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SUMMARY

PHD SUPERVISOR::

PROF. UNIV. HABIL. DR. ENG. LEBA MONICA

PHD STUDENT:

ENG. ZAHA (SĂLĂGEAN) GABRIELA LAURA

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RESEARCH ON THE AUTOMATIC RECOGNITION OF MACRO AND MICRO FACIAL EXPRESSIONS USING ARTIFICIAL INTELLIGENCE METHODS

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The doctoral thesis entitled "Research on the Automatic Recognition of Macro- and Micro-Facial Expressions Using Artificial Intelligence Methods" explores an interdisciplinary research domain situated at the intersection of psychology, neuroscience, and artificial intelligence.

Facial expressions are universal manifestations of human emotions and play a fundamental role in nonverbal communication. The development of systems capable of automatically recognizing and interpreting these expressions has significant implications in fields such as human-computer interaction, security, education, and healthcare.

In recent years, the advancement of facial expression recognition technologies has accelerated considerably, driven by progress in artificial intelligence, deep learning, and computer vision.

However, the field still faces major challenges in the accurate detection and interpretation of both macroexpressions—clearly visible emotional displays characterized by high intensity and longer duration—and microexpressions, which are subtle, fleeting facial movements that occur for extremely short periods and may reveal concealed or suppressed emotions.

The doctoral thesis follows the natural flow of the scientific research process, progressing methodically from theoretical foundations through the applied methodology and conducted experiments to the final results and conclusions. The structure of the thesis reflects both the complexity of the addressed field and the rigorous methodology employed to achieve the proposed objectives.

Main Objectives Pursued:

a. Leveraging facial symmetry and addressing asymmetry in facial expressions to enhance performance of emotion recognition algorithms.

b. Developing and validating a customized real-time CNN model for efficient facial emotion recognition, adapted to handle the variability and asymmetry of expressions.

c. Developing a comprehensive theoretical framework for facial recognition, integrating the psychological theory of facial expressions (FACS) with modern technological approaches.

d. Implementing a robust system for real-time detection and classification of microexpressions, combining traditional computer vision techniques with advanced machine learning algorithms.

e. Solving specific confusion issues between similar emotions through expert rules and the amplification of distinctive features.

f. Conducting a rigorous evaluation of the developed systems' performance using standard metrics and benchmarking against existing methods.

1. Introduction

The thesis begins with an introductory chapter that establishes the conceptual and methodological framework of the research. It outlines the current scientific context in the field of facial expression recognition, emphasizing the relevance and timeliness of the topic in today's digital era. The chapter highlights the major challenges faced by researchers in this domain, ranging from the variability of facial expressions influenced by cultural and individual factors to the technical difficulties associated with acquiring and processing facial images in real-world conditions.

The motivation behind this research is presented in detail, highlighting the extensive application potential of automated facial expression recognition systems in areas such as mental health, security, education, and human-computer interaction. Particular emphasis is given to the distinction between macroexpressions and microexpressions—a fundamental differentiation that represents one of the original contributions of this study. This distinction supports the development of tailored approaches for the detection and interpretation of each type of expression .

The first approach focuses on the recognition of macro-facial expressions by proposing a model based on convolutional neural networks (CNNs), with particular emphasis on assessing the impact of data augmentation techniques. This approach employs the FER-2013 dataset and includes the implementation of the model in a real-time environment.

The second approach involves a hybrid system dedicated to the analysis of micro-facial expressions. This system integrates advanced computer vision techniques, expert rules grounded in the Facial Action Coding System (FACS), and artificial intelligence algorithms. It has been implemented in real time and tested on the CASME II and SAMM databases.

The research questions that guide the entire scientific endeavor are clearly and explicitly articulated, thereby establishing the main directions of investigation and the criteria for evaluating the results.

The research was guided by the following fundamental questions:

1. What are the most effective techniques and algorithms for facial recognition and emotion detection across various contexts and conditions?
2. How can facial symmetry be leveraged and addressed to enhance the performance of emotion recognition systems?
3. How can convolutional neural networks be optimized to effectively manage the specific challenges of facial emotion recognition, considering class imbalance and expression variability?
4. To what extent can a hybrid approach—combining advanced computer vision techniques, expert rules based on the Facial Action Coding System (FACS), and artificial intelligence algorithms—improve the detection of micro-facial expressions?
5. What are the most effective strategies for differentiating between facial expressions associated with similar emotions?

