Dainattor: A Web System for Real-Time Facial Expression Recognition and Prediction of Emotional Disorders Using Machine Learning and Computer Vision—Systematic Review, Development and Usability Evaluation

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***Abstract*—Recognition of facial expressions in real-time has established itself as a prominent area of research. This field explores machine learning techniques to analyze expressions from text, voice, and facial features. In this context, we present Dainattor, derived from the Latin term "Inordinatio-prediktor", which means predictor of emotional disorders. This web system specializes in identifying the seven universal facial expressions: anger, disgust, fear, happiness, neutrality, sadness, and surprise. It uses advanced machine learning techniques to monitor these expressions and predict emotional disturbances, based on a history of facial data. The research was divided into two main phases: in the first phase, a systematic mapping study was conducted to identify relevant research that would guide the development of Dainattor. In the second phase, the Extreme Programming methodology was implemented to design the system, incorporating the FER13 dataset to train a convolutional neural network. This model achieved an accuracy of 86.28% after 50 epochs. The polynomial regression technique was also used to predict emotional disorders. The usability of Dainattor was evaluated through Tree Testing with ten users, confirming its effectiveness in recognizing facial expressions and predicting emotional disorders in a satisfactory manner.**

***Keywords*—machine learning, facial recognition, facial expression detection, prediction of emotional disorders, convolutional neural network**

I. Introduction

In recent years, Artificial Intelligence (AI) has grown significantly, becoming a key tool for solving various problems. Its applications range from traffic control to home assistance, offering benefits such as time optimization, reduced effort in routine tasks, and improved decision-making [1]. In the future, Machine Learning (ML) is expected to become increasingly common, providing notable advantages in daily activities.

A prominent application of AI is the creation of intelligent systems capable of recognizing facial expressions [2]. However, these intelligent systems face the challenge of detecting false emotions, as people can hide their emotions, which may affect their mental well-being. Despite advances, these systems do not always accurately identify when someone is lying. This can occur due to factors such as gender, age, mental health, and social context. The World Health Organization (WHO) estimates that depression affects 300 million people and is considered the leading disease.

Facial expressions are fundamental in human communication, transmitting non-verbal information. However, the lack of effective communication or the simulation of expressions can alter the message received [3]. An efficient web system for recognizing facial expressions is crucial to identify emotional changes and predict potential emotional disorders. This ability contributes significantly to emotional health, encouraging the early seeking of professional help.

For facial expression recognition with machine learning, it is crucial to use datasets that represent a diversity of emotional states. In the study by Yue *et al.* [4], a Convolutional Neural Network (CNN) was implemented and trained with the "FER2013" dataset, which has been widely used in various research initiatives. Additionally, in the study by Zamsuri *et al.* [5], different machine learning algorithms were compared for classifying emotions from Indonesian texts, illustrating how machine learning techniques can adapt to specific linguistic and cultural contexts.

In this context, the purpose of this study is twofold. First, it aims to develop Dainattor, a web system that uses machine learning techniques to recognize facial expressions and predict potential emotional disorders. Second, it proposes to carry out a usability evaluation to

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analyze the ease of use of Dainattor. To achieve this, a Systematic Mapping (SMS) was conducted across four recognized digital databases: ACM Digital Library, IEEE Xplore, SCOPUS, and Springer. The results of this mapping confirm the scarcity of research that uses machine learning techniques to predict emotional disorders. The web system called Dainattor demonstrated its ability to identify seven emotional states: anger, disgust, happiness, fear, neutrality, surprise, and sadness. However, the prediction of emotional disorders may be limited if a person hides or simulates their emotions, which could introduce a margin of error into the results.

Dainattor, the web system under study, was evaluated in terms of usability with a group of ten users who had basic computer skills. For this evaluation, the "Tree Testing" usability technique was applied with the aim of analyzing the ease of navigation within the system structure. This technique involved presenting participants with the Dainattor navigation structure and assigning them specific tasks to complete [5].

The SMS identified 26 primary studies, mostly in journals and conference proceedings. Although none focused on predicting emotional disorders with machine learning, these studies did address the detection of facial expressions through facial scanning. Several of these studies used datasets such as FER2013 and CK+ to train computational models, demonstrating their effectiveness in various investigations [6–30] .

The main contribution of this research is Dainattor, a web system designed for users who spend long periods in front of computers, either working or studying in various environments. Dainattor performs several processes: (i) face detection, (ii) facial expression recognition, (iii) recording a history of expressions, (iv) prediction of possible emotional disorders, and (v) recommendation of activities to support the emotional state.

This study further contextualizes Dainattor's novelty by highlighting its superior integration of machine learning techniques for both facial expression recognition and emotional disorder prediction, outperforming existing systems in accuracy and usability. Moreover, Dainattor uniquely combines an Extreme Programming methodology and a usability study to guarantee methodological rigor and user-centered design.

This study is organized as follows. Section II describes related works concerning the research topic. Section III details the research methodology used in the study. Section IV describes the results obtained from Dainattor's systematic review, system development, and usability evaluation. Section V presents the analysis and discussion of the results obtained in the study. Section VI describes the threats to the validity of the study. Finally, Section VII presents the conclusions and future work.

II. Literature Review

The field of facial expression recognition and prediction of emotional disorders has been significantly transformed by machine learning and computer vision techniques. These advances have created new opportunities and challenges in emotional health, requiring a comprehensive approach. Research has demonstrated how Convolutional Neural Networks (CNNs) and other machine learning techniques have been effective in identifying emotions and predicting emotional states. Yue *et al.* [4] highlights the importance of selecting robust datasets, such as FER13, and employing adaptive CNN architectures to improve accuracy in emotion identification [1]. These studies emphasize the need for adaptive approaches and the significance of strong research communities that contribute to continuous progress in this field [2].

