Detecting Emotions with Deep Learning Models: Strategies to Optimize the Work Environment and Organizational Productivity

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***Abstract*—This study proposes the implementation of a facial emotion recognition system based on Convolutional Neural Networks to detect emotions in real time, aiming to optimize the workplace environment and enhance organizational productivity. Six deep learning models were evaluated: Standard CNN, AlexNet, VGG16, InceptionV3, ResNet152 and DenseNet201, with DenseNet201 achieving the best performance, delivering an accuracy of 87.7% and recall of 96.3%. The system demonstrated significant improvements in key performance indicators (KPIs), including a 72.59% reduction in data collection time, a 63.4% reduction in diagnosis time, and a 66.59% increase in job satisfaction. These findings highlight the potential of Deep Learning technologies for workplace emotional management, enabling timely interventions and fostering a healthier, more efficient organizational environment.**

Keywords*—Facial recognition; real-time emotions; convolutional neural networks; work environment; artificial intelligence in human resources

I. Introduction

Many companies today face the challenge of effectively managing their employees' emotions to improve the work environment. As noted in study [1], mental health is a state of well-being that allows you to manage stress and work effectively. In addition, a high percentage of workers suffer from work-related stress, which affects their mental health, performance and interpersonal relationships, generating significant economic and social costs [2]. This impact is linked to the “emotional sphere”, a model in which emotions influence group processes and outcomes [3].

In this way, it is [4] highlighted that positive socio-emotional interactions foster collaboration and teamwork. For its part, [5]it underlines that emotional management is a crucial skill for work success, since it allows regulating one's own and others' emotions. In Peru, job dissatisfaction is a growing problem, with 78% of Peruvians reporting burnout in 2023 [6]. This problem affects both the quality of life of employees and talent retention, since workers with high levels of stress are 4.5 times more likely to quit [7].

Traditional emotional management methodologies are limited, technologies such as facial recognition integrated with AI emerge as effective solutions to analyze emotions in real time and optimize organizational decisions [8]. Facial recognition has been integrated into multiple industries for its ability to authenticate identities and analyze emotions [9]. However, identifying similar expressions such as fear, and surprise remains a challenge [10]. Since 55% of communicative information comes from non-verbal elements [11], these tools are essential to address emotional problems in organizations.

In this context, there is a need to implement an intelligent system for the detection of emotions in real time in controlled work environments. This approach seeks to optimize the identification of emotional states with high precision, contributing to the improvement of the work environment and the productivity of organizations.

The paper is organized as follows. Section II includes the literature review, where previous studies and key concepts are presented. Section III describes the methodology used. Section IV presents the results obtained from the experiment performed. Section V addresses the discussion of the findings. Finally, Section VI presents the conclusions and possible future work.

II. Literature Review

Facial recognition, based on computer vision and deep learning techniques, allows for the identification and analysis of emotional expressions with high precision. Artificial Intelligence (AI) algorithms are trained with large data sets to learn distinctive patterns, applicable in areas such as security, education, medicine and marketing [12], [13], [14]. In addition, its non-intrusive capacity and operational autonomy make it versatile technology for machine learning tasks [13].

Although effective, emotion recognition faces significant challenges, cultural differences and expression ambiguity are obstacles highlighting the need for high-quality data [15]. In [16], their DenseNet201 model showed the highest accuracy, with 86.85%, in detecting fake faces, outperforming other convolutional neural network architectures by using advanced transfer learning techniques and medicine benefits from AI to understand emotions [17], although they require advanced methods to address the complexity of facial expressions. Additionally, a BLTSM-based model based on attention mechanisms was shown to be effective in describing emotional attitudes and recognizing emotions [18].

Recent advances have greatly improved accuracy, for example, the “IPSOBSA-QCNN” was developed, a quantum neural network that achieves 98% success in emotion classification [19]. On the other hand, local binary patterns and extreme learning were integrated to maximize effectiveness on data sets such as CK+ and JFFE [20]. In addition, histograms of oriented gradients (HOG) and fast networks were used [21], achieving 95.04% accuracy.

Specialized applications reinforce the potential of facial recognition, where the “EigenFaces” algorithm was used with libraries such as OpenCV and SKlearn to analyze emotions [22], emotional changes were detected from low-resolution images [23]. In addition, the effectiveness of convolutional neural networks to identify emotions in real time with an accuracy greater than 80% was highlighted [24], [25]; on the other hand, it was shown how scalable models allow the classification of seven emotions in video game, security and education applications [26].

Automatic recognition of facial emotions has seen significant advances thanks to convolutional neural networks (CNNs), which allow for highly accurate classifications. However, the effectiveness of these models largely depends on the quality and diversity of the data sets used for their training, highlighting the need for careful and representative data collection [27]. Recent advances in deep neural networks have achieved accuracy rates above 90% in emotion classification, while future research aims to develop more robust models that adapt to diverse contexts and environmental conditions [28]. On the other hand, emotion recognition from visual data faces significant challenges due to the subjective nature of human emotions and the complexity of visual information, which has led to the use of convolutional neural networks to improve sentiment classification accuracy [29]; In addition, they have benefited from genetic algorithms (GA) [30] to optimize the hyperparameters of CNN models, achieving an accuracy of 76.11% in the third generation, consolidating the potential of the CNN-GA approach in facial emotion recognition [30].

