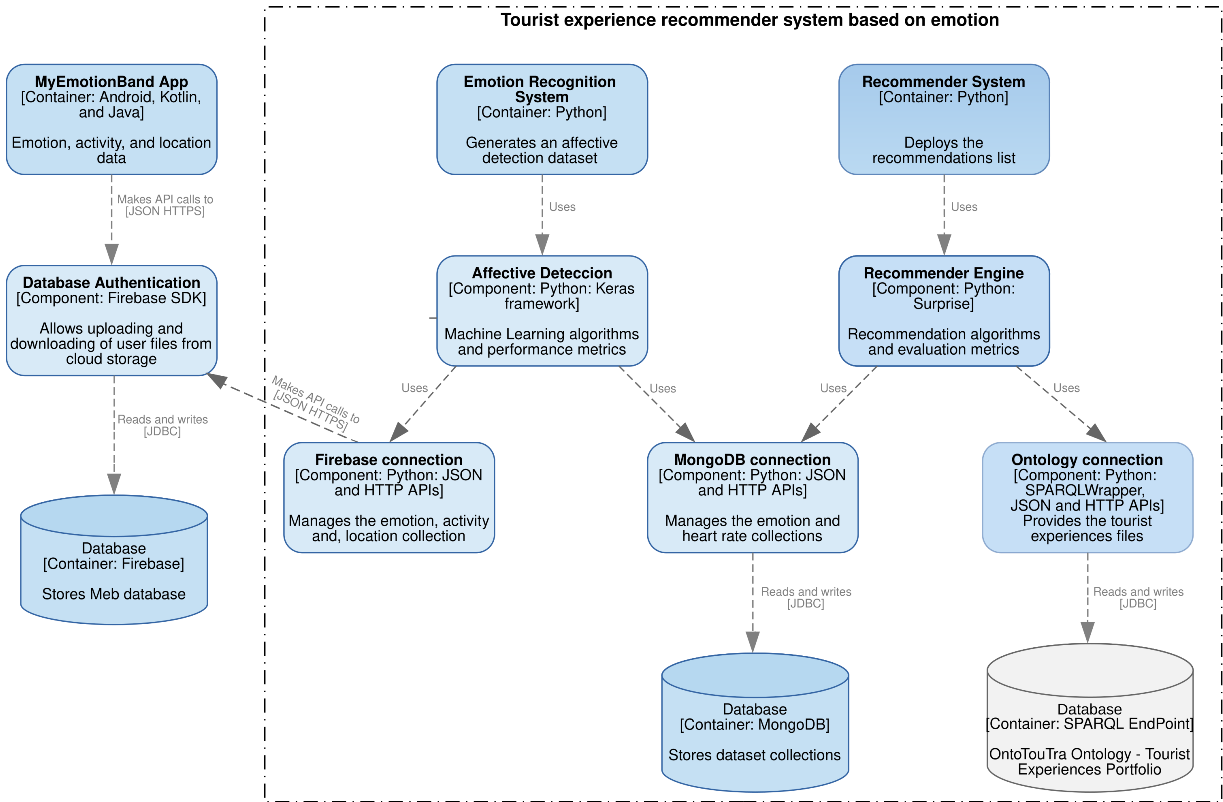
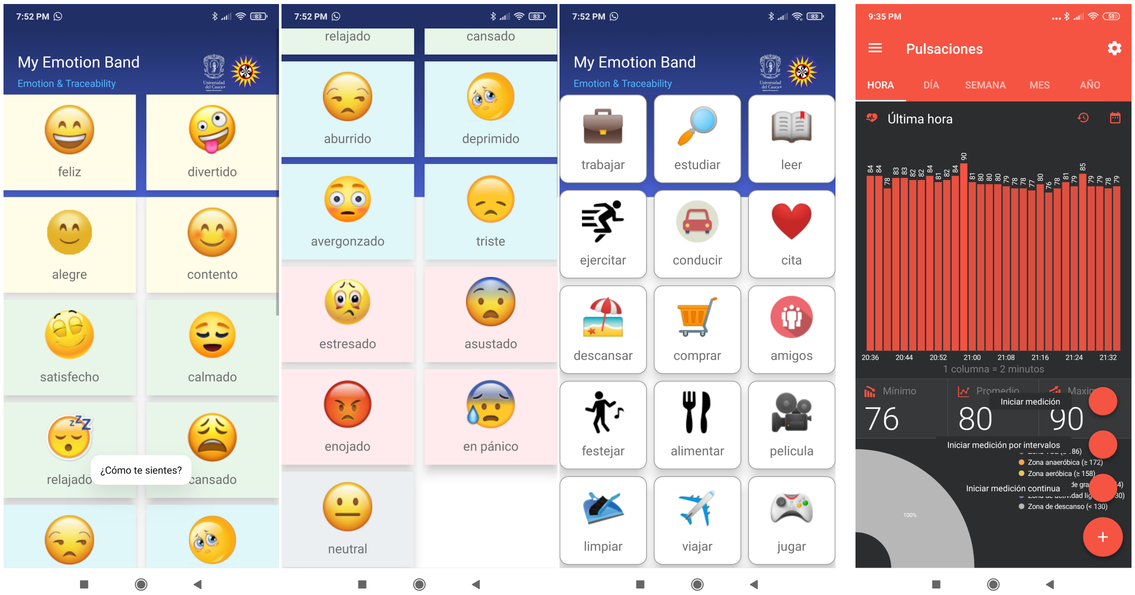


Fig. 4.6 Modular components of the TERS-ER architecture

- Affective detection was developed with the Keras framework and the ML library Scikit-learn [343, 344]. In section 4.4.5, the algorithms for segmenting the dataset, analyzing emotional patterns, and predicting affective states are explained.
- The connection to the SPARQL endpoint was made from the Python SPARQLWrapper library to extract the knowledge base of the Ontotoutra [314] and retrieve the JSON documents for creating the tourist experiences portfolio.
- The recommendation system was constructed with the Simple Python Recommendation System Engine (Surprise) [315], Keras, and Scikit-learn libraries. In section A.4, the prediction algorithms based on the similarity of the items and the users' interests are analyzed to generate the recommendation list.

4.4.5 Apps Architecture

Figure 4.7 shows the user interface of the mobile applications developed and used by the participants during the experiment. Also, Figure A.1 depicts the functional structure of the MEB mobile application for consolidating the emotional dataset.



(a) (b)

Fig. 4.7 The mobile app's graphic interface used by the participants: (**a**) MyEmotionBand for recording emotional state, activity, and location; (**b**) MFB [331] for HR measurement.

The MEB app provided the user interface for recording the affective state (16 emotions and one neutral state) and the activity performed (21 tasks). According to the context of the participants, categorical emotions were associated with activation (Arousal) and emotional polarity (Valence) of Russell's bi-dimensional model [193, 304]. That is, four emotions were defined for each emotional quadrant: happy (HAHV: excited, amused, glad, and pleased), calm (LAHV: satisfied, calm, relaxed, and tired), sad (LALV: bored, depressed, embarrassed, and sad), and anger (HALV: stressed, afraid, angry, and alarmed). The location (latitude and longitude), the date, and time were obtained from the smartphone GPS. In addition, the authentication and synchronization methods were created to store the data on the Firebase server. In particular, the emotional dataset collected 21,000 records from the participants (see Figure A.3). The SQLite files of the MFB application were converted into CSV files, and a dataset of 1,535,992 HR instances was collected (see Figure A.4).

In other studies [1, 304] the recording of emotions, either by the participant of the experiment or by an observer, was carried out manually on a sheet of paper; this instrument is called SAM [318]. SAM can be used in controlled experiments, but its use is inappropriate in the context of a person's daily life. For this reason, the MEB app was developed (see Figure 4.7a). Although the emotion recording is still manual, it is more practical and complete than SAM because the user makes a tap on the emoticon that depicts the emotion that he was feeling at that moment and then another tap on the icon of the activity performed. In this way, MEB correlates the variables of emotion and activity.

4.4.6 Sliding and Adjustable Window Algorithm

Figure A.2 depicts the model implemented for affective detection based on data collected from the context of the participants. ER model is integrated by dataset consolidation, data preprocessing, ES analysis, balancing of emotion classes, and prediction of the affective condition.

The preprocessing of the datasets was made with the synchronization algorithm called a Sliding and Adjustable Window. Because it uses the time series of each participant's HR and emotional state, this algorithm is sliding because the timestamp window is located in the segment that contains data for both datasets. It is adjustable because the size of the timestamp window is configured depending on the behavior of the data (see Figure 4.8). The Algorithm 1 loads the two MongoDB data collections (HR and emotion) to tag the emotion in each participant's HR instances:

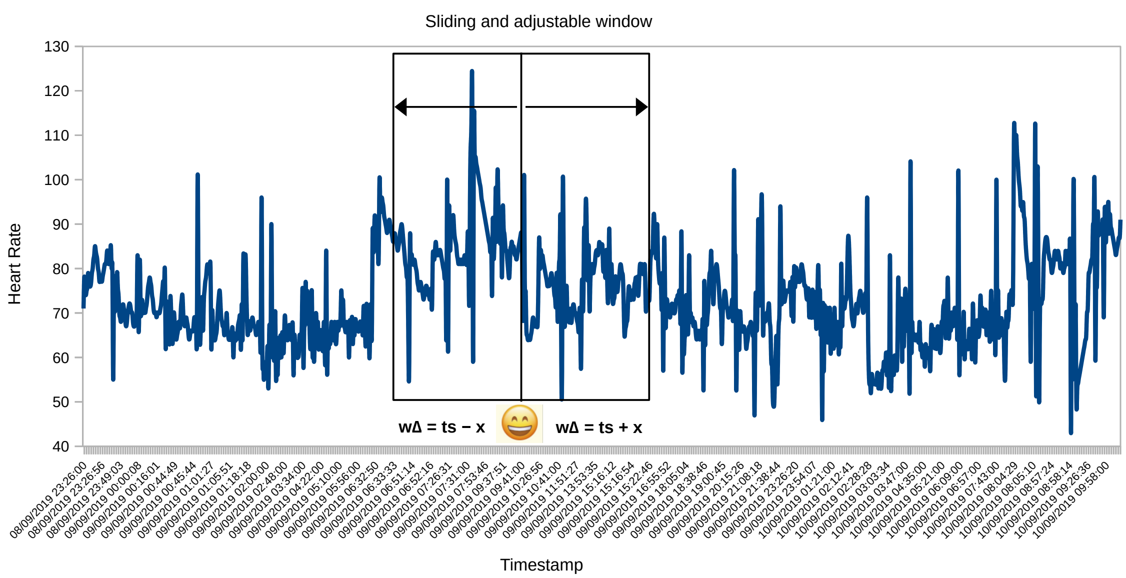


Fig. 4.8 A participant's sample of HR data with the configuration of a dynamic window adjusted to the HR and emotion timestamp.

- Initially, set up a loop to iteratively go through the HR instances dictionary of the participants.

- Obtains the timestamp and HR measurement of each record. Defines a time variable (W_Δ) that controls the window size setting.
- Establishes an iterative cycle through the dictionary of the experiment participants' emotion, activity, and location.
- Gets the HR and emotional data that correspond to the same participant.
- If the emotion label is not found within the maximum window size (for example, 180 s), it loops through the collection of emotions and gets the tag that matches the timestamp of the HR instance. If the label cannot be found, the size of the window is increased.
- Then, set the emotion tag on HR time series instances. In addition, it adds the activity data and geographical location in the HR dictionary.
- Finally, build a new collection in MongoDB with the HR dataset labeled.

Hence, the method (see Algorithm 1) that we developed is adaptive and dynamic to the time series windows of the physiological and emotional datasets.

Algorithm 1 Sliding and adjustable window for the time series data tagging.

```
procedure getTagDataset
    max_size_window = 180;
    for k, v in hrData.items() do
        hr = {};
        for hrTimestamp, heartRate in v.items() do
            W_Δ = 0;
            for k1, v1 in emotion.items() do
                if k1 = k then
                    for key, value in v1.items() do
                        while W_Δ ≤ max_size_window do
                            window_start = hrTimestamp - W_Δ;
                            window_end = hrTimestamp + W_Δ;
                            find = False;
                            for eTimestamp in v1.keys() do
                                if window_start ≤ eTimestamp ≤ window_end then
                                    hr.update(hrTimestamp(v1, hr));
                                    find = True;
                                    break;
                                end if
                            end for
                            if find = True then
                                break;
                            else
                                hr.update(hrTimestamp(v1, hr));
                            end if
                            W_Δ = W_Δ + 1;
                        end while
                    end for
                end if
            end for
        end for
        hrData.update(hrTimestamp(k, hr));
    end for
end procedure
```

As a result of the preprocessing, a tagged data collection of 218,297 records (documents in JSON format) was generated. The data structure is made up of a document identifier (_id), a participant number (IMEI), the emotion timestamp (emotionts), the affective state (emotion), type of activity (activity), HR (hr), location (longitude and latitude) and HR timestamp (hrTimestamp).

4.4.7 Emotional Slicing Algorithm

The size of the segment parameterizes the Emotional Slicing (ES) algorithm (by default 30 HR instances), the time between instances (for example, 60 s), and the limit size of instances (for default 20). The algorithm loads the MongoDB HR collection, consolidates the labeled instance blocks, and generates the physiological dataset used in the affective detection module. This algorithm was created for detecting the duration of the emotion (See Section 4.3.1).