The integration of technologies such as OpenCV and frameworks like Keras has been crucial in developing systems that not only detect emotions but also predict emotional disorders [2, 3]. Recent studies stress the importance of usability in the adoption of these tools, emphasizing that user-centered design and an intuitive interface are essential for ensuring successful interaction and sustained engagement [31]. This research on the Dainattor Web System is based on three key areas: (i) facial expression recognition, (ii) prediction of emotional disorders, and (iii) usability evaluation in emotional monitoring systems. These areas are outlined below.

A. Facial Expression Recognition Using Machine Learning

Machine Learning applications in facial expression recognition have advanced significantly, highlighting the use of Convolutional Neural Networks (CNNs) to identify and classify human emotions with high accuracy. These applications have expanded to areas such as mental health, aiding in the early detection of emotional disorders and improving clinical interventions [3, 32]. These advances have been crucial in technology-assisted therapies and emotional crisis intervention [2].

The development of facial recognition models depends on the quality of the databases used for their training, such as FER-2013, CK+ and AffectNet. Even though these databases have been critical, their lack of cultural diversity limits their applicability. Newer databases are more inclusive and allow models to improve their accuracy and generalization in different multicultural contexts [33, 34]. These enriched databases are essential to advance the robustness of systems.

B. Predicting Emotional Disorders Using Computer Vision

Computer vision techniques have proven instrumental in detecting emotional disorders by analyzing facial patterns related to emotional states. These techniques include the use of Convolutional Neural Networks (CNNs) that extract key facial features to identify signs of depression, anxiety, and other emotional disorders [35]. The combination of computer vision with dynamic feature analysis of facial expressions has allowed for more accurate and earlier detection of these conditions, which is crucial for effective preventive interventions [3, 32].

Predictive models for emotional disorders have evolved significantly with the use of deep learning algorithms that can handle large volumes of facial data. Models such as Recurrent Neural Networks (RNNs) and Vector Support Machines (SVMs) have been applied to predict the onset of emotional disorders from historical and real-time data [32]. These models are trained on data obtained from multiple sources, including facial records, to improve their accuracy and adaptability in different contexts and populations [36, 37].

C. Development and Evaluation of Usability of Web Systems for Emotional Recognition and Prediction

Development frameworks and tools, such as TensorFlow, Keras, and OpenCV, are critical to building efficient facial recognition systems. These frameworks allow the handling of large volumes of data and the implementation of complex deep learning models [38, 39]. These tools make it easy to integrate advanced computer vision capabilities into web applications, providing a robust foundation for real-time system development.

Usability evaluation in facial recognition systems is crucial to ensure that technological solutions are accurate and accessible. Usability testing makes it possible to identify problems in the interface and improve the user experience through continuous feedback. Including metrics such as efficiency and satisfaction ensures that the system is adjusted to the needs of users before it is implemented on a large scale [40–42].

III. RESEARCH METHODOLOGY

The methodology of this research was divided into three main phases: A systematic review, the development and evaluation of the Dainattor web system.

A. Systematic Review (SMS)

This section outlines the systematic review process used to identify studies pertinent to the topic of this research. A Systematic Mapping Study (SMS) was conducted in accordance with the guidelines proposed by Kitchenham *et al.* [43]. The SMS is organized into several phases, all of which were executed during this study. The primary objective was to identify machine learning techniques for predicting emotional disorders based on facial expression recognition in individuals. The research question guiding the SMS process was: RQ1: How can emotional disorders be detected in individuals using a machine learning system that analyzes facial expressions?

The search strategy commenced with the identification of keywords through a quantitative study. Initially, a Control Group (CG) was established, comprising relevant studies that addressed the research question. These studies were gathered through an initial pilot search. Subsequently, Atlas.ti software was employed to generate all keyword combinations, along with their respective frequencies and weights. Ultimately, the control group yielded the most relevant keywords aligned with the core objective of the research. Table I presents the studies from the control group that contribute to answering the research question.

After identifying the keywords, multiple search strings were constructed. This process encompassed three fundamental components: the research action to be performed, the object or phenomenon under study, and the domains or activities related to Software Engineering. Each search string underwent a rigorous review to ensure it could retrieve more than 50% of the studies from the Control Group (CG). Finally, the average effectiveness of all search strings was calculated based on the articles retrieved from the CG.

TABLE I. CONTROL GROUP

ID	Studies
1	Attendance System with Emotion Detection: A case study with CNN and OpenCV Emotion Detection: A case study with CNN and OpenCV
2	AutoDep: automatic depression detection using facial expressions based on linear binary pattern descriptor based on linear binary pattern descriptor
3	Development of a Real-Time Emotion Recognition System Using Facial Expressions and EEG based on machine learning and deep neural network methods
4	Emotion recognition system for autism disordered people
5	Facial Recognition, Expression Recognition, and Gender Identification
6	A Hybrid Model for Driver Emotion Detection Using Feature Fusion Approach

The formulas used to calculate XRatio, YRatio, and the average were as follows:

$$\text{XRatio} = \frac{\text{\# of articles found from the GC}}{\text{Total items in the GC}} \tag{1}$$

$$\text{YRatio} = \frac{\text{\# of articles found from the GC}}{\text{Total items per search string}} \tag{2}$$

$$\text{Average} = \frac{\text{XRatio+YRatio}}{2} \tag{3}$$

The process of selecting the best search string to make an SMS is detailed in the supplementary online material [44]. The winning search string based on the highest average compared to the other strings is C1: (recognition AND (emotional disorder OR facial expressions) AND machine learning). Table II illustrates the search fields used in each scientific database.

