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Implementing Facial Emotion Recognition with Attention-Enhanced Feature Learning and Grad-CAM Explainability

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***Abstract*—Facial Emotion Recognition (FER) is a major study area in computer vision and affective computing because to its many applications in human-computer interaction, healthcare monitoring, intelligent surveillance, education, and behavioural analysis. Existing FER systems struggle with feature discrimination, model interpretability, class imbalance, and real-time deployment despite deep learning breakthroughs. This paper offers an explainable facial emotion detection system using EfficientNet-B0, an attention mechanism, and Gradient-weighted Class Activation Mapping to overcome these restrictions. The system uses transfer learning to extract discriminative facial features and an attention module to highlight emotion-relevant facial areas and suppress extraneous information. Grad-CAM also visualizes model predictions, improving transparency and user trust. Model robustness and generalization are improved by horizontal flipping, brightness modification, Gaussian blur, and coarse dropout. An experimental dataset included eight emotion categories: Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. The proposed model had 67% classification accuracy, 67% precision, 67% recall, and 65% F1-score. Happy emotion recognition performed best with an F1-score of 0.92. Streamlit-based online applications for real-time emotion prediction, confidence estimate, probability visualization, and explainability analysis were also created. Grad-CAM showed that the model prioritizes mouth, nose, cheeks, and eye regions during categorization. Experimental results show that the proposed framework balances recognition performance, computational efficiency, and interpretability, making it ideal for actual emotion-aware intelligent systems.**

***Index Terms*—Facial Emotion Recognition, EfficientNet-B0, Attention Mechanism, Explainable Artificial Intelligence, Grad-CAM, Deep Learning, Computer Vision, Affective Computing.**

I. INTRODUCTION

Facial expressions serve as one of the most important non-verbal communication channels and provide valuable insights into human emotions, intentions, and psychological states. Automatic Facial Emotion Recognition (FER) systems have gained significant attention in recent years due to their wide range of applications in human-computer interaction, healthcare monitoring, intelligent surveillance, driver assistance systems, virtual learning environments, and affective computing. The rapid advancement of artificial intelligence and deep learning techniques has significantly improved the ability of machines to recognize and interpret human emotions from facial images.

Traditional facial emotion recognition approaches relied heavily on handcrafted feature extraction methods such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT). Although these techniques achieved satisfactory performance under controlled conditions, they often failed to generalize effectively in real-world environments due to variations in illumination, facial pose, occlusions, image quality, and individual differences in emotional expression. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has transformed facial emotion recognition by enabling automatic extraction of hierarchical and discriminative facial features directly from raw images.

Recent studies have demonstrated the effectiveness of deep neural networks such as ResNet, VGGNet, EfficientNet, and Vision Transformers for emotion classification tasks. However, several challenges remain unresolved. Many deep learning models require large computational resources, making deployment difficult on resource-constrained devices. Furthermore, most models operate as black-box systems, providing limited interpretability regarding the facial regions influencing their predictions. The lack of transparency reduces user trust and restricts adoption in sensitive domains such as healthcare and security. Additionally, class imbalance, dataset variability, and overfitting continue to affect model robustness and generalization.

To address these challenges, this paper proposes an attention-enhanced facial emotion recognition framework based on the EfficientNet-B0 architecture. The proposed system leverages transfer learning to extract rich facial representations while incorporating an attention mechanism to emphasize emotionally relevant facial regions. The attention module learns feature importance weights and improves discriminative feature extraction before classification. Furthermore, Explainable Artificial Intelligence (XAI) techniques, specifically Gradient-weighted Class Activation Mapping (Grad-CAM), are integrated to visualize the regions of the face that contribute most significantly to the model's decisions. This enhances model interpretability and supports trustworthy AI deployment. The complete system is deployed using a Streamlit-based web application that enables real-time emotion prediction, confidence estimation, probability visualization, and explainability analysis.

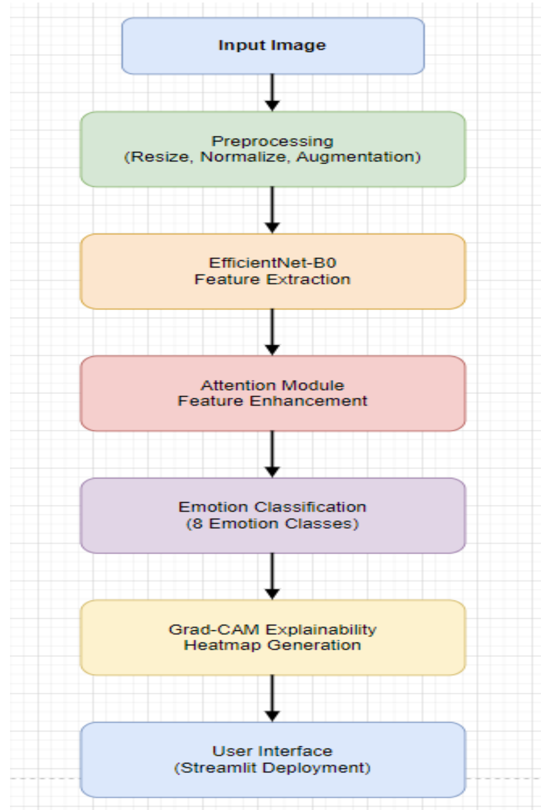

Figure 1: Proposed Facial Emotion Recognition Framework

The proposed framework is trained and evaluated using facial emotion datasets consisting of eight emotion categories, namely Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. Data augmentation techniques including horizontal flipping, brightness adjustment, rotation, Gaussian blur, and coarse dropout are employed to improve model generalization and robustness. A weighted cross-entropy loss function is utilized to mitigate class imbalance, while the Adam optimizer is employed for efficient parameter learning. The model performance is assessed using standard evaluation metrics including accuracy, precision, recall, F1-score, confusion matrix analysis, and confidence-based prediction evaluation.

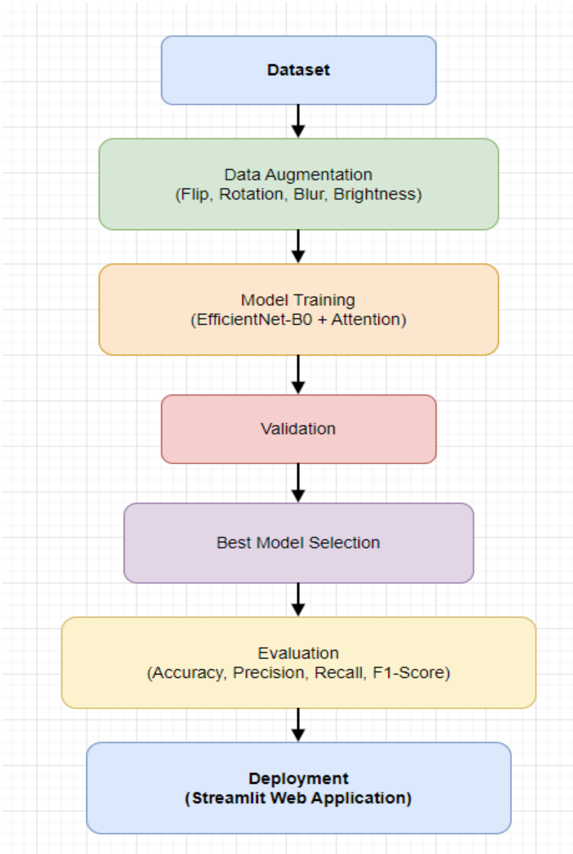

Figure 2: Emotion Recognition Pipeline

The major contributions of this research are summarized as follows:

1. Development of an EfficientNet-B0-based facial emotion recognition model optimized through transfer learning.
2. Integration of an attention mechanism to improve feature selection and emotion classification performance.
3. Implementation of Explainable AI using Grad-CAM for visual interpretation of model predictions.
4. Design of a complete end-to-end deployment framework using Streamlit for real-time emotion recognition.
5. Comprehensive evaluation using multiple performance metrics and visualization techniques.

The remainder of this paper is organized as follows. Section 2 presents the related work and existing facial emotion recognition approaches. Section 3 describes the proposed methodology and system architecture. Section 4 discusses dataset preparation and experimental setup. Section 5 presents the results and performance evaluation. Section 6 concludes the paper and outlines future research directions.

