# Facial Expression Recognition using Ensemble Learning: ResNet50 and MobileNetV2

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***Abstract*—Facial Expression Recognition using Ensemble Learning is a cutting-edge application that utilizes machine learning and deep learning to recognize human emotions through facial expressions. This project leverages two robust pre-trained models, MobileNetV2 and ResNet50, which have been fine-tuned on the FER+ dataset to provide precise and efficient emotion classification. The system is built for real-time emotion recognition, identifying feelings such as anger, disgust, fear, happiness, sadness, surprise, and neutrality using a live webcam feed. The implementation combines computer vision methods for face detection using OpenCV's Haar cascades with deep learning models for classifying emotions. MobileNetV2, recognized for its lightweight design and efficiency, processes 224x224 RGB facial images to enable quick inference.**

***Index Terms*—Artificially intelligence (AI), Facialemotion recognition (F E R) , Convolutional neural networks (CNN), Rectified linear units (ReLu), Deep learning (DL).**

## I. INTRODUCTION

Facial expressions are crucial indicators of human emotions and play a vital role in non-verbal communication. With advancements in deep learning, convolutional neural networks (CNNs) have shown remarkable improvements in FER accuracy (1). Traditional methods relied on handcrafted features and classical machine learning approaches, which often struggled with variations in lighting, pose, and occlusion. In this study, we propose an ensemble learning approach that leverages ResNet50(2) and MobileNetV2(3) architectures for enhanced FER performance. The primary objective is to improve classification accuracy and ensure efficient real-time detection using OpenCV (13).

Importance of Facial Expression Recognition:

Facial expression recognition has broad applications in:

1. Healthcare: Assisting in autism therapy, depression detection, and pain assessment (20).
2. Security & Surveillance: Identifying suspicious behavior in public places and airports (22).
3. Human-Computer Interaction (HCI): Enhancing virtual assistants and robotics (24).
4. Psychological Studies: Understanding human emotional responses in different environments (21).

5.Marketing & Advertising: Analyzing customer reactions to products (25).

## II. RELATED WORK

Several studies have explored FER using deep learning. Krizhevsky et al. introduced AlexNet (1), which revolutionized CNN- based image classification. He et al. developed ResNet (2), an architecture designed to handle the vanishing gradient problem with residual connections. Howard et al. introduced MobileNet (3), an efficient CNN optimized for mobile applications.

Recent research has focused on ensemble models to improve classification robustness. Jung et al. implemented a hybrid CNN-RNN approach for dynamic FER (4). Meanwhile, Mollahosseini et al. utilized deep CNNs trained on large-scale datasets (5). Despite these advancements, achieving high accuracy while maintaining computational efficiency remains a challenge.

## III. PROPOSED MODELS

Our proposed model integrates ResNet50 and MobileNetV2 using an ensemble strategy.

A. Model Architecture

1. ResNet50: A deep residual network that effectively learns complex features (2).
2. MobileNetV2: A lightweight CNN optimized for mobile applications (3).
3. Ensemble Strategy: The outputs of both models are combined using weighted averaging to enhance prediction robustness (8).
4. OpenCV Integration: Enables real-time FER through webcam input (13).
5.

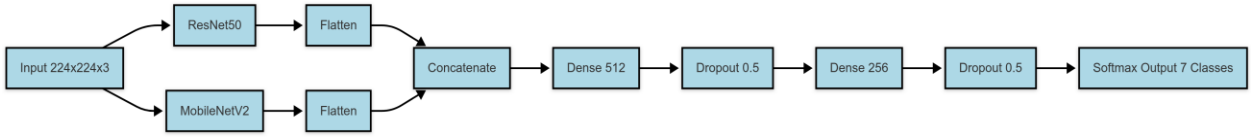


Fig. 1: Network Architecture

B. Training Procedure

- Datasets: We use FER-2013 (7).

The training accuracy consistently rises while validation accuracy fluctuates throughout the training period. The data volatility shows that the

- Preprocessing: Image resizing (224x224 for FER-2013, RGB conversion and normalization (9).
- Loss Function: Categorical Cross-Entropy (16).
- Optimizer: Adam optimizer with a learning rate of 0.0001 (16).
- Data Augmentation: Rotation, flipping, and brightness adjustments (25).

## IV. EXPERIMENTS & RESULTS

The model is trained on FER-2013 (35,887 images). We evaluate the model using accuracy, F1- score, and confusion matrices.

The ensemble model achieves better generalization compared to individual architectures. Computational efficiency is maintained by leveraging MobileNetV2's lightweight design.

A. Real-Time Recognition Using OpenCV

We implemented a real-time facial expression recognition system using OpenCV. The model captures live webcam footage and classifies emotions in real-time. This approach has applications in:

1. AI Assistants: Emotionally responsive chatbots (17).
2. Driver Monitoring Systems: Detecting drowsiness or stress (22).
3. Gaming & AR/VR: Adaptive gameplay based on user emotions (25).