In summary, these studies demonstrate that AI-based emotion detection has great potential across multiple sectors, although challenges remain related to cultural interpretation, data quality, and ethical applications. Table I compares recent studies on emotion detection using neural networks, highlighting their objectives, methods, datasets, and key results, along with the approach proposed in this work.

TABLE I. WORK RELATED TO EMOTION DETECTION USING DEEP LEARNING

Study	Goals	Method	Evidence	Results
[12]	Emotion detection in low-resolution images using residual networks	Residual network with voting	RAF-DB dataset (low resolution images)	Accuracy: 85.69%
[38]	Feature Extraction in Detection with EfficientNetB0	EfficientNetB0	FER2013 dataset	Accuracy: 95.82%
[31]	Real-time emotion detection for human-robot collaboration in smart factories	DeepFace	Industrial contexts (real-time testing)	High precision in real-time collaboration scenarios
[26]	Emotion recognition in low-resolution images	CNN	FER2013 dataset (low resolution images)	Accuracy: 66.85%
[19]	Quantum CNN for emotion detection in mental health contexts	Quantum CNN (QCNN)	Mental health context	Improved efficiency and reduced training times
Proposed	Real-time emotion detection in controlled work environments	Standard CNN, AlexNet, VGG16, InceptionV3, ResNet152, DenseNet201	Controlled work environment (real-time testing)	High precision in real-time emotion detection

III. PROPOSED METHODOLOGY

In this research, the CRISP-DM model was taken as inspiration as a basis to address the different stages of the project, from understanding to deployment, widely used as a standard in data mining [32]. This framework, widely accepted in data analysis [33], stands out for its adaptability, allowing its application in areas such as medicine [34], signal processing [35], and the manufacturing industry [36], [37]. Fig. 1 shows the methodological graph that will be followed in this research.

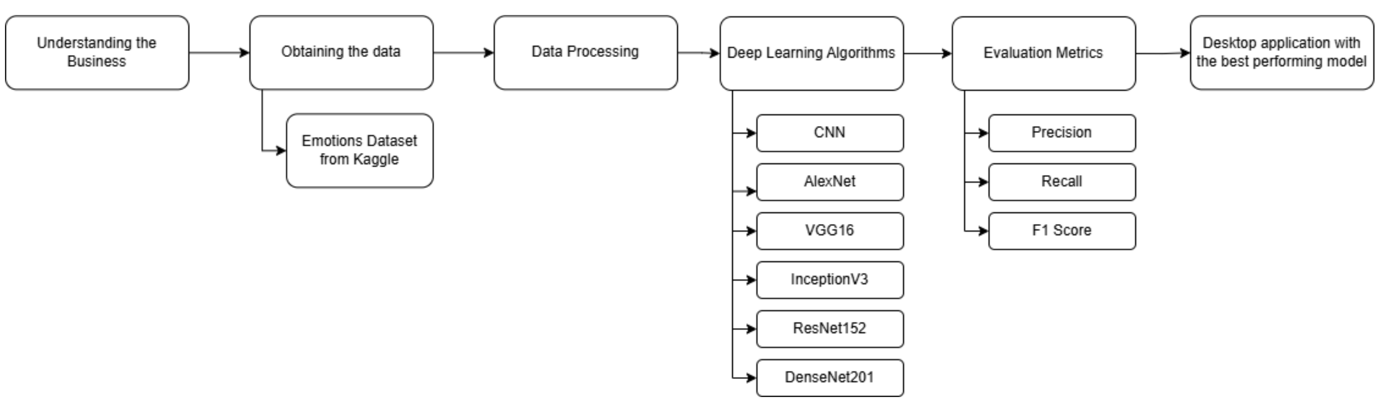


Fig. 1. Diagram of the methodology.

A. Understanding the Business

The present study aims to optimize the work environment and productivity of the organization by implementing a facial recognition system based on deep learning models. To achieve this, the following key business objectives were identified:

- Improve the emotional well-being of employees in real-time.
- Detect and address negative emotions that may impact team productivity.
- Provide technological tools that support data-driven decision-making.
- Reduce work stress and foster a healthier organizational environment.
- Increase job satisfaction through timely interventions.

Evaluation of the Current Situation: Employee dissatisfaction and stress impact performance. Traditional methods are subjective, requiring an automated solution.

Research Population: A sample of 17 workers was selected for relevant data collection, ensuring that despite constraints.

Expected Impact: Real-time emotion detection enables timely interventions, improving the work environment and decision-making.