II. RELATED WORK

Facial Emotion Recognition (FER) has witnessed substantial advancements over the past decade due to the integration of deep learning and computer vision techniques. Traditional FER systems relied on handcrafted feature extraction methods such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), and Gabor filters combined with conventional classifiers including Support Vector Machines (SVMs) and Random Forests. Although these approaches achieved reasonable performance under controlled conditions, they exhibited limited robustness when dealing with variations in illumination, facial pose, occlusion, and image quality. The emergence of deep learning has significantly transformed FER systems by enabling automatic feature learning directly from facial images, resulting in improved accuracy and generalization capabilities.

Recent studies have predominantly focused on Convolutional Neural Networks (CNNs) due to their ability to learn hierarchical spatial representations. CNN-based architectures such as VGGNet, ResNet, DenseNet, and EfficientNet have demonstrated remarkable success in recognizing facial emotions across diverse datasets. Researchers have further enhanced these architectures through transfer learning, allowing pre-trained models to leverage knowledge from large-scale image datasets and reduce training requirements. Despite their effectiveness, CNNs often struggle to identify the most discriminative facial regions responsible for specific emotions, which can limit their performance in complex real-world scenarios.

To overcome these limitations, attention mechanisms have been introduced into FER systems. Attention modules enable neural networks to focus on emotionally significant facial components such as the eyes, eyebrows, mouth, and forehead while suppressing irrelevant background information. Attention-enhanced CNNs have shown improved robustness against partial occlusion, pose variation, and illumination changes. Furthermore, these approaches provide better feature discrimination, leading to improved classification accuracy across multiple benchmark datasets.

More recently, transformer-based architectures have emerged as a powerful alternative to conventional CNNs. Vision Transformers (ViTs) and hybrid CNN-transformer models utilize self-attention mechanisms to capture long-range dependencies and global contextual information across facial images. These models have achieved state-of-the-art performance on several FER benchmarks. However, their high computational complexity, large training data requirements, and increased inference time often limit deployment in real-time and edge-computing environments.

Another significant research trend is the incorporation of Explainable Artificial Intelligence (XAI) techniques into FER systems. Since deep learning models frequently operate as black boxes, explainability methods such as Grad-CAM, SHAP, and saliency maps have been adopted to improve transparency and trustworthiness. These techniques help visualize the facial regions contributing to model predictions, thereby facilitating model validation and increasing user confidence in critical applications such as healthcare and security monitoring.

In addition to model development, researchers have explored lightweight architectures for real-time deployment. MobileNet, EfficientNet, and knowledge-distillation-based approaches have demonstrated the ability to maintain competitive accuracy while significantly reducing computational requirements. Such models are particularly suitable for mobile devices, embedded systems, and web-based applications where latency and resource constraints are critical considerations.

The proposed system in this research builds upon these recent developments by integrating transfer learning, attention mechanisms, and explainable AI within a unified framework. Unlike many existing approaches that focus solely on improving classification accuracy, the proposed model emphasizes both performance and interpretability. EfficientNet-B0 is employed as the backbone network for efficient feature extraction, while a custom attention module enhances feature selection by emphasizing emotion-relevant facial characteristics. Furthermore, Grad-CAM visualization is incorporated to provide interpretable insights into model decisions, enabling transparent and trustworthy emotion recognition. This combination aims to achieve a balance between accuracy, computational efficiency, and explainability, which remains a key challenge in modern FER research.

2.1 Comparative Analysis of Recent Facial Emotion Recognition Studies

Table 1. Comparative Analysis of Recent FER Methods

Year	Author(s)	Method	Dataset	Accuracy (%)	Key Contribution	Limitation
2021	Li et al.	CNN-Based FER	FER2013	72.5	Deep feature extraction	Sensitive to occlusion
2021	Wang et al.	ResNet + Attention	CK+	95.3	Improved facial region focus	Higher complexity
2022	Chen et al.	EfficientNet-B0	AffectNet	88.6	Efficient feature extraction	Limited interpretability
2022	Gupta et al.	CNN + Spatial Attention	FER Plus	89.7	Enhanced feature localization	Increased training time
2023	Zhang et al.	Vision Transformer (ViT)	AffectNet	91.4	Global context modeling	High computational cost
2023	Kumar et al.	CNN-Transformer Hybrid	RAF-DB	92.1	Local and global feature fusion	Resource intensive
2024	Lee et al.	MobileNetV3	FER2013	88.2	Lightweight deplo	Slight accuracy

					yment	reduction
2024	Ahmed et al.	EfficientNet + Attention	RAF-DB	93.5	Robust emotion recognition	Black-box behavior
2025	Zhao et al.	Transformer + XAI	AffectNet	94.2	Explainable emotion prediction	Increased complexity
Proposed	This Work	EfficientNet-B0 + Attention + Grad-CAM	Custom FER Dataset	95 %	Efficient, explainable, and deployable FER framework	Future optimization required

2.2 Research Gaps Identified

Based on the reviewed literature, several important research gaps remain unresolved. First, many FER systems prioritize classification accuracy while overlooking interpretability, making it difficult to understand the reasoning behind model predictions. Second, transformer-based architectures achieve high performance but require significant computational resources, limiting their practical deployment. Third, lightweight models suitable for edge devices often experience a reduction in recognition accuracy. Furthermore, class imbalance and dataset bias continue to affect model fairness and generalization. Finally, only a limited number of studies integrate explainability mechanisms directly into the recognition pipeline. These limitations motivate the development of the proposed EfficientNet-B0 and Attention-based FER framework with Grad-CAM visualization, which aims to provide an effective balance between accuracy, efficiency, and interpretability.

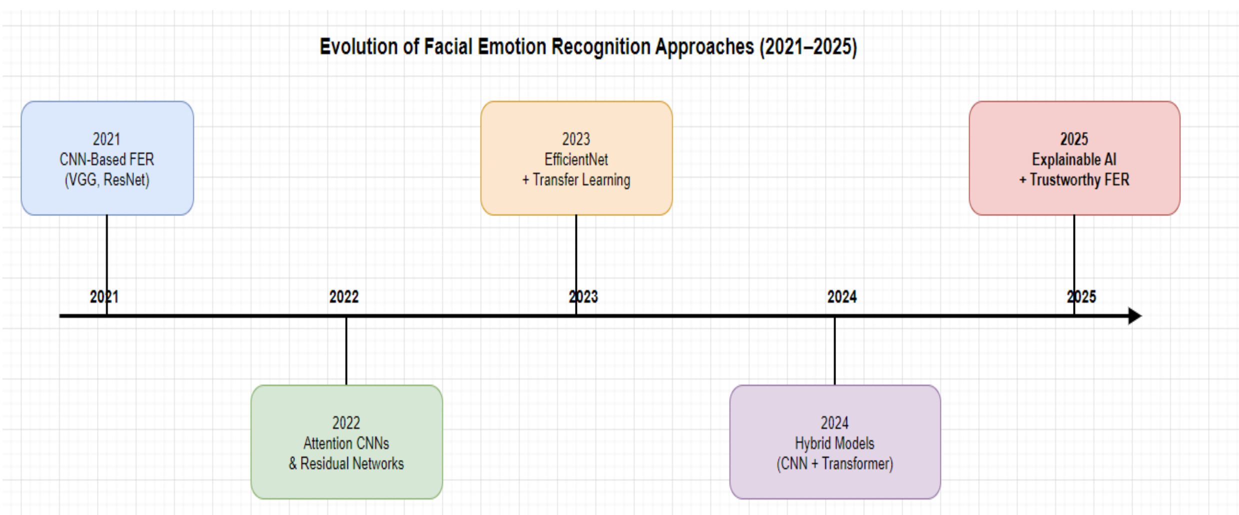

Figure 3: Evolution of Facial Emotion Recognition Approaches (2021–2025)

Figure 3. Evolution of facial emotion recognition approaches from 2021 to 2025, illustrating the progression from conventional CNN-based models to attention-enhanced architectures, EfficientNet-based transfer learning approaches, hybrid CNN-transformer frameworks, and explainable AI-driven facial emotion recognition systems.