Algorithm 2 has the following activities:

- Loads the preprocessed collection into a list and gets the first HR instance.
- Initializes a new physiological slice.
- Add the values to the HR, timestamp, and emotion vectors.
- Creates a list with the minimum and maximum HR values for each participant to normalize the data.
- Browses the records of the HR collection. Each iteration verifies that the instance belongs to the same emotional slice of the participant and complies with the limit size of instances. It controls that when the activity is a movie and has the same emotion, it adds the instance to the data vectors. It checks the addition of new instances to other activities that meet the established parameters.
- Then, creates the list of affective segments with the predominant emotion of the HR instances.

Furthermore, the algorithm uses the duplication time-series values technique to adjust the number of HR instances (for instance, a record of 20 HR instances repeats the initial sequence of the vector until it completes the default size of 30). Lastly, the new collection of 5247 ES is stored in MongoDB. The data structure of each participant (JSON format) handles a vector of timestamp and affective segment data (_Id, imei, instances number, slice duration, activity, emotion, longitude, and latitude), together with an HR vector normalized through the linear transformation function depicted in Equation (4.1) [313]. This method reduces the standard deviation in the data and suppresses the event of outlier values.

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4.1}$$

where:

x = measurement of a user's heart rate;

x_{min} = minimum measurement of all a user's heart rates;

x_{max} = maximum measurement of all a user's heart rates;

Algorithm 2 Emotional slicing.

```
procedure buildSlices
    timeBetweenInstance = 60; sliceSize = 30; sliceLimit = 20; slicesCounter = 0;
    tagHrList = dataLoad(hrData); previous = tagHrList[0];
    initSlice();
    addInstanceToSlice();
    getMinMaxByImei();
    for row in range(1, len(tagHrList) do
        previous = tagHrList[row − 1];
        current = tagHrList[row];
        if previous[0] = current[0] then
            if int(current[0]) - int(previous[0]) ≤ timeBetweenInstance then
                if current[4] =' movie' then
                    if previous[3] ≠ current[3] then
                        closeSlice();
                    end if
                    addInstanceToSlice();
                else
                    addInstanceToSlice();
                end if
            else
                closeSlice();
                addInstanceToSlice();
            end if
        else
            closeSlice();
            addInstanceToSlice();
        end if
    end for
end procedure
```

4.4.8 DNN Models

The ER component defines the DNN approaches for detecting affective states based on HR data (see Figure 4.9) using the Deep Convolutional Neural Network (DCNN) model [1]. This model was built by stacking four 1D CNN layers that reached emotional patterns of physiological signals and three Fully Connected (FC) Layers to predict emotion. Furthermore, two models based on 1D CNN and LSTM architectures [311, 313] were defined. Initially, both models used a 1D-CNN to extract the emotion features related to the input vectors. The convolution has a kernel size of 10 and a filter of 128. The second MaxPooling layer reduces the dimensionality of the feature map and has a pool size of two. The first model uses a third flatten layer to convert the feature map into a one-dimensional vector. Then, the fourth FC layer that receives the learned features is connected.

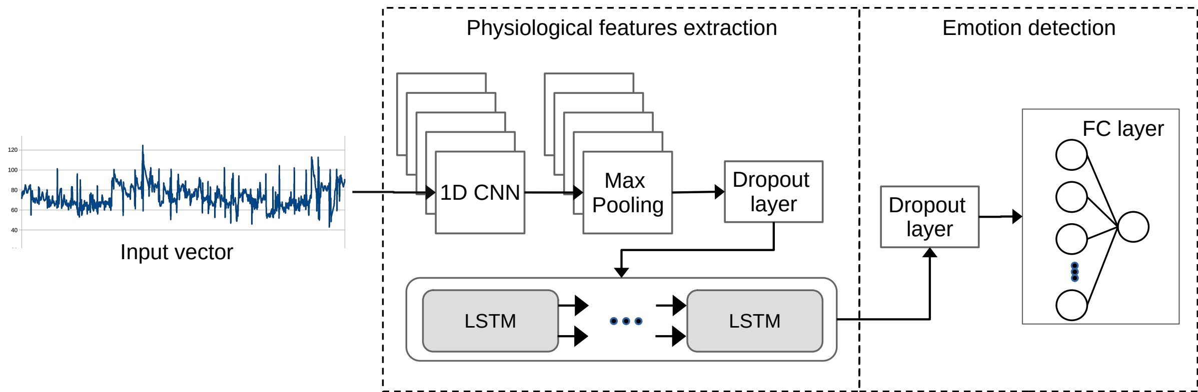


Fig. 4.9 1D CNN LSTM Architecture.

On the other hand, in the second model (Figure 4.9), after the connections of the 1D CNN and Maxpoling layers, a third dropout layer of 0.5 is added as an exclusion mask to the LSTM that can improve the generalizability. This fourth LSTM layer learns the order of the contextual dependencies of the local features entered. Then, in both models, the 0.5 dropouts fifth layer prevents overfitting during model training and transfers the learned features to the FC sixth layer. Besides, the Rectified Linear Unit (ReLU) activation function is used in the middle layers of the network. While in the output layer, the Softmax trigger function defines the predicted emotion of the multiclass classification.

4.4.9 Recommender Components

Figure A.5 depicts the technological components of TERS related to dataset management, data evaluation, evaluation of prediction models, and contextualized recommendations of tourist destinations (see Appendix A.4). The TERS approaches are explained below:

The CBF approach computes the similarity between all the pairs of hotels (see Equation 4.2) with the scalar product of categories of TE (binarized vector of TE), location (longitude and latitude), description (summary of services related to TE), and the hotel review tags (for instance exceptional, fantastic and outstanding). The CS metric determines the likeness between TE categories, and the Haversine distance establishes the closeness of locations.

On the other hand, the fuzzy match metric [345] compares the description of hotels, and the Python tool "difflib.SequenceMatcher" measures the similarity of the categorical rating of the reviews. As a result, a matrix correlates the similarity of the hotel ratings during the model training and estimates the prediction of the hotel rating for a user. Furthermore, the KNN algorithm derived from the AlgoBase class [315] was used. Afterward, the split of the dataset, the evaluation of the recommendation algorithm's performance is backed up in the evaluation framework proposed in [316].

$$\begin{aligned} TE(h_i, h_j) &= 1 - spatial.distance.cosine(te[h_i], te[h_j]) \\ Location(h_i, h_j) &= mt.exp(-haversine(te[h_i], te[h_j])/1.0e3) \\ Category(h_i, h_j) &= SequenceMatcher(cat[h_i], cat[h_j]).ratio() \\ Description(h_i, h_j) &= fuzz.token\_sort\_ratio(des[h_i], des[h_j])/1.0e2 \\ Sim(h_i, h_j) &= TE_{ij} \cdot Location_{ij} \cdot Category_{ij} \cdot Description_{ij} \end{aligned} \tag{4.2}$$

where:
h_i, h_j = pair of hotels related to the users' rating;
te = binarized vector of hotels' tourist experiences.;
cat = the hotels' score category string;
des = the hotels' services description string;

The CF-CNN model preprocesses the user and hotel identifiers of the rating dataset. Then, the 50-dimensional feature vectors to train and evaluate the algorithm [317] were generated. Initially, the embedment layers transformed the input vectors into matrices and regularized the embeddings using the Gradient Descent (GD) technique [313]. Furthermore, a concatenation layer decreased the dimensionality of the embedding layers. The developed model CF-CNN employed a 1D CNN layer to automatically extract the patterns from the concatenated vector and a Max-Pooling layer to reduce the convolution features map (see Figure 4.10) [304, 313]. Also, a dropout layer to regularize the model during training was added. The FC layers later compressed the extracted features and used a ReLu activation function to produce the predicted rating of the tourist destinations. In contrast to the CF-CNN approach, the embedding matrices-based CF approach (CF-Net) proposed in [317] was implemented. A scalar product between the incrustations (users and hotels matrices) was computed, and, finally, the CF-Net model was trained to apply the GD through a sigmoid function.

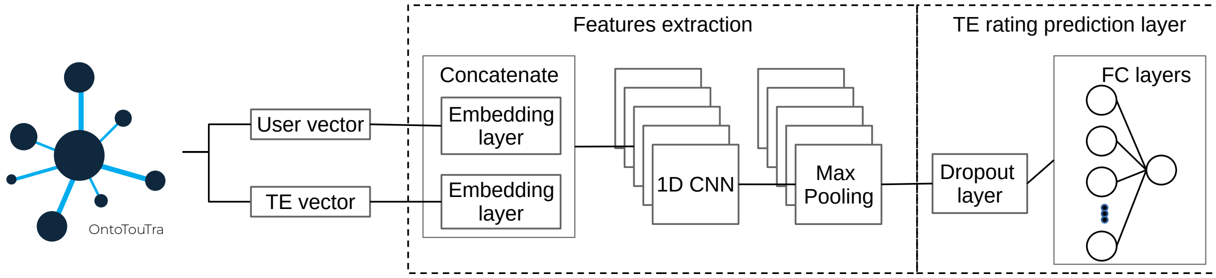


Fig. 4.10 Collaborative Filtering based on 1D CNN.

The CBF model used the prediction method of KNN [315, 316] for estimating the rating of an item based on the average similarity score of the hotels and the ratings registered by a user of the testing dataset.

Finally, the recommendation list was adjusted to 10 items, and the binary vector of TE was added. Also, depending on the predominance of the emotion, the similarity with the TE (cosine similarity in Equation (4.2)) and the location (Haversine distance in Equation (4.2)) of the hotels in the top-N list were calculated. The top-N list of tourist recommendations was ordered according to the geographic proximity of the person. Subsequently, the final top-N list of TE recommendations performed better in the proposed algorithms compared to the SVD, SVD++, and normalPredictor algorithms [315].

The source code of the technological components of the ER subsystems and TERS is available in the following public repository: https://github.com/luzsantamariag/terser.

Chapter 5

Results

The datasets were split into a meaningful percentage to train the approaches (80%) and the other percentage to test the performance of the emotional detection and recommendation models. The training and testing environment was run on a computer with Fedora 34 operating system, Intel Core i7, and 16 Gb memory.

5.1 Emotion Recognition

When evaluating the classification of the imbalanced AV classes, we used k-fold Cross-Validation (CV) to guarantee the presence of all affective states. As defined in Section 4.4.6, we analyzed the ES dataset with different times between HR instances. Then, we used the ES dataset to predict emotions with shallow ML algorithms and with imbalanced AV classes. Subsequently, we used the parameters of the ES with the best performance to test the ER of the DNN models with balanced AV classes.

5.1.1 Multi-Class Imbalanced Classification

Figure 4.2 depicts the distribution by emotional quadrant of the physiological dataset and shows an imbalance between the observations of the minority classes (LVHA with 16.3% and LVLA with 10.8%) concerning the majority classes (HVHA with 36.7% and HVLA with 36.2%). Therefore, we used the Scikit-learn library to evaluate the dataset with assembly classification algorithms using stratified 5-fold CV [337]. The dataset was parameterized with ES of 30 HR measurements and different times between instances (60 and five seconds). Figure 5.1b shows a better performance in the prediction by affective quadrants with less time between instances (five seconds) than the longest time (60 s) (see Figure 5.1a).

Also, the results of the Random Forest (RF), Gradient Boosting (GB), and Extra Trees (ET) algorithms tend to be slightly better in each case, compared to the Bagging (BAG) and Ada Boost (AB) algorithms that recorded less accuracy in the emotion detection. It should be noted that tests with ES of 20 HR instances were also performed, and the accuracy scores were slightly lower than the tests with 30 HR instances for each ES, as reported in Figure 5.1. Therefore, the experiments with the DNN models are parameterized with ES of the size of 30 HR instances.

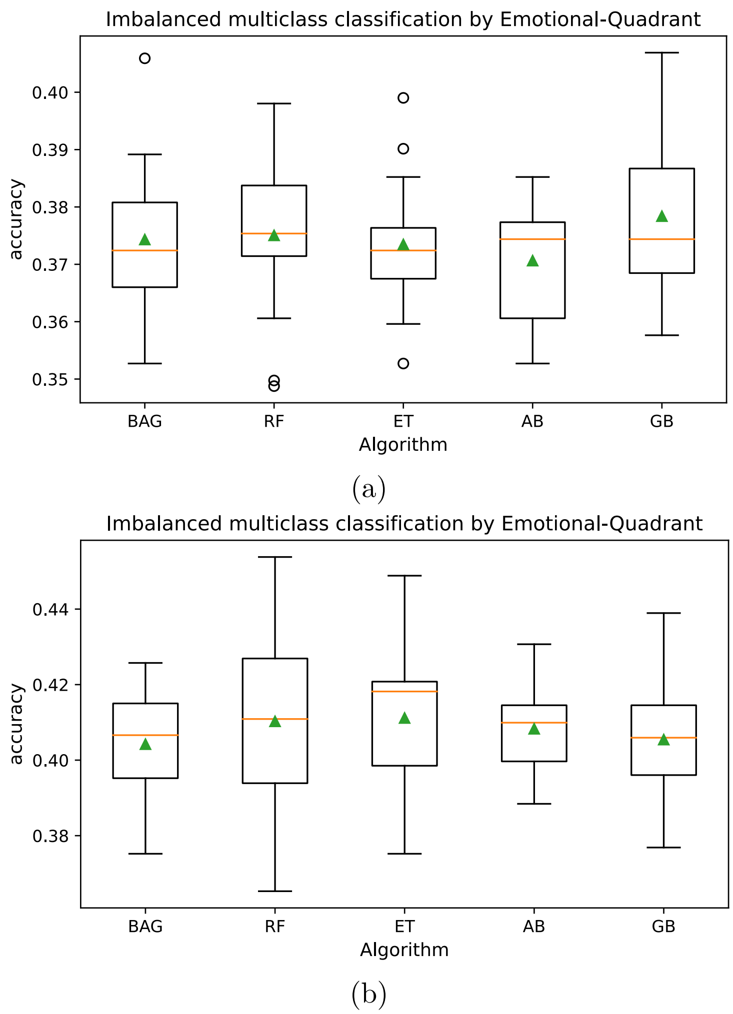


Fig. 5.1 Multiclass classification for ES dataset of 30 HR instances: (**a**) with 60 s between instances; (**b**) with five seconds between instances.