TABLE II. SEARCH FIELDS

Database	Search fields
ACM	Abstract
IEEE	Abstract
SCOPUS	Title-Abs-Key
Springer	All

The inclusion criteria used in the search process are:

- The study is directly related to identifying facial expressions using images of the face or predicting emotional distress by analyzing facial expressions.
- The study uses machine learning techniques.
- The study is written in English.
- The publication date falls within the range of 2018 to 2024.
- Conversely, the exclusion criteria were as follows:
- The study does not address any aspect related to the development of systems utilizing machine learning techniques to detect facial expressions or predict emotional disorders.
- The article does not provide a detailed explanation of the application of machine learning techniques.

- The machine learning technique employed by the researchers does not involve facial images for the recognition of expressions.
- The accuracy of the machine learning techniques implemented was below 70%.
- The study objectives are ambiguous, or the study is presented as a brief article, abstract, or editorial.
- The study constitutes ongoing research or does not report successfully completed work.

Regarding the selection of studies, the results of applying various filters during the selection process in each database are presented in Table III. The set of articles retrieved through the search was termed “Studies Found.” These studies were initially assessed by reviewing their titles, keywords, and abstracts. Those meeting the inclusion criteria formed the “Shortlisted Studies” group. Upon finalizing this group, duplicates across different scientific databases were removed. The selection criteria were then reapplied to the full text of the articles included in the “Different Pre-selected Articles” group. The final resulting set of articles was designated as “Primary Studies”.

TABLE III. RESULTS OF THE LITERATURE REVIEW

Database	Studies Found	Pre-Selected Studies	Different preselected	Primary studies
ACM	10	4	4	2
IEEE	76	38	38	9
SCOPUS	815	43	41	12
Springer	25	5	5	3
Total	926	90	88	26

B. Development of Dainattor

The development of the Dainattor proposal followed three steps: (I) choice of the software development methodology, (II) choice of machine learning techniques and (III) development of the web system following the development methodology and the chosen machine learning techniques.

1) Description of the XP methodology

In this research, the Extreme Programming (XP) development methodology was employed [45]. This methodology facilitated an in-depth analysis of the essential elements required for the design, development, testing, and implementation of the proposed web system. These phases are executed iteratively, with the frequency and application of the methodology varying based on the project’s nature, as well as the knowledge, skills, and experience of the project team members.

Planning: Planning involves an ongoing dialogue within the development team, spanning from the project’s inception to its conclusion. It begins with gathering customer requirements and providing rapid estimates for the development time of each requirement. Subsequently, a planning meeting with key stakeholders is conducted to establish a delivery schedule. During this phase, the following activities were performed: (i) Identification of the requirements for the Dainattor web system, and (ii) Selection of development and modeling tools. Daily meetings enabled the team to share updates, discuss challenges, and propose solutions, ensuring the project’s objectives were met [45].

Design: In this phase, a solution tailored to the requirements identified during planning is developed, emphasizing simplicity and clarity in the design. A straightforward design ensures faster implementation compared to a more complex one [45]. The activities undertaken included: (i) Creation of the system’s general use case diagram, and (ii) Development of the database’s physical model.

Development: The development phase adhered to the principles of Extreme Programming (XP), which advocates pair programming—two developers working together on the same system. This approach minimizes errors, enhances product quality, fosters collaborative learning, and strengthens team dynamics by facilitating the joint resolution of potential blockers [45].

Testing: The testing phase guarantees the product is error-free and fulfills all the requirements established during planning. In this project, unit tests were conducted for each module of the system. Detected errors were corrected, followed by additional testing to confirm that the issues were fully resolved [45].

2) Selected machine learning technique

This section outlines the machine learning technique employed for facial expression recognition and emotional disturbance prediction in the development of Dainattor. The chosen technique is the Convolutional Neural Network (CNN). The CNN architecture was adapted based on the work of Russia and Singh [18], who utilized this approach to detect distracted students in virtual reality educational environments.

In Dainattor’s implementation for recognizing seven facial expressions, the network comprises four convolutional hidden layers (Conv2D) that incorporate the ReLU activation function as a parameter. Additionally, three MaxPooling2D layers were used to aggregate 2D spatial data, facilitating feature extraction from the images. Finally, two fully connected (Dense) layers were included: one employing ReLU activation and the other utilizing Softmax activation. The Softmax layer is configured with a parameter value of 7, corresponding to the classification output layers representing the seven facial expressions intended for recognition.

TABLE IV. ADAPTED CNN ARCHITECTURE

Layer	Layer type	Parameters	Function
1	Conv2D	(3, 32)	ReLu
2	Conv2D	(3, 64)	ReLu
3	MaxPooling2D	(2)	-
4	Dropout	(0.25)	-
5	Conv2D	(3, 128)	ReLu
6	MaxPooling2D	(2)	-
7	Conv2D	(3, 128)	ReLu
8	MaxPooling2D	(2)	-
9	Dropout	(0.25)	-
10	Flatten	-	-
11	Dense	(1024)	ReLu
12	Dropout	(0.50)	-
13	Dense	(7)	Softmax

Table IV provides an overview of the CNN architecture, detailing the types of layers, parameters, and activation functions utilized. Once the neural network architecture was built, the "FER13" dataset was used to train the CNN. The hyperparameter tuning process involved grid search to optimize parameters such as learning rate (tested values: 0.001, 0.0005, 0.0001), batch size (values: 16, 32, 64), and the number of epochs (up to 50). Data preprocessing included normalization of pixel values to [0, 1], resizing to 48×48 pixels, and data augmentation techniques such as horizontal flips and random rotations to enhance model generalization.