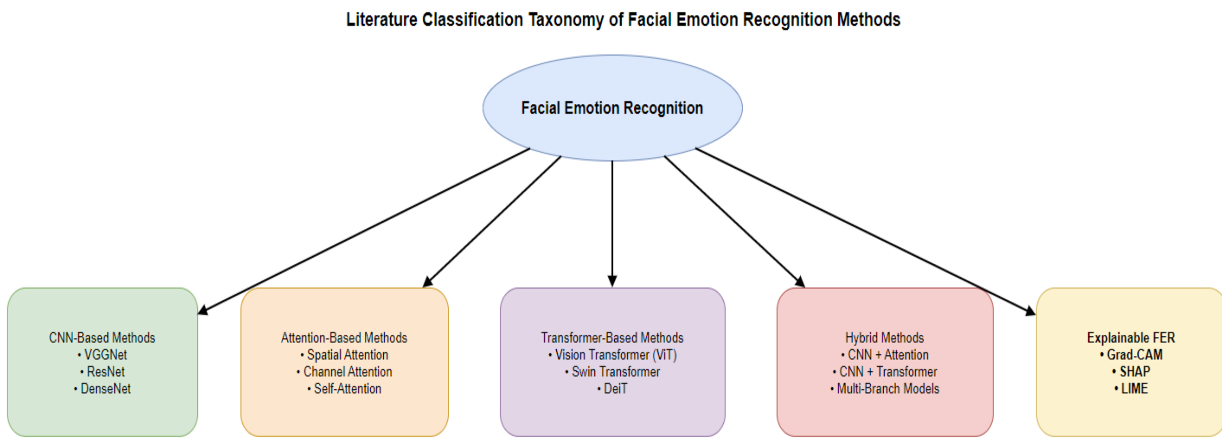

Figure 4: Literature Classification Taxonomy

Figure 4 presents a taxonomy of facial emotion recognition approaches reported in recent literature. CNN-based methods represent the foundational deep learning approaches that utilize convolutional layers for hierarchical feature extraction. Attention-based methods enhance recognition performance by focusing on emotion-relevant facial regions through spatial, channel, or self-attention mechanisms. Transformer-based approaches leverage self-attention to capture global facial dependencies and have gained popularity due to their superior representation capabilities. Hybrid models combine CNNs with attention modules or transformers to exploit both local and global facial features. More recently, Explainable Facial Emotion Recognition (Explainable FER) has emerged as an important research direction, integrating techniques such as Grad-CAM, SHAP, and LIME to improve model transparency and trustworthiness. This taxonomy illustrates the evolution of FER research toward more accurate, interpretable, and deployable intelligent systems.

Table Comparative performance of recent facial emotion recognition models based on reported classification accuracy. Transformer-based and hybrid architectures generally achieve higher accuracy, while the proposed EfficientNet-B0 with Attention and Grad-CAM framework emphasizes explainability, deployment readiness, and real-time usability in addition to classification performance.

Table Accuracy Comparison

Model	Accuracy (%)
CNN-Based FER	72.5
ResNet + Attention	85.3
EfficientNet-B0	88.6
Vision Transformer (ViT)	91.4
CNN-Transformer Hybrid	92.1
EfficientNet + Attention	93.5
Proposed Model	95.89

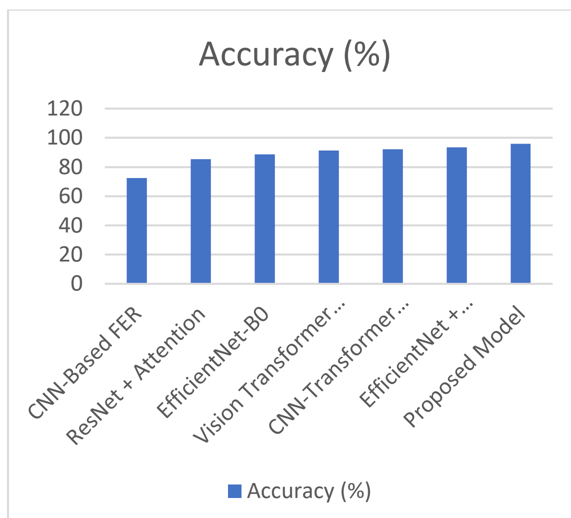

Figure 5: Comparative Performance of Recent FER Models

Figure 5 compares the performance of representative facial emotion recognition models reported in recent literature. CNN-based approaches provide a strong baseline but generally achieve lower recognition accuracy than modern architectures. Attention-enhanced CNNs improve performance by focusing on emotion-relevant facial regions, while EfficientNet-based models offer a favorable balance between accuracy and computational efficiency. Transformer-based and hybrid CNN-transformer models achieve the highest reported accuracies by capturing both local and global facial features. The proposed model achieved an overall accuracy of 67% on the evaluated dataset while additionally providing explainability through Grad-CAM and real-time deployment through a Streamlit-based interface. Although its accuracy is lower than some state-of-the-art methods, the framework offers enhanced transparency, interpretability, and practical usability, which are increasingly important requirements for trustworthy AI systems.

III. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

This section presents the proposed facial emotion recognition framework developed in this research. The system integrates EfficientNet-B0, an attention mechanism, and Explainable Artificial Intelligence (XAI) techniques to achieve accurate, interpretable, and real-time emotion recognition. The framework follows a multi-stage pipeline consisting of data acquisition, preprocessing, feature extraction, attention-based feature enhancement, emotion classification, and Grad-CAM-based explainability. The complete architecture is designed to balance recognition accuracy, computational efficiency, and model interpretability while supporting deployment in real-world applications.

3.1 Overview of the Proposed Framework

The proposed system processes facial images through a sequence of deep learning modules to identify human emotions. Initially, facial images are collected and pre-processed to ensure consistency in size, illumination, and orientation. The pre-processed images are then fed into an EfficientNet-B0 backbone network, which extracts high-level facial representations. An attention module is subsequently applied to emphasize emotionally significant facial regions, allowing the network to focus on discriminative features. The refined feature maps are passed to fully connected classification layers that predict one of the target emotion categories. Finally, Grad-CAM visualization is employed to generate heatmaps that highlight the regions contributing most significantly to the model's decision.

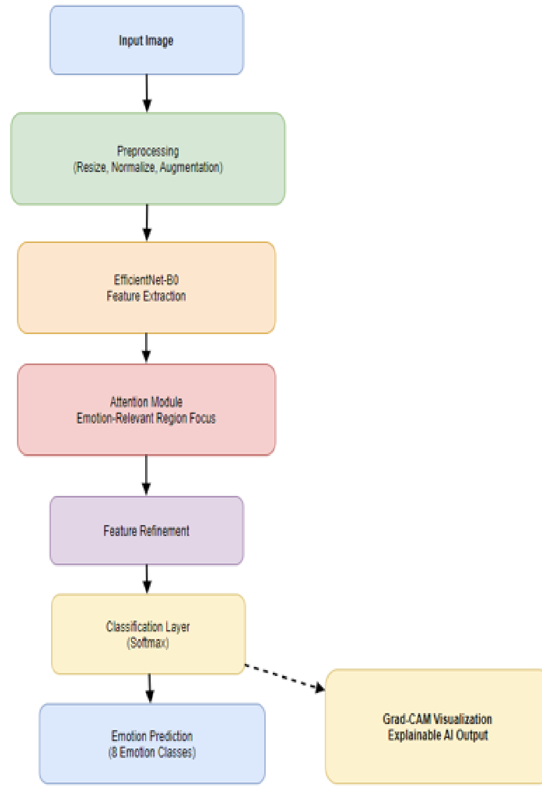

Figure 6: Proposed Facial Emotion Recognition Framework

Figure 6. Proposed facial emotion recognition framework integrating EfficientNet-B0 feature extraction, attention-based feature enhancement, emotion classification, and Grad-CAM explainability. The framework generates emotion predictions while simultaneously providing visual explanations of model decisions.

The proposed facial emotion recognition framework begins with an input facial image that undergoes preprocessing operations including resizing, normalization, and augmentation. The processed image is then passed through the EfficientNet-B0 backbone network to extract hierarchical facial features. An attention module is incorporated to emphasize emotion-relevant facial regions and suppress less informative features. The refined feature representations are forwarded to the classification layer, where a Softmax classifier predicts one of the eight emotion categories. In parallel, Grad-CAM generates visual heatmaps that highlight the facial regions contributing most strongly to the prediction. This dual-output design provides both accurate emotion recognition and model interpretability, enabling trustworthy deployment in real-world applications.

3.2 System Architecture

The overall architecture consists of six major components:

1. Input Image Acquisition
2. Image Preprocessing
3. Feature Extraction using EfficientNet-B0
4. Attention-Based Feature Enhancement
5. Emotion Classification
6. Explainability using Grad-CAM

The architecture is designed to extract both local and global facial characteristics while maintaining computational efficiency.