5.1.2 Affective Classification Using DNN Models

The performance of DNN models depends on the volume and quality of the datasets. Therefore, the implementation of heuristic sampling methods compensates for the imbalance in the distribution of affective classes [334, 333]. Table 5.1 shows the results of the DNN models proposed in Section 4.4.8 for affective detection from the physiological dataset balanced with the K-SMOTE and TL techniques. The three models (1D CNN LSTM, 1D CNN Flatten, and DCNN) used a batch size of 32, with repetitions of 50 epochs and a loss parameter calculated with the categorical cross-entropy function. We configured the Adam optimizer and the learning rate 1×10^{-3} to train the physiological dataset in these models. The accuracy results in the testing were slightly better than shallow ML approaches (see Figure 5.1).

Table 5.1 ES dataset performance with CNN-based ER models and four-class balancing methods.

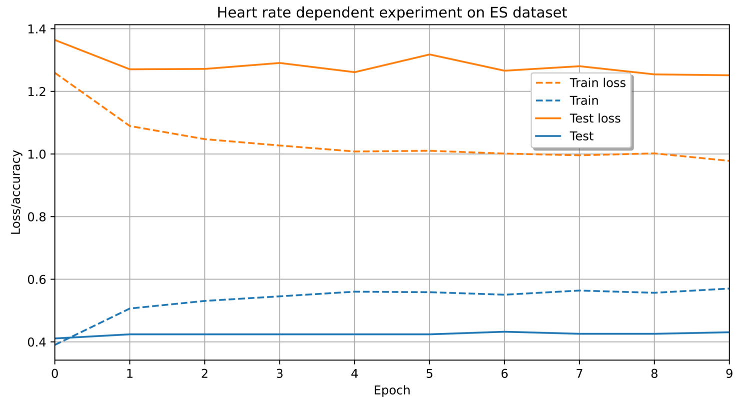
Model	**Data balancing Method**	**Dataset**		**Train Accuracy**		**Test Accuracy**	
		Labels	**HR Slices**	**Better**	**Average**	**Better**	**Average**
DCNN [1]	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVLA, LVHA	1231, 1141, 200, 456	0.60 0.61	0.56 0.57	0.46 0.44	0.41 0.43
1D CNN, Flatten, and FC	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVLA, LVHA	1231, 1141, 200, 456	0.65 0.69	0.61 0.64	0.45 0.46	0.41 0.43
1D CNN, LSTM, and FC	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVLA, LVHA	1231, 1141, 200, 456	0.63 0.67	0.58 0.63	0.47 0.46	0.42 0.44

Combined sampling methods tend to improve accuracy results in both the training and testing of DNN models. Although the AV classes in Table 5.1 showed an imbalance in positive affective states (HVHA: excited and HVLA: calm) related to negative emotions (LVLA: sad and LVHA: angry), accuracy results performed better with CNN models that used the K-SMOTE and TL data balancing methods. This same trend was confirmed in Table 5.2, where the emotional class with the lowest number of instances (LVLA: sad) was eliminated. Therefore, the results during training and testing indicate that this dataset with more ES instances may increase the accuracy.

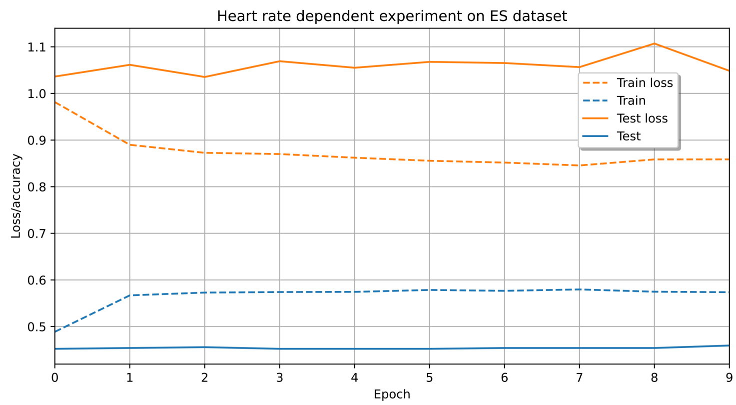
Table 5.2 ES dataset performance with CNN-based ER models and three-class balancing methods.

Model	**Data balancing Method**	**Dataset**		**Train Accuracy**		**Test Accuracy**	
		Labels	**HR Slices**	**Better**	**Average**	**Better**	**Average**
DCNN [1]	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVHA	1231, 1141, 456	0.54 0.58	0.53 0.58	0.48 0.46	0.45 0.46
1D CNN, Flatten, and FC	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVHA	1231, 1141, 456	0.63 0.67	0.57 0.62	0.50 0.50	0.46 0.47
1D CNN, LSTM, and FC	K-SMOTE K-SMOTE + TL	HVHA, HVLA, LVHA	1231, 1141, 456	0.56 0.56	0.54 0.54	0.50 0.51	0.47 0.47

The 1D CNN LSTM model showed better performance in detecting AV classes (see Figure 5.2a,b). However, the efficiency of ER models could be affected by imbalanced spontaneous emotion data and poor measurements of people's HR. Hence, we defined the dataset evaluation protocol by grouping emotions by VA classes due to the importance of including all affective states during training and testing. Furthermore, we compared the MIC between ES of 30 HR measures with different times between instances and showed that the ES dataset of 5-second interval HR instances performed better. Likely, this ER framework will enhance the accuracy outcomes obtained in a new controlled experiment with more participants to consolidate a more robust dataset.



(a)



(b)

Fig. 5.2 Training and validation of the 1D CNN LSTM model in the Emotional Slices (ES) dataset. The accuracy outcomes correspond to the classification of: (**a**) four emotional quadrants in Table 5.1; (**b**) three emotional quadrants in Table 5.2.

In this way, we got the prediction of the emotional quadrant. The analysis of the distribution of emotions showed a high rate of participants who registered positive emotions (happy: HAHV and calm: LAHV) instead of negative emotions (LALV: sad and HALV: anger). Therefore, we show that people increasingly seek to improve their TE. Although the imbalance of the emotional dataset limited the prediction results of the ER models, we achieved a better performance of 44% accuracy in the 1D CNN LSTM approach in contrast to the shallow ML algorithms of 41% (see the middle part of Figure 6.1).

5.2 Evaluation of the TERS-ER

The evaluation determined the effectiveness of the approaches proposed in the TERS-ER architecture using the emotional and destinations datasets (see Table 4.3). The evaluation was carried out with the Mean Absolute Error (MAE) and Root Mean Square Error

(RMSE) metrics. These accuracy metrics estimate the average prediction error based on the closeness of the predicted hotel ratings and the actual data (see Equations (5.1) and (5.2)). The best performance tends to a zero value, while a result equal to or greater than one indicates a high error rate in the estimation.

The first CBF model was implemented using the Surprise [315] framework. For this reason, the performance tests were compared with the SVD and SVD ++ matrix factoring algorithms. The second CF-CNN model compared its performance with the CF-Net algorithm during the training and testing phases. Subsequently, we analyzed the performance results of the proposed models in comparison with the base algorithms.

$$\mathrm{MAE} = \frac{\sum\limits_{(i,j)\in TS} |r_{ij} - \hat{r}_{ij}|}{|TS|} \tag{5.1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum\limits_{(i,j)\in TS} (r_{ij} - \hat{r}_{ij})^2}{|TS|}} \tag{5.2}$$

where:

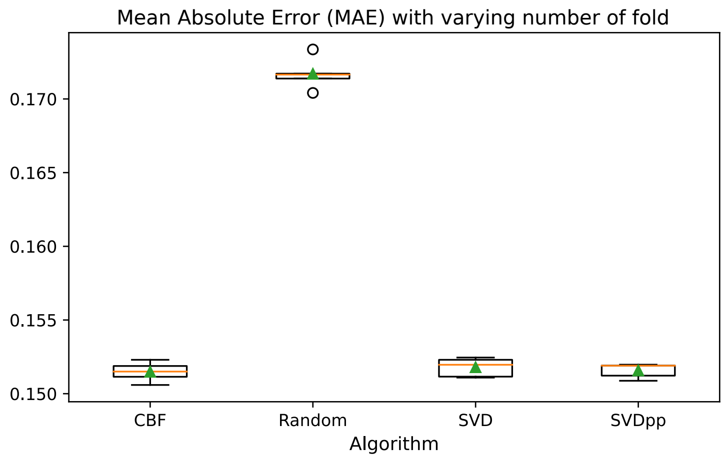
TS = represents the number of ratings of all users in the test set;

r_{ij} = depicts the actual rating of a user u_i for the hotel's TE h_j;

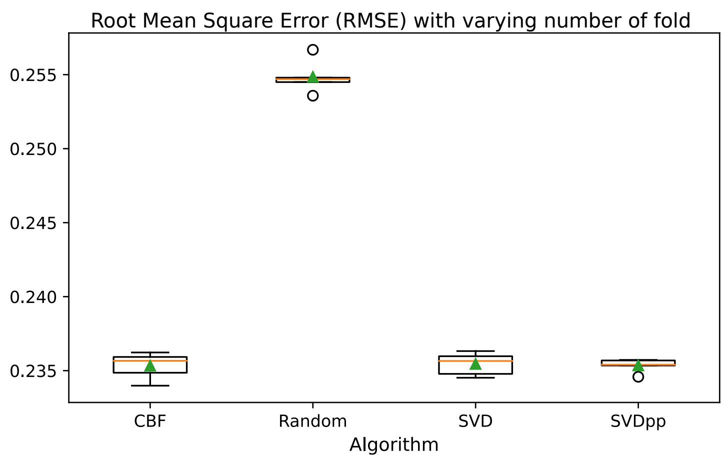
$\hat{r}_{ij}$ = represents the estimated rating of a user u_i for the hotel's TE h_j;

5.2.1 Validation of CBF and Model-Based Approaches

The results of the tourist datasets training had a positive effect on the performance of the CBF model compared to the algorithms for reducing the dimensionality of latent factors since the CBF algorithm, unlike matrix factorization, correlated the similarity of hotel destinations through the features of TE, location, and description. Moreover, Figure 5.3 depicts a similar behavior in the five folds of the CV of the algorithms CBF, SVD [346], and the model derived from the latter with the addition of implicit feedback information SVD ++ [347]. Further, it shows the distribution of performance measurements and the rising rate according to the hotels' TE dataset size.



(**a**)



(**b**)

Fig. 5.3 CBF evaluation: (**a**) MAE; (**b**) RMSE.

5.2.2 Training and Testing of CF Models

The hotels' TE datasets were used for evaluating the CF models during the training and testing. The validation parameters of the models were defined by the batch size of 64, a loss function MeanSquaredError (MSE), repetitions of 10 epochs, Adam optimizer, and learning rate of 1×10^{-3}.

Figure 5.4 shows the iterations of the recommendation models during the training and testing with their respective MSE losses. The MAE metric in training and testing shows our CF-CNN model's better performance than the CF-Net model.

