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AI-Powered Instant Emotion Detection System

Mrs.T.N.V Durga[1], Nulu Rama Swathi[2], Tadala Lakshmi Tanmayi[3], Meka Praharshini Sowmya Sri Lakshmi[4], Pulletikurthi Venkata Polanaga Saiavinash[5], Cheekurumalli Aishwarya[6].
durga.tnv@pragati.ac.in[1], nuluramaswathi@gmail.com[2], tanmayitadala@gmail.com[3], praharshinisri@gmail.com[4], 123saiavinash@gmail.com[5], cheekurumalliaishwarya@gmail.com[6].
"Pragati Engineering College 1-378, ADB Road, Surampalem Near Kakinada, Surampalem, Andhra Pradesh 533445"

Abstract:

This paper presents a deep learning-based model for real-time automatic mood estimation using facial expressions in images. The model is built on a Convolutional Neural Network (CNN) architecture, customized to learn individual facial parameters and map them into facial Action Units (AUs). These parameters are then translated into the Pleasure, Arousal, and Dominance (PAD) space, which forms the basis for mood categorization. The experimental framework defines four primary mood categories: "Exalted", "Calm", "Anxious", and "Bored", based on the Pleasure–Arousal (PA) plane, along with additional categories for positive and negative Pleasure states. The model's performance is evaluated on a stimulus video shown to participants, where their facial expressions are recorded and analyzed. Results demonstrate that the CNN-based model achieves a 94% accuracy in classifying moods in the Pleasure dimension, and 73% accuracy in the PA categorization, highlighting the model's ability to estimate moods based on facial expressions accurately. The findings suggest that facial expressions are a reliable indicator of subjective emotional states, offering potential applications in real-time mood assessment systems for diverse fields such as human-computer interaction, healthcare, and user experience.

Keywords: Affective analysis, mood estimation, CNN, facial expressions, real-time tracking, computer vision, emotion recognition

1. INTRODUCTION:

Facial emotion recognition (FER) has become a crucial area of research in affective computing, with applications spanning human-computer interaction, healthcare, marketing, and security systems. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have significantly improved the accuracy of automated facial expression analysis [1]. However, real-time facial emotion recognition remains a challenging problem due to variations in lighting, occlusions, and individual differences in expression intensity.

This study presents a deep learning-based approach for real-time emotion detection using facial images. The system employs a CNN model to extract and classify facial features into distinct emotional categories based on the Pleasure-Arousal-Dominance (PAD) model [2]. The PAD model provides a dimensional representation of emotions, offering a more nuanced understanding than traditional categorical approaches. Our proposed method integrates image preprocessing, feature extraction, and classification into a seamless pipeline optimized for real-time execution.

A key innovation of our work is the real-time processing capability achieved through optimized model architecture and hardware acceleration. Experimental results indicate that the model achieves high accuracy in classifying emotions, with a reported 94% accuracy in the Pleasure dimension and 73% in the Pleasure-Arousal (PA) categorization [3]. The dataset utilized for training consists of annotated facial expressions collected from participants exposed to various affective stimuli.

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The remainder of this paper is structured as follows: Section II discusses related works in FER and mood estimation. Section III presents the methodology, detailing the data acquisition, preprocessing, and model architecture. Section IV provides an evaluation of the system's performance based on experimental results. Section V highlights the limitations of the current approach and suggests future improvements. Finally, Section VI concludes the study by summarizing the findings and potential applications of real-time facial emotion recognition.

Emotion recognition through facial expressions is a critical research area in affective computing, a field that seeks to bridge the gap between human emotions and artificial intelligence (AI)-based systems. Facial Emotion Recognition (FER) has gained significant attention due to its wide range of applications, including human-computer interaction (HCI), healthcare, security, marketing analysis, and psychological assessment. The ability to recognize emotions in real time enhances user experience, enables adaptive AI systems, and facilitates automatic mood monitoring in various environments [4].