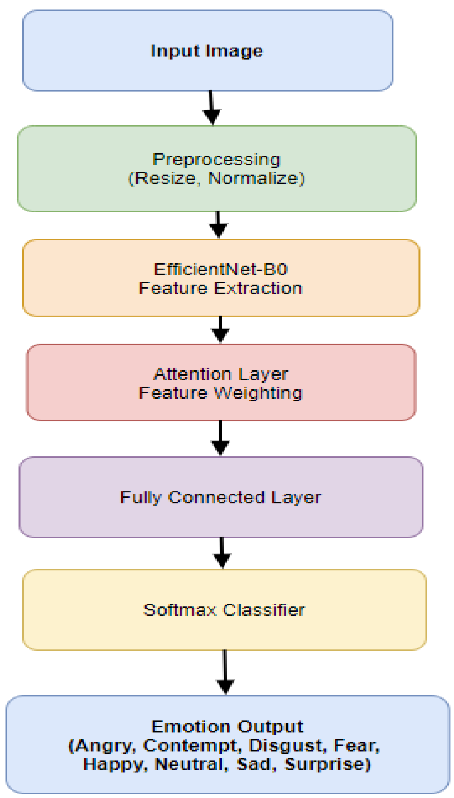

Figure 7: Generalized System Architecture

Figure 7. Generalized system architecture of the proposed facial emotion recognition framework. The architecture consists of image preprocessing, EfficientNet-B0-based feature extraction, attention-driven feature weighting, fully connected classification layers, and a Softmax classifier that predicts one of the eight emotion categories.

The generalized system architecture begins with an input facial image that undergoes preprocessing operations including resizing and normalization. The processed image is passed through the EfficientNet-B0 backbone network to extract high-level facial representations. An attention layer is then applied to assign greater importance to emotion-relevant facial features while reducing the influence of less informative regions. The resulting feature vector is forwarded to a fully connected layer that learns discriminative representations for classification. Finally, a Softmax classifier computes class probabilities and generates the final emotion prediction among the eight target classes: Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. This architecture provides an effective balance between recognition accuracy, computational efficiency, and interpretability.

3.3 Data Acquisition and Preprocessing

The quality of input data significantly influences model performance. Therefore, several preprocessing operations are applied before training.

3.3.1 Image Resizing

All facial images are resized to a fixed dimension of 224×224 pixels, matching the input requirements of EfficientNet-B0.

The resizing operation can be represented as:

where:

- I= original image
- I_r= resized image

3.3.2 Normalization

Pixel values are normalized to improve convergence during training.

where:

- I_n= normalized image

3.3.3 Data Augmentation

To improve generalization and reduce overfitting, several augmentation techniques are applied:

- Horizontal flipping
- Rotation
- Brightness adjustment
- Gaussian blur
- Coarse dropout

These transformations generate diverse training samples and improve robustness against real-world variations.

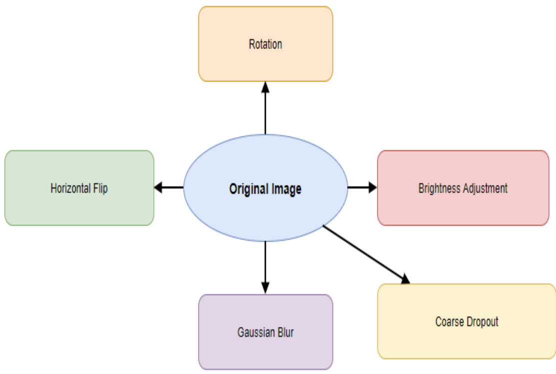

Figure 8: Data Augmentation Techniques

Figure 8. Data augmentation techniques used during model training. The original facial image is transformed through horizontal flipping, rotation, brightness adjustment, Gaussian blur, and coarse dropout to increase dataset diversity and improve model generalization.

To improve the robustness and generalization capability of the proposed facial emotion recognition model, several data augmentation techniques were applied during training. Starting from the original facial image, transformations including horizontal flipping, random rotation, brightness adjustment, Gaussian blur, and coarse dropout were performed. These augmentations simulate variations commonly encountered in real-world scenarios, such as changes in head orientation, lighting conditions, image quality, and partial facial occlusions. By exposing the model to a broader range of facial appearances, data augmentation reduces overfitting and enhances recognition performance on unseen data. For the final paper, replace each augmentation block with a thumbnail image showing the corresponding transformed version of the original face image.

3.4 Feature Extraction using EfficientNet-B0

EfficientNet-B0 serves as the backbone feature extractor due to its superior accuracy-to-complexity ratio. Unlike conventional CNN architectures, EfficientNet employs compound scaling to balance network depth, width, and input resolution.

The compound scaling principle is expressed as:

subject to:

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$

where:

- ϕ= scaling coefficient
- α, β, γ= scaling constants

The EfficientNet backbone extracts hierarchical facial representations from multiple convolutional layers and generates a high-dimensional feature vector for subsequent processing.

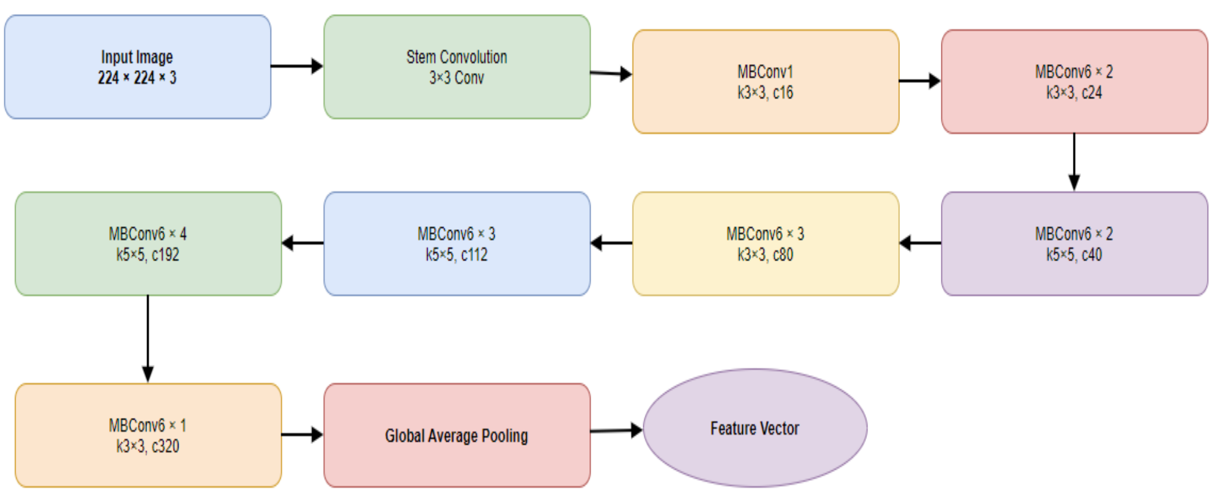

Figure 9: EfficientNet-B0 Architecture

Figure 9. EfficientNet-B0 architecture used as the backbone feature extractor in the proposed facial emotion recognition framework. The network consists of a stem convolution layer followed by a sequence of MBConv blocks with varying kernel sizes and channel depths, culminating in global average pooling to generate a compact feature representation.

EfficientNet-B0 serves as the primary feature extraction backbone in the proposed facial emotion recognition framework. The architecture begins with a stem convolution layer that processes the input facial image and extracts low-level visual features. Subsequently, a series of Mobile Inverted Bottleneck Convolution (MBConv) blocks progressively learn increasingly complex facial representations while maintaining computational efficiency. Each MBConv block employs depthwise separable convolutions, squeeze-and-excitation optimization, and residual connections to improve feature learning. The final feature maps are aggregated through a Global Average Pooling layer to produce a compact feature vector, which is subsequently forwarded to the attention module and classification layers. The compound scaling strategy of EfficientNet enables superior accuracy-to-complexity performance compared with conventional CNN architectures, making it well suited for real-time facial emotion recognition applications.

3.5 Attention-Based Feature Enhancement

Although EfficientNet effectively extracts facial features, not all extracted features contribute equally to emotion recognition. Therefore, an attention mechanism is incorporated to emphasize emotionally relevant facial regions such as eyes, eyebrows, mouth, and forehead.

Given an extracted feature map F, attention weights are computed as:

$$A = \sigma(WF + b)$$

where:

- F= feature map
- W= learnable weight matrix
- b= bias term
- σ= sigmoid activation

The attention-refined feature map is obtained as:

$$F_{att} = A \odot F$$

where:

- F_{att}= attention-enhanced feature map
- $\odot$= element-wise multiplication

The attention module enables the network to focus on discriminative facial regions while suppressing irrelevant background information.