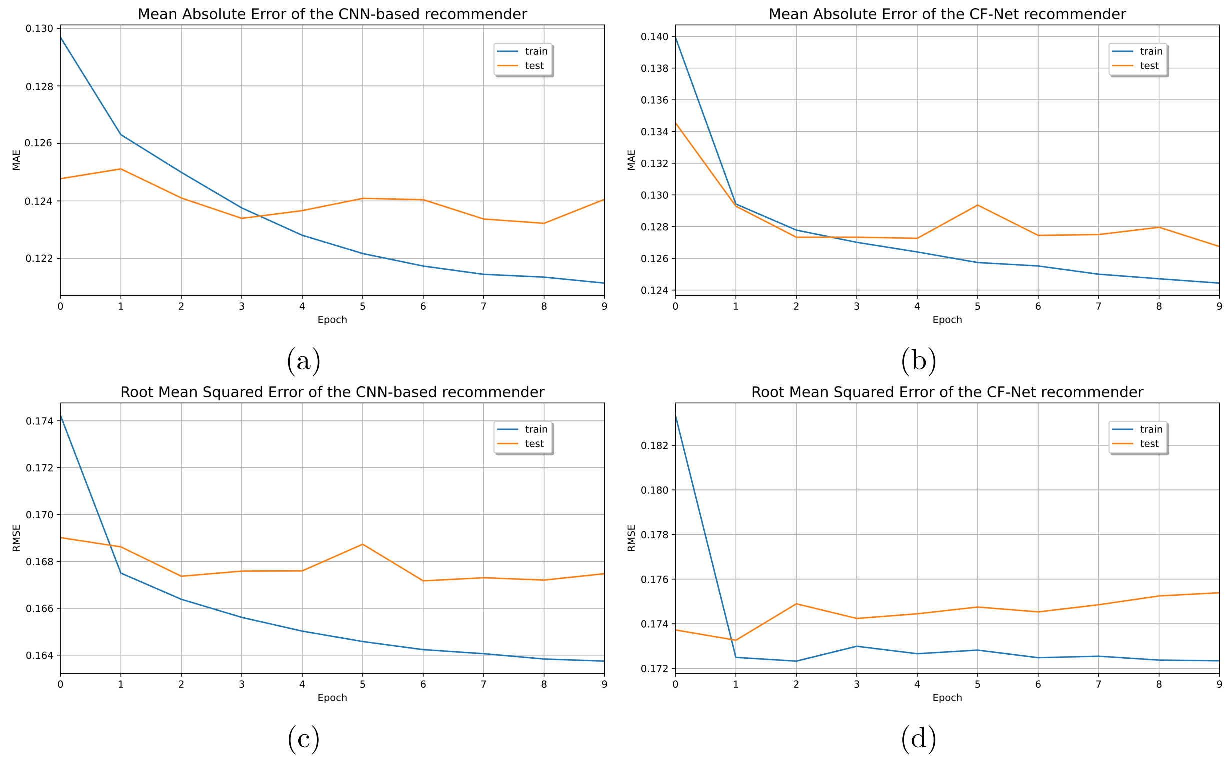
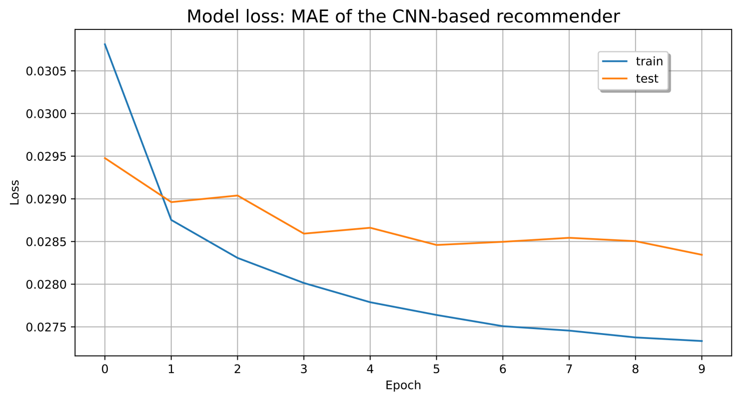
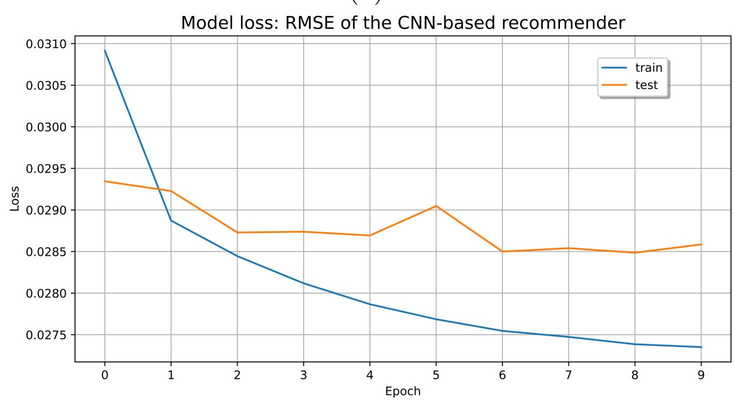


Fig. 5.4 Recommender system evaluation over (**a**) MAE of CF-CNN model; (**b**) MAE of CF-Net model; (**c**) RMSE of CF-CNN model; (**d**) RMSE of CF-Net model.

Therefore, the CF-CNN capacity increased by reducing the regularized overfit by a 0.1 dropout. Furthermore, the loss of the model denotes a positive impact on the training and testing data and is well below 0.1 (see Figure 5.5).



(a)



(b)

Fig. 5.5 Loss value of CF-CNN (**a**) MAE; (**b**) RMSE.

Likewise, Figure 5.4 shows the RMSE variation of the epochs of the CF models during the training and testing with their MSE losses. The behavior of the iterations is very similar in both metrics. Also, the performance results of the CF-CNN model are better than those of the CF-Net model.

5.2.3 Comparison of Performance Metrics

Unlike the CF-CNN model, the CBF model incorporated similarity metrics between destinations to estimate the rating. Precisely, Figure 5.6 confirms that the proposed approaches outperform the MAE performance for the predicted rating of the recommendation of tourist destinations concerning the matrix factoring algorithms. However, in the RMSE metric, the model's performance is better for the CF-CNN approach than the other models.

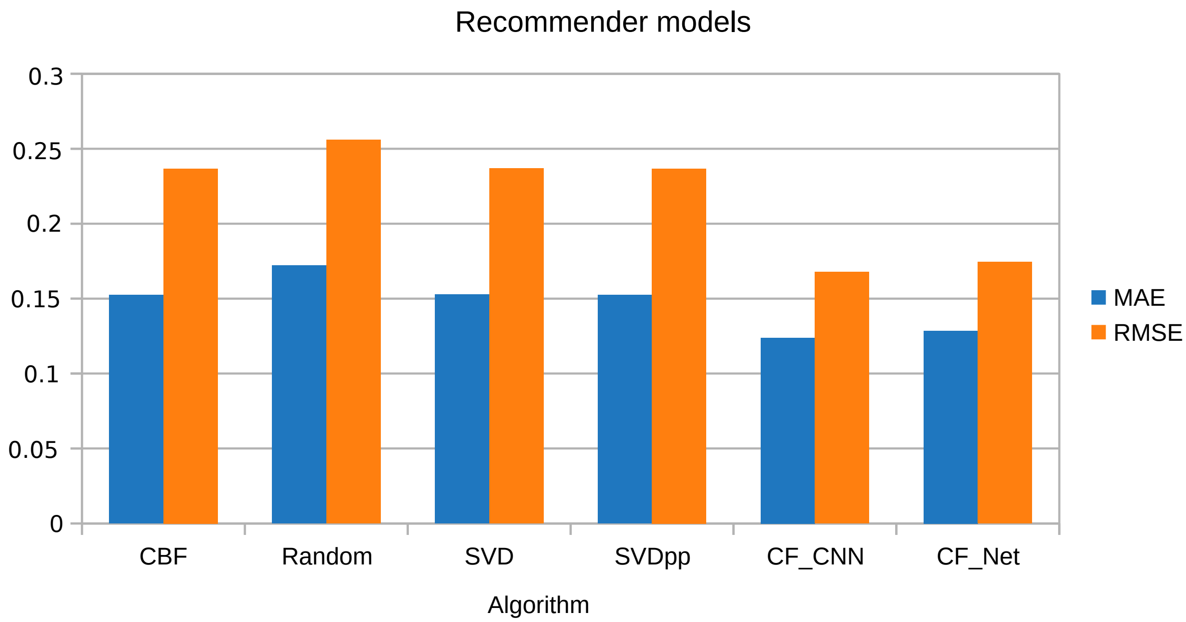


Fig. 5.6 TERS-ER Evaluation.

Furthermore, Table 5.3 describes the performance of the proposed models and indicates an outstanding improvement in the accuracy of the list of top-N TE. Since the evaluation metrics in both MAE and RMSE were the lowest in the CF-CNN model. In addition, the experimental results with the tourist datasets of the traditional recommendation models had a slightly lower performance than the models based on DNN.

Table 5.3 Performance statistics with different TERS algorithms.

Algorithm	**MAE**	**RMSE**
CBF (This study)	0.152	0.237
Random [315]	0.172	0.256
SVD [315]	0.153	0.237
SVD++ [315]	0.153	0.237
CF-CNN (This study)	0.124	0.168
CF-Net [317]	0.128	0.175

The general outcomes show that the information of the TE, the geographic location, and the attributes of the tourist destinations can affect the performance in the prediction. Finally, the performance results show that the proposed CF-CNN and CBF algorithms perform better in the TERS-ER architecture.

Chapter 6

Conclusions and future work

The proposed architecture is a reference for developing recommendation systems based on users' emotional states in different contexts (see Figure 6.1). Furthermore, this model allows adding wearable devices with more accuracy physiological sensors [306, 348, 308, 323]. However, when cheap wearable devices become more popular in the market, manufacturers will probably include more accuracy sensors for monitoring biosignals and physical activity [327, 325, 328, 321, 326, 320]. For this research, we opted for massive and cheap devices that are probably the most used by people in their daily lives. The disadvantage of these devices is the low accuracy of measuring physiological signals that would be very sensitive in medical or specialized applications but are tolerable precisions for tourism. For this reason, an accuracy of 44% in the emotion detection is tolerable to maximize the user experience of these types of devices. Also, it's important to take into account that this accuracy can be improved with new versions of the wearables used, as with a more robust ES dataset, through another experiment with a more significant number of participants and controlled elicitations, which serves as a cold start for the TERS. It could involve other physiological signals different from HR, such as, for instance, electrodermal activity and temperature.

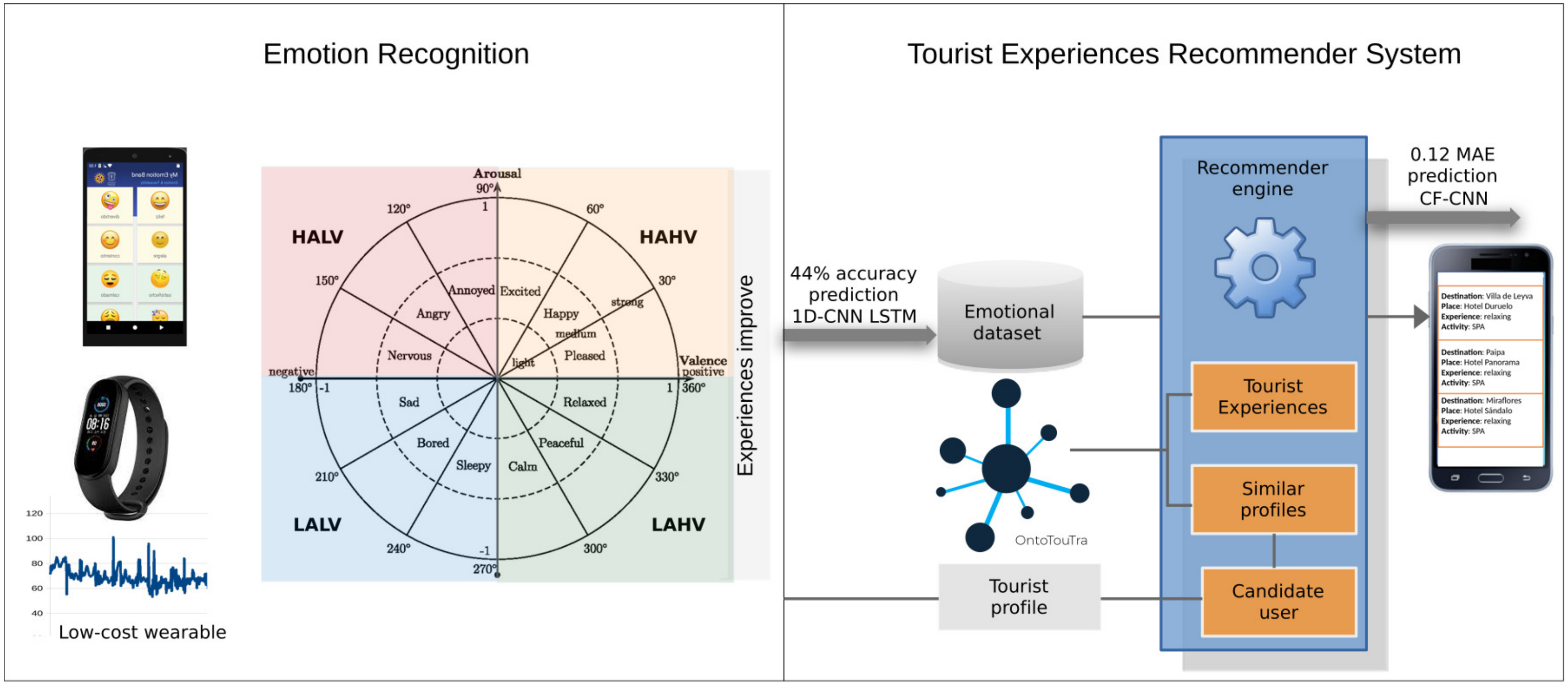


Fig. 6.1 Data model of the TERS-ER architecture.

Regarding the related work represented in Table 4.2, the use of shallow ML classifiers with an accuracy of around 0.7 can be seen. ER used the 1D CNN-LSTM hybrid classifier with an accuracy result of 0.44. This level of performance is tolerable due to the significant differences in the conditions of the design of the experiments (see Table 6.1). However, the conditions of this study were planned to meet the requirements of the context, that is, anyone in their daily lives that uses a cheap wearable device. The emotion detection performance of this system is acceptable for recognition, generating an additional contextual factor to a recommender system to improve its accuracy. This contextual factor is emotion, which is a new contribution to recommender systems for the domain of tourism.

Table 6.1 Differences between emotion recognition studies.