B. *Obtaining the Data*

The development of the facial recognition system for emotion detection began with the collection of high-quality data, using the public Kaggle database where a dataset of 35,960 images of faces with the emotions required for training was found. In addition, special attention was paid to the diversity of the images, ensuring the representation of different demographic groups and emotional expressions (happiness, anger, sadness, surprise, fear, disgust and neutrality). Fig. 2 shows the dataset used in this study.

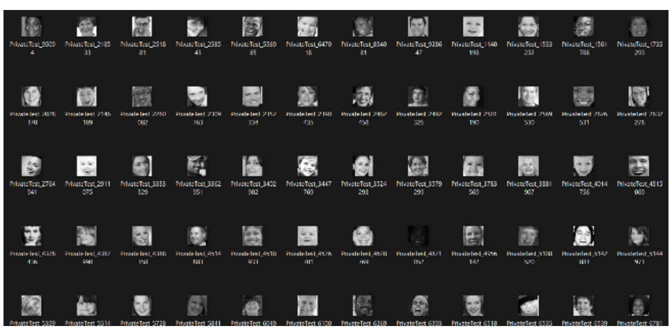


Fig. 2. Images of dataset.

C. *Data Processing*

In this phase of development, a series of essential steps were taken to ensure that the data collected from the dataset was suitable for training Deep Learning models, maximizing their effectiveness and precision. First, images were filtered, eliminating those that were of low quality or had characteristics that could hinder learning, such as insufficient resolutions or irrelevant elements in the background. This process made it possible to work with high-quality data.

Subsequently, image resizing was implemented, adjusting all images to a standard size defined for the models, which ensured consistency and homogeneity in the system input. Data normalization was then conducted, adjusting pixel values to a uniform range, which facilitated processing and improved the model's ability to identify significant patterns during training.

Additionally, data augmentation techniques such as rotation, shifting and horizontal flipping were applied to increase the diversity of the dataset. These modifications helped simulate various capture conditions, increasing the robustness and generalization capacity of the model.

Finally, the processed images were transformed into tensors, ensuring that the emotional labels remained correctly aligned with each image. This set of steps established a solid foundation for efficient training of the models, minimizing errors and improving their predictive ability. Furthermore, the emotions were divided into folders as shown in Fig. 3.

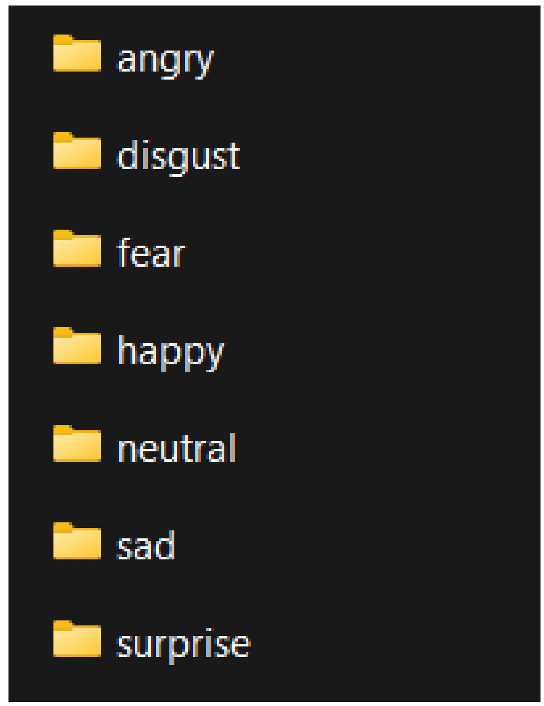


Fig. 3. Organization of folders by emotions.

D. *Deep Learning Algorithms*

In the modeling stage, six deep learning models were developed and trained for emotion detection from facial images: standard CNN, AlexNet, VGG16, DenseNet201, ResNet152, and InceptionV3. Each model was selected for its characteristics and proven performance in classification and computer vision tasks, allowing the problem to be approached from different architectural perspectives.

The CNN model was implemented in this study to see its level of prediction. On the other hand, AlexNet, known for being a pioneer in the use of deep networks, was included for its ability to extract relevant features through efficient convolutional layers. Likewise, VGG16, with its architecture based on small convolutional layers, allowed capturing fine details of the images, benefiting from greater depth.

As for the advanced models, DenseNet201 stood out for its dense structure, which connects each layer to all the following ones, maximizing the reuse of residual features and redundancy in learning. Meanwhile, ResNet152 used residual connections to mitigate the gradient vanishing problem, effectively training a deep network. Finally, InceptionV3 incorporated convolutions of multiple sizes in a single layer, capturing information at different spatial scales, making it especially robust against the complexity of emotional expressions. Fig. 4 illustrates the trained models divided by folders.