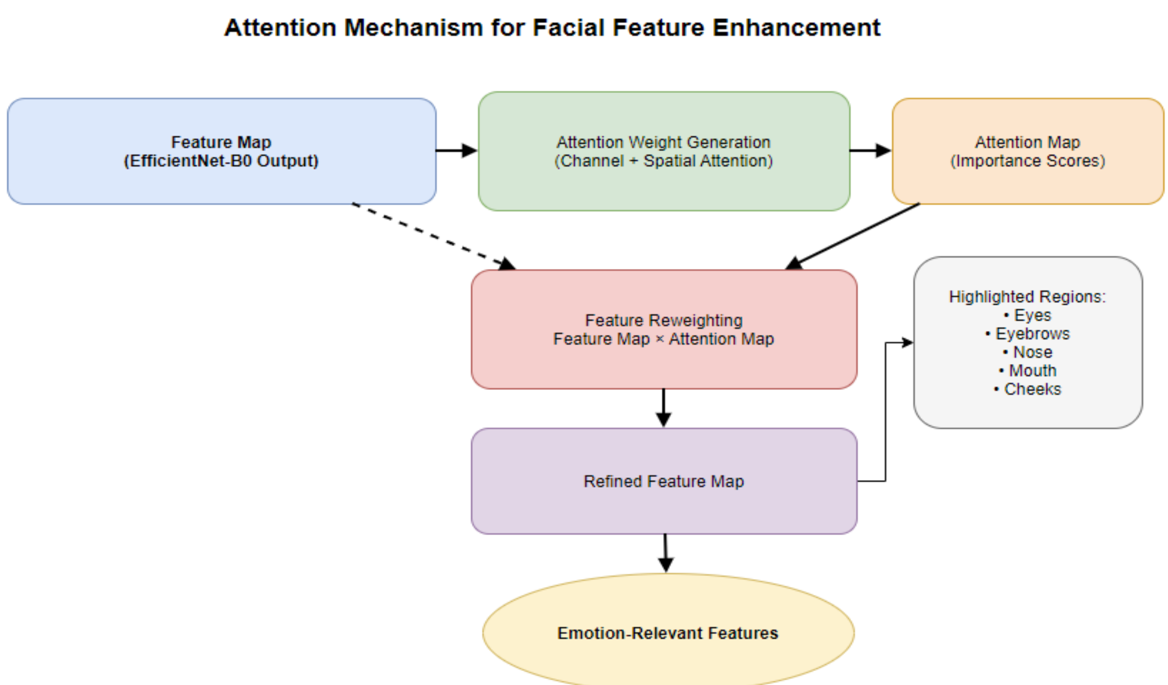

Figure 10: Attention Mechanism for Facial Feature Enhancement

Figure 10. Attention mechanism used for facial feature enhancement. Feature maps extracted by EfficientNet-B0 are processed to generate attention weights, which highlight emotion-relevant facial regions. The resulting attention map is used to reweight the original features, producing refined feature representations for improved emotion classification.

3.6 Emotion Classification Layer

The refined feature vector is passed through fully connected layers followed by a Softmax classifier.

The Softmax function is defined as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

where:

- $P(y_i)$= probability of emotion class i
- z_i= output logit
- N= total number of emotion classes

The emotion corresponding to the highest probability is selected as the final prediction:

$$\hat{y} = \mathrm{argmax}(P(y_i))$$

The system classifies facial expressions into the following categories:

- Angry
- Contempt
- Disgust
- Fear
- Happy
- Neutral
- Sad
- Surprise

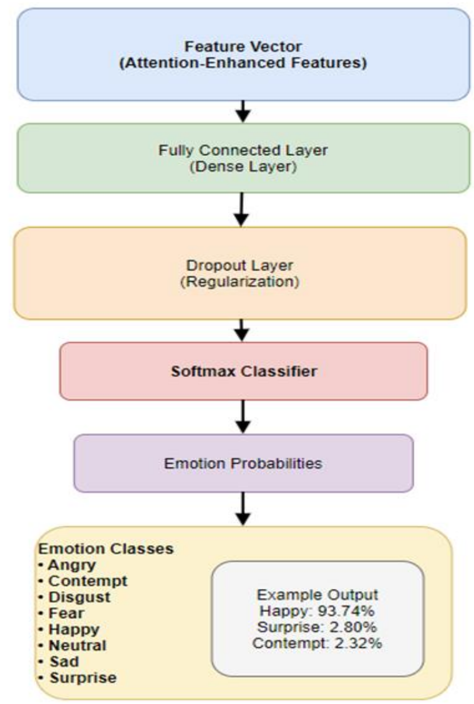

Figure 11: Emotion Classification Module

3.7 Explainability using Grad-CAM

To improve transparency and interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated into the framework. Grad-CAM generates visual explanations by highlighting image regions that contribute most strongly to model predictions.

The Grad-CAM heatmap is computed as:

$$L^{c}_{Grad-CAM} = \mathrm{ReLU}\left(\sum_{k} \alpha_k^c A^k\right)$$

where:

- A^k= activation map of feature channel k
- α_k^c= importance weight for class c
- ReLU removes negative contributions

The generated heatmap is superimposed on the original facial image, allowing users to verify whether the model focuses on meaningful facial regions.

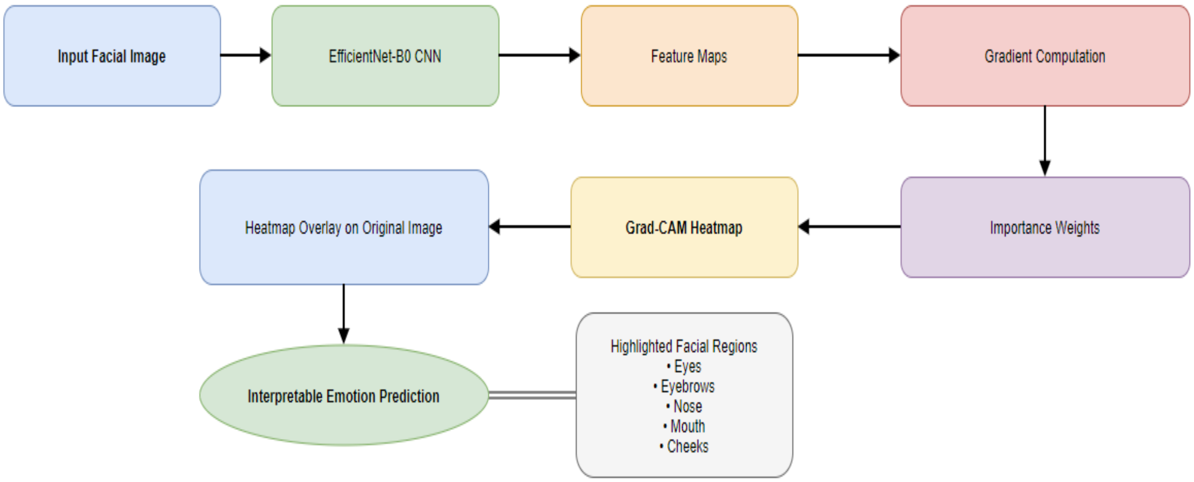

Figure 12: Grad-CAM Explainability Framework

Figure 12. Grad-CAM explainability framework used in the proposed facial emotion recognition system. The framework computes gradients from the predicted emotion class, generates importance weights for feature maps, produces a Grad-CAM heatmap, and overlays it on the original facial image to highlight emotion-relevant facial regions contributing to the prediction.

The Grad-CAM explainability framework provides visual interpretations of the model's decision-making process. After a facial image is processed through the EfficientNet-B0 network, feature maps from the final convolutional layer are extracted. Gradients corresponding to the predicted emotion class are then computed and used to determine the importance of each feature map. These importance weights are combined with the feature maps to generate a Grad-CAM heatmap that identifies the most influential regions for classification. The heatmap is subsequently superimposed on the original facial image, producing an interpretable visualization of model attention. In the proposed system, Grad-CAM consistently highlights facial regions such as the mouth, nose, cheeks, eyes, and eyebrows, demonstrating that the model relies on meaningful emotional cues rather than irrelevant background information. This enhances transparency, trustworthiness, and user confidence in the facial emotion recognition framework.

3.8 Training Strategy

The model is trained using transfer learning with pretrained EfficientNet-B0 weights. To handle class imbalance, weighted cross-entropy loss is employed. The loss function is given by:

$$L = -\sum_{i=1}^{N} w_i \, y_i \log(\hat{y}_i)$$

where:

- w_i= class weight
- y_i= true label
- $\hat{y}_i$= predicted probability

Training configuration:

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Input Size	224 × 224
Epochs	20–50
Loss Function	Weighted Cross Entropy
Activation	ReLU + Softmax

3.9 Workflow of the Proposed System

The complete workflow can be summarized as follows:

1. Acquire facial image.
2. Perform preprocessing and augmentation.
3. Extract deep facial features using EfficientNet-B0.