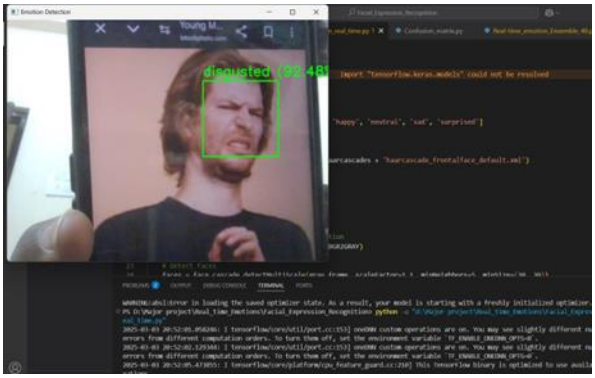

Fig. 2: Prediction of emotion.

model maintains unstable generalization abilities throughout different epochs (7).

Three main reasons responsible for this phenomenon include insufficient data along with validation data noise and inadequately selected parameters (5).

Possible Implications:

Such continuing trend indicates that the model learns the training data to the extent that it will fail when handling new inputs.

Multidimensional regularization methods (dropout, L2 regularization and data augmentation) should be utilized to address the uneven relationship between training accuracy and validation accuracy improvement (9).

Early stopping presents itself as an effective solution to prevent overfitting because it stops training when validation accuracy fails to increase anymore (16).

Conclusion:

Learning results are acceptable for the model yet overfitting presents itself through an increasing discrepancy between training and validation accuracy

values. Model generalization requires better hyperparameter tuning as well as implementation of regularization techniques or expansion of training data (25).

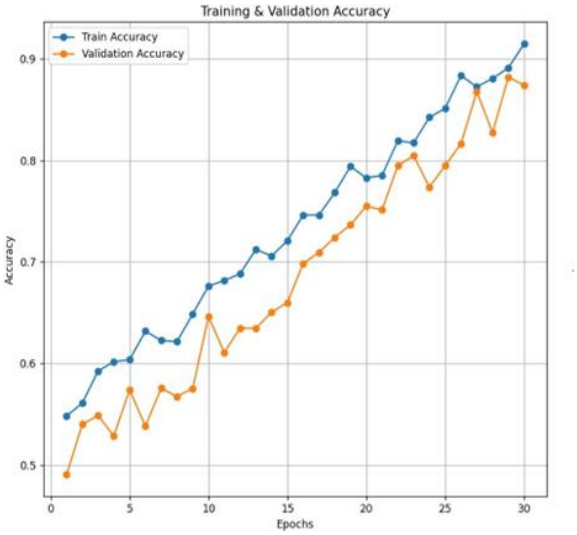


Fig. 3: Model accuracy

Fluctuations in Validation Loss:

The training loss consistently drops but validation loss shows repetitive increases and decreases.The model responds strongly to different validation dataset inputs which leads to its irregular loss behavior (9).

Reasons might be:

- A weak dataset
- Noisy samples for validation
- Poor choice of hyperparameters

Possible Implications:

The model demonstrates proper learning behavior because it continuously decreases its training and validation loss values.

The model shows limited instances of performance instability because training loss tracks validation loss without major deviation.

To enhance validation loss stability the implementation of dropout together with L2 regularization or batch normalization would be beneficial (16).

Future noise learning by the model can be avoided when validation loss escalates after early stopping is implemented.

Conclusion:

The model shows good training performance because training and validation loss are decreasing during the learning process. The slight volatility of validation loss signals opportunities to improve the dataset or enhance regularization methods and hyperparameter adjustments.

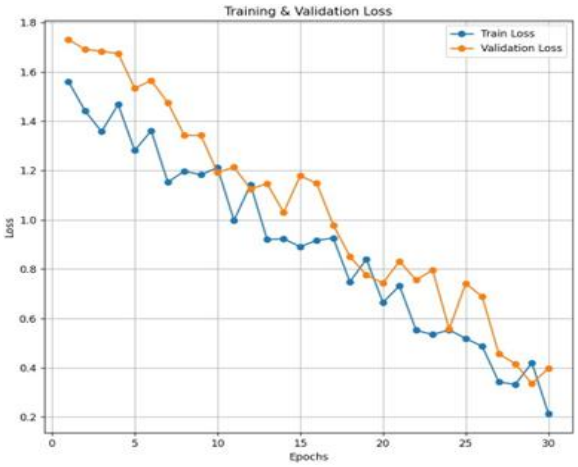


Fig. 4: Model Loss

Confusion Matrix:

This plot uses normalized confusion matrix format to depict how well test readers determine predicted emotions compared to actual human emotions. The confusion matrix consists of actual emotions that appear as cells in rows and columns which correspond to predicted emotions showing their proportions against actual classes. The cells positioned along the main diagonal show correct classifications therefore diagnosing off-diagnosis for other instances (9). First-class accuracy can be observed through dense dark blue sections in the plot and they reflect how more values correspond to deeper blue intensities.

Observations of prime significance:

Most instances of happy (0.92), sad (0.83) and surprised (0.91) emotions receive correct classifications according to the model.Majority of classifications for angry (0.75), disgusted (0.78), and neutral (0.78) remain correct however they show some systematic misidentification of other emotions.