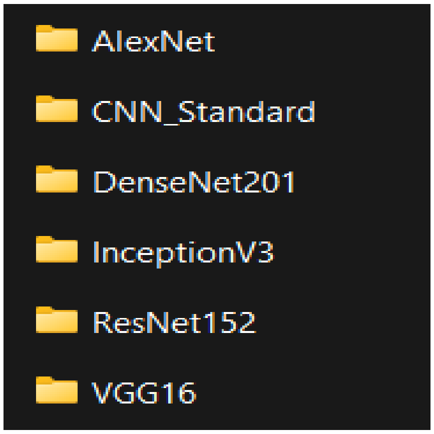


Fig. 4. Folder organization by trained model.

E. Evaluation Metrics

In this phase, the performance of the trained deep learning models for facial emotion detection was evaluated using the following quantitative metrics.

- Precision: Represents the percentage of correct predictions made by the model compared to the total number of predictions.

$$Precision = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

- Recall: Evaluates the model's ability to correctly detect positive instances, minimizing false negatives.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

- F1 Score: Combines precision and sensitivity in a harmonic average.

$$F1\ Score = 2\ x\ \frac{Precisi\acute{o}n\ x\ Recall}{Precisi\acute{o}n+Recall} \quad (3)$$

Where:

- TP: True Positive
- TN: True Negative
- FP: False Positives
- FN; False negatives (False Negative)

F. Performance Evaluation Instrument

To evaluate the effectiveness of the models, an experimental instrument was designed in which the 17 individuals (sample) participated. Each participant performed specific tests in which they were asked to express emotions such as happiness, sadness, anger, surprise, fear, disgust and neutrality towards the system, while the system tried to recognize them. The predictions made by each model were compared with real emotions, generating a confusion matrix for each architecture. This approach allowed recording detailed data on the performance of the models in a controlled environment.

Precision, recall, and F1-score metrics were manually calculated from the results obtained using standard formulas. This procedure ensures that the calculations are accurate and reflect the real performance of the models under experimental conditions.

G. Desktop Application with the Best Performing Model

This section aims to present and analyze the results obtained after the implementation of the face recognition system based on convolutional neural networks. It was first based on a comparison of six main architectures: standard CNN, AlexNet, VGG16, DenseNet201, ResNet152, and InceptionV3; comparing their performance in terms of precision, recall, and F1 score. This comparison allows us to identify the most suitable model for the final implementation, based on its ability to classify emotions accurately and efficiently.

In addition to the comparison of models, the effects of the implementation of the selected system in the work environment were analyzed, which included metrics related to productivity, organizational climate, and diagnosis and data collection times.

Table II shows the results of applying the metrics to each model, with DenseNet201 being the best performing model.

TABLE II. MODEL COMPARISON

Model	Precision	Recall	F1 Score
CNN	78.59%	86.60%	82.45%
AlexNet	77.87%	88.64%	82..90%
VGG16	80.59%	90%	84.98%
DenseNet201	87.70%	96.30%	91.80%
ResNet152	82.79%	93.48%	87.81%
InceptionV3	81.15%	88.17%	84.51%

H. Confusion Matrices

Below are the confusion matrices for each model used. These matrices complement the global metrics presented in the comparison table, providing a more granular view of the classification. The confusion matrices reflect the individual performance of each model in classifying emotions. In each matrix, the balance between correct predictions (main diagonal) and errors can be observed, highlighting the relative precision of the most robust models. The matrices can be seen in Fig. 5.