3) Development of the Dainattor intelligent system

As part of the value proposition, Dainattor (comes from the Latin Inordinatio Predictor, which means Predictor of disorder) is proposed, a web system that records a history of facial expression recognition to predict a possible emotional disorder in people. Below is the execution of each of the phases of the XP development methodology for the development of Dainattor.

a) Planning

In the planning phase, the different activities to be carried out in the project were organized. The development team identified the functional and non-functional requirements of the system and then chose the development and modeling tools to be used in the project. Table V mentions the functional and non-functional requirements for the Dainattor system.

TABLE V. FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS OF DAINATTOR

No.	Requirements	
1	The system must recognize facial expressions in real time to record a history	Functional requirements
2	The system must allow a filtered search of the history and the display of an image of the recognized facial expression	
3	The system must allow the display of a report with a bar graph with the frequency of occurrence of the seven facial expressions	
4	The system must predict an emotional disorder related to facial expressions from the generated history	
5	The system should allow the display of a list of activities of daily living to support the mood of the person being monitored	
1	The system must be intuitive	Non-functional requirements
2	The system must be efficient in loading data and information	
3	The system must provide informational messages for troubleshooting	

TABLE VI. DEVELOPMENT AND MODELING TOOLS

Software Used	Other options	Selection criteria
Postgresql 14 [46]	MySQL, Oracle, among others	It is an open-source database management system and the most recommended for web application development
Visual Studio Code [47]	Sublime text	It is a free code editor developed by Microsoft, it includes a variety of plugins that facilitate software development
Diagrams.net [48]	Powerdesigner	It is an online tool for diagram modeling, it allows collaborative work with a group of people

Table VI shows the software development and modeling tools used to build the Dainattor proposal.

a) Design

In this phase, the architecture of the Dainattor system was designed using the modeling tools chosen in the planning stage. The Diagrams.net tool was used to design the use cases. Fig. 1 shows the physical model of the database, the entities with their data fields, and the relationships between data entities.

b) Development

The Dainattor web system was developed with the Python programming language in version 3.10.1 together with the Django web development framework in version 3.0.8. The tool used to write the source code is the open-source text editor Visual Studio Code. In addition, the open-source database manager PostgreSQL in version 14.0 was used for data management. Finally, these tools and development languages were chosen based on the experience of the work team.

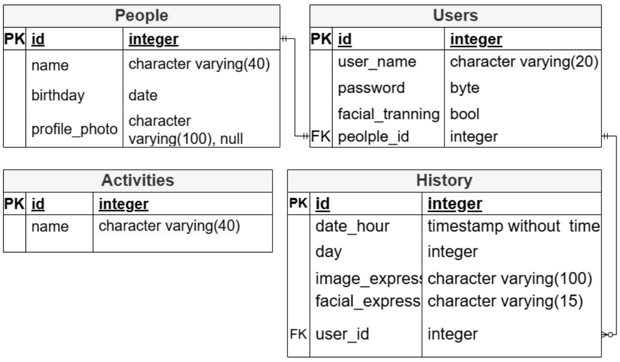

Fig. 1. Physical model of the Dainattor database.

c) Tests

In this phase, unit tests of the Dainattor system were carried out. Table VII then describes the unit tests that were applied to each functional requirement

TABLE VII. UNIT TEST CASES FOR DAINATTOR

No.	Test case name	Method or function being evaluated	Test case being evaluated
1	Take photos	tomar_fotos ()	Capture 70 photos for facial training
2	Activate monitoring	activar_monit()	Perform monitoring activation successfully
3	Disable monitoring	desactivar_monit()	Successfully deactivate monitoring
4	View the history of recognized facial expressions	ver_historial(fecha)	Filter on history with a date where no history exists
5	Modify user	editar_usuario(usuario)	Modify a user and check if the changes have been saved
6	Login	iniciar_sesion(usuario, clave)	Send the corresponding user data and check if the user exists
7	Sign out	cerrar_sesion()	Delete the active session

C. Dainattor System Evaluation

The evaluation of Dainattor was carried out in two phases:

Technical Evaluation: Key performance metrics and system accuracy in predicting emotional disorders were measured from a test dataset. The effectiveness of facial expression recognition in different lighting conditions and shooting angles was also verified.

User Evaluation: A pilot study was conducted with a group of selected users to evaluate the user experience, the accuracy of the predictions, and the usefulness of the recommendations generated by the system. The results of this evaluation guided the final improvements to Dainattor's interface and functionalities.

IV. Results

This section presents the results obtained from the research. Subsection IV.A outlines the findings from the Systematic Mapping Study (SMS). Subsection IV.B details the development process of the Dainattor software system. Subsection IV.C provides an overview of the steps and tasks involved in applying the Tree Testing technique. Finally, Subsection IV.D presents the results of Dainattor's usability evaluation.

A. SMS Results

This section presents the results of the Systematic Mapping Study (SMS), divided into two parts: (i) an overview of the primary studies and (ii) the response to the research question formulated in this study.

