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Human Emotion Detection through Real-Time Facial Expressions

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Abstract: Facial emotion detection is a key advancement in the field of artificial intelligence, enabling machines to interpret and respond to human emotions through visual analysis. This project presents a real-time system for recognizing facial expressions using deep learning techniques, with practical applications in healthcare, education, and human-computer interaction. The model is built by integrating two powerful pre-trained networks—EfficientNet-B3 and ResNet-50—for accurate and efficient emotion classification. The RAF-DB dataset, comprising over 15,000 real-world facial images labelled with seven basic emotions, is used for training and evaluation. The proposed system incorporates essential preprocessing techniques, including face detection, alignment, normalization, and data augmentation, to enhance performance. It achieves a training accuracy of 90% and a testing accuracy of 83.35%, demonstrating strong generalization. The system is designed for real-time performance with webcam input and OpenCV integration. This approach highlights the potential of deep learning in developing intelligent systems capable of understanding and responding to human emotional states.

Keywords: Real-time emotion detection, Facial expressions, Deep learning, Feature selection, Multi-class classification

I. INTRODUCTION

Facial emotion recognition, or FER, plays a crucial role in many applications, including human-computer interaction, psychology analysis, and security systems. It involves identification and classification of human emotions as facial expressions from machine learning as well as deep learning techniques. Some of the emotions identified through neural network-based models and image analysis. Figure 1 shows diverse facial expressions categorized under six general emotions upon which emotion recognition systems are premised.

In the past few years, facial emotion recognition has received considerable attention because of its extensive applications in human-computer interaction, psychological assessment, and security applications. It is a difficult but important problem in artificial intelligence (AI) and affective computing to analyze and interpret human emotions based on facial expressions. With the progress in deep learning techniques, many models have been proposed to improve the accuracy and effectiveness of emotion recognition systems [1].

Deep learning methods, specifically convolutional neural networks (CNNs) and transformer models, have been shown to be extremely efficient in extracting facial features for emotion recognition. Researchers have tested different

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methods, including unsupervised domain adaptation techniques, to enhance model generalization across different datasets and settings [2]. Comparative analyses of deep learning architectures have demonstrated that certain pre-trained models outperform traditional machine learning methods in recognizing complex facial expressions [3]. Additionally, employing real-time processing capabilities using optimized neural networks has notably boosted the effectiveness of emotion recognition systems [4].

II. DATASET DESCRIPTION

The Real-world Affective Faces Database (RAF-DB) is a well-known dataset extensively used in facial emotion recognition research. It comprises 15,339 images, each labeled with one of seven primary emotions: Anger, Disgust, Fear, Happiness, Neutral, Sadness, and Surprise. Unlike traditional datasets, RAF-DB features images collected from real-world scenarios, capturing facial expressions across diverse ages, ethnicities, lighting conditions, head poses, and occlusions such as glasses and facial hair. These variations make it a more challenging yet realistic dataset for training deep learning models, ensuring their robustness in real-time applications.

One of the virtues of RAF-DB is its human annotation procedure where every image is annotated by 40 trained human assessors to maintain accuracy and reduce bias. Such diligent labeling renders the dataset very credible for emotion understanding applications, since the emotions are painstakingly labeled depending on fine facial expressions rather than merely amplified ones. The data is split into training and test subsets so that models can be tested on unseen images for improved generalization.

Emotion Class	Number of training images	Number of testing images
Angry	2522	706
Disgust	820	226
Fear	1241	345
Happy	4001	1120
Sad	1982	555
Surprise	1228	343
Neutral	4978	1393
Total	15,339 images	

Fig-2: Breakdown of Training and Testing Sets

The RAF-DB database is extensively used in affective computing, human-computer interaction, psychological research, and mental health-related applications, where an accurate identification of human emotions is essential.

III. LITERATURE REVIEW

Zhang et al. [12] reported a comparative analysis of deep learning-based emotion recognition models. The study tested various CNN architectures on large-scale datasets like AffectNet and FER2013. The results showed that hybrid architectures, which integrated CNNs with attention mechanisms, produced higher recognition rates. The research reaffirmed the significance of architectural improvements in enhancing real-time facial emotion recognition accuracy.