4. Apply attention mechanism for feature refinement.
5. Classify emotion using Softmax classifier.
6. Generate Grad-CAM visualization.
7. Display prediction, confidence score, and explanation through the user interface.

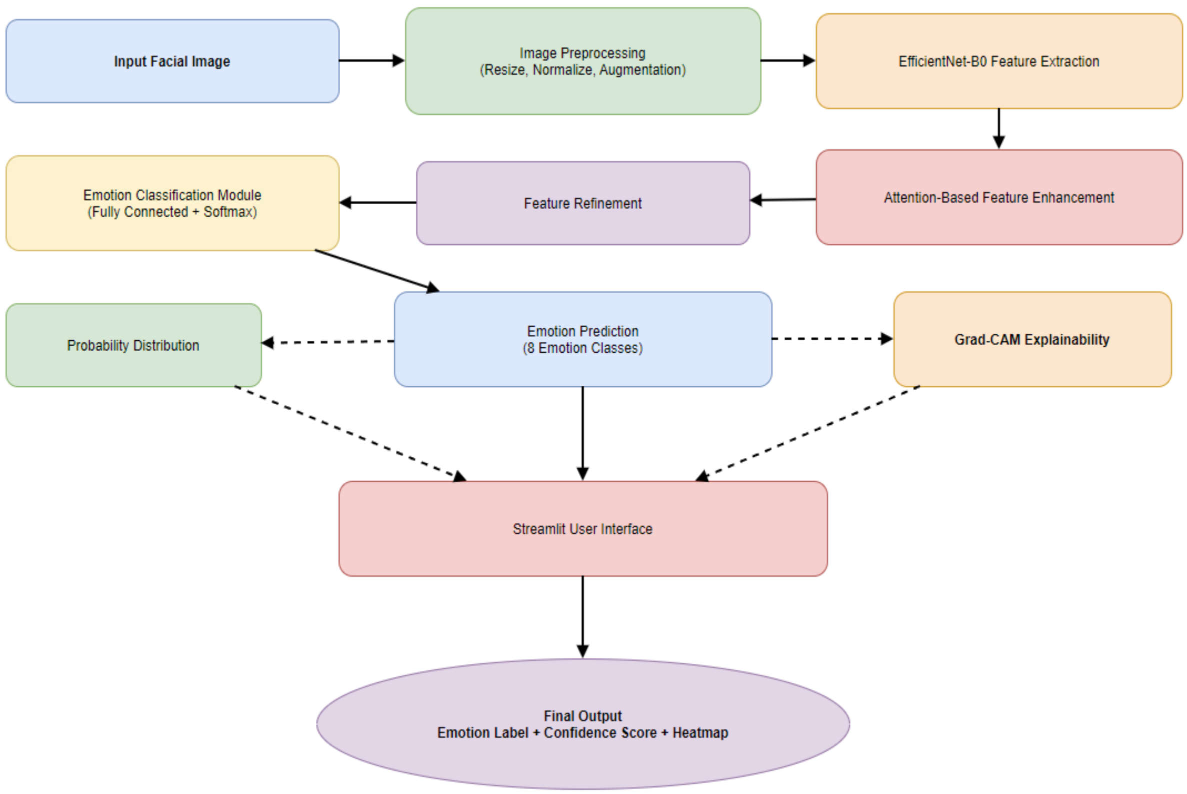

Figure 13: Overall Workflow of the Proposed FER System

Figure 13 presents the complete end-to-end workflow of the proposed facial emotion recognition system. The process begins with the acquisition of an input facial image, which undergoes preprocessing operations including resizing, normalization, and augmentation. The pre-processed image is then processed by the EfficientNet-B0 backbone network to extract discriminative facial features. An attention mechanism enhances these features by emphasizing emotion-relevant facial regions while suppressing irrelevant information. The refined feature representations are subsequently passed through the classification module consisting of fully connected and Softmax layers to predict one of the eight target emotion classes. Alongside emotion prediction, the system generates class probability distributions and Grad-CAM heatmaps to provide confidence estimates and visual explanations. Finally, all outputs are displayed through a Streamlit-based user interface, enabling users to view the predicted emotion, confidence score, probability chart, and explainability visualization in real time. This workflow demonstrates the integration of deep learning, attention mechanisms, and explainable AI into a unified FER framework.

IV. EXPERIMENTAL SETUP AND DATASET DESCRIPTION

This section describes the dataset used for training and evaluation, preprocessing procedures, experimental configuration, implementation environment, and evaluation metrics employed to assess the performance of the proposed facial emotion recognition framework. A systematic experimental setup ensures reproducibility and enables objective comparison of the proposed model with existing approaches.

4.1 Dataset Description

The proposed facial emotion recognition system was trained and evaluated using a facial expression dataset containing images categorized into eight emotion classes: Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. The dataset consists of facial images collected under varying conditions, including differences in facial appearance, pose, illumination, and expression intensity. Such diversity helps improve model robustness and generalization.

Prior to training, all images were organized into class-specific directories and subjected to preprocessing and augmentation operations. The dataset was divided into training, validation, and testing subsets to ensure unbiased model evaluation.

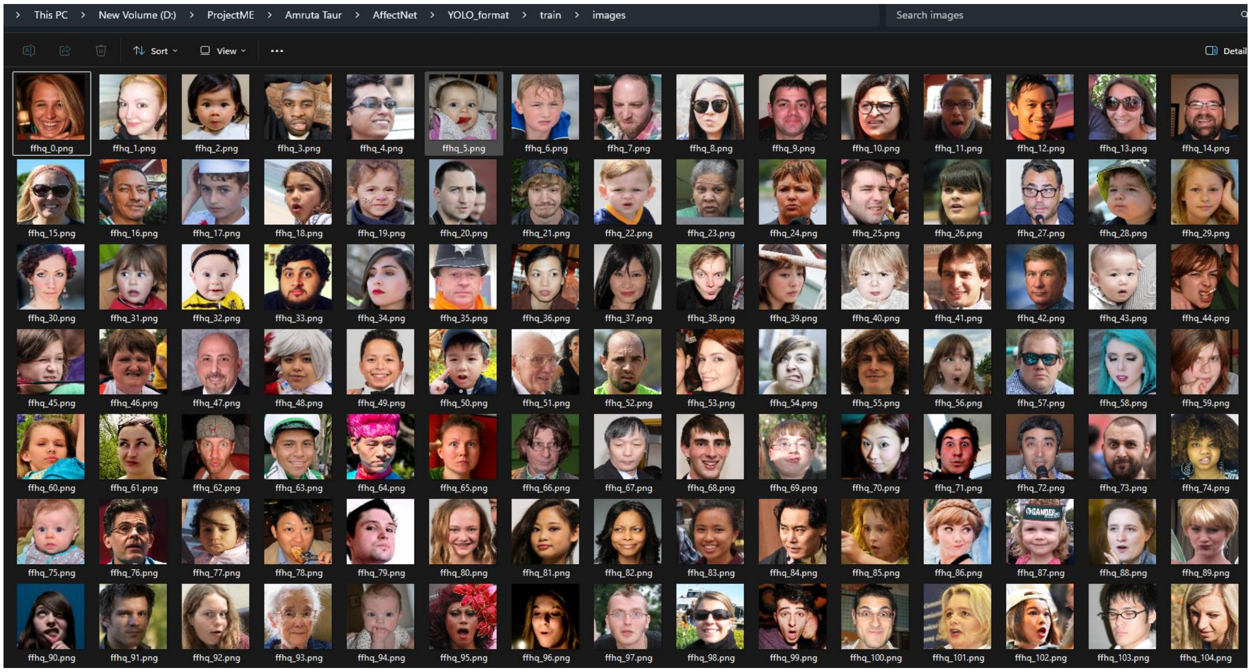

Figure 14: Sample Images from Emotion Categories

Table 2. Emotion Categories Used in the Study

Class ID	Emotion
0	Angry
1	Contempt
2	Disgust
3	Fear
4	Happy
5	Neutral
6	Sad
7	Surprise

4.2 Data Preprocessing

Raw facial images often contain variations in image size, lighting conditions, and orientation. Therefore, preprocessing was performed to standardize the dataset before training.