	This study	**Related Studies**
Context	Daily life	Laboratory
Devices	Cheap wearable	Specialized sensors and wearables
Annotators	Self-annotation (MEB app)	Team of annotators (external and internal)
Participants	18	20 (average)
Stimuli	Daily life–spontaneous	Videos and images–controlled
Emotion duration	Variable	Constant (1–2 minutes)
Emotion annotation	Voluntary	Mandatory
Experiment duration	11 weeks	1 day
Signals	HR (PPG)	PPG, GSR, EEG, ECG (multi-channel)
Signal recording	Sampling (third-party app)	Continous
Domain	Tourist	Various

Regarding the analysis of RS-related works based on emotions, these works focused mainly on analyzing sentiments of reviews. Their MAE and RMSE results are very close to 1 (see Table 4.3). On the contrary, in our study, the CF-CNN and CBF classifiers were used, the similarity between users was determined, and the context, preferences, and profile were taken into account. This way, optimal MAE and RMSE results were achieved compared to the other studies (see Section 5.2).

Concerning MIC and following the comparison of results (see Section 5.1.1), it is recommended to parameterize the number of sufficient physiological instances for each ES. In the experiment, better results were obtained with 30 instances of HR for each ES, with a distance between instances of five seconds.

It is necessary to deal with the imbalance of emotion classes in this ER system, which is logical since human behavior predominates in certain emotional types, although the contextual stimulus differs. For instance, a happy person tends to feel more frequent emotions from the happiness quadrant (HVHA). Then in the emotional register, an imbalance of classes is created for the other quadrants. For this reason, combined K-SMOTE and TL techniques were applied for balancing the minority emotional classes. It was also experimented with the elimination of the instances of a minority class, in this case, sadness (LVLA), to improve the performance of the classifier, although the performance improved (see Tables 5.1 and 5.2). This procedure is not recommended because it biases the emotional behavior and this can lead to overfitting of the model.

The main contributions of this research were:

- The TERS-ER model (see Section 4.4)
- An algorithm that synchronizes the emotional labeling of a physiological time series in an adjustable and sliding window (see Section 4.4.6).
- An algorithm that creates emotional segments (see Section 4.4.7) according to the process of an emotion formulated by Norman [309].
- The MEB app (see Section 4.4.5) replaces the paper recording of the emotional spectrum that was done with SAM.
- An emotional dataset, heart rate recording, and emotion recording were created from the data collection of the Xiaomi Mi Band wearable devices and the MEB app of 18 participants of the experiment (see Section 4.3).
- Source code for the implementation of the TERS-ER model (see Section 4.4.9).

The results of the TERS-ER model were published in the journal Sensors [349], the review of the state of the art of this research was published in the journal Future Internet [304], and the emotion detection model using deep learning in a multimodal dataset AMIGOS was published in the journal IEEE Access [1]. Another collaborative investigation (both investigations belonging to the same call for MinCiencias 733) was published in Applied Sciences [314]. Finally, the cooperative paper published in IEEE Access was an input for this research project, especially in feature extraction and ML algorithms for sensor signal analysis [240].

Future research would focus on merging multimodal physiological datasets to the TERS-ER architecture to optimize the affective detection of users. The system could incorporate contextual information on the environment and travel routes to increase user satisfaction.

Furthermore, this research is part of the second of five phases of a TE recommendation macro-project. Future areas of research would involve the following:

- Definition of an emotion recognition model from a publicly available emotional dataset. In this case, the AMIGOS dataset was used [1].
- Definition of the model: This corresponds to the results of this study, where the TERS-ER architecture was proposed (see Figure 6.1).
- Consolidation of the ES dataset for the cold start: Replicating the experiment on a larger scale and in a controlled environment to consolidate a large ES dataset with better performance indicators in emotional detection from HR data (see Figure 6.2).
- TERS-ER production: users in the context of their daily life, months or weeks before planning their TE, use low-cost wearable devices (Xiaomi mi band) and the application (TE recommender) on their smartphone to collect in this period the HR data. Subsequently, the HR data collected from the user will be labeled with the emotions according to the ES dataset, and the remaining stages of the model are applied to make the respective recommendation (see Figure 6.2).
- Improvement of the TERS-ER: Defines the ability of the dataset to learn by itself from the new instances generated by the production environment, using advanced ML techniques such as, for instance, reinforcement learning or deep reinforcement learning [313] (see Figure 6.2).

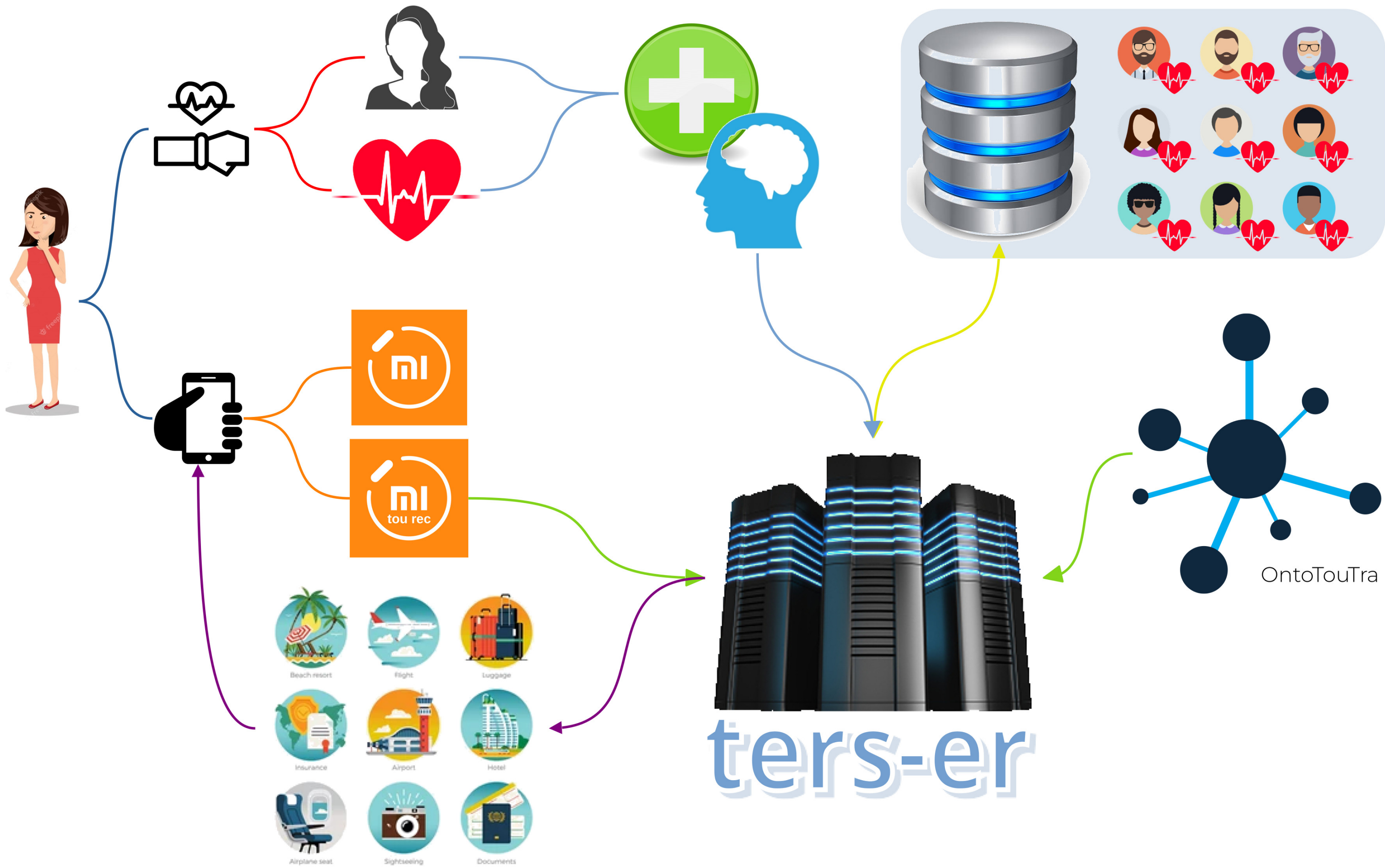


Fig. 6.2 Production scenario for the TERS-ER architecture

Contributions of this research

Papers

The papers published as the results of this research are mentioned below:

1. **Santamaria-Granados, Luz**; Mendoza-Moreno, Juan Francisco; Ramirez-Gonzalez, Gustavo. Tourist Recommender Systems Based on Emotion Recognition—A Scientometric Review. Future Internet 2021, 13, 2. https://doi.org/10.3390/fi13010002, 1-37.
   - Paper available at: https://www.mdpi.com/1999-5903/13/1/2/htm
   - Journal indexed in: **JCR Q2, SJR Q2, and Publindex A2.**
   - Citations: **7**
   - Contribution for this study: **State of the art**.
2. **L. Santamaria-Granados**, M. Munoz-Organero, G. Ramirez-González, E. Abdulhay and N. Arunkumar, "Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset (AMIGOS)," in IEEE Access, vol. 7, pp. 57-67, 2019, https://doi.org/10.1109/ACCESS.2018.2883213.
   - Paper available at: https://ieeexplore.ieee.org/document/8543567
   - Journal indexed in: **JCR Q1, SJR Q1, and Publindex A1.**
   - Citations: **102**
   - Contribution for this study: **Emotion Detection Model Based on Physiological Signals and TERS-ER**
3. A. F. Hussein, N. Arunkumar, C. Gomes, A. Alzubaidi, Q. Habash, **L. Santamaria-Granados**, J. F. Mendoza-Moreno and G. Ramirez-Gonzalez, "Focal and Non-Focal Epilepsy Localization: A Review," in IEEE Access, vol. 6, pp. 49306-49324, 2018, https://doi.org/10.1109/ACCESS.2018.2867078.

- Paper available at: https://ieeexplore.ieee.org/document/8445554
- Journal indexed in: **JCR Q1, SJR Q1, and Publindex A1.**
- Citations: **32**
- Contribution for this study: **State of the art and Emotion Detection Model Based on Physiological Signals.**

4. **Santamaria-Granados, Luz**; Mendoza-Moreno, Juan Francisco; Chantre-Astaiza, Angela; Munoz-Organero, Mario; Ramirez-Gonzalez, Gustavo. "Tourist Experiences Recommender System based on Emotion Recognition with Wearable Data". Sensors, 2021, 21 No. 23, 7854, https://doi.org/10.3390/s21237854, 1-28.

    - Paper available at: https://www.mdpi.com/1424-8220/21/23/7854/htm
    - Journal indexed in: **JCR Q1, SJR Q2, and Publindex A1.**
    - Contribution for this study: **TERS-ER, results and conclusions**

5. Mendoza-Moreno, Juan Francisco; **Santamaria-Granados, Luz**; Fraga-Vázquez, Anabel; Ramirez-Gonzalez, Gustavo. OntoTouTra: Tourist Traceability Ontology based on Big Data Analytics. Applied Sciences, 2021, 11, 11061. https://doi.org/10.3390/app112211061, 1-39.

    - Paper available at: https://www.mdpi.com/2076-3417/11/22/11061/htm
    - Journal indexed in: **JCR Q2, SJR Q2, and Publindex A1.**
    - Citations: **1**
    - Contribution for this study: **TERS-ER**

Datasets

The raw datasets of annotations of emotional states and heart rate measurements, which were collected in the experimental phase of this research, are available in the following repository: https://github.com/luzsantamariag/terser.

Source Code

The source code of the technological components of the ER subsystems and TERS is available in the following public repository: https://github.com/luzsantamariag/terser.

Chapter 7

List of Acronyms

The following abbreviations are used in this document:

A	Arousal
CARS	Context-Aware Recommender System
CBF	Content-Basic Filtering
CF	Collaborative Filtering
CS	Cosine Similarity
CNN	Convolutional Neural Network
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
ECG	Electrocardiogram
EEG	Electroencephalogram
ER	Emotion Recognition
ES	Emotional Slicing
FC	Fully Connected
GSR	Galvanic Skin Response
HR	Heart Rate
HVHA	High Valence High Arousal
HVLA	High Valence Low Arousal
IBI	Inter-Beat-Interval
IoT	Internet of Things
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
LVHA	Low Valence High Arousal

LVLA	Low Valence Low Arousal
MAE	Mean Absolute Error
MEB	MyEmotionBand app
MFB	Master For mi Band
MIC	Multi-class Imbalanced Classification
ML	Machine Learning
NLP	Natural Language Processing
OntoTouTra	Ontology for Tourist Traceability
OTA	Online Travel Agency
POI	Point of Interest
PPG	Photoplethysmogram
RF	Random Forest
RMSE	Root Mean Square Error
RS	Recommender System
SAM	Self-Assessment Manikin
SMOTE	Synthetic Minority Oversampling Technique
SPARQL	SPARQL Protocol and RDF Query Language
SVM	Support Vector Machine
TE	Tourist Experiences
TERS	Tourist Experiences Recommender System
TERS-ER	Tourist Experiences Recommender System based on Emotion Recognition
TL	TomekLinks
V	Valence

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Appendix A

Implementation of Functional Components of TERS-ER

A.1 MyEmotionBand Application

Figure A.1 depicts the functional structure of the MEB app for consolidating the emotional dataset. For this purpose, the classes (MainEmotionBand and ActivityData) provided the user interface for recording the emotion and activity.

A.2 ER System

ER model is integrated by dataset consolidation, data preprocessing, ES analysis, balancing of emotion classes, and prediction of the affective condition (see Figure A.2). The first component manages the collections of physiological data, emotions (emotional state, activity, and location), labeled data (HR with emotion tag), and segmented (number of HR instances). Also, it manages the connections to the database servers (getFirebaseConnection, getConnectionMongoDB) and maintains the emotional dataset resulting from the ER.