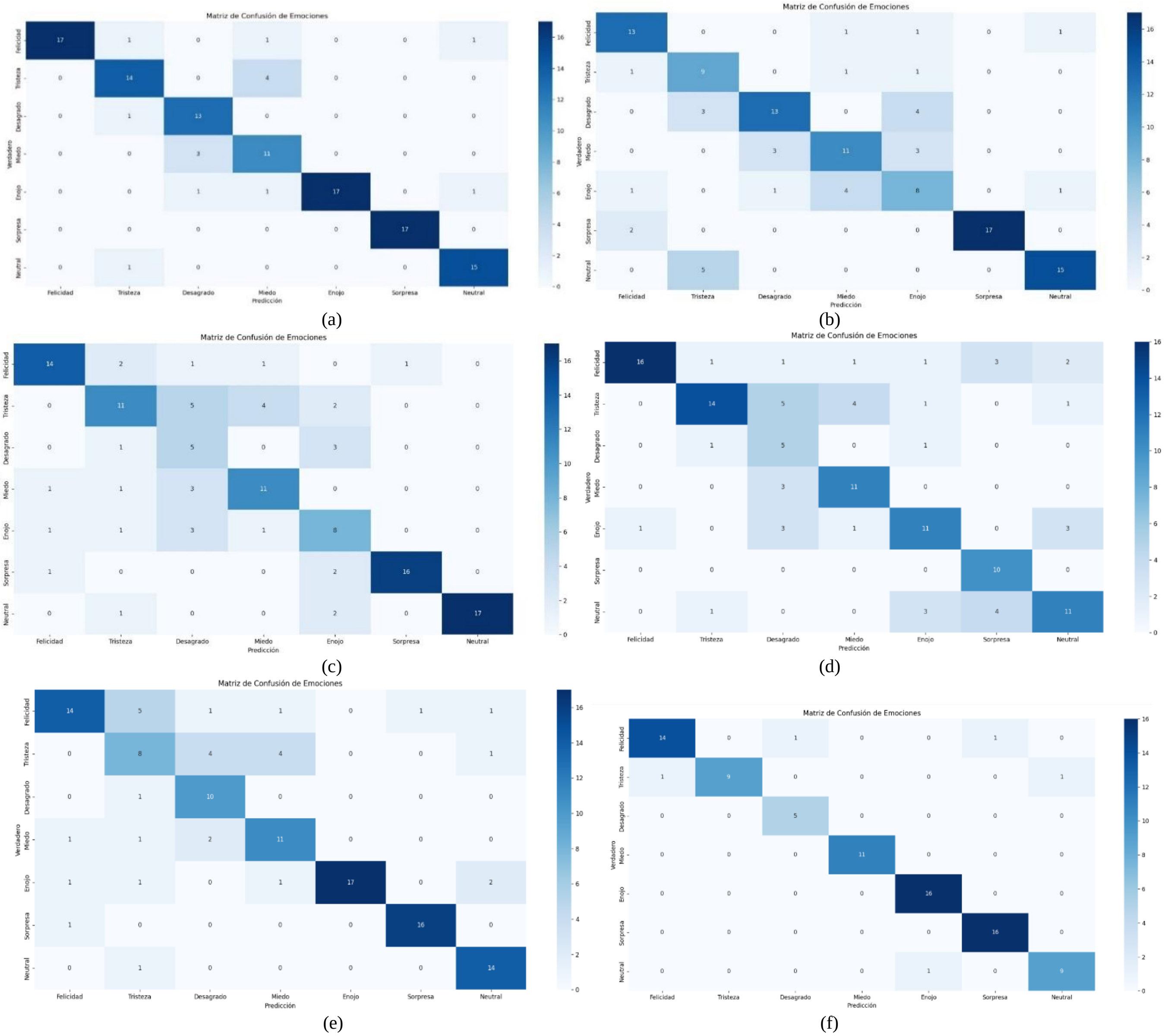
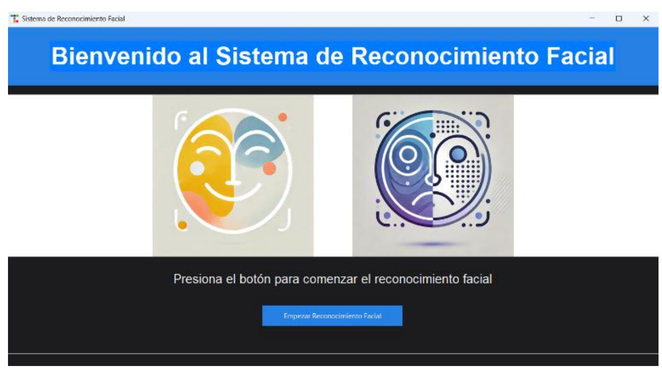


Fig. 5. (a) Confusion Matrix of DenseNet201. (b) Confusion Matrix of ResNet152. (c) Confusion Matrix of InceptionV3. (d) Confusion Matrix of AlexNet. (e) Confusion Matrix of VGG16. (f) Confusion Matrix of CNN.

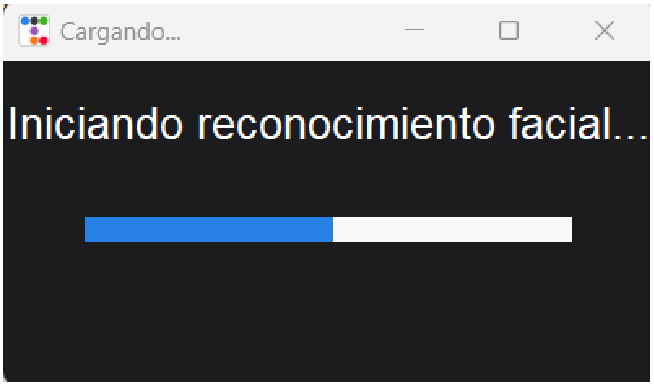
IV. Results

A. About the Prototype

The emotion detection application was developed using Python and the Tkinter library to create an intuitive and functional graphical user interface (GUI). Tkinter allowed the design of a visual environment where users could interact with the system in real time. The best performing model, DenseNet201, was implemented, pre-trained, and integrated into the application using libraries such as TensorFlow and OpenCV. This combination allowed the predictions to be processed quickly and accurately, ensuring that the user experience was efficient and aligned with the system's objectives (see Fig. 6).



