Development of a Web-Based Deep Learning Model for Real-Time Emotion Recognition Using Facial Expressions that Leverages Convolutional Neural Networks (CNN) and Attention Mechanisms

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DOI: 10.56201/ijcsmt.vol.11.no11.2025.pg203.216

Abstract
The automatic recognition of human emotions from facial expressions is a critical component of affective computing, with applications spanning human-computer interaction, customer service, and mental health. While traditional methods often rely on handcrafted features, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance. However, challenges remain in model interpretability and robustness to real-world variations. To address these limitations, this study proposes a web-based deep learning model for real-time emotion recognition. An enhanced facial emotion recognition model using a deep CNN integrated with a Convolutional Block Attention Module (CBAM) and Grad-CAM explainability was developed. Using the Extended Cohn-Kanade (CK+) dataset comprising 981 images across seven emotion classes, the model was trained with rigorous preprocessing and data augmentation. Results show that the proposed model achieved 98.71% accuracy, 98.7% recall, and an F1-score of 98.9%, with perfect AUC and Average Precision scores of 1.00 for all classes. The integration of CBAM improved feature focus on salient facial regions, while Grad-CAM provided visual explanations, enhancing clinical and practical trustworthiness. The system was successfully deployed as a browser-based application, demonstrating real-time inference capabilities. This study highlights the potential of attention-enhanced deep learning models in advancing transparent and efficient emotion diagnostics for real-world deployment.

Keywords: *Facial Emotion Recognition (FER), Convolutional Neural Network (CNN), Attention Mechanism, CBAM, Explainable AI (XAI), Grad-CAM, Real-Time System.*

1. Introduction

The automatic detection and interpretation of human emotions from facial expressions is a cornerstone of affective computing, with transformative potential for human-computer interaction (HCI), mental health monitoring, and customer experience analytics. This discipline, known as Facial Emotion Recognition (FER), has evolved from relying on psychological frameworks like Ekman's basic emotions and manual feature extraction to being dominated by data-driven deep learning approaches. The contemporary FER pipeline involves face detection, landmark alignment, and deep feature learning to classify discrete emotions from visual data. This technology is crucial for developing empathetic AI systems that can respond to human affective

states in real-time, enabling applications from responsive virtual assistants to diagnostic tools in healthcare (Zhang et al., 2021).

The paradigm shift in FER has been largely driven by Convolutional Neural Networks (CNNs), which automate the process of hierarchical feature extraction. Unlike traditional methods that required handcrafted features, CNNs learn directly from pixel data, capturing everything from low-level edges to high-level semantic features that define complex expressions. This capability has led to unprecedented accuracy on controlled benchmark datasets. However, a significant challenge has emerged as research has moved towards "in-the-wild" conditions; models trained in laboratory settings often suffer from performance degradation when faced with real-world variations in illumination, pose, and occlusion (Li & Deng, 2020). This highlights a critical need for architectures that are not only accurate but also robust and generalizable.

A parallel challenge in deploying these sophisticated models is their inherent lack of transparency. The "black-box" nature of deep CNNs undermines trust and impedes adoption in high-stakes domains like clinical psychology or security, where understanding the rationale behind a decision is as important as the decision itself (Arrieta et al., 2020). In response, the field of Explainable AI (XAI) has gained significant traction. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have become essential for visualizing the regions of an input image that most influence a model's prediction, providing a critical layer of interpretability and enabling model validation. Its continued relevance and application in modern deep learning frameworks for providing transparent AI decisions have been extensively documented in recent comprehensive reviews of explainable AI (Saputra et al., 2023).

To concurrently address the issues of robustness and interpretability, recent research has increasingly turned to attention mechanisms. These mechanisms, particularly the Convolutional Block Attention Module (CBAM), allow models to dynamically focus computational resources on the most salient facial regions—such as the eyes, eyebrows, and mouth—while suppressing less informative features. The efficacy of CBAM and its subsequent variants in boosting the performance and focus of CNNs for tasks like facial expression recognition has been consistently validated in contemporary literature and surveys on attention-based deep learning (Chen et al., 2024; Wang & Wang, 2023). This selective focus mimics human perceptual processes and has been shown to improve both accuracy and resilience to noise. This study builds upon these cutting-edge advancements by proposing an integrated framework that combines a deep CNN backbone with a CBAM attention mechanism for enhanced feature discrimination, alongside Grad-CAM for post-hoc explainability. Furthermore, we demonstrate the practical viability of this approach through deployment as a real-time, web-based application, bridging the gap between theoretical model performance and tangible, usable technology in affective computing.