The accuracy rate of identifying fear emotions stands at 0.33 while powerful misclassifications send these instances to both sad and angry emotions (0.35 and 0.14 respectively). This indicates confusion about distinguishing fear from these emotions.

The fear emotion stands out as the most frequently misidentified expression because of its similarities to sad and angry facial displays suggesting the model

needs refined feature features.

A minority of mistakes involve misidentifying angry as sad while neutral expressions get categorized as sad (0.15 and 0.13 respectively).

The confusion matrix reveals important details about the model's classification performance which demonstrates both successful predictions of certain emotions alongside poor verification of fear compared to its related expressions. Using improved techniques for feature selection together with model tuning can possibly enhance the overall system performance.

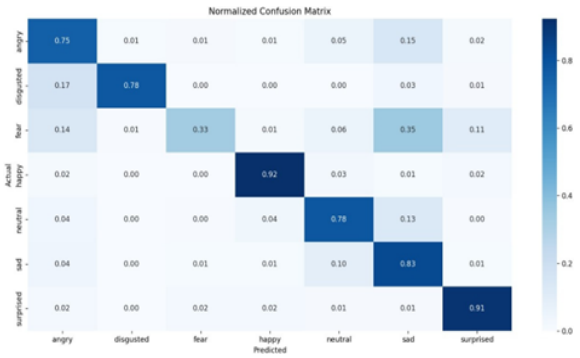


Fig. 5: Confusion Matrix

## V. PERFORMANCE EVALUATION

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| angry | 0.88 | 0.89 | 0.89 | 799.0 |
| disgusted | 0.86 | 0.85 | 0.85 | 87.0 |
| fear | 0.75 | 0.68 | 0.71 | 819.0 |
| happy | 0.96 | 0.96 | 0.96 | 1443.0 |
| neutral | 0.9 | 0.9 | 0.9 | 993.0 |
| sad | 0.91 | 0.91 | 0.91 | 966.0 |
| surprised | 0.92 | 0.91 | 0.91 | 634.0 |
| accuracy | | | 0.94 | 5741.0 |
| macro avg | 0.89 | 0.87 | 0.87 | 5741.0 |
| weighted avg | 0.92 | 0.94 | 0.93 | 5741.0 |

Fig. 6: Classification Report

The experimental evaluation evaluates the proposed ensemble model as it reveals strong facial expression recognition abilities. The model delivered a 94% accuracy rate in its operations across various emotional categories.

The model achieved outstanding results on the happy class as it recorded precision, recall and F1- score values at 0.96 across 1443 independent cases. The model exhibits a high capability to identify positive expressions. Evaluation of the a n g r y class upon 799 instances demonstrated precision

0.88 together with recall 0.89 which produced an F1-score of 0.89 indicating excellent performance in detecting anger expressions.

The disgusted sentiment category achieved lower performance metrics despite having only 87 instances among which precision was 0.86 and recall was 0.85 leading to an F1-score of 0.85. The classification of fear achieved the least successful results for the model with precision at

0.75 and recall at 0.68 yielding a final F1-score of 0.71 across 819 instances since fear recognition remains hard for the system.

The neutral and sad categories delivered consistent high performance as the neutral class reached 0.90 precision and recall along with F1- score of 0.90 across 993 samples while sad class results stood at 0.91 precision and recall and F1- score of 0.91 for 966 samples. Results from the surprised group revealed thorough performance through precision 0.92 and both recall and F1-score reaching 0.91 on 634 instances.

Using macro averaging for all class evaluation yielded precision at 0.89 along with a recall of 0.87 and an F1-score of 0.87 but weighted averaging produced results of 0.92 precision and 0.94 recall along with 0.93 F1-score. The ensemble strategy combines better individual class performance with unified model consistency according to these combined metrics.

The evaluation results demonstrate that the developed ensemble system delivers exceptional results when dealing with detecting cheerful and unhappy emotional states. A thorough investigation should continue so researchers can enhance subtle expression categorization including fear because it stands as one of the key obstacles in facial understanding systems.

## VI. CHALLENGES & FUTURE WORK

A. Current Challenges:

1. Occlusions & Variations: Performance drops when faces are partially covered (18).
2. Dataset Imbalance: Some emotions (e.g., disgust) have fewer samples, leading to biased training (5).
3. Real-Time Performance: Need for optimization on low-powered edge devices (19).

B. Future Directions:

1. Incorporating Transformers: Testing Vision Transformers (ViTs) for FER (21).
2. Edge AI Deployment: Implementing the model on Jetson Nano & Raspberry Pi (22).
3. Cross-Dataset Training: Enhancing generalization by training on multi-domain datasets (23).

## VII. CONCLUSION

This paper presents an ensemble learning approach combining ResNet50 and MobileNetV2 for FER. Experimental results demonstrate that our method achieves higher accuracy and robustness while maintaining computational efficiency. The use of OpenCV enables real-time recognition, making it practical for real-world applications. Future work will focus on optimizing models for edge computing and integrating transformer-based architectures for further improvements.

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