A.3 HR and Emotion Dataset Records

The emotional dataset collected 21.000 records from the experiment participants. Figure A.3 shows the time series of the emotion record. The HR dataset gathered 1.535.992 HR instances from the experiment participants. Figure A.3 shows the time series of the HR record.

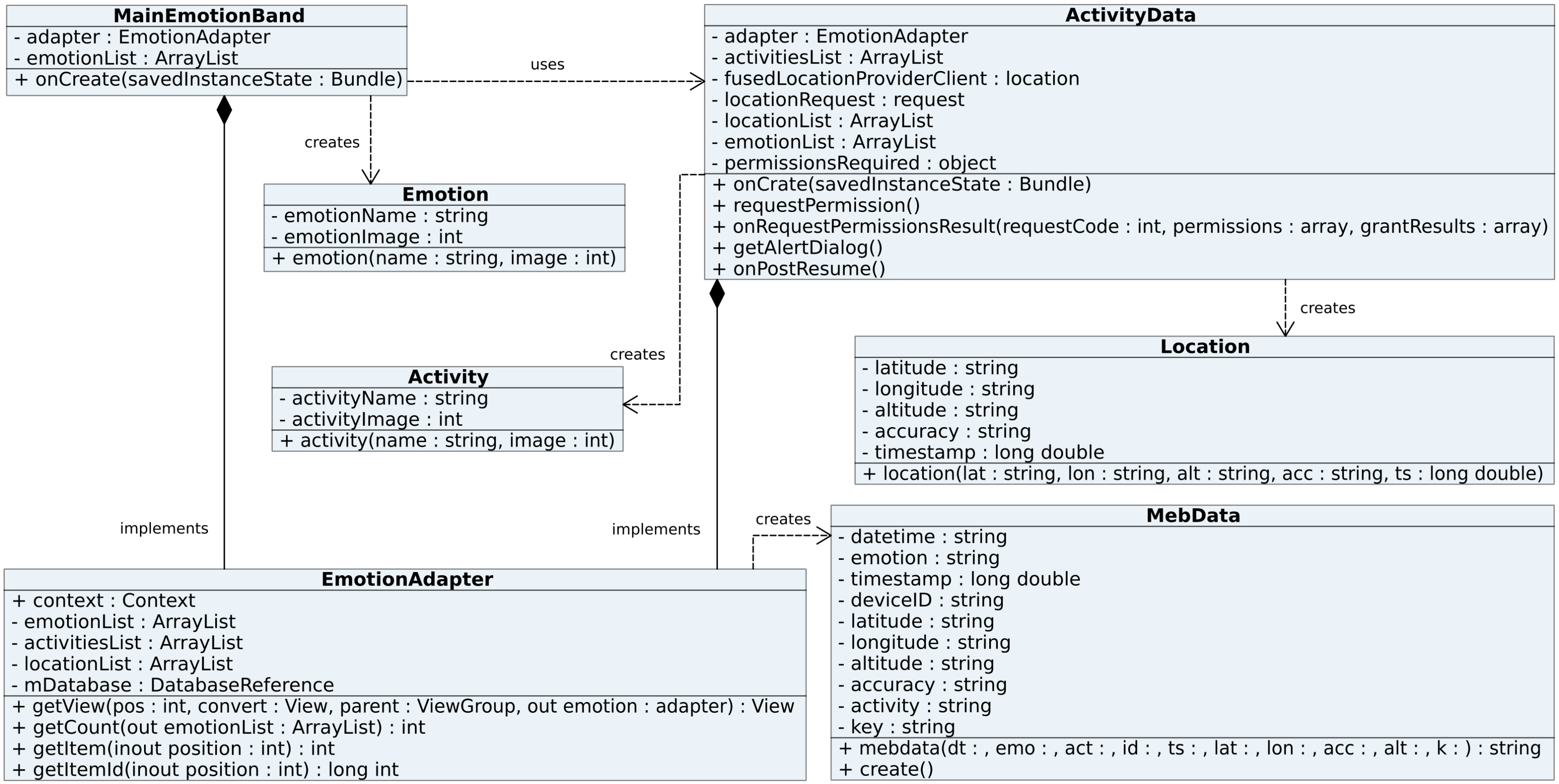

Fig. A.1 Components of the MyEmotionBand application.

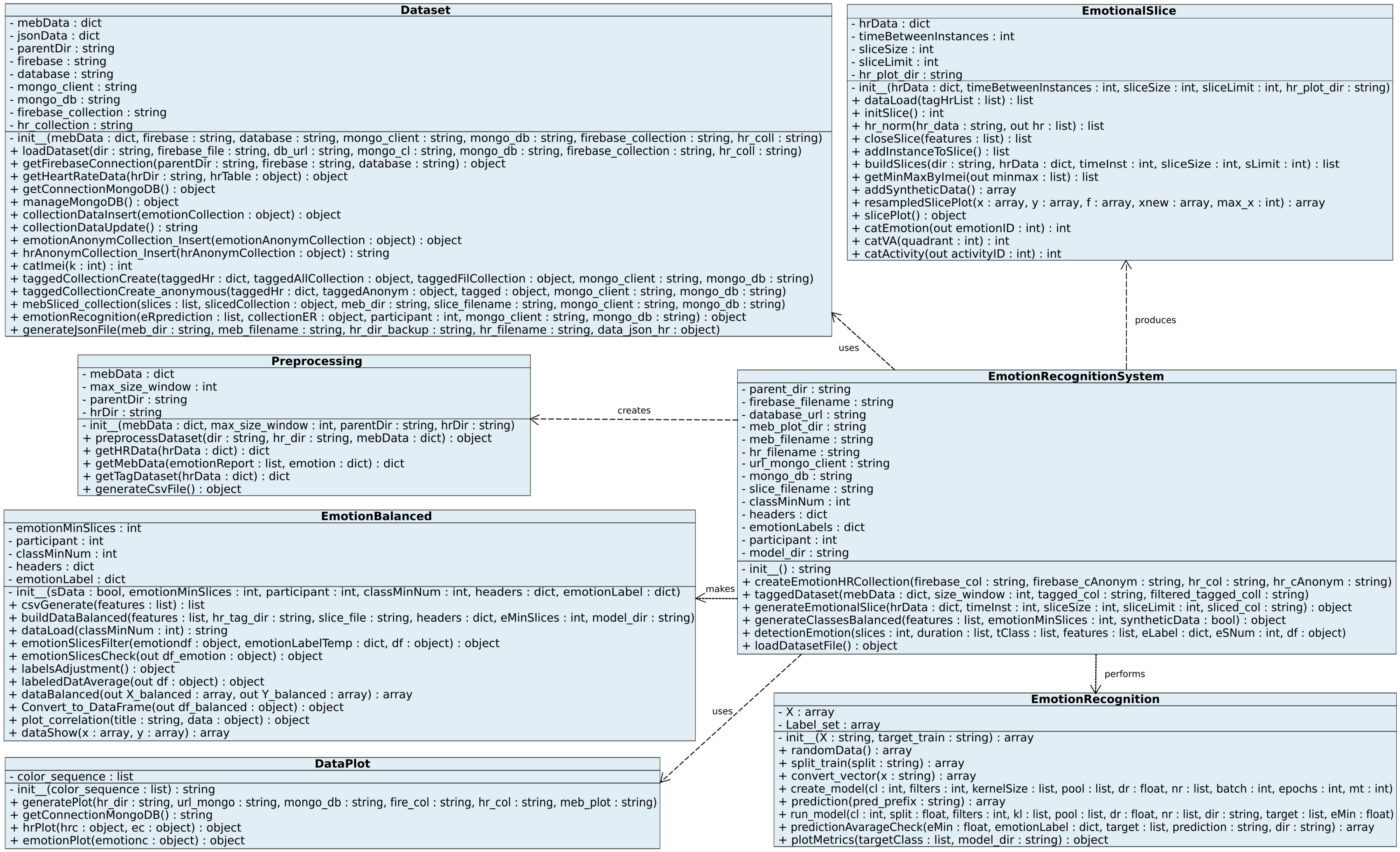

Fig. A.2 Components of the emotion recognition system

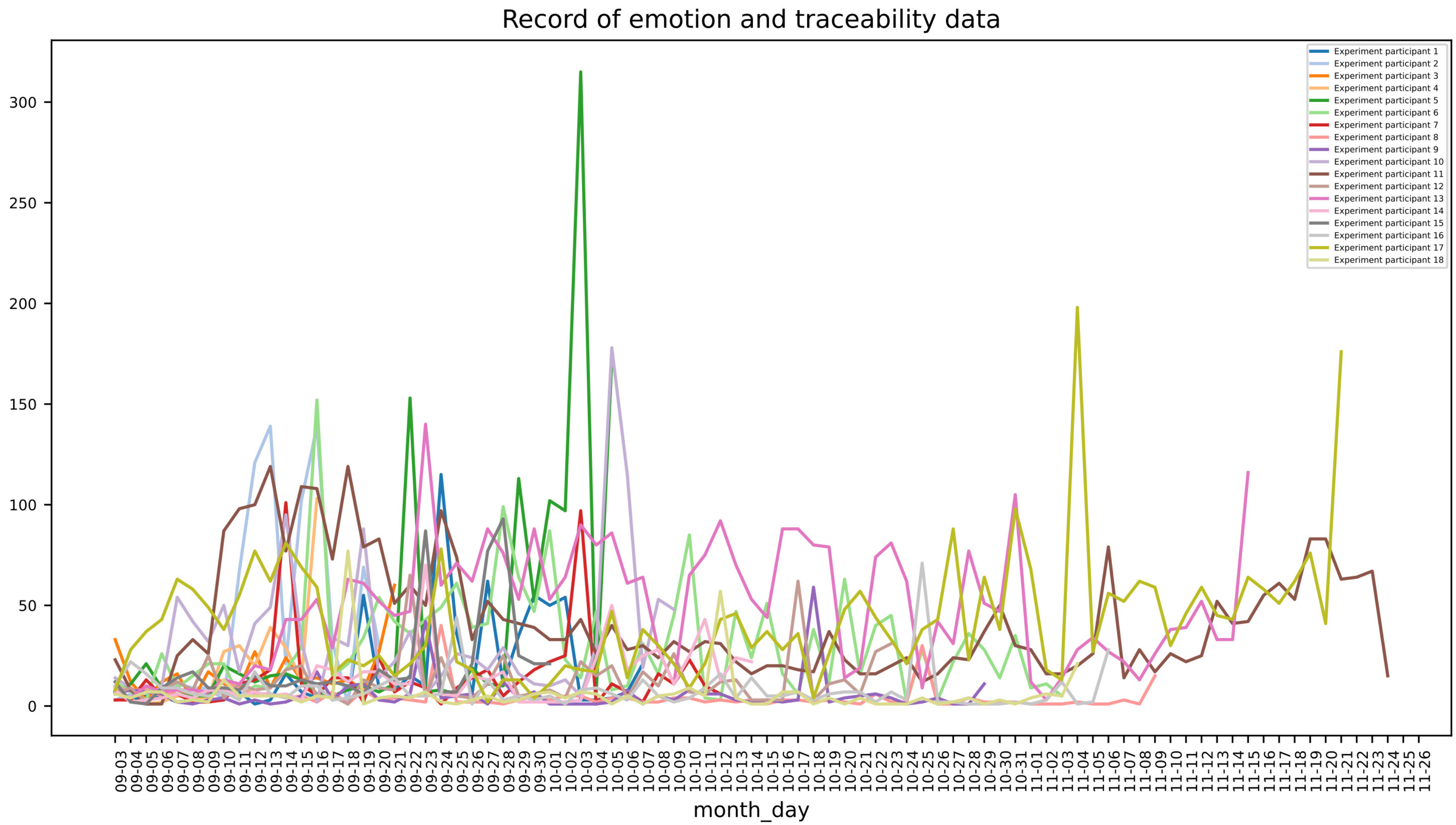

Fig. A.3 Emotion data of experiment participants.