(a)



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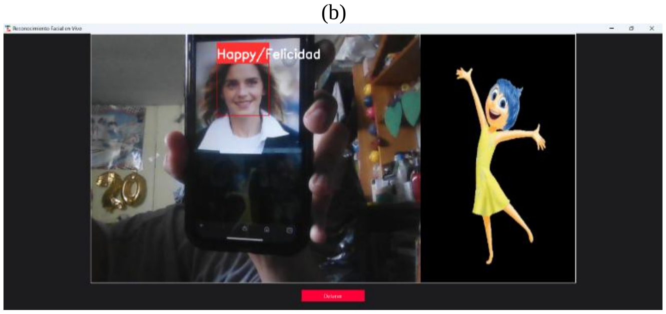

(c)

Fig. 6. (a) Startup interface (b) Progress bar (c) Running system.

B. *About the Population*

The research work approach is quantitative, so there was a population of 17 people, as specified in Table III.

TABLE III. WORKER'S POPULATION

Population	Number
Workers	17

In the present study, the samples require delimiting the population according to the available resources and the time allocated to conduct the research. For this reason, it was decided to use a non-probabilistic convenience sampling approach, which allows selecting participants intentionally, considering criteria such as accessibility, availability and ease of contact with them. This method is especially suitable in contexts where the total population is small. In this case, the same 17 people who make up the target population were selected, who meet the requirements to participate in the study, guaranteeing the obtaining of relevant data within the existing limitations, without compromising the validity of the analysis proposed in this document.

C. *About the Indicators*

This section presents the results obtained after the implementation of the facial recognition system based on deep learning, with the aim of optimizing the work environment and productivity in the organization. To evaluate the impact of the system, four key performance indicators (KPIs) were defined: i) Data collection time, ii) diagnosis time and iii) job satisfaction. These indicators were measured at two times: before and after the implementation of the system, using a pre-experimental design with a population of 17 workers. The results obtained reflect the effects of the system on operational effectiveness and organizational well-being, providing empirical evidence on the contribution of emotional recognition technology in the workplace. Next, the results of each KPI are analyzed in detail, highlighting the most significant changes and their implication in organizational management.

1) KPI - Data collection time: The implementation of the automated facial recognition system has proven to be an effective solution to address the inefficiencies associated with manual emotional data collection. Before the intervention, the average time required for this process was 98.5 minutes, which implied not only a significant investment of time, but also a high dependence on human factors that could introduce biases and errors. With the integration of the proposed system, this time was drastically reduced to 27 minutes, which constitutes an improvement of 72.59%. This result demonstrates the transformative impact of AI-based technologies on organizational processes.

The optimization achieved is not limited only to time reduction; it also represents an advance in resource allocation, allowing staff to focus on strategic activities with greater added value. In addition, the automation of the process guarantees greater consistency and precision in data collection, eliminating variations derived from subjectivity or human limitations. This change not only improves operational efficiency but also strengthens the organization's ability to make informed decisions based on reliable data.

In terms of organizational impact, this reduction in data collection time has significant implications for overall productivity and responsiveness to emerging emotional issues. As illustrated in Fig. 7, the bar chart clearly compares the average times before and after implementation, providing a visual representation of the positive change achieved. This finding highlights how the adoption of advanced technologies can not only solve technical challenges but also contribute to the well-being of workers by freeing up time and resources to more effectively address their emotional needs in real time.

In summary, these results underline the strategic value of incorporating automated tools into organizational management. The ability to significantly reduce time, together with the improvement in the quality and consistency of the data collected, positions the facial recognition system as a key innovation to optimize both operational processes and the work environment in organizational environments.

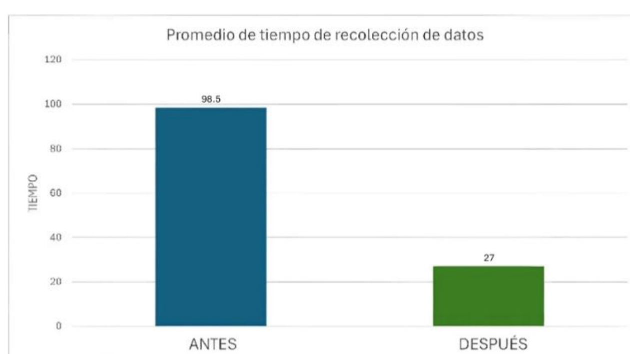

Fig. 7. Before and after bar graph.

2) KPI - Diagnostic time: Following the implementation of the facial recognition system, a substantial improvement in the efficiency of emotional diagnosis was seen, with a reduction in the average time from 93 minutes to 34 minutes, representing a 63.4% increase in the speed of the process. This result not only optimized the workflow but also increased the precision in emotion detection by reducing the reliance on traditional methods, such as manual interviews, which are often subject to human bias and variability in results. Automation allowed for greater uniformity in diagnoses, which is key to addressing emotional problems more quickly and effectively.