2. Current State of Research

This chapter provides a comprehensive and critical analysis of the specialized literature, highlighting the evolution of methods and techniques used in facial expression recognition over time. It begins with a historical overview of the development of emotion and facial expression theories, starting with the foundational works of Charles Darwin and Paul Ekman, who established the conceptual basis for the universality of certain emotional expressions.

Traditional approaches to facial expression recognition methods are presented, particularly those based on manual feature extraction and the use of classical classifiers. The chronological development of the field is traced through the transition toward machine learning-based paradigms, with a focus on the emergence and advancement of convolutional neural networks (CNNs), which have revolutionized the domain of visual pattern recognition.

The chapter provides a comparative analysis of various CNN architectures that have been successfully applied to facial expression recognition, including VGG, ResNet, Inception, and EfficientNet, emphasizing the specific strengths and limitations of each model.

A substantial section is dedicated to specialized methods for the detection and recognition of microexpressions. It presents motion analysis techniques based on optical flow, video magnification, and the temporal analysis of facial changes—approaches that are essential for capturing the fleeting and subtle nature of microexpressions.

The chapter also includes an analysis of hybrid systems that combine multiple approaches to enhance recognition performance, as well as an exploration of the potential of large language models (LLMs) in interpreting emotional context. The literature review concludes with a clear identification of the current limitations of existing systems, thereby laying the groundwork for the original contributions proposed in this thesis.

3. Datasets and Resources

The FER-2013 (Facial Emotion Recognition 2013) dataset is analyzed in detail, as it comprises over 35,000 grayscale facial images categorized into seven emotional classes: happiness, sadness, fear, anger, disgust, surprise, and neutrality.

The advantages of this dataset are thoroughly discussed, including its large volume of images and the diversity of capture conditions, which contribute to the generalizability of models trained on it. However, its limitations are also acknowledged—most notably the class imbalance, which may bias model performance toward more frequently represented emotions, and the relatively low image resolution, which can hinder the accurate extraction of fine-grained facial features.

For the study of microexpressions, two specialized datasets are examined: CASME II (Chinese Academy of Sciences Micro-Expression Database II) and SAMM (Spontaneous Actions and Micro-Movements).

CASME II consists of 255 microexpressions captured at a high frame rate of 200 frames per second (fps), classified into five core emotional classes. In contrast, SAMM provides 159 microexpressions, also recorded at 200 fps, but with greater demographic diversity, making it particularly valuable for cross-cultural and cross-subject analysis.

The chapter continues with a detailed description of the software and hardware tools used for the development of the proposed system. It introduces specialized Python libraries for image processing and deep learning, such as:

- OpenCV for image manipulation and preprocessing,
- TensorFlow and Keras for implementing convolutional neural networks,
- MediaPipe for real-time facial landmark detection and tracking, and
- OpenAI technologies for the integration of language models in emotionally aware systems.

The hardware specifications used for model training and testing are also outlined, emphasizing the importance of appropriate computational resources—such as GPUs—for the efficient execution of deep learning algorithms. This infrastructure supports the real-time capabilities and high-performance requirements of the proposed facial expression recognition systems.

Lastly, the hardware configuration used in the research is presented. The system is built around an Intel Core i7-10700K processor, equipped with 32GB of DDR4 RAM, a 1TB SSD for fast data access and storage, and a NVIDIA GeForce RTX 3080 GPU with 10GB of dedicated VRAM.

4. Research Methodology

This chapter constitutes the conceptual core of the doctoral thesis, detailing the overall architectures of the developed emotion recognition systems. It begins with the presentation of the general methodological framework, grounded in the principles of deep learning and the morphological analysis of facial expressions.

A key aspect of the methodology is the distinctive approach adopted for macroexpressions and microexpressions, justified by the inherently distinct nature of these two types of emotional manifestations.

For macroexpressions, the architecture of the convolutional neural network (CNN)-based model is presented in detail, beginning with the structure of the convolutional layers, the activation functions employed, and the mechanisms implemented to prevent overfitting. The rationale behind each architectural decision is thoroughly explained, including the choice of filter sizes, pooling strategies, and the organization of the final dense layers.

Special attention is given to facial image preprocessing methods, which are critical to the model’s performance. These include face detection, normalization, and various data augmentation techniques designed to enhance the model's robustness to variations in pose, lighting, and expression intensity.

For the microexpression-focused system, a hybrid architecture is presented, which combines temporal analysis of video sequences with the extraction of spatial features. The chapter details the techniques employed to amplify subtle facial muscle movements, such as motion magnification, and the methods used to capture the temporal dynamics characteristic of microexpressions. These include optical flow analysis and high-frame-rate segmentation strategies, designed to detect transient, low-intensity facial events.

A significant contribution presented in this chapter is the integration of large language models (LLMs)—specifically GPT-3.5-turbo—into the processing pipeline to handle ambiguous situations in which rule-based classification fails to yield a conclusive decision. This process involves: the automatic generation of a structured prompt, which includes the list of detected Action Units (AUs), explicit classification rules, and relevant contextual information; the processing of this prompt by the LLM; the validation of the generated response by checking its compliance with predefined rules and system constraints; and the application of correction and filtering mechanisms to manage potential inconsistencies or erroneous outputs.

The chapter also includes a description of the facial segmentation algorithms used to isolate emotion-relevant regions of interest, as well as the implementation of facial asymmetry analysis modules. Additionally, it outlines the training methodology for the proposed models, covering: optimization strategies, loss functions employed, hyperparameter tuning techniques, and evaluation metrics, including the confusion matrix, precision, recall, and F1-score.

5.Experiments

The experimental section of the doctoral thesis details the testing and evaluation protocols for the proposed models. The chapter begins with the presentation of the general experimental methodology, emphasizing the importance of cross-validation in obtaining robust and reliable estimates of the proposed system's performance.

Within the study, six distinct experiments were conducted, aimed at analyzing the efficiency of the Convolutional Neural Network (CNN) in recognizing facial macroexpressions, tested on the FER2013 database. Each experiment evaluated a different configuration of the training process:

- Case 1: The CNN was trained using the Shuffle function.
- Case 2: The CNN was trained using the Shuffle function and the Vertical Flip function.
- Case 3: The CNN was trained using the Loss Weight function.
- Case 4: The CNN was trained using both the Shuffle and Loss Weight functions.
- Case 5: The CNN was trained using a complex configuration that simultaneously integrated the Vertical Flip, Shuffle, and Loss Weight functions.
- Case 6: The CNN was trained using the Shuffle function; however, an additional modification was introduced by increasing the test batch size.

The training process of the Convolutional Neural Network (CNN) is described in detail, including the weight initialization strategies, the optimization algorithms employed, and the data normalization techniques. These elements were essential in preventing overfitting and ensuring effective model generalization.

Furthermore, the methods used for tuning hyperparameters—such as learning rate, batch size, and the number of epochs—are also presented.

The real-time implementation of the proposed CNN model is described as well, in order to assess its ability to operate efficiently in an applied environment.

For the experiments involving microexpressions, the procedures for extracting relevant sequences from video recordings, frame synchronization, and the applied amplification techniques are discussed in detail.

The hybrid system was tested on the CASME II and SAMM databases and aimed to evaluate the following aspects:

- The accuracy of facial action unit (AU) detection in comparison with the manual annotations provided in the databases;
- The efficiency of expert rules in the classification of microexpressions;
- The effectiveness of integrating the Large Language Model (LLM) in resolving ambiguous cases;
- The overall performance of the hybrid system under real-time operating conditions.

6. Results and Analysis of Results

The results obtained from the experiments are rigorously analyzed, and the performance of the proposed models is interpreted using a set of standardized metrics, including the confusion matrix, overall accuracy, precision, recall, and the F1-score.

The chapter is structured into two main sections: the performance analysis of the proposed CNN model and the performance analysis of the proposed hybrid model.

The first section evaluates the performance of the proposed Convolutional Neural Network (CNN) model for facial macroexpression classification. The model was tested in six different experimental configurations, employing various data augmentation strategies described in the previous chapter. The model achieved an overall accuracy of 92%.

The confusion matrices generated for the six experimental cases revealed high performance of the proposed model across each emotion class. Emotion categories prone to frequent misclassifications—such as fear and surprise, or sadness and neutral (absence of emotional expression)—were identified.

The class-wise precision analysis (Table 6.1) highlighted the following:

- High performance for distinct emotions such as happiness (precision > 94%);
- Good precision for the neutral and surprised emotion classes (precision > 88%);
- Challenges in accurately classifying similar emotions such as fear and sadness;

• A significant impact of data augmentation techniques on the precision for certain emotion classes.

Table 6.1 — Precision (%) for Each Emotion Across the Six Experimental Cases

Emotion	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
angry	0.88	0.88	0.88	0.89	0.88	0.90
disgust	0.95	0.99	0.97	0.84	0.94	0.98
fear	0.89	0.92	0.89	0.90	0.90	0.85
happiness	0.96	0.94	0.95	0.96	0.95	0.94
neutral	0.88	0.89	0.91	0.87	0.87	0.87
sadness	0.88	0.89	0.88	0.87	0.89	0.86
surprise	0.95	0.95	0.92	0.95	0.93	0.87

The recall analysis for each emotional class (Table 6.2) revealed the following: High recall values for happiness and neutral expressions; Moderate values for surprise and anger; Challenges in fully detecting instances of fear and disgust; Significant variations in recall depending on the data augmentation techniques employed.

Table 6.2 Recall (%) for Each Emotion Across the Six Experimental Cases

Emotion	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
angry	0.86	0.88	0.89	0.89	0.88	0.92
disgust	0.87	0.88	0.86	0.89	0.88	0.90
fear	0.88	0.88	0.90	0.88	0.87	0.82
happiness	0.95	0.96	0.94	0.94	0.94	0.95
neutral	0.93	0.91	0.91	0.92	0.93	0.89
sadness	0.88	0.88	0.88	0.88	0.86	0.82
surprise	0.94	0.95	0.94	0.94	0.94	0.88

The F1-score provided a balanced perspective on the model’s performance (Table 6.3): high F1-scores were recorded for happiness (>85%), good values for the neutral and surprise emotion classes, moderate scores for anger, and lower scores for fear and disgust.

Table 6.3 — F1-Score (%) for Each Emotion Across the Six Experimental Cases

Emotion	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
angry	0.88	0.88	0.89	0.89	0.88	0.91
disgust	0.91	0.93	0.91	0.92	0.91	0.94
fear	0.88	0.90	0.89	0.89	0.89	0.83
happiness	0.96	0.95	0.95	0.95	0.94	0.94
neutral	0.90	0.90	0.91	0.89	0.90	0.88
sadness	0.88	0.89	0.88	0.87	0.88	0.84
surprise	0.94	0.95	0.93	0.94	0.94	0.87

A significant aspect of the results is the consistency of the F1-scores across all six experimental configurations, which reflects the operational stability of the model in the presence of external variability.

The real-time implementation of the CNN model demonstrated the system's ability to operate efficiently under practical conditions, achieving a processing rate of over 25 frames per second.

The second section evaluates the performance of the proposed hybrid model for microexpression recognition. When tested on the CASME II database, the model achieved a precision of 93.3%, while on the SAMM database it reached 98.4%.

The testing of the hybrid model highlighted the effectiveness of the LLM integration mechanism in resolving ambiguous cases and the robustness of classification in the face of expression variability across different subjects.

The specific challenges encountered in detecting various types of microexpressions are evaluated, with correlations drawn to the physiological aspects of the facial muscles involved. The results obtained from the real-time implementation validated the robustness and practical applicability of the proposed system.

The chapter also addresses the impact of class imbalance on recognition performance. Emotion confusion cases are analyzed in detail, with interpretations grounded in psychological theories on similarities and overlaps between certain emotional expressions, as well as the inherent limitations of visual representations in capturing the full spectrum of human emotions.

7. Discussion

The discussions presented in this chapter place the obtained results within the broader context of the scientific literature, highlighting the original contributions of the doctoral thesis.

The main strengths of the proposed CNN model for macroexpression recognition are as follows:

- Optimal use of facial symmetry to enhance classification accuracy;
- Data augmentation techniques significantly improved the model's robustness, reducing overfitting and enhancing its generalization capability;
- Computational efficiency — the model achieves a balance between complexity and performance, being optimized for real-time use;
- Robustness to variability — the system is capable of handling variations in lighting, head positioning, and individual expressiveness;
- Classification accuracy — competitive performance (approximately 90–91%) on the FER2013 dataset, compared to other models reported in the literature;
- Practical implementation — the system has demonstrated its functionality under real-time operating conditions.

The proposed hybrid system for microexpression detection represents a significant contribution to the field, offering the following advantages:

- A modular approach that enhances transparency and control over the decision-making flow;
- Flexibility in adapting to imbalanced datasets, with improved efficiency in handling minority classes and rare or atypical expressions;
- Effective resolution of ambiguities between similar emotions (e.g., fear-surprise or sadness-disgust);
- Innovative integration of Large Language Models (LLMs) to enhance the decision-making process through a hybrid approach that combines automatic detection of Action Units (AUs) with classification performed by an LLM (GPT-3.5-turbo);
- Superior performance — achieving 93.3% accuracy on the CASME II database and 98.46% on the SAMM database, representing a significant improvement over traditional methods.

A critical analysis of the identified limitations within the developed models is presented, along with proposed directions for future research.

Regarding the proposed CNN model for macroexpression recognition, the main limitations identified include:

- The use of the FER2013 dataset, which exhibits class imbalance, negatively impacts the model's performance in recognizing underrepresented emotions such as disgust and surprise.
- The reliance on grayscale images limits the model's applicability in real-time scenarios, where input data are typically in color and subject to natural variations in lighting and contrast.
- Testing on a limited number of subjects may restrict the model's generalizability to a broader population with diverse cultural and demographic backgrounds.

- Sensitivity to variations in lighting and facial orientation remains a challenge, despite the data augmentation techniques employed, potentially affecting system performance in uncontrolled environments.

8. Limitations and Future Research Directions

Regarding the hybrid system for microexpression recognition, the main limitations identified are as follows:

- Dependence on the initial accuracy of Action Unit (AU) detection may affect the entire classification pipeline, introducing errors that propagate throughout the system.
- Cultural and demographic variability in the expression of microexpressions has not been fully tested in the current model, which may limit its universal applicability.
- The requirement for significant computational resources to run the hybrid model may pose a barrier to implementation on resource-constrained devices or in applications requiring edge computing.
- Ethical and privacy challenges associated with real-time emotion recognition remain critical concerns that require responsible approaches in the development and deployment of systems based on such technologies.

The main future development directions, derived from the analysis of the results and the identified limitations in this study, include:

- Multimodal systems that combine facial expression analysis with other modalities such as voice and gestures;
- Personalized adaptive architectures tailored to individual users, capable of adjusting to each person's expressive patterns through calibration techniques and transfer learning;
- Explainable and transparent systems (XAI) to support the interpretability of model decisions;
- Context-aware approaches that integrate situational factors into emotion recognition;
- Extensions to specific applications in fields such as education, healthcare, and security;
- Exploration of ethical implications, ensuring responsible development and deployment of emotion recognition technologies.

9. General Conclusions

This chapter synthesizes the main contributions and achievements of the doctoral thesis, offering an integrated perspective on its theoretical and practical implications. The initial objectives are revisited, highlighting how they were accomplished through the proposed methodology and the results obtained.

The first objective of the research focused on exploring how facial symmetry can be used to enhance the performance of emotion recognition algorithms. It was demonstrated that facial symmetry plays a key role in the accurate recognition of emotions, while asymmetry—whether natural or induced by emotional factors—can significantly affect classification accuracy.

These techniques contributed to a more nuanced and precise interpretation of expressed emotions, leading to a substantial improvement in the accuracy of the recognition algorithms, achieving an accuracy of 92%,

The second objective focused on the development and validation of a CNN model capable of operating in real time while effectively managing variability and asymmetry in facial expressions. This objective was achieved through the design and implementation of a custom CNN architecture, optimized for facial emotion recognition under diverse conditions of lighting, angle, and individual variability.

The implementation of this model confirmed the effectiveness of the proposed approach, highlighting its potential for real-time applications in domains such as human-computer interaction, security, and behavioral analysis.

The third objective aimed to develop a comprehensive theoretical framework that integrates psychological theories of facial expressions with modern technological approaches. This objective was fulfilled by establishing a solid conceptual foundation that combines the Facial Action Coding System (FACS) with advanced techniques from the fields of machine learning and computer vision.

This integration enabled a more holistic approach to the study of facial expressions, supporting both the analysis of emotions and the development of algorithms capable of interpreting these expressions efficiently and with greater nuance.

The fourth objective aimed at implementing a robust system for the real-time detection and classification of facial microexpressions. This objective was achieved through the development of a hybrid system that combines traditional computer vision techniques with advanced machine learning and artificial intelligence algorithms.

This system not only enables rapid detection of subtle emotional cues but also ensures accurate real-time classification, offering promising applications in fields such as psychology and security.

The fifth objective addressed the specific challenges of emotion confusion between similar expressions by implementing expert rules and enhancing distinctive features. This objective was fulfilled through the development of specialized mechanisms for differentiating frequently confused emotions, such as happiness and surprise or sadness and fear.

These rules were integrated into the classification process, allowing the system to distinguish between often-confused emotions and deliver accurate results, contributing to an achieved accuracy of 93.3% on the CASME II dataset.

The sixth objective focused on the rigorous evaluation of the performance of the developed systems using standard metrics and comparing them with existing methods. This objective was achieved through a detailed and comprehensive assessment of the proposed systems, employing domain-standard evaluation metrics and benchmarking the results against state-of-the-art approaches.

The outcomes of this evaluation confirmed the significant improvements introduced by the proposed methods, establishing a solid foundation for future implementation and adoption of these technologies in practical applications.

The dissemination of the results obtained within this doctoral thesis was carried out through the publication of two scientific papers presented at international conferences (ITEMA 2023 and ICIE 2025) and two scientific articles published in prestigious international journals indexed in the Web of Science, contributing to the visibility and validation of the contributions made in the field.

Thus, the article entitled "Face Recognition: A Literature Review", presented at the 7th International Scientific Conference ITEMA 2023 [203], provides an extensive synthesis of facial recognition techniques, analyzing the evolution of algorithms from traditional methods to convolutional neural network-based solutions.

Additionally, the paper "Origami Complexity Decoded: Leveraging SqueezeNet for Image Classification", published in the volume Innovations in Mechatronics Engineering IV (Springer Lecture Notes in Mechanical Engineering), following participation in the ICIE 2025 conference [204], proposes an innovative approach to image classification by using SqueezeNet architectures to optimize visual recognition processes in complex scenarios.

The article entitled "Leveraging Symmetry and Addressing Asymmetry Challenges for Improved Convolutional Neural Network-Based Facial Emotion Recognition", published in the journal Symmetry [135], presents an innovative approach that leverages facial symmetry in emotion recognition using a customized convolutional neural network. Furthermore, the developed solution was integrated and validated in a real-time facial emotion recognition application, thus demonstrating the feasibility of practical implementation.

The article "Seeing the Unseen: Real-Time Micro-Expression Recognition with Action Units and GPT-Based Reasoning", published in Applied Sciences [182], proposes an advanced system for real-time micro-expression recognition by integrating facial action unit models with large language model (LLM) reasoning algorithms (GPT-3.5-turbo).

These contributions have enabled the valorization and dissemination of the research results within the international scientific community, facilitating the exchange of ideas, the discussion of the proposed solutions, and the validation of the developed methodologies through peer review.

The publication of these works attests to the scientific relevance of the research carried out within this doctoral thesis and contributes to expanding the frontiers of knowledge in the field of automatic macro- and micro-expression recognition.

Moreover, the thesis brings in spotlight the ethical implications associated with such technologies, emphasizing the importance of their responsible use, with full respect for individual rights, privacy, and personal autonomy.

The applicability of the proposed models is also analyzed in real-world contexts such as healthcare, education, and security, with a focus on their social impact and potential to generate substantial benefits.

In conclusion, this doctoral thesis makes a significant contribution to the field of micro- and macroexpression recognition, proposing innovative approaches for the differentiated treatment of macro- and microexpressions, and opening new perspectives for the development of intelligent systems with advanced capabilities for perceiving and interpreting human emotions.

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