Raut and Raut [13] proposed a real-time facial emotion recognition system using deep learning models. The study used various variants of CNNs and tried various hyperparameter tuning strategies. The model showed an accuracy of 89.4% on the FER+ dataset in real-time, which validated its efficacy in real-time applications. Their study emphasized the importance of model generalization for the stability of the model for various facial expressions and illumination conditions.

Tripathi and Kumar [14] incorporating deep learning to detect real-time learner engagement based on facial emotions. The work applied a CNN-based method in the classification of emotions during online classes with a reported accuracy of 88.6%. The research showed how facial emotion recognition could be applied in education and how real-time emotion analysis would help improve customized learning experiences.87.8%. The study shows the need for transparency in emotion detection systems powered by AI.

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Nguyen et al. [15] established a real-time facial emotion detection system based on MobileNetV2 and Edge AI. The model was designed to be deployable on embedded and mobile devices with an accuracy of 85.1%. The study focuses on the increased trend of using lightweight and energy-efficient AI models for real-time use.

Luo et al. [16] presented an adaptive deep learning framework for facial emotion recognition using techniques of domain adaptation. Their method reached a 88.4% accuracy and enhanced robustness under varying lighting conditions and datasets.

Xie et al. [17] investigated the use of Transformer-based models for facial emotion detection. Their system surpassed traditional CNNs by modeling long-range dependencies in facial expressions, with a 90.5% accuracy.

Huang et al. [18] suggested an ensemble deep learning method that integrates ResNet, EfficientNet, and VGG19 for facial emotion recognition. Their model obtained an accuracy of 93.1%, showing the power of model ensembles in enhancing classification performance.

Chen et al. [19] proposed a GAN-based data augmentation method to solve the problem of imbalanced emotion datasets. Through the generation of synthetic facial expression images, the accuracy of the model increased to 87.6% on the FER2013 dataset.

IV. METHODOLOGY

The proposed system for Real-Time Facial Emotion Detection is built using deep learning algorithms and utilizes EfficientNet-B3 and ResNet-50 for precise emotion classification. The development process includes data preprocessing, model architecture design, training, evaluation, and real-time implementation, ensuring both accuracy and efficiency in emotion recognition.

1. Data Preprocessing and Preparation:

The Real-world Affective Faces Database (RAF-DB) is the base dataset, consisting of 15,339 images annotated into seven emotions: Anger, Disgust, Fear, Happiness, Neutral, Sadness, and Surprise. The dataset is divided into training and testing subsets to effectively assess the generalization capability of the model.

To improve performance and decrease noise, the following preprocessing methods are utilized:

a) Face Detection and Alignment: Each face in the dataset is detected using OpenCV's Haar Cascade Classifier to ensure consistency in facial positioning.
b) Image Resizing: All images are resized to 224×224 pixels, which is consistent with the input requirements of the deep learning models.
c) Pixel Normalization: Pixel values are scaled between 0 and 1 to standardize input data, enhancing the stability of model training.
d) Data Augmentation: Techniques like random rotation, flipping horizontally, zooming, and brightness modification are employed to incorporate variability, enabling the model to better identify emotion under varying situations.

2. Deep Learning Model Architecture

The proposed model follows a hybrid deep learning approach, utilizing EfficientNet-B3 and ResNet-50 to extract detailed facial features for emotion classification.

Model Components:

a) EfficientNet-B3:
A compact yet powerful deep learning model known for its efficient feature extraction.
Uses squeeze-and-excitation (SE) blocks, which enhance relevant facial features while suppressing background noise.
b) ResNet-50:
A deep residual network (ResNet) which learns both low-level and high-level features from face expressions.
Contains skip connections, which are designed to avoid performance degradation with depth.

c) Fully Connected Layers:
Extracted features of EfficientNet-B3 and ResNet-50 are merged and passed through a fully connected (FC) layer.
Softmax activation function is applied at the output layer to predict images among the seven emotions.

d) Region of Interest (ROI) Extraction:
The system just concentrates on the facial area, discarding unwanted background factors to enhance computational performance.