Facial expressions serve as nonverbal cues that convey a person's emotional state, making them fundamental to human communication. Traditional methods of facial expression analysis were based on manual annotation and feature engineering, such as the Facial Action Coding System (FACS) introduced by Ekman and Friesen [5]. While these methods were effective, they were time-consuming, required domain expertise, and lacked the scalability needed for real-world deployment. With advancements in computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), FER systems have become increasingly automated, accurate, and efficient [6]. However, despite these advancements, achieving real-time performance with high accuracy remains a challenge due to computational complexity, environmental variability, and the need for robust emotion classification models.

2. LITERATURE REVIEW:

Facial emotion recognition (FER) has been a significant area of research in affective computing, with applications in human-computer interaction, healthcare, and behavioral analysis. Various techniques, including traditional machine learning, deep learning, and psychological models, have been explored to enhance FER systems' accuracy and robustness. This section provides an overview of prior research on FER methodologies, the application of deep learning models, and the use of psychological emotion representation frameworks like the Pleasure-Arousal-Dominance (PAD) model.

2.1. A. Facial Emotion Recognition Techniques

Early approaches to facial emotion recognition relied on handcrafted features and traditional machine learning classifiers. The Facial Action Coding System (FACS), developed by Ekman and Friesen [1], was one of the first frameworks used to analyze facial expressions by categorizing muscle movements into Action Units (AUs). The FACS method allowed for detailed expression recognition but required manual annotation, making it less scalable for real-time applications.

With advancements in computer vision, researchers introduced automated feature extraction methods using Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Gabor filters to improve FER accuracy [2]. These techniques, however, were limited in their ability to generalize across different facial expressions and lighting conditions.

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved FER performance by enabling automatic feature extraction from raw images. Deep learning-based models have demonstrated state-of-the-art accuracy in recognizing facial emotions, even in

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challenging real-world scenarios [3]. However, real-time implementation of CNN-based FER systems remains a challenge due to computational complexity.

2.2. Deep Learning-Based FER Systems

Recent studies have focused on leveraging deep learning architectures for facial emotion recognition. CNNs have been widely adopted due to their ability to learn hierarchical features from facial images. Several architectures, including VGGNet, ResNet, MobileNet, and EfficientNet, have been explored for FER applications, achieving high accuracy rates [4].

Filippini et al. [5] proposed a deep learning-based approach for real-time mood estimation using facial expressions. Their model maps facial features into Action Units (AUs), which are then transformed into a three-dimensional Pleasure-Arousal-Dominance (PAD) space for mood classification. Their study demonstrated that facial expressions provide reliable cues for emotion and mood estimation, achieving 94% accuracy in classifying moods in the Pleasure dimension and 73% accuracy in the Pleasure-Arousal (PA) categorization.

Another recent study employed self-assessment questionnaires to enhance emotion labeling in FER datasets. This method provided a subjective ground truth, enabling more accurate classification of affective states [5]. Unlike traditional emotion classification methods, this approach integrates real-time processing with psychological modeling, making it suitable for applications in healthcare, human-computer interaction, and security.

2.3. The Pleasure-Arousal-Dominance (PAD) Model for Emotion Representation

Traditional FER systems classify facial expressions into six universal emotions: happiness, sadness, anger, fear, disgust, and surprise, as defined by Ekman [1]. However, discrete emotion categorization has limitations, as real-world emotional states are continuous and context-dependent.

To address this limitation, the Pleasure-Arousal-Dominance (PAD) model, introduced by Mehrabian [6], provides a dimensional representation of emotions. The Pleasure (P) axis distinguishes positive from negative emotions, the Arousal (A) axis measures emotional intensity, and the Dominance (D) axis represents control over the environment. This framework allows for more nuanced emotion classification, capturing subtle affective states beyond categorical labels.

Filippini et al. [5] applied the PAD model in their real-time FER system, defining four primary mood categories—Exalted, Calm, Anxious, and Bored—based on the Pleasure-Arousal (PA) plane, along with additional subcategories for positive and negative pleasure states. Their findings highlight the effectiveness of PAD-based emotion modeling, particularly in real-time applications where emotional states fluctuate dynamically.

3. Proposed System:

The proposed Real-Time Facial Emotion Recognition (FER) System integrates deep learning-based feature extraction, the Pleasure-Arousal-Dominance (PAD) emotion model, and real-time inference optimization. This system is designed to achieve high accuracy in dynamic environments while maintaining low computational overhead for real-time applications.