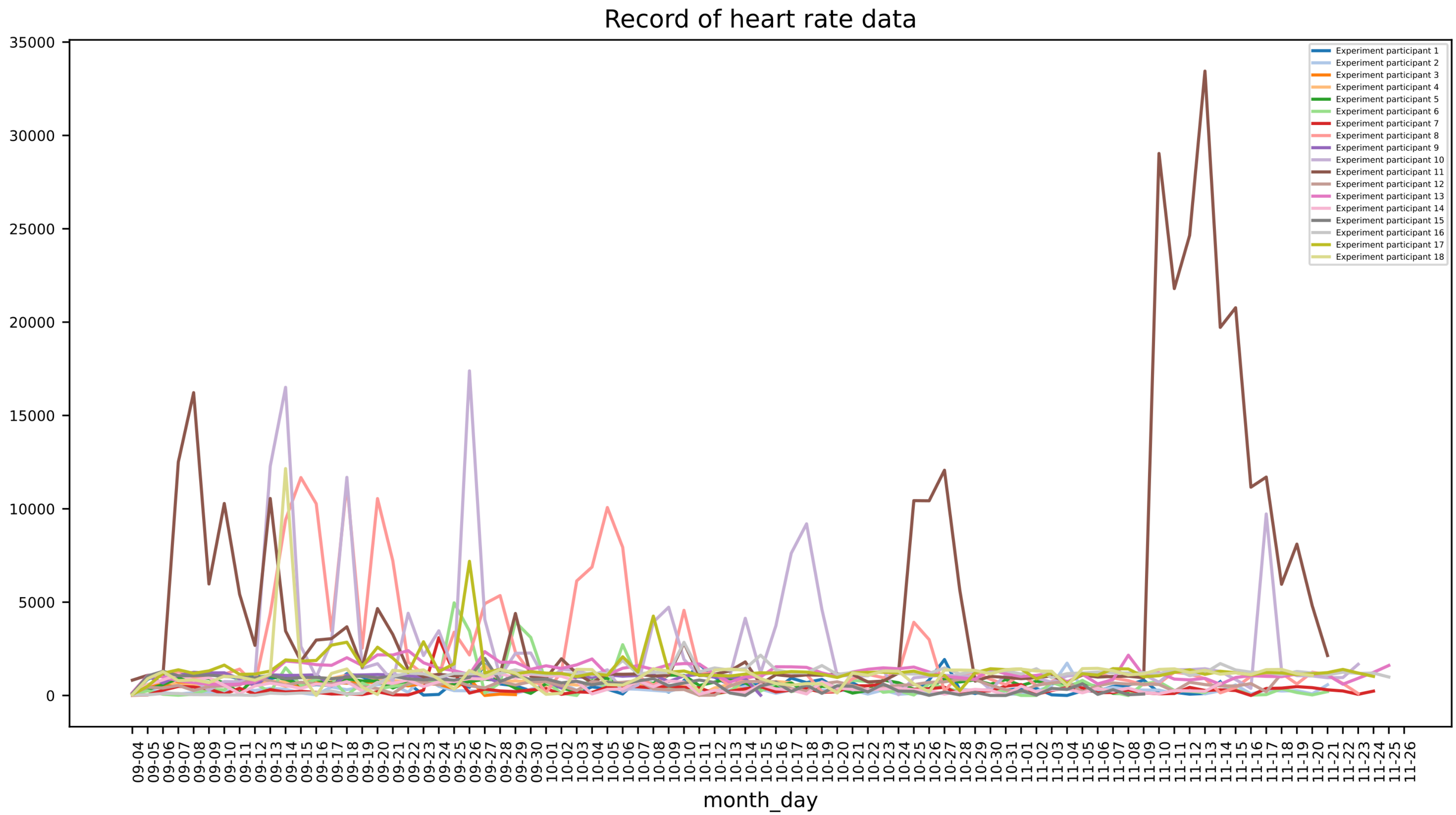

Fig. A.4 HR of experiment participants.

A.4 Components of the TERS

This part is presented the technological components of TERS related to dataset management, data evaluation, evaluation of prediction models, and contextualized recommendations of tourist destinations (see figureA.5).

For building the TE categories, OntoTouTra [314] supplied a knowledge base. Also, the recommender managed the collections of emotion and TE preferences of the participant's (see Figure A.6). From these collections, a candidate user algorithm that calculated the similarity of the participant with the users of the tourism dataset was proposed. The recommender generated the list of top-N TE that the candidate user had not yet visited. Subsequently, the recommendations are filtered by the interests of TE, affective status, and location of the participant.

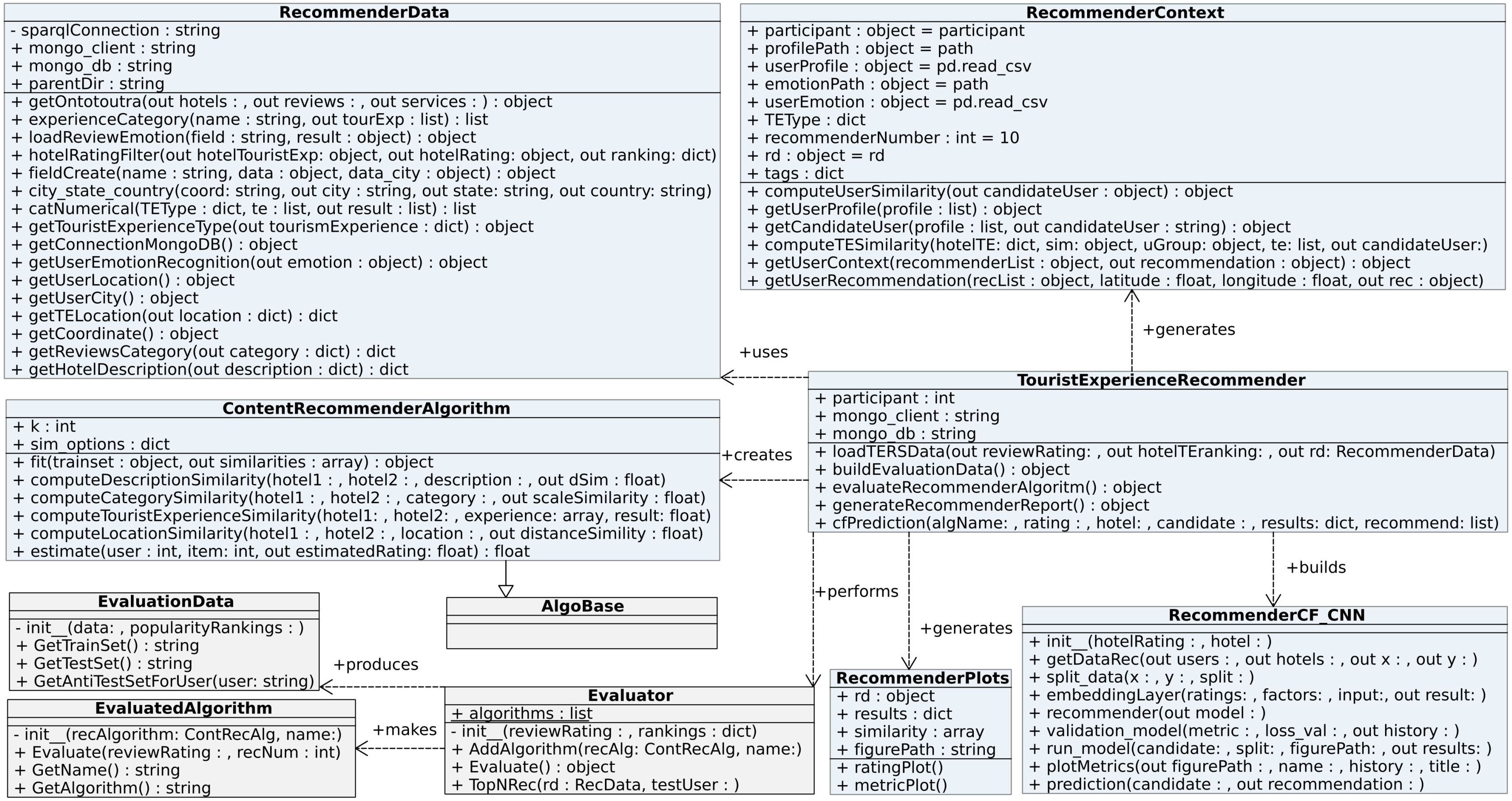

Fig. A.5 Components of the TERS. The EvaluationData, EvaluatedAlgorithm, Evaluator, and AlgoBase classes are based in [316, 315].

Emotion Recognition System

imei	emotion	duration	slices	feltEmotion	city	longitude	latitude
11	feliz	13,52	16	1%	Tunja	-73,352604	5,558712
11	satisfecho	92,7	95	7%	Tunja	-73,352604	5,558712
11	relajado	113,23	108	8%	Tunja	-73,352604	5,558712
11	cansado	306,9	281	22%	Tunja	-73,352604	5,558712
11	triste	119,12	101	8%	Tunja	-73,352604	5,558712
11	estresado	316,43	283	22%	Tunja	-73,352604	5,558712
13	divertido	105,33	44	7%	Tunja	-73,364054	5,532522
13	calmado	118,55	51	8%	Tunja	-73,364054	5,532522
13	triste	143,83	68	10%	Tunja	-73,364054	5,532522
13	asustado	79,2	37	6%	Tunja	-73,364054	5,532522

Tourist experiences portfolio of Hotels' Booking (OntoTouTra ontology)

hotelID	hotelName	reviewScore	reviewNum	hotelCity	hotelAddress	hotelLon	hotelLat	touristExperience
2235095	Campo Escondido	9,4	29	Toca	Finca La Esperanza V	-73,1897914	5,716832515	['Romance', 'Entertainment', 'Family', 'Relaxation']
273320	Estelar Paipa Hotel Spa	9,2	442	Paipa	A Orillas Del Lago So	-73,1248605	5,759647569	['Adventure', 'Ecological', 'Family', 'Relaxation']
322912	D'Acosta Hotel Sochagota	9,1	535	Paipa	Km 2 Via a las Piscin	-73,1147003	5,759471437	['Fitness', 'Romance', 'Adventure', 'Ecological', 'Family']
1111475	Hotel Hacienda Baza	8,9	122	Tibaná	Vereda Lavaderos, 15	-73,4216309	5,311817266	['Ecological', 'Adventure', 'Family']
321930	Hotel Hacienda El Salitre	9,0	454	Paipa	Kilometro 3 Via Toca-	-73,1153011	5,742647898	['Entertainment', 'Adventure', 'Ecological']
1834344	Hotel Gran Sirius	9,0	554	Sáchica	Kilometro 5 via Sachic	-73,5418598	5,58835996	['Romance', 'Adventure', 'Ecological', 'Heritage/Culture']
3846483	Hostal El Caminante	9,5	149	El Cocuy	Carrera 4 #7-30 El Co	-72,443896	6,408499	['Heritage/Culture', 'Ecological', 'Entertainment']
2955365	Best Western Duitama	9,3	268	Duitama	Cr. 13 # 18-191 Duita	-73,032455	5,830918	['Fitness']
4273653	Big Day Hotels-Lago de Tota	8,9	252	Tota	Km 7, Llano Alarcón C	-72,926123	5,581771	['Family']
389264	La Posada de San Antonio	8,8	338	Villa de Leyva	Carrera 8 No 11-80, 5	-73,5235468	5,631678627	['Romance', 'Ecological', 'Heritage/Culture', 'Family']

Participant profile

imei	gender	age	CivStatus	emotion	city	touristExperience
1	male	19	single	Relajado	Tunja	['Heritage/Culture', 'Family']
2	female	19	single	Asustado	Tunja	['Heritage/Culture']
3	male	23	single	Relajado	Tunja	['Heritage/Culture', 'Family']
4	male	24	single	Calmado	Tunja	['Heritage/Culture']
5	female	22	single	Contento	Tunja	['Family', 'Romance', 'Ecological']
6	male	21	single	Alegre	Tunja	['Family', 'Entertainment', 'Heritage/Cultu
7	male	30	single	Feliz	Tunja	['Family', 'Relaxation', 'Adventure']
8	female	24	married	Calmado	Tunja	['Relaxation', 'Family']
9	male	19	single	Relajado	Tunja	['Heritage/Culture']
10	female	22	single	Calmado	Tunja	['Family', 'Heritage/Culture']
11	female	44	married	Contento	Tunja	['Family', 'Relaxation', 'Heritage/Culture'
12	female	21	single	Feliz	Tunja	['Heritage/Culture', 'Family', 'Ecological']
13	female	20	single	Asustado	Toca	['Family', 'Ecological']
14	male	20	single	Relajado	Tunja	['Family']
15	male	20	single	Calmado	Tunja	['Heritage/Culture']
16	male	27	single	Calmado	Tunja	['Family', 'Heritage/Culture']
17	female	20	single	Relajado	Tunja	['Heritage/Culture', 'Ecological']
18	female	24	single	Calmado	Tunja	['Heritage/Culture']

Hotel reviews (ratings)

hotelID	userId	rating	country	felt_emotion	reviewDate	accommodation	accommodationDate	positiveReview	negativeReview
2235095	Paola	10	Colombia	feliz	noviembre de 2018	Tienda	Noviembre de 2018	La atención de todos	
2235095	Jorge	9	Colombia	feliz	enero de 2020	Habitación	Enero de 2020	La tranquilidad	La falta de bicicletas
2235095	Alicia	10	Colombia	feliz	enero de 2020	Tienda	Enero de 2020	Todo es maravilloso!	
2235095	David	10	Colombia	feliz	diciembre de 2019	Habitación	Diciembre de 2019	El servicio y la amabilidad	
2235095	Graciela	9,6	Colombia	feliz	noviembre de 2019	Habitación	Octubre de 2019	Linda experiencia	
2235095	Claudia	9,6	Colombia	feliz	octubre de 2019	Habitación	Octubre de 2019		
2235095	Laura	9,6	Colombia	feliz	octubre de 2019	Habitación	Octubre de 2019		
2235095	Natalia	9,6	Colombia	feliz	septiembre de 2019	Apartamento	Septiembre de 2019		
2235095	Daniel	9,2	Colombia	feliz	septiembre de 2019	Tienda	Septiembre de 2019		

Relationship between emotion and tourist experience

quadrant	emotions	touristExperience
happy	['feliz','divertido','alegre','contento']	['Adventure','Family','Heritage/Culture','Romance']
calm	['calmado','relajado','cansado','aburrido']	['Ecological','Entertainment','Fitness','Relaxation']
sad	['aburrido','deprimido','avergonzado','triste']	['Adventure','Family','Heritage/Culture','Romance']
annoy	['estresado','asustado','enojado','En pánico']	['Ecological','Entertainment','Fitness','Relaxation']

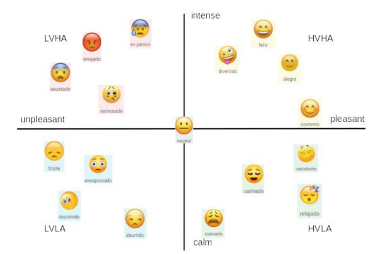

Fig. A.6 Data model of TERS-ER.