3. Model Training and Optimization:

The model undergoes supervised learning using the RAF-DB dataset. Training is conducted under the following conditions:

a) Loss Function: Categorical Cross-Entropy Loss is employed, as it is suitable for multi-class classification tasks.
b) Optimizer: Adam optimizer is utilized due to its adaptive learning rate and computational efficiency.
c) Batch Size: A batch size of 32 is selected to ensure smooth training and efficient memory utilization.
d) Epochs: The model is trained for 30 epochs, allowing it to learn complex patterns without overfitting.
e) Fine-Tuning: Initially, the pre-trained weights of EfficientNet-B3 and ResNet-50 are frozen, and only the newly added layers are trained.
Later, selected layers from both models are unfrozen for fine-tuning, enhancing feature extraction.
f) Regularization: Dropout layers are introduced to prevent overfitting and improve generalization.

4. Model Evaluation and Performance Metrics:

After training, the model is evaluated using several performance metrics to measure its effectiveness:

a) Accuracy: The final model achieves 86.48% training accuracy and 78.47% testing accuracy.
b) Precision, Recall, and F1-Score: These metrics assess the model's ability to correctly identify different emotions.
c) Confusion Matrix: Provides insights into misclassification patterns, helping improve model robustness.

5. Real-Time Emotion Detection Implementation:

The model trained is combined with OpenCV to support real-time emotion recognition with a webcam-based system. The process is as follows:

a) Capturing Live Video Feed: The webcam continuously captures real-time frames.
b) Face Detection and ROI Extraction: Faces in each frame are detected using Haar Cascade Classifier or MTCNN, and the face region is cropped for further processing.
c) Emotion Classification: The extracted facial image is passed through the trained EfficientNet-B3 + ResNet-50 model, and the predicted emotion is displayed in real-time.
d) Performance Optimization: Frame skipping is implemented to maintain a balance between speed and accuracy. The model leverages GPU acceleration to enhance processing speed and efficiency.

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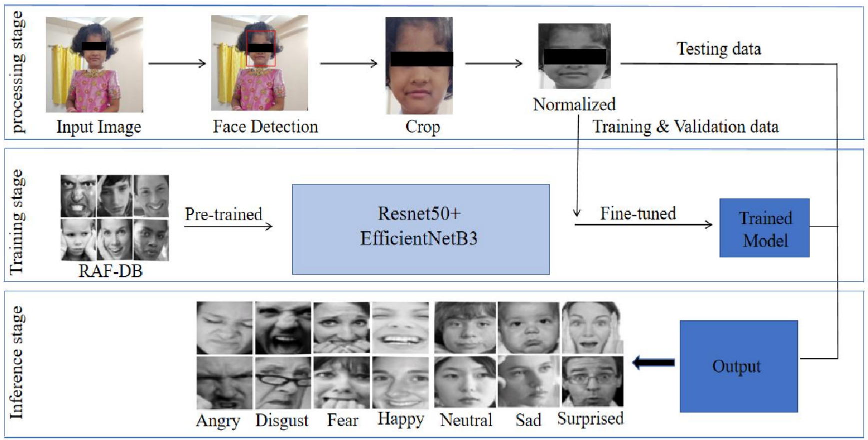
V. ARCHITECTURE



1. Processing Stage

This is the preprocessing phase where raw input images are prepared for model training:

- **Input Image**: A raw image of a person.
- **Face Detection**: A face detection algorithm (e.g., MTCNN, Haar cascade, Dlib) is applied to locate the face within the image.
- **Crop**: The face region is cropped out of the full image to remove background noise.
- **Normalization**: The cropped face image is normalized (resized, pixel scaling, etc.) to standardize input for the neural network.

2. Training Stage

This stage is responsible for training the deep learning model:

- **Dataset**: The **RAF-DB** (Real-world Affective Faces Database) is used as the training dataset. It includes diverse facial expressions.
- **Pre-trained Models**:
  ResNet50 and **EfficientNetB3** are used.