Fig. 2 illustrates a bubble chart displaying the distribution of primary studies by year of publication and type of publication (journal or conference). Notably, there has been an increasing interest in facial expression recognition since 2021.

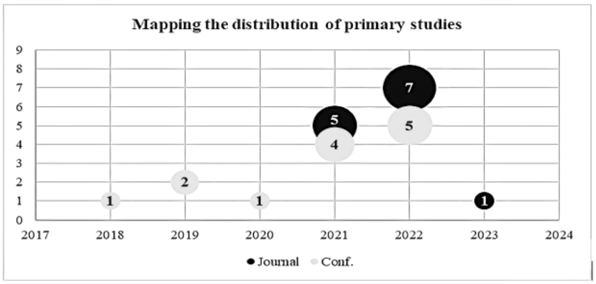

Fig. 2. Distribution of primary studies.

The response to RQ1, derived from the analysis of the primary studies identified in our SMS, is detailed below:

RQ1: How can emotional disorders be detected in individuals through a machine learning system that analyzes facial expressions?

Studies by Kandjimi *et al.* [6], Indolia *et al.* [8], Fan *et al.* [16], Russia and Singh [18], Verma *et al.* [10], and Maurya and Sharma [29] emphasize the application of CNNs to enhance emotion recognition across diverse domains, including automated assistance systems and human-computer interaction. These studies employ advanced preprocessing techniques and optimized architectures to mitigate overfitting and enhance accuracy.

Additionally, Prospero *et al.* [7], Kousalya *et al.* [13], and Inthiyaz *et al.* [30] evaluate the effectiveness of supervised machine learning algorithms and pre-trained CNN models for emotion classification and detection. These studies underscore the importance of robust datasets for training. Concurrently, Arabian *et al.* [9], Ramu and Muthukumar [11], Manewa and Mayurathan [12], innovate by selecting regions of interest and incorporating advanced architectures, such as GoogleNet-7, for accurate emotion detection in specific contexts.

Furthermore, Subudhiray *et al.* [17], Albraikan *et al.* [21], and Kothuri and Rajalakshmi [22] investigate transfer learning techniques and hybrid models that integrate multiple data modalities to enhance emotion recognition accuracy. These approaches are applied in areas such as psychological therapy and facial biometric authentication systems .Following this line, Subudhiray *et al.* [17], Albraikan *et al.* [21], and Kothuri and Rajalakshmi [22] explore transfer learning techniques and hybrid models that combine different data modalities to improve the accuracy of emotion recognition, applying these techniques in psychological therapies and authentication systems based on facial biometrics.

Additional research such as that by Vinusha *et al.* [14], Zaghbani and Bouhlel [19], Punithavathi *et al.* [20], Gao and Zhao [25], Nguyen *et al.* [26], Sathyamoorthy *et al.* [27], and Hegde *et al.* [28] address facial emotion recognition in emotional health, safety, and human-computer interaction, using methods such as Random Forest, multimodal classification, and thermal imaging analysis to provide effective solutions in real-time.

Finally, specific studies, such as Wang *et al.* [15], leverage a neural network architecture called Feelings-Net combined with principal component extraction techniques for applications in security and healthcare. Dudekula and Purnachand [23] introduce a linear fusion algorithm to recognize seven basic facial emotions, demonstrating the effectiveness of DNNs in improving recognition performance. Li *et al.* [24] propose a recursive convolutional network method for recognizing microexpressions, with applications in educational assessment.

B. Software System Development: Dainattor

The development of the Dainattor proposal was carried out in two steps: (i) selecting the machine learning techniques and (ii) developing the web system based on the selected methodology and techniques.

Regarding machine learning techniques, those employed for facial expression recognition and emotional disorder prediction in Dainattor are described below. A key technique used was the Convolutional Neural Network (CNN), whose architecture was adapted from the work of Russia and Singh [18], which focused on detecting distracted students in virtual reality educational environments.

In Dainattor's implementation, the CNN architecture for recognizing seven facial expressions includes four Conv2D hidden layers, each configured with the ReLU activation function. Additionally, three MaxPooling2D layers were incorporated to aggregate 2D spatial data, enabling effective feature extraction from the images. Finally, two fully connected (Dense) layers were employed: one with ReLU activation and the other with Softmax activation. The Softmax layer is configured to classify the seven facial expressions targeted for recognition. Detailed specifications of the CNN architecture, including layer types, parameters, and activation functions, are provided in the supplementary online material [49].

Following the construction of the architecture, the "FER13" dataset was utilized to train the CNN. It is noteworthy that this dataset has been widely adopted in several studies [6, 12, 18]. FER13 comprises 28,709 grayscale images, each with dimensions of 48×48 pixels, representing seven universal facial expressions: anger, disgust, happiness, fear, neutral, surprise, and sadness (see Fig. 3).

Fig. 3. FER13 dataset, adapted from [6].

As part of the value proposition, Dainattor (derived from the Latin Inordinatio Predictor, meaning "Predictor of Disorder") is introduced as a web system designed to record a history of facial expression recognition in order to predict potential emotional disorders in individuals. Below is an overview of the execution of each phase of the Extreme Programming (XP) development methodology applied to Dainattor's development.

In the planning phase, various activities required for the project were organized. The development team identified both the functional and non-functional requirements of the system, which are detailed in the supplementary online material [50]. Subsequently, they selected the development and modeling tools to be used, including Postgresql [46], Visual Studio Code [47], and Diagrams.net [48].