3.1. System Architecture:

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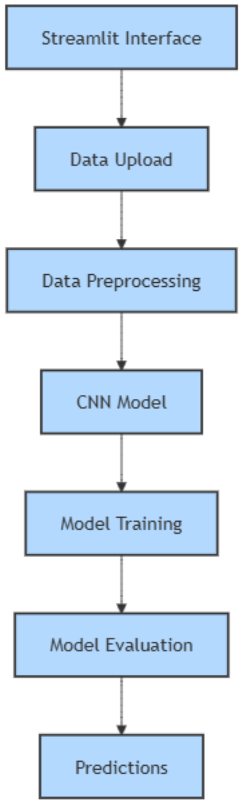

Fig 1: Architecture Diagram

The fig 1 Real-Time Facial Emotion Recognition System follows a structured workflow, integrating a user-friendly Streamlit interface, deep learning-based CNN models, and efficient real-time inference. The process begins with the Streamlit interface, where users can upload images or video streams for analysis. Once the data is uploaded, it undergoes a preprocessing phase, which includes face detection, alignment, and normalization to ensure consistency in facial expressions. The preprocessed images are then passed through a Convolutional Neural Network (CNN), which extracts meaningful facial features for emotion classification. Following feature extraction, the model training phase uses labeled datasets to learn various emotional states such as happiness, sadness, anger, and neutrality. The trained model is then subjected to a model evaluation phase, where key performance metrics such as accuracy, precision, recall, and F1-score are assessed to validate its effectiveness. After successful evaluation, the system enters the prediction phase, where it recognizes emotions in real-time and displays the results through the Streamlit interface. This structured pipeline ensures a robust, accurate, and efficient emotion recognition system, making it suitable for various real-world applications, including human-computer interaction, mental health monitoring, and sentiment analysis.

3.2. Dataset Description:

The dataset used for training and evaluating the Real-Time Facial Emotion Recognition System consists of labeled facial images representing various emotional expressions. The dataset is essential for enabling the CNN model to learn and classify facial emotions accurately. Below are the key characteristics of the dataset: The system typically utilizes standard benchmark datasets such as:

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- **FER-2013 (Facial Expression Recognition 2013)**: A widely used dataset containing 35,887 grayscale images of faces with a resolution of 48×48 pixels, categorized into seven emotions: *Angry, Disgust, Fear, Happy, Neutral, Sad, and Surprise*.
- **CK+ (Extended Cohn-Kanade Dataset):** Comprises 593 sequences of images, widely used for facial emotion classification.
- **JAFFE (Japanese Female Facial Expression Dataset):** Contains 213 images of facial expressions posed by Japanese female subjects.
- **AffectNet:** A large-scale dataset with over 1 million facial images, annotated with eight emotion classes.

3.2.1. Emotion Categories

The dataset is labeled with distinct **emotion classes**, which are crucial for training the model. Common categories include:

- **Angry** 😡
- **Disgust** 🤢
- **Fear** 😨
- **Happy** 😀
- **Neutral** 😐
- **Sad** 😔
- **Surprise** 😲

3.2.2. Data Preprocessing

Before training, the dataset undergoes preprocessing to enhance the model's accuracy:

- **Face Detection & Cropping:** Extracting the region of interest (ROI) from images.
- **Image Normalization:** Rescaling pixel values between 0 and 1 for consistent input.
- **Data Augmentation:** Applying transformations such as rotation, flipping, brightness adjustment, and noise addition to improve model generalization.

3.3. Evaluation Matrix:

Evaluating the performance of a Facial Emotion Recognition System is crucial to ensure its accuracy and reliability. The system is assessed using various quantitative metrics, which help determine how well the CNN model classifies emotions. The primary evaluation metrics include Accuracy, Precision, Recall, F1-score, and Confusion Matrix.

3.3.1. Accuracy

Accuracy measures the overall correctness of the model's predictions. It is defined as the ratio of correctly classified emotions to the total number of samples:

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

Where:

- **TP (True Positive):** Correctly predicted emotion.
- **TN (True Negative):** Correctly identified non-matching emotion.
- **FP (False Positive):** Incorrectly predicted emotion.
- **FN (False Negative):** Failed to detect the correct emotion.