A.4.1 Data Management

This module managed the MongoDB server datasets related to the profile (gender and age), TE preferences (for instance, relaxation, family, entertainment, and ecological), and affective states of the participants (felt emotion). Moreover, the OntoTouTra ontology supplied the knowledge base of hotels (hotel identifier, description, location, and categorical rating), hotel services (hotel identifier, wellness facilities, and activities), and user ratings of the satisfaction of the services consumed in the destination (hotel identifier, user identifier, and rating) [314]. Afterward, we defined the algorithms to recovery the datasets of the tourist destinations from an endpoint, created the TE from the hotel services, and calculated the frequency of the predominance of the emotion felt by the ER participants (see Figure A.6).

The information Linked Data dispose of a large number of datasets of diverse application domains published on endpoints [330]. Precisely, TERS-ER gathered the explicit information from OntoTouTra through declarations of graphic patterns defined in SPARQL queries. The data model is structured in triples of an object, predicate, and subject (for instance, object:? Hotel, predicate: RDF:type, and subject: ott:Hotel). Therefore, we developed Algorithm 3 to access an endpoint server that contains the tourist ontology. Then, we implemented the scripts in the SPARQL query language to collect the information from the Colombia datasets. The JSON documents retrieved from the SPARQL query were stored in DataFrames. A similar procedure was carried out to execute the SPARQL queries for reviews and services of the hotel destinations.

Algorithm 3 For getting the OntoTouTra knowledge base.

```
procedure getOntotoutra
    sparql = sparqlConnection; hotels = [];
    stringQuery = """
    PREFIX ott :< http : //tourdata.org/ontotoutra/ontotoutra.owl#
    PREFIX rdf :< http : //www.w3.org/1999/02/22 − rdf − syntax − ns#
    SELECT ?hotelID ?cityName ?hotelDes ?hotelLat ?hotelLon ?hotelCatScore
        WHERE {;
            ?hotel          rdf : type              ott : Hotel;
                            ott : hotelID           ?hotelID;
                            ott : hotelDes          ?hotelDes;
                            ott : hotelLat          ?hotelLat;
                            ott : hotelLon          ?hotelLon;
                            ott : hotelCatScore     ?hotelCatScore;
                            ott : hasCityParent     ?city.
            ?city           rdf : type              ott : City;
                            ott : cityID            ?cityID;
                            ott : cityName          ?cityName;
                            ott : hasStateParent    ?department.
            ?department     rdf : type              ott : State;
                            ott : stateName         ?stateName.
            FILTER(?stateName = "Boyaca")
        }"""
    sparql.setQuery(stringQuery); sparql.setMethod('POST');
    sparql.setReturnFormat(JSON); results = sparql.query().convert();
    for result in results["results"]["bindings"] do
        hotel = [];
        for k, v in result.items() do
            hotel.append(v['value']);
        end for
        hotels.append(hotel);
    end for
    return pd.DataFrame(data = hotels, columns = list(results["results"]);
end procedure
```

Algorithm 4 to create the TE categories of hotels from the features of wellness facilities (for example, thermal baths, spa, and body scrub) and activities (for instance, hiking, canoeing, museum tours, and beach) was developed. These features belong to the dataset of the services offered by the hotels. We implemented the string division method to replace the separator characters and get a list of strings from each category of services. Then, we extracted from a Dataframe of hotel experience categories the labels of each TE corresponding to the service elements of activities (for example, the ecological experience includes the hiking activity) and well-being (for instance, the relaxation experience is related to the spa facilities). Finally, the TE lists are added to the hotels' dataset (for this case, the TE list comprises: Ecological, Relaxation, Adventure, Heritage / Culture, and Family).

Algorithm 4 Creating the tourist experiences in the hotels' dataset.

```
procedure getTouristExperience
    service['activityExperience'] = experienceCategory(tags['activity']['tag']);
    service['wellnessExperience'] = experienceCategory(tags['wellness']['tag']);
    hotel['touristExperience'] = service.apply(;
        lambda x : list(set(x['activityExp'] + x['wellnessExp'])), axis = 1);
end procedure
procedure experienceCategory(name)
    tourExp = [];
    for j in range(service) do
        temp = [];
        if str(service[name][j]) ≠ 'nan' then
            item = service[name][j].replace('[','').replace("'",'').replace("'",'').split(',');
            for i in item do
                if len(touristE[touristE['services'] = i]['exp'].tolist()) > 0 then
                    temp.append(touristE[touristE['services'] = i]['exp'].tolist()[0]);
                end if
            end for
            tourExp.append(list(set(temp)));
        else
            tourExp.append([]);
        end if
    end for
    return tourExp;
end procedure
```

Algorithm 5 to determine the frequency of the emotion felt by the participants during the affective detection stage was implemented. Initially, to identify the contextual features of the affective state and the location of the participants, we created the Dataframes of the collections of ER (imei, emotion, duration, and quantity of ES) and ES (imei, hr, ts, emotion, latitude, and longitude). Then, the percentage of predominance between the duration of ES of the same category and the total time of ES of each participant was computed. Furthermore, we extracted the longitude and latitude parameters of the ES and used the OpenStreetMap library to get the participants' location (city, state, and country). Afterward, we integrated the features of the emotion with the most significant predominance, the VA quadrant (happy, calm, sad, and angry) and the location of each participant.

Algorithm 5 For getting the predominance of the emotion felt by participants, using the ES and ER collections.

```
procedure getUserEmotionRecognition
    getUserLocation();
    df_emotion = pd.DataFrame(columns = emotion.columns);
    df_emotion['felt_emotion'] = "";
    for i, user in enumerate(emotion["imei"].unique()) do
        data = emotion.loc[emotion['imei'] = user];
        emotion['felt_emotion'] = emotion.loc[;
            data.index.values[0] : data.index.values[len(data) − 1]].apply(;
            lambda x : x['duration']/data["duration"].sum(), axis = 1);
        df_emotion = df_emotion.append(emotion.loc[;
            data.index.values[0] : data.index.values[len(data) − 1]]);
    end for
    emotion.update(df_emotion);
    getUserCity();
    return emotion;
end procedure
```

A.4.2 Recommender Engine

We developed two approaches to the TERS engine (see Algorithm 6). The prediction algorithms processed the filtered information from the hotels' dataset and extracted the most relevant TE items for the recommendation process. Besides, we developed the algorithms of candidate user similarity and contextual features filtering to create the top-N list of TE. Finally, we generated the list of recommended TE based on the target user's preferences and emotions.

Algorithm 6 TE recommendation based on contextual data.

```
procedure generateRecommenderReport
    rd = recommenderData();
    recommendation, algorithmName, mae, rmse = []; results = evaluator.results;
    rc = RecommenderContext(rd, user, profile);
    candidateUser = rc.computeUserSimilarity();
    prediction = evaluator.TopNRecs(rd, candidateUser);
    for algorithm in range(prediction) do
        prediction = (pd.DataFrame(prediction[algorithm])).sortValues();
        recommendationList = pd.merge(prediction, rd.hotels);
        result = rc.getUserContext(recommendationList);
        name = evaluator.algorithms[algorithm].GetName();
        recommendation.append([result, name, results[name]]);
    end for
    recommendation, results = cfPrediction('CF_Cnn', rd.rating, rd.hotels, candidateUser);
    recommendation, results = cfPrediction('CF_Net', rd.rating, rd.hotels, candidateUser);
    for k, v in results.items() do
        algorithmName.append(k);
        for key, value in v.items() do
            if key == 'MAE' then
                mae.append(value);
            else
                rmse.append(value);
            end if
        end for
    end for
    userRecommendation = recommendation[mae.index(min(mae))][0];
end procedure
```

We proposed filtering candidate users via profiles similar to the target user to generate the list of top-N TE (see Algorithm 7). Initially, similar features are selected among users of the hotel review dataset and ER participants. Then, a binary vector of TE is created from the participant's profile data. On the other hand, in the hotels rating Dataframe, we calculated the gender of the users by applying the gender_guesser.detector library. Besides, we defined the aggregation functions to filter the candidate users by selected features (gender, country, and TE). Also, we computed the similarity between the chosen participant and the candidate users filtered by hotels visited. The cosine similarity metric between the TE was estimated (see equation 4.2). Afterward, the number of user visits per hotel, the average hotel review score, and the average TE similarity of the candidate users are computed.

Algorithm 7 For computing the similarity of the profile of an ER participant with the users of the hotels' tourist experiences dataset.

```
procedure COMPUTEUSERSIMILARITY
    participant = imei; profile = []; candidateUser = []; userNum = 25; reviews = rd.rating;
    uProfile['TEType'] = uProfile.apply(
        lambda x : rd.catToNumerical(TEType, ast.literal_eval(x.touExp)), axis = 1);
    userER = rd.getUserEmotionRecognition();
    if len(userER[userER.imei = participant])! = 0 : then
        gender = list(uProfile[uProfile.imei = participant]['gender'])[0];
        country = list(userER[userER.imei = participant]['country'])[0].lstrip();
        te = list(uProfile[uProfile.imei = participant]['TEType'])[0];
    end if
    profile.append([participant, gender, country, te]);
    detectorGender = gender.Detector();
    sim = reviews.groupby('userId').filter( lambda x : x['userId'].count() > 1);
    sim['gender'] = sim.apply( lambda x : detectorG.get_gender(x.userId), axis = 1);
    sim = sim.filter(['userId', 'gender', 'country', 'hotelID', 'rating', 'emotion'], axis = 1);
    sim = sim[sim.gender == profile[0][1]];
    sim = sim[sim.country == profile[0][2]];
    hotelTE = rd.getTouristExperienceType();
    userGr = sim.groupby(['userId', 'gender', 'country']).agg(
        ['count', 'nunique']).sort_values([('hotelID', 'nunique')], ascending = False);
    for i in range(userNum) do
        groupSim = {};
        user = sim[sim.userId = userGr.index[i][0]].filter(['hotelID']);
        user['touExp'] = sim['hotelID'].map(hotelTE);
        user['teSim'] = teSim(user.touExp, profile[0][3]);
        groupSim['userId'] = userGr.index[i][0];
        rating = (sim[sim.userId = userGr.index[i][0]]).groupby(['userId']).agg(['mean']);
        groupSim['meanRating'] = rating.iloc[0][1];
        groupSim['teSim'] = user.teSim.mean();
        groupSim['uniqueHotel'] = len(user);
        candidateUser.append(groupSim);
    end for
end procedure
```

Furthermore, we implemented the prediction methods to generate the list of top-N TE that the target user has not visited yet. This user was selected from the list of candidate users ordered by TE similarity and average rating. The rating estimated of the list of hotel destinations not visited by the target user for the CF-CNN model was calculated. While the CBF model used the prediction method of KNN [315, 316] for estimating the rating of an item based on the average similarity score of the hotels and the ratings registered by a user of the testing dataset.

We developed the algorithm to filter the list of top-N TE by the contextual features of the affective state and the location of the target user (see Algorithm 8). Initially, the participant's record with the maximum percentage of the emotion felt, latitude, and longitude was obtained from the ER collection. Then, the recommendation list was adjusted to 10 items, and the binary vector of TE was added. Also, depending on the predominance of the emotion felt by the target user, the similarity with the TE (cosine similarity in equation 4.2) and the geographical location (haversine distance in equation 4.2) of the hotels in the top-N list were calculated. The top-N list of tourist recommendations was ordered according to the geographic proximity of the ER participant. Subsequently, the final list of top-N TE recommendations performed better in the proposed algorithms compared to the SVD, SVD++, and normalPredictor algorithms [315].

Algorithm 8 To filter the top-N recommendation list of hotels' tourist experiences by contextual features of an ER participant.

```
procedure getUserContext
    userER = rd.getUserEmotionRecognition(); topN = 10;
    er = userER.loc[(userER.felt_emotion == (
        userER[userER.imei == participant].felt_emotion.max()))];
    emotion = er.iloc[0]['emotion'];
    lat = er.iloc[0]['latitude'];
    lon = er.iloc[0]['longitude'];
    userEmotion['te'] = userEmotion.apply(
        lambda x : rd.catToNumerical(TEType, ast.literal_eval(x.touExp)), axis = 1);
    user['check'] = user.apply(lambda x: (emotion in x.emotions), axis = 1);
    user = user.loc[(user.check == True)];
    rec = rec.filter(
        ['hotelID', 'hotelName', 'touExp', 'Lon', 'Lat',' score' ,' number',
    'hotelCity', 'hotelAddress', 'hotelUrl'], axis = 1).iloc[0 : topN];
    rec['te'] = rec['hotelID'].map(rd.getTouristExperienceType());
    rec['teSimilarity'] =teSim(rec.te, userEmotion.iloc[0]['te']);
    rec['locationSim'] =locationSim(str(lat+','+lon), str(rec.hotelLat+','+rec.hotelLon));
    rec['locNormalized'] =valueNormalized(rec['locationSim']);
    rec['similarity'] = rec[['teSim',' locNormalized']].mean(axis = 1);
    userRecommendation = rec.sort_values(['similarity'], ascending = False);
end procedure
```