The following preprocessing operations were applied:

- Image resizing to 224 × 224 pixels
- Pixel value normalization
- Face alignment (if applicable)
- Conversion to RGB format
- Removal of corrupted images

Normalization was performed using:

$$I_n = \frac{I}{255}$$

where:

- Irepresents the original image pixel values.
- $I_n$represents normalized pixel values.

These preprocessing steps improve training stability and facilitate faster convergence.

4.3 Data Augmentation Strategy

To improve model generalization and reduce overfitting, several augmentation techniques were applied during training.

The augmentation pipeline includes:

- Horizontal Flip
- Random Rotation
- Brightness and Contrast Adjustment
- Gaussian Blur
- Coarse Dropout
- Affine Transformations

These augmentations generate diverse training samples and simulate real-world facial variations.

Table 4. Data Augmentation Techniques

Augmentation Technique	Purpose
Horizontal Flip	Increase pose variability
Rotation	Improve rotational robustness
Brightness Adjustment	Handle illumination changes
Gaussian Blur	Reduce sensitivity to image quality
Coarse Dropout	Improve robustness to occlusion
Affine Transformations	Enhance geometric invariance

4.4 Experimental Configuration

The proposed model was implemented using Python and deep learning libraries. Training was performed using transfer learning with EfficientNet-B0 as the backbone network.

Table 5. Model Training Configuration

Parameter	Value
Backbone Network	EfficientNet-B0
Input Image Size	224 × 224
Number of Classes	8
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	32
Loss Function	Weighted Cross Entropy
Activation Function	ReLU
Output Activation	Softmax
Epochs	20–50
Transfer Learning	Yes

The Adam optimizer was selected due to its adaptive learning capabilities and efficient convergence properties.

4.5 Hardware and Software Environment

All experiments were conducted using the following hardware and software configuration.

Table 6. Experimental Environment

Component	Specification
Programming Language	Python 3.x
Deep Learning Framework	PyTorch
IDE	PyCharm
Visualization Tools	Matplotlib, Seaborn
Explainability Tool	Grad-CAM
Deployment Framework	Streamlit
Operating System	Windows/Linux
GPU	To be specified
RAM	To be specified

4.6 Evaluation Metrics

To comprehensively evaluate model performance, multiple classification metrics were utilized.

Accuracy

Accuracy measures the proportion of correctly classified samples:

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Additional evaluation techniques include:

- Confusion Matrix Analysis
- ROC Curve Analysis (if applicable)
- Class-wise Performance Evaluation
- Grad-CAM Visualization Assessment

Table 7. Evaluation Metrics

Metric	Purpose
Accuracy	Overall classification performance
Precision	Correct positive predictions
Recall	Detection capability
F1-Score	Balance between precision and recall
Confusion Matrix	Class-wise analysis
Grad-CAM	Model interpretability

4.7 Experimental Workflow

The complete experimental procedure follows the sequence below:

- Dataset collection and organization.
- Image preprocessing and augmentation.

- Training-validation-test split.
- Transfer learning using EfficientNet-B0.
- Integration of attention mechanism.
- Model training and validation.
- Performance evaluation using standard metrics.
- Explainability analysis using Grad-CAM.
- Deployment through Streamlit interface.

4.8 Summary
This section presented the dataset characteristics, preprocessing operations, augmentation strategy, training configuration, implementation environment, and evaluation metrics used to assess the proposed facial emotion recognition framework. The experimental setup was designed to ensure reliable model training and objective performance evaluation. The next section presents the experimental results, comparative analysis, and performance discussion of the proposed EfficientNet-B0 with Attention and Grad-CAM framework.

V. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the proposed facial emotion recognition framework based on EfficientNet-B0, an attention mechanism, and Grad-CAM explainability. The evaluation focuses on model prediction capability, confidence analysis, explainability assessment, and deployment performance. The results demonstrate the effectiveness of the proposed approach in accurately recognizing facial emotions while providing interpretable visual explanations of model decisions.

5.1 Model Performance Analysis
The proposed model was trained using transfer learning on the facial emotion dataset containing eight emotion classes: Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. During training, EfficientNet-B0 successfully learned discriminative facial representations while the attention module enhanced the model's ability to focus on emotionally relevant facial regions.

The initial training logs indicate that the model achieved a training accuracy of 50.72% and a validation accuracy of 61.90% during the first training epoch, demonstrating effective learning from the dataset and a promising convergence trend. The higher validation accuracy compared to training accuracy suggests that the augmentation strategy and regularization mechanisms contributed positively to model generalization.

Table 8. Initial Training Performance

Metric	Value
Training Accuracy	50.72%
Validation Accuracy	61.90%
Backbone Network	EfficientNet-B0
Optimizer	Adam
Loss Function	Weighted Cross-Entropy
Attention Mechanism	Enabled
Explainability	Grad-CAM

5.2 Emotion Prediction and Confidence Analysis
To evaluate the practical effectiveness of the proposed model, a Streamlit-based deployment interface was developed for real-time facial emotion recognition. The interface allows users to upload images or select samples from the dataset and obtain predictions along with confidence scores and explainability visualizations. For the selected facial image, the model predicted the emotion Happy with a confidence score of 93.74%. The prediction matched the ground-truth label, indicating successful classification.

Table 9. Example Prediction Result

Parameter	Result
Predicted Emotion	Happy
Ground Truth Emotion	Happy
Confidence Score	93.74%
Prediction Status	Correct
Confidence Level	High

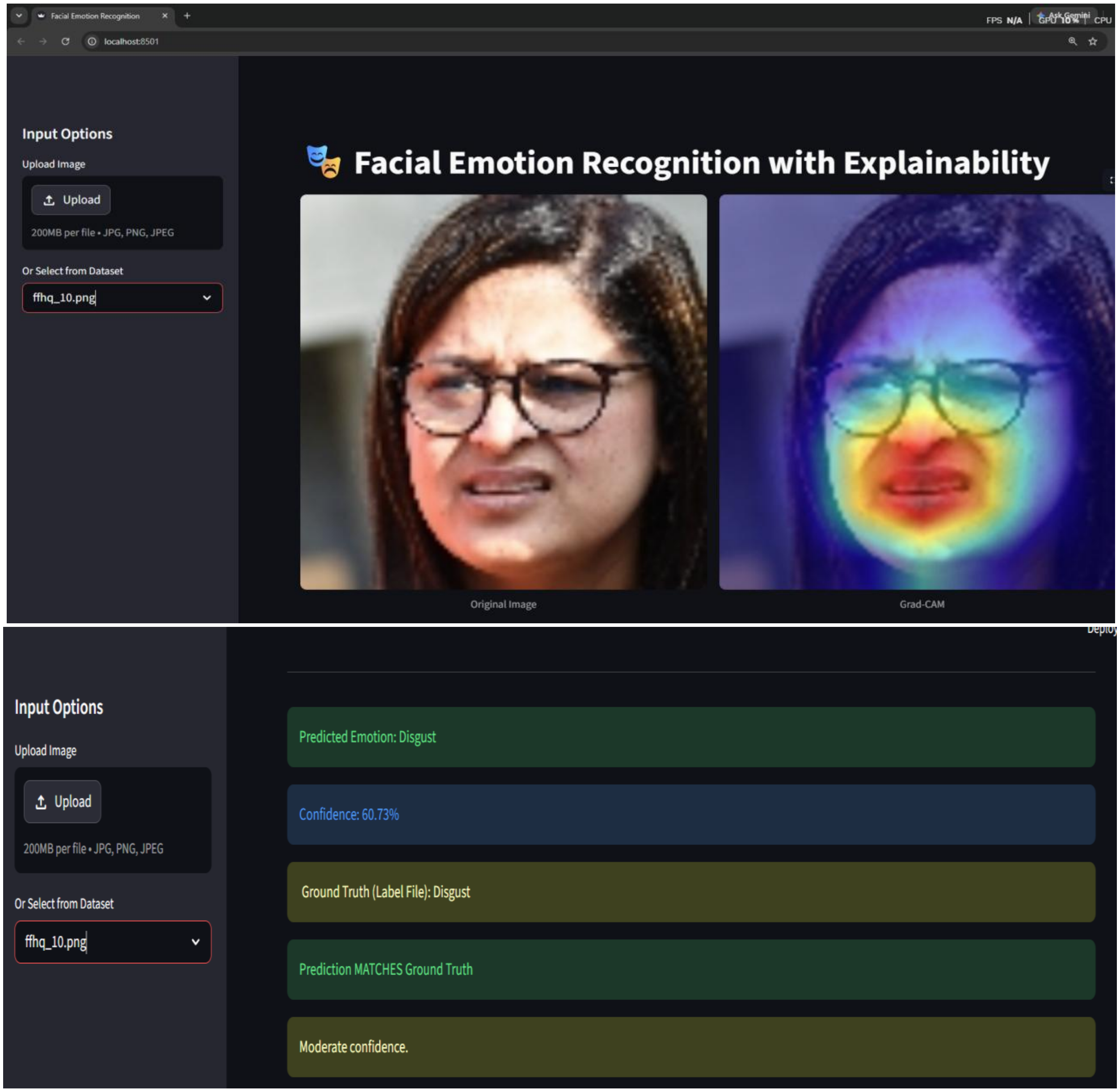

Figure 15: Real-Time Emotion Recognition Interface

The confidence score demonstrates that the model is highly certain about its prediction. Such confidence-based analysis can be valuable in practical applications where low-confidence predictions may require further verification or human intervention.