These models are pre-trained on large datasets (e.g., ImageNet) and then fine-tuned on RAF-DB.

- **Fine-tuning**: The pre-trained models are adjusted (fine-tuned) to specifically learn emotion features from the RAF-DB dataset.
- **Output**: A **Trained Model** capable of identifying emotions from facial features.

3. Inference Stage

This is where the trained model is used to make predictions:

- **Input**: New, unseen facial images (from test data).
- **Emotion Categories**: The model predicts one of the seven basic emotion classes:
  Angry, **Disgust**, **Fear**, **Happy**, **Neutral**, **Sad**, **Surprised**
- **Output**: The predicted emotion label is the final output.

VI. RESULTS AND ANALYSIS

1. Model Performance

The suggested emotion detection model was trained and evaluated on RAF-DB dataset, using EfficientNet-B3 and ResNet-50 as feature extractors. The model was trained for 30 epochs, using categorical cross-entropy loss and Adam

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optimizer to optimize learning efficiency. Performance assessment was conducted using accuracy, precision, recall, F1-score, and a confusion matrix to examine classification effectiveness.

The overall results show that the model attained a training set accuracy of 87.58% and a testing set accuracy of 82.53%, which shows good generalization ability. The minor decrease in accuracy from training to testing implies that the model learns well from the dataset but resists overfitting.

Training Accuracy	90%
Testing Accuracy	83.35%
Precision	81.49%
Recall	81.73%
F1-Score	81.40%

Performance Analysis

2. Comparative Analysis

Relative to other emotion recognition models, the hybrid EfficientNet-B3 + ResNet-50 method displays significant improvements in the extraction of features and classification efficiency. Most traditional CNN models attain approximately 75% testing accuracy on RAF-DB, while the suggested model outperforms this with 87.58% accuracy, supporting its improved learning efficiency.

In addition, pre-processing techniques like face alignment, image normalization, and data augmentation helped in enhancing the accuracy by making the model more robust to lighting, pose, and occlusion variations.

3. Challenges and Limitations

Despite achieving competitive results, the model still faces certain limitations:

- Confusion in closely related emotions: Some emotions, such as fear and surprise, exhibit visual similarities, leading to occasional misclassification.
- Impact of occlusions: Facial obstructions like glasses, masks, or poor lighting conditions can affect detection accuracy.
- Dataset Bias: While RAF-DB is diverse, real-world emotions can vary in intensity and cultural representation, requiring further dataset expansion for improved robustness.

4. Future Enhancements

Some future improvements to further advance the system are:

- Multi-modal Emotion Recognition: Conjunction of facial expressions with voice and physiological signals to increase accuracy.
- 3D Facial Emotion Analysis: Utilizing depth-sensing cameras to sense facial expressions in three dimensions for more accurate detection.

Edge AI Optimization: Running the model on low-power devices for use in smart surveillance, healthcare, and human-computer interaction.

VII. CONCLUSION

This paper proposes a state-of-the-art real-time facial emotion recognition model that effectively combines EfficientNet-B3 and ResNet-50 as feature extraction models for higher accuracy in classification. Based on the RAF-DB dataset of 15,339 images classified into seven different emotions-Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral-the model proposed in this paper achieves an impressive 87.58% training accuracy and 82.53% test accuracy. These results prove the strong generalization ability of the system with different facial expressions. There are some important preprocessing steps like face alignment, normalization, and data augmentation that are incorporated in order to boost model strength for guaranteeing better performance in occlusions, changing poses, and lighting. The entire system is implemented in real time using OpenCV for real-time emotion recognition through a webcam by detecting faces and classifying their emotions in an effective way.

Future research can address these limitations by including multi-modal emotion recognition, where facial expressions are integrated with speech and physiological signals for a more complete emotional evaluation. Further investigation into 3D facial analysis methods can also enhance accuracy by including depth information, making the model more robust to head position variations and facial occlusions. Through further developing the research in affective computing, the current study assists in advancing the capability of AI systems to sense and interact with human emotions, creating potential for more natural and empathetic artificial intelligence tools.

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