In the design phase, the Dainattor system architecture was developed using the previously chosen modeling tools. Diagrams.net was used to represent the system's use cases, illustrating the processes performed by the system (see Fig. 4). Additionally, the physical model of the database was created, detailing the entities, their data fields, and the relationships between them. This information is available in the supplementary online material [51].

During the development phase, the Dainattor web system was implemented using Python 3.10.1 and the Django 3.0.8 framework. The source code was written in the Visual Studio Code text editor, while data management was handled using PostgreSQL 14.0. These tools were selected based on the expertise of the development team. In the testing phase, unit tests were conducted to ensure the proper functioning of the system, the details of which are provided in the supplementary online material [52].

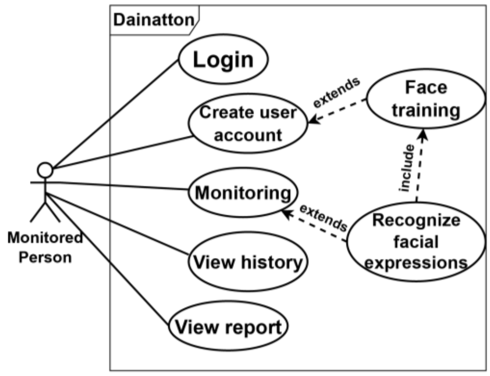

Fig. 4. General diagram of use cases of the Dainattor system.

Based on the results obtained from the Systematic Mapping Study (SMS), various machine learning techniques and relevant technologies were identified. A Convolutional Neural Network (CNN) based on the work of Russia and Singh [18] was adapted for facial expression recognition, while polynomial regression was applied to predict emotional disorders. The FER13 dataset played a crucial role in training the CNN for facial expression recognition. OpenCV was used for face recognition, TensorFlow was employed to implement the CNN, and NumPy facilitated the application of polynomial regression for prediction.

The CNN was trained on the FER13 dataset over 50 epochs or iterations. Prior to using the architecture, a facial training process was carried out, which involved capturing 70 images of the individual's face to exclusively record their identity for expression monitoring. Subsequently, a monitoring interval was set, with possible durations of 15, 30, 45, or 60 seconds. At the end of the selected interval, the CNN was activated to recognize seven facial expressions: anger, disgust, fear, happiness, neutral, sadness, and surprise. The CNN always requires an image as input to perform both the training and recognition processes for facial expressions.

C. *Usability Evaluation of the Dainattor via Tree Testing*

The evaluation of Dainattor's usability was carried out using the Tree Testing technique. Tree Testing is a technique for performing usability testing. In particular, it is used to evaluate the user-friendliness of a website's navigational structure. This technique aims to ensure that users can easily find the information they are looking for and navigate the site intuitively. In a Tree Testing test, participants are presented with an outline of the site's navigation structure and asked to find certain specific tasks or pieces of information. Participants can click on the links in the scheme to "navigate" through the site and the actions they take are recorded. The results are then analyzed to identify navigation issues such as broken links, confusing categories, or hard-to-find tasks [31]. According to Shneiderman [53], the Tree Testing technique consists of 4 steps, which are detailed below:

Bulleted lists look like this:

- Step 1: Propose the tasks to be carried out by users in the usability evaluation: The researcher performs a series of tasks or system activities to illustrate them through a task tree. In this study, five key tasks were identified during the use of the Dainattor system, details of which can be found in the supplementary online material [54].
- Step 2: Run the usability test: The usability test was carried out with 10 users according to the work of Arslan *et al.* [55]. A group of people who meet the user profile established for the evaluation was recruited. The user profile of the participants are students with basic computer skills. The invitation to participate in the usability evaluation was made via email and telephone. The selection of 10 participants aligns with best practices and provides a robust evaluation. While Nielsen recommends that 3 to 5 users are sufficient to identify most usability issues, increasing the sample size to 10 enhances the reliability of the findings without compromising the practicality and efficiency of the testing process. Once the invitation was sent with the link to access the web system, the participants executed the assigned tasks. In addition, metrics (time, clicks, and satisfaction) were recorded in the "Metrics Tracking" template, as well as errors identified in the "Error Logging" template. The format of these templates can be found in the supplementary online material [56].
- Step 3: Analyze the results of the usability evaluation. The researchers analyzed the results obtained in the usability evaluation to find a solution. The variables Efficiency and Satisfaction were studied, collecting data on the number of clicks, time and level of satisfaction of the participants when performing five tasks. Details of the data collected can be found in the supplementary online material [57]. The usability evaluation criteria included metrics such as task completion time, number of clicks required per task, error frequency, and user satisfaction levels, as measured by a post-test questionnaire. The results indicated that 80% of the users successfully completed all assigned tasks with an average satisfaction score of 4.2 out of 5. Key areas for improvement were identified, including reducing response times during facial training and improving interface intuitiveness.
- Step 4: System refinement: System refinement was performed based on the number of bugs encountered by participating users, based on the summary of steps and activities of the tree testing technique used for usability evaluation. Further details can be found in the supplementary online material [58].

D. Results of Applying the Tree Testing Technique

The data collected on the metrics of clicks made and the time spent in the execution of the five tasks by the participants in the Dainattor system is detailed in the supplementary online material [59]. The five tasks are: (i) Create user account and log in (ii) Perform facial training, (iii) Perform facial expression recognition, (iv) View facial expression history, and (v) View the report of the prediction of emotional disturbance and recommended activities. Fig. 5 illustrates the time results and the number of clicks made by the ten participants while performing the second assigned task in the evaluation of the Dainattor system.