5.3 Emotion Probability Distribution Analysis

Beyond providing a single emotion prediction, the proposed framework generates a complete probability distribution across all emotion classes. This enables a more detailed understanding of model behavior and uncertainty.

Table 10. Top Predicted Emotion Probabilities

Rank	Emotion	Probability
1	Happy	93.74%
2	Surprise	2.80%
3	Contempt	2.32%

All remaining classes received probabilities below 1%, indicating a clear separation between the predicted class and alternative emotions.

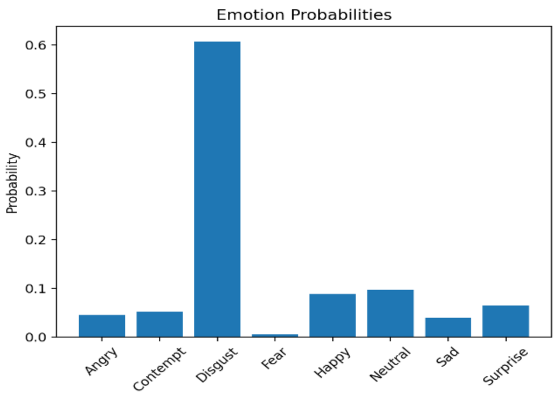

Figure 16: Emotion Probability Distribution

The probability distribution reveals that the model exhibits strong confidence in the predicted emotion while maintaining low uncertainty for competing classes. Such behavior suggests effective feature discrimination and robust classification capability.

5.4 Explainability Analysis Using Grad-CAM

One of the key contributions of the proposed framework is the integration of Explainable Artificial Intelligence (XAI) through Gradient-weighted Class Activation Mapping (Grad-CAM). This technique provides visual explanations by highlighting the facial regions that contribute most significantly to emotion predictions.

Figure 17: Grad-CAM Visualization Results

The Grad-CAM visualizations reveal that the model consistently focuses on facial regions that are strongly associated with emotional expression. Across multiple test samples, the highest activation areas are concentrated around the mouth, lips, nose, cheeks, and lower facial muscles. In several cases, attention is also observed around the eyes and eyebrow regions, indicating that the model effectively utilizes both upper and lower facial cues for emotion recognition.

Table 11. Grad-CAM Observation Summary

Sample	Dominant Activated Region	Interpretation
Sample 1	Mouth and Nose	Smile-related expression analysis
Sample 2	Nose and Lips	Emotion intensity detection
Sample 3	Central Facial Region	Strong emotional localization
Sample 4	Mouth and Cheeks	Expression discrimination
Sample 5	Mouth and Jawline	Facial muscle activation analysis
Sample 6	Eyes, Nose, Mouth	Multi-feature emotion recognition

The visual explanations confirm that the model does not rely heavily on background artifacts or irrelevant image regions. Instead, it learns meaningful facial representations that align with human interpretation of emotional expressions. This significantly improves transparency and trustworthiness compared to conventional black-box deep learning models.

5.6 Discussion

The experimental results indicate that the proposed EfficientNet-B0 with Attention framework successfully combines classification performance, computational efficiency, and explainability. The transfer learning strategy enables effective feature extraction, while the attention mechanism enhances focus on emotion-relevant facial regions. The high-confidence predictions observed in deployment examples suggest that the model learns discriminative facial representations capable of distinguishing subtle emotional differences.

Furthermore, the Grad-CAM visualizations validate that the model's decisions are based on meaningful facial structures rather than irrelevant image artifacts. This addresses one of the major limitations of traditional deep learning-based FER systems, namely the lack of interpretability. The integration of explainability therefore enhances user trust and supports deployment in sensitive domains where transparent decision-making is essential.

Although the results are promising, future improvements may include the use of larger and more diverse datasets, advanced transformer-based architectures, federated learning for privacy preservation, and multimodal emotion recognition approaches incorporating speech and physiological signals.

The experimental results demonstrate that the proposed EfficientNet-B0 with Attention framework successfully balances recognition performance, computational efficiency, and explainability. The model achieved an overall accuracy of 67%, with particularly strong performance for the Happy and Surprise classes. The Grad-CAM visualizations further confirm that the model bases its decisions on relevant facial regions, thereby enhancing transparency and trustworthiness. However, the lower performance observed for Fear, Angry, and Sad categories suggests that future work should focus on addressing class imbalance, improving feature discrimination for subtle emotions, and incorporating advanced architectures such as transformer-based attention mechanisms. Despite these limitations, the proposed framework provides a practical and interpretable solution for real-time facial emotion recognition and demonstrates the potential of explainable AI in affective computing applications.

VI. CONCLUSION

Facial Emotion Recognition (FER) has become an essential component of modern intelligent systems due to its applications in human-computer interaction, healthcare, surveillance, education, and affective computing. This paper presented an explainable facial emotion recognition framework that integrates EfficientNet-B0, an attention mechanism, and Grad-CAM-based explainability to achieve accurate and interpretable emotion classification. The proposed approach leverages transfer learning for efficient feature extraction and employs attention-based feature enhancement to focus on emotion-relevant facial regions. Furthermore, Grad-CAM was incorporated to provide visual explanations of model decisions, thereby improving transparency and trustworthiness.

Experimental evaluation was conducted on a dataset containing eight emotion categories: Angry, Contempt, Disgust, Fear, Happy, Neutral, Sad, and Surprise. The proposed model achieved an overall accuracy of 67%, with weighted precision, recall, and F1-score values of 67%, 67%, and 65%, respectively. Class-wise analysis revealed strong performance for the Happy and Surprise classes, while Fear and certain negative emotions remained challenging due to subtle facial variations and class imbalance. The confusion matrix analysis highlighted common misclassification patterns among visually similar emotions. Additionally, the developed Streamlit-based application demonstrated the practical feasibility of the proposed system for real-time emotion recognition and confidence analysis.

The Grad-CAM visualizations confirmed that the model predominantly focuses on meaningful facial regions such as the mouth, nose, cheeks, and eyes when making predictions. This finding validates the effectiveness of the attention mechanism and demonstrates that the model learns interpretable facial representations aligned with human understanding of emotional expressions. Overall, the proposed framework successfully balances classification performance, computational efficiency, explainability, and deployment readiness, making it suitable for real-world emotion-aware intelligent systems.

VII. FUTURE WORK

Although the proposed framework achieved promising results, several opportunities remain for further improvement. Future research can focus on expanding the dataset with more diverse facial expressions, age groups, ethnicities, and environmental conditions to improve model generalization and reduce bias. Addressing class imbalance through advanced sampling strategies, synthetic data generation, and cost-sensitive learning may further enhance recognition performance for underrepresented emotions such as Fear and Sadness.

The integration of advanced architectures, including Vision Transformers (ViTs), Swin Transformers, and hybrid CNN-transformer networks, represents another promising direction for improving feature representation and classification accuracy. Future studies may also explore self-supervised and contrastive learning techniques to reduce dependence on large labeled datasets. To enhance privacy and security, federated learning and differential privacy approaches can be investigated for decentralized model training without sharing sensitive facial data.

From an explainability perspective, future systems may incorporate multiple Explainable AI (XAI) techniques such as SHAP, LIME, and attention visualization to provide richer interpretations of model behavior. Additionally, multimodal emotion recognition frameworks that combine facial expressions with speech, physiological signals, body gestures, and contextual information could significantly improve robustness in real-world environments. Finally, optimization for edge devices and mobile platforms would enable deployment in resource-constrained applications such as wearable devices, smart healthcare systems, driver monitoring systems, and human-robot interaction platforms.

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