Furthermore, this advancement directly contributed to operational efficiency by freeing up resources that can now be allocated to higher-value strategic organizational activities. Fig. 8 graphically shows this significant reduction using a bar chart, highlighting the positive impact of the system not only in terms of time, but also on the quality of diagnosis and the organization's responsiveness to complex emotional challenges. This finding underlines the transformative role of artificial intelligence in improving critical organizational processes.

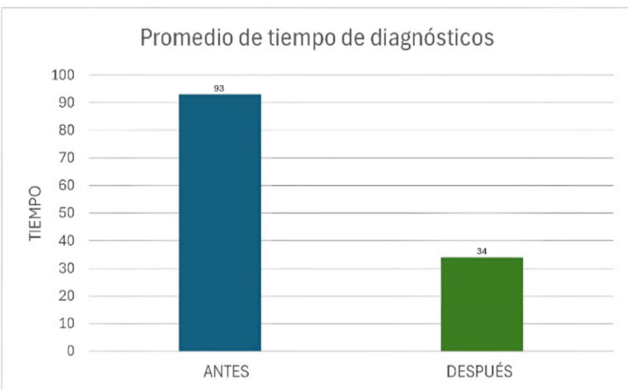

Fig. 8. Before and after bar graph.

3) KPI - Job satisfaction: One of the key indicators evaluated was the impact of the facial recognition system on employee job satisfaction, which is considered crucial for emotional well-being and organizational climate. To measure it, questionnaires with a 5-point Likert scale were applied to a sample of 17 employees, before and after implementing the system. The 15 questions in the questionnaire addressed aspects such as communication, leadership and emotional support.

The analysis consisted of comparing the averages of the pre- and post-implementation responses, allowing the identification of quantitative changes in the workers' perception of their work environment.

The graph in Fig. 9 illustrates the general trends, where the orange line (after) reflects a high and stable perception compared to the blue line (before), which shows lower and less consistent scores. This graph highlights the positive impact of the system on the organizational climate and employee well-being. Furthermore, the figures show that, before implementation, employee responses were more diverse. After the changes, there was evidence of higher job satisfaction and uniformity in the aspects evaluated. The decrease in negative perceptions suggests an improvement in emotional stability and trust in the work environment, with a 66.59% increase in satisfaction.

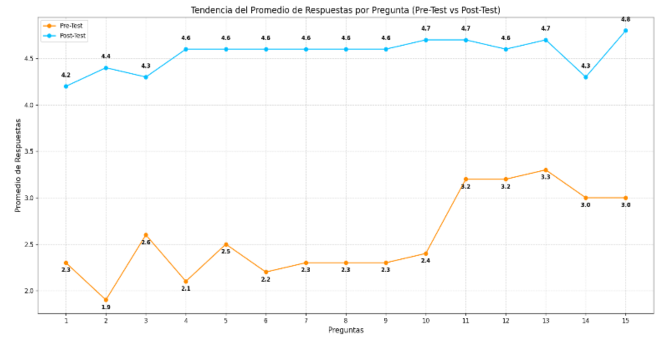

Fig. 9. Before and after response trends.

D. About the Survey and Expert Evaluation

To ensure the validity of the instrument designed to measure job satisfaction, the questionnaire was reviewed by three experts with experience in the development and evaluation of applied technological systems. The experts analyzed the structure, clarity and relevance of the questions, providing feedback to ensure that the instrument met the objectives of the study. This process allowed key adjustments to be made that strengthened the validity of the questionnaire, ensuring that the data collected accurately reflected the perception of the participants. Table IV presents the indicators that were used on the validity test approved by the experts. Where the following footage was graded:

- Poor (0 - 20%)
- Average (21 - 40%)
- Good (41 - 60%)
- Very Good (61 - 80%)
- Excellent (81 - 100%)

E. About the Methodology

The research was guided by the CRISP-DM model, recognized for its flexibility and focus on data mining and machine learning projects. This model divides the process into well-defined stages, allowing systematic progress from problem identification to the deployment of a functional solution.

The choice to take inspiration from CRISP-DM was based on its ability to adapt to the specific challenges of the research, such as handling large volumes of data and the need to train highly accurate deep learning models. Throughout this process, each stage was adapted to address key aspects of the project, such as the selection and preparation of the dataset, the training of advanced neural network models, and the implementation of a facial recognition system that meets the objectives of optimizing the work environment and productivity.

Table V presents the stages of the CRISP-DM-inspired methodology along with the activities carried out in each of them. This allows a clear visualization of how this approach was applied to ensure the effectiveness and reproducibility of the project.