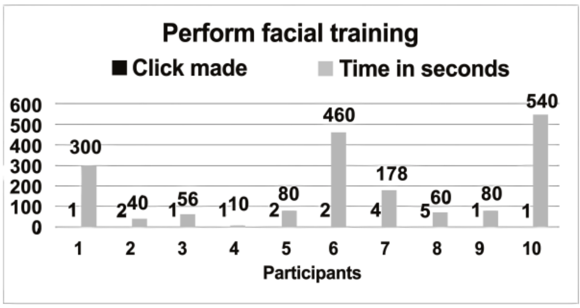

Fig. 5. Perform facial training.

Table VIII describes a classification of the errors detected by the participants during the use of Dainattor in the usability evaluation.

TABLE VIII. ERRORS IDENTIFIED BY PARTICIPANTS DURING USABILITY EVALUATION OF DAINATTOR

No.	Errors detected	Participants who affirm the error
1	Excessive waiting time in facial training	5
2	Failure to recognize true facial expression	6
3	Lack of better camera focus and mirror mode view	2
4	Failures in the validation of data and/or actions	6
5	Excessive waiting time to recognize facial expression	2

V. DISCUSSIONS

To enhance the relevance of this study, a detailed comparison of dainattor's performance metrics (e.g., accuracy of 86.28%) with state-of-the-art results in recent literature will be included. This comparison will highlight its competitive advantages and limitations. Machine learning techniques were key to recognizing facial expressions and predicting emotional disorders. Following the research of Wang *et al.* [60], for Dainattor a CNN was developed that reached an accuracy of 86.28%. This accuracy was improved by adjustments made to the architecture, as well as to the number of convolution layers and training times. This improved percentage was obtained at the end of the CNN training using TensorFlow. The adaptability of Dainattor to recognize more nuanced emotional states, such as mixed or masked emotions, and its potential applications in clinical psychology could facilitate the early diagnosis of emotional disorders in patients. Therefore, the inclusion of microexpressions analysis within the scope of facial recognition systems addresses a critical gap in the detection of subtle emotional states. Unlike the widely studied seven primary emotions, micro-expressions provide nuanced insights that are often involuntary and reveal hidden emotional responses. Also, their application in high-stress work environments would allow real-time monitoring of the emotional well-being of employees, favoring timely interventions for their future development and greater impact. This perspective underscores the importance of advancing beyond basic emotional categories to achieve more comprehensive and accurate emotional assessments.

During the usability evaluation, some users experienced delays in completing tasks in the Dainattor system. Users 6, 7, and 10 needed the most time to complete their tasks. After consultations via chat, three main causes were identified: (i) the need to familiarize with certain concepts before using Dainattor, (ii) the delay of the system during facial training and (iii) the time spent in the search for possible failures through a trial and error approach. To address the delays observed in facial training and system response times, several optimizations were implemented. The image capture and preprocessing processes were refined, significantly reducing the time required for the initial 70 photos. The Convolutional Neural Network (CNN) architecture was modified to enhance efficiency in facial expression recognition by incorporating advanced techniques such as Dropout and Max-Pooling. Furthermore, state-of-the-art tools, including TensorFlow and OpenCV, were adopted alongside a more efficient PostgreSQL database. These improvements, validated through usability testing, resulted in increased system speed and simplicity, thereby enhancing the overall user experience. Therefore, it is necessary to improve Dainattor so that users can complete their tasks more efficiently, optimizing the usability of the system.

CNNs have proven to be highly effective in computer vision, as shown by the work of Verma *et al.* [10], where a CNN network with interconnected convolutional layers achieved excellent results in the classification of facial expressions. However, significant challenges remain in understanding human expressions, as these can vary according to context, culture, gender, age, mental health, and social environment. These variabilities complicate the accurate recognition of facial expressions.

It is essential to recognize that emotion recognition is not limited to facial image analysis but can also be addressed through voice analysis. Bhanusree *et al.* [61] highlight how Deep Neural Networks can be used for acoustic-based emotion recognition, and how capsule networks can improve accuracy in this task. This approach is useful for developing systems that capture and analyze human emotions in various contexts, enhancing decision-making and performance in work environments.

As shown in Table IX, our study achieved an accuracy of 86.28% by implementing a CNN model developed using the Keras and OpenCV libraries and trained on the FER-13 dataset over 50 epochs. This performance slightly exceeds the 85% accuracy reported in [6], which employed a similar methodology, highlighting the effectiveness of our implementation. The observed improvement may be attributed to specific adjustments in training procedures or model architecture. In comparison, Zaghbani and Bouhlel [19] using a Multi-Task Convolutional Neural Network (MTCNN) and the Fabo dataset, achieved a significantly higher accuracy of 99.75%. This disparity underscores the critical impact of both model architecture and dataset selection on performance. Similarly, Dudekula and Purnachand [23] reported accuracies of 98.3% and 92.4% by integrating a pre-trained CNN model (VGG19) with datasets such as CK+ and JAFFE, demonstrating the potential of pre-trained architectures combined with domain-specific datasets to enhance results. These findings identify promising avenues for the further refinement of our model, such as leveraging pre-trained networks and exploring more diverse and specialized datasets.

TABLE IX. METRICS OF PRIMARY STUDIES

Study	Technology and/or Technique employed	Accuracy obtained
[6]	• Integration of the CNN model. • Using the Keras library. • Using the OpenCV library. • Use of the FER-13 data set.	85% of accuracy
[19]	• Use of a multi-task CNN model composed of two subnetworks (MTCNN). • Use of the "Fabo" data set.	99.75% of accuracy
[23]	• Integration of the CNN model. • Use of the pre-trained model (VGG19). • Use of standard data sets "CK+" and "JAFFE".	Accuracy with CK is 98.3% and with JAFFE is 92.4%.