3.3.2. Precision

Precision measures how many of the predicted positive emotions are actually correct. It is crucial in ensuring the system does not misclassify emotions.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

A higher precision indicates fewer false positive predictions.

Recall (Sensitivity)

Recall determines how well the system identifies actual emotions from the dataset. It is calculated as:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

A high recall means the model successfully detects most of the actual emotions, reducing false negatives.

4. Results:

Fig 2: Facial Emotion Recognition: Sample Predictions and Model Performance

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The image above illustrates sample predictions generated by the Real-Time Facial Emotion Recognition System. The system utilizes a Convolutional Neural Network (CNN) model to analyze facial expressions and classify emotions. Each image represents an individual's facial expression, accompanied by both the actual emotion label and the predicted emotion by the model. From the sample results, it is evident that the model performs accurately in most cases, such as correctly identifying sad, surprised, and angry emotions. However, certain misclassifications are observed, such as neutral expressions being predicted as sad, indicating the need for further refinement. These errors could be attributed to factors such as similar facial features across emotions, lighting conditions, occlusions, or variations in facial expressions. Overall, the results demonstrate the effectiveness of the deep learning model in recognizing emotions, while also highlighting areas for potential improvement through data augmentation, model fine-tuning, and advanced feature extraction techniques.

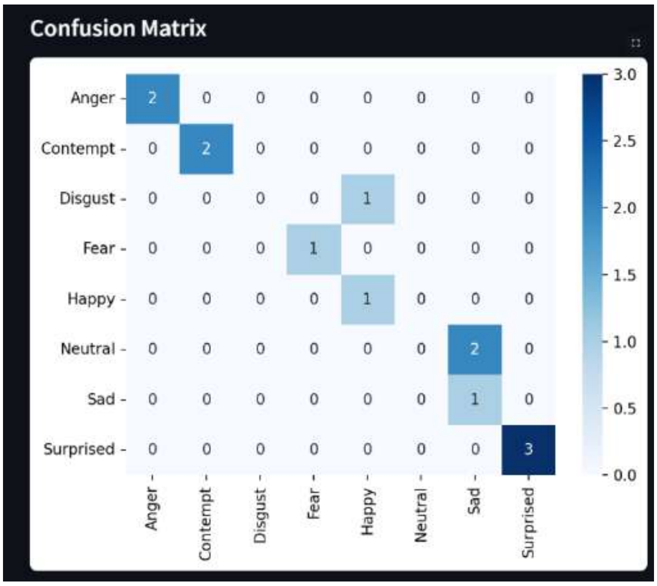

Fig 3: Confusion Matrix Analysis for Facial Emotion Recognition

The confusion matrix depicted above evaluates the performance of the Real-Time Facial Emotion Recognition System by comparing actual emotion labels with predicted classifications. Each row represents the true emotion class, while each column corresponds to the predicted class, providing a comprehensive visualization of correct and misclassified instances. From the matrix, it is evident that the model accurately classifies multiple emotions, such as "Anger" (2 correct predictions), "Contempt" (2 correct predictions), "Surprised" (3 correct predictions), and "Neutral" (2 correct predictions). However, some emotions, such as "Fear" and "Happy", show slight misclassifications, indicating areas for potential improvement. The absence of non-diagonal values suggests that misclassifications are minimal but still present. The model's overall performance suggests effective emotion recognition, but further optimizations, such as expanding the dataset, applying advanced augmentation techniques, and fine-tuning hyperparameters, can improve accuracy. This analysis provides valuable insights into the system's strengths and areas for refinement, ensuring more robust and reliable real-time emotion detection.