TABLE IV. INDICATORS OF VALIDITY

Indicator	Criterion	Score		
		Expert 1	Expert 2	Expert 3
Clarity	It is formulated with appropriate language	80%	85%	90%
Objectivity	It is expressed in a coherent and logical manner	85%	85%	85%
Currentness	It is appropriate for advances in technology.	90%	85%	90%
Organization	There is a logical organization of variables and indicators.	80%	80%	80%
Sufficiency	It is coherent between indicators and dimensions	95%	90%	80%
Intentionality	It is appropriate to values and aspects related to the topic.	100%	82%	85%
Consistency	It is considered that the items used in this instrument are all and each one is specific to the field being investigated.	100%	90%	80%
Coherence	It is considered that the structure of this instrument is appropriate to the type of user to whom the instrument is directed.	85%	80%	90%
Methodology	The strategy responds to the purpose of the research.	85%	80%	85%
Relevance	It is appropriate to deal with the research topic.	80%	81%	85%

TABLE V. METHODOLOGY USED

Stage	Activity Completed
Understanding the Business	Problem identification: Job dissatisfaction and productivity; literature review to define objectives and approaches.
Obtaining the Data	Selection of the emotional images dataset (Kaggle), analysis of its structure and quality, initial data cleaning.
Data Processing	Normalization of pixel values, image resizing, data augmentation (rotation, flip, shift) and organization into folders according to emotions.
Deep Learning Algorithms	Training models such as standard CNN, DenseNet201, VGG16, ResNet152, AlexNet and InceptionV3.
Evaluation Metrics	Comparison of key metrics: accuracy, sensitivity and F1 score; analysis of confusion matrices to validate the effectiveness of each model.
Desktop App with the best performing model	Implementation of the DenseNet201 model in a functional prototype with a graphical interface, using Python and Tkinter.

This approach allowed theory to be integrated with practice in a structured manner, facilitating the achievement of the research objectives and the validation of the results obtained. The table summarizes the essential steps that led to the success of the project, highlighting the rigor at each stage of the proposed methodology.

V. DISCUSSION

A. About KPI's

The results of this study show significant improvements in the operational efficiency of this company in the wholesale sector after the implementation of the facial recognition system based on convolutional neural networks. Significant reductions were recorded in data collection times with an improvement of 72.59%, emotional diagnosis with an improvement of 63.4% and job satisfaction with 66.59%, optimizing the company's internal processes. In addition, the analysis showed an increase in productivity, reflecting a positive impact on employee performance.

B. About the Models

This chapter analyzes the results obtained with the system implemented using DenseNet201, highlighting both productivity and work environment. The findings are compared with previous research, such as those that achieved 85.69% accuracy in RAF-DB using residual networks applied to low-resolution environments [12], and studies that achieved 85.82% accuracy with EfficientNetB0 on the FER2013 dataset [38]. Likewise, the integration of DeepFace in smart factories was explored, evidencing its ability to adapt to real-time scenarios [31]. In contrast, other research reported 66.85% accuracy with CNN in FER2013, highlighting the challenges associated with generalizing less-represented emotions [26].

On the other hand, the Bayesian CNN-LSTM model demonstrated outstanding performance on metrics such as accuracy, sensitivity, and F1-score, underlining its effectiveness in correlating emotions expressed in forums with the dropout rate in MOOCs [39]. Similarly, the model proposed in this study employs sequential and residual identity blocks, allowing for high-accuracy facial feature extraction, outperforming other state-of-the-art methods, especially in distance education contexts [40]. Furthermore, CNN-based architecture designed for gender and emotion classification have achieved accuracy levels above 98%, successfully addressing challenges such as emotional changes reflected in vocal features [41].

Finally, quantum convolutional networks (QCNNs) have shown significant improvements in the efficiency of emotional detection systems in mental health contexts [19]. These advances highlight the importance of factors such as controlled environments and robust computational resources to maximize the performance of these systems. Furthermore, recurrent neural networks (RNNs) have recorded 95% accuracy in classifying emotions in videos, evidencing their ability to capture complex temporal patterns in dynamic data [42]. Together, these studies illustrate how advanced technologies can transform emotional detection, successfully addressing the limitations and challenges present in this field.

C. About Limitations

First, the research was conducted in a controlled setting with a small sample size of 17 participants, limiting the generalizability of the findings to larger populations. While the data set ensured multicultural representation, the system was evaluated within a single cultural context.

VI. Conclusions and Future Work

In conclusion, the implementation of a facial recognition system based on convolutional neural networks (DenseNet201) in the context of a wholesale company has proven to be an effective tool to comprehensively address the challenges related to emotional management in work environments. This system allowed real-time monitoring of employees' emotions, which facilitated the early identification of negative emotions and enabled the implementation of timely interventions aimed at optimizing the organizational climate and promoting a healthier and more productive work environment.

A significant decrease was also observed in the time associated with data collection and emotional diagnosis, which translated into a substantial improvement in the efficiency of processes related to the management of workplace well-being. These findings highlight the transformative potential of AI-based technologies to promote more resilient, efficient and human-centered work environments.

Future studies could focus on evaluating the adaptability and applicability of this system in different sectors and work contexts, with the aim of validating its effectiveness and exploring new areas for improvement. Additionally, it is recommended that they can further enhance the system's capacity to address the dynamic challenges of emotional management in the organizational setting.

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