While Dainattor achieved a commendable accuracy of 86.28%, it also demonstrated advantages beyond accuracy. Its scalable architecture supports the integration of broader datasets, offering adaptability absent in single-purpose models. Regarding usability, the Tree Testing method revealed a satisfaction rate of 4.2/5, emphasizing its user-centered design and ease of use compared to traditional implementations. Although systems like MTCNN outperform in accuracy, their scalability for real-time applications remains limited, further highlighting Dainattor's practical strengths.

VI. THREATS TO VALIDITY

Like any other study, this work is subject to various threats that may impact the validity of its contributions to the research problem.

Regarding the validity of the conclusions, during the usability evaluation of the Dainattor web system, a limitation related to the hardware resources of the web server was encountered. Long wait times were experienced during the facial training process, leading to frustration among users as they had to wait for the completion of the

70 photos required for facial training. Despite these limitations, the need to improve Dainattor was evident in order to enable it to compete effectively with other systems and provide a more satisfactory user experience.

In terms of reliability, the results of the Systematic Mapping Study (SMS) are subject to threats, as only articles written in English were considered. There is a possibility that errors in judgment were made during the selection of primary studies, which may have led to the omission of significant work relevant to this research.

Internal validity was affected by the time constraints imposed during the development of this work. These limitations influenced the implementation of improvements in Dainattor to address issues identified during its evaluation, which may have, in turn, impacted the results obtained. Despite these challenges, future research proposes the implementation of more effective measures to mitigate complications arising from time limitations.

With regard to external validity, during the usability evaluation of Dainattor, the sample was limited to a small group of participants. This limitation raises concerns about the accuracy of the results, as the evaluation was conducted on a group with very similar profiles. It is crucial to recruit a larger, more diverse group of users to identify more significant usability issues. Moving forward, plans include increasing the number of participants with varied profiles and characteristics in subsequent research.

VII. Conclusion and Future Work

The primary objective of this research has been to recognize facial expressions and predict potential emotional disorders in individuals through the application of machine learning techniques.

Facial expression recognition and prediction are valuable tools for understanding and managing emotions. These techniques are particularly useful in identifying when specialized help is required for emotional disorders such as depression and bipolar disorder. Dainattor, by recording a history of emotional states, enables the prediction of emotional disorders based on this data.

Dainattor is an effective system for supporting emotional well-being. Users can visualize graphs depicting the frequency of their facial expressions and receive daily recommendations to improve their mood. These suggestions assist users in determining when to seek professional mental health support.

This article describes a systematic mapping study that addresses the question, “How to detect emotional disorders through a machine learning system that analyzes facial expressions?” We identified 26 primary studies, mainly in scientific journals and conference proceedings. While none focused on predicting emotional disorders, they did address facial expression recognition by scanning faces. Several studies used datasets such as FER13 and CK+ to train their models, demonstrating that these sets have been crucial to the success of various research.

The web system was evaluated in terms of usability with ten students with basic computer skills, using the Tree Testing technique. This evaluation, together with the analysis of metrics and errors, made it possible to identify areas for improvement in Dainattor, which will contribute to a more satisfactory user experience in future iterations of the system.

In future work, one of the key priorities will be the integration of culturally diverse datasets to reduce potential biases and improve the generalizability of the model, ensuring its effectiveness across a broader range of populations. Additionally, the process of recognizing moods and predicting emotional disorders in individuals’ mental health can be further refined. Future developments may involve incorporating the identification of body gestures and other human body cues, which could provide a more comprehensive understanding of emotional states. Other possible improvements for Dainattor could focus on expanding its capabilities and exploring new applications to enhance its overall functionality. It is proposed to expand the dataset used, incorporating more diverse cultural and emotional data, to improve the system’s accuracy. Additionally, advanced machine learning techniques, such as hybrid deep learning models or transfer learning, will be explored to optimize the prediction of emotional disorders. Finally, the system’s scope will be extended to other use cases, such as educational or workplace environments, where emotional monitoring can provide significant benefits. In the future, it is proposed to extend Dainattor’s capabilities to identify more nuanced emotions, including mixed or masked emotional states. In addition, practical applications will be explored in areas such as clinical psychology and stress management in high-pressure work environments. As well as the use of super-resolution techniques guided by self-supervised learning to generate high-resolution facial expression images. This approach has the potential to significantly enhance recognition accuracy and overall system performance.

In future iterations of Dainattor, we plan to incorporate voice and gesture recognition capabilities. These features will complement facial expression analysis, providing a more comprehensive approach to predicting emotional disorders. Additionally, we aim to test Dainattor in real-world scenarios, such as workplace stress monitoring and educational applications, to assess its effectiveness and scalability in diverse environments. To further improve the system’s accuracy and efficiency, we will explore the integration of transfer learning techniques and hybrid models. These methods have the potential to enhance both facial expression recognition and emotional disorder prediction, ultimately refining Dainattor’s performance.

Conflict of Interest

The authors declare no competing interests.

Author Contributions

Conceptualization, L.LL. and A.C; methodology, L.LL., B.R., R.N. and A.C; validation L.LL., B.R., R.N. and A.C.; supervision, A.C.; project administration, L.LL.; funding acquisition, L.LL. and A.C. All authors have contributed to the writing and editing of the paper. All

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