2. Related Works

2.1. Evolution from Traditional to Deep Learning-based FER

Early FER systems were fundamentally anchored in psychological frameworks, most notably Paul Ekman's theory of universal basic emotions—anger, disgust, fear, happiness, sadness, and surprise—which provided a categorical basis for labeling expressions (Ekman & Friesen, 1971). This was operationalized through the Facial Action Coding System (FACS), a comprehensive, anatomically-based taxonomy for describing facial movements. Computationally, early systems relied on a two-stage process: first, extracting handcrafted features such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or Gabor filters to encode texture and edges; and second, feeding these features into classifiers like Support Vector Machines (SVMs) or Random

Forests (Pantic & Rothkrantz, 2000). While these methods achieved moderate success on controlled, lab-collected datasets, their performance severely degraded in real-world scenarios due to their sensitivity to variations in illumination, head pose, and occlusion (Zhang et al., 2021).

The paradigm shift in FER was catalyzed by the success of deep learning, particularly Convolutional Neural Networks (CNNs). CNNs automated the feature engineering process by learning hierarchical representations directly from raw pixel data, with early layers capturing primitive features like edges and corners, and deeper layers synthesizing these into complex, semantically meaningful patterns relevant to facial expressions (LeCun et al., 2015). This led to a significant leap in performance on benchmarks. Subsequent research extensively explored transfer learning, where models like VGGNet, ResNet, and Inception, pre-trained on massive datasets like ImageNet, were fine-tuned on specific FER datasets. This approach proved highly effective in overcoming data scarcity and achieving state-of-the-art results (Minaee et al., 2021). More recently, Vision Transformers (ViTs) have emerged as a competitive alternative, leveraging self-attention mechanisms to model global dependencies in images, showing promising results in FER, though often requiring substantial data and computational resources (Arrieta et al., 2023).

2.2. Attention Mechanisms for Enhanced Feature Learning

A significant trend in modern FER is the strategic incorporation of attention mechanisms into CNN architectures. Inspired by their success in natural language processing, attention modules enable networks to dynamically weigh the importance of different spatial regions and feature channels. This allows the model to focus its capacity on the most informative facial regions—such as the eyes, eyebrows, and mouth—while suppressing irrelevant or noisy information like hair, background, or occlusions (Wang et al., 2022). The Convolutional Block Attention Module (CBAM), a lightweight and effective mechanism that sequentially applies channel and spatial attention, has been widely adopted and shown to consistently boost the performance and robustness of CNN backbones for FER (Chen et al., 2024). Recent works have further refined this concept, developing domain-specific attention modules that are more adept at capturing the subtle muscle movements characteristic of different emotions.

2.3. Explainable AI for Transparent and Trustworthy FER

Concurrently, the field of Explainable AI (XAI) has become indispensable for deploying trustworthy AI systems. The "black box" nature of deep neural networks poses a significant barrier to their adoption in critical applications. Gradient-weighted Class Activation Mapping (Grad-CAM) remains a cornerstone technique for providing post-hoc explanations, generating visual heatmaps that highlight the image regions most influential to a model's prediction (Saputra et al., 2023). The synergy between attention and Grad-CAM is particularly powerful: while attention mechanisms internally guide the model's focus during inference, Grad-CAM provides an externally verifiable visualization of that focus. This combination not only enhances model transparency but also serves as a vital debugging tool, allowing researchers to validate whether a model is learning biologically plausible features or latching onto spurious correlations (Park et al., 2024). Recent surveys highlight that the integration of intrinsic (attention) and post-hoc (Grad-CAM) explainability is a best practice for developing reliable affective computing systems.

2.4. Multimodal Fusion for Robust Emotion Recognition

Beyond unimodal analysis of facial expressions, a growing