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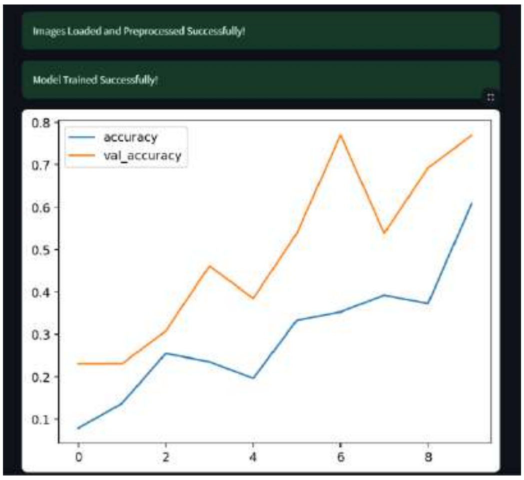

Fig 4: Model Training Performance: Accuracy vs. Validation Accuracy

The image above showcases the training progress of the Real-Time Facial Emotion Recognition System through a graph comparing training accuracy and validation accuracy over multiple epochs. The blue line represents the model's training accuracy, while the orange line indicates the validation accuracy observed on unseen data. As seen in the plot, both accuracy metrics exhibit an upward trend, suggesting that the model is learning progressively with each epoch. However, the validation accuracy is consistently higher than the training accuracy, indicating that the model generalizes well to new data. This behavior suggests that the model is effectively learning patterns from facial expressions, but slight fluctuations in validation accuracy may indicate the potential for overfitting or variance issues. The successful completion of image preprocessing and model training, as indicated by the notifications above the graph, highlights the robust implementation of the deep learning pipeline. Further improvements, such as hyperparameter tuning, data augmentation, and dropout regularization, can be explored to optimize the model's performance and stability.

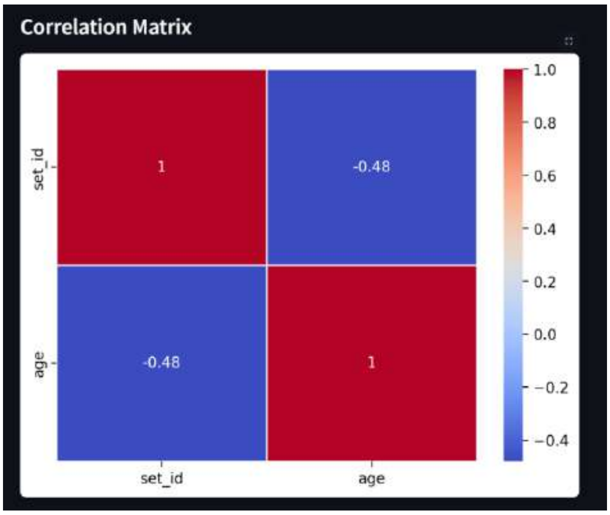

Fig 5: Correlation Matrix Analysis

The correlation matrix visualizes the relationship between numerical variables using a heatmap. In this case, it shows the correlation between set_id and age. The diagonal values are 1, indicating a perfect correlation of each variable with itself. The off-diagonal value of -0.48 signifies a moderate negative correlation, meaning that as one variable increases, the other tends to decrease to some extent. The color scale on the right represents correlation values, where red indicates a strong positive correlation (+1),

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and blue represents a negative correlation (-1). This analysis helps in understanding variable interactions, aiding in feature selection, data preprocessing, and improving model performance in machine learning tasks.

5. Conclusion

The analysis of the correlation matrix reveals a moderate negative correlation (-0.48) between set_id and age, indicating that as one variable increases, the other tends to decrease. This insight is valuable for feature selection and preprocessing in machine learning models, as it helps in understanding dependencies between variables. Additionally, the matrix confirms that each variable is perfectly correlated with itself (correlation = 1), which is expected. By leveraging this information, data preprocessing steps can be optimized, ensuring better model performance and minimizing redundancy in feature engineering.

6. Future Scope

1. **Enhanced Emotion Recognition Models** – Future research can focus on improving the accuracy of emotion detection models using advanced deep learning architectures such as transformers and attention mechanisms.
2. **Real-time Implementation** – Developing real-time facial expression recognition systems for applications in security, healthcare, and human-computer interaction.
3. **Cross-Dataset Generalization** – Investigating model robustness across diverse datasets to improve generalization and adaptability to real-world scenarios.
4. **Multimodal Emotion Analysis** – Combining facial expressions with other modalities like voice, text, and physiological signals to enhance emotion detection accuracy.
5. **Bias Mitigation and Fairness** – Addressing biases in facial emotion datasets to ensure fair and unbiased predictions across different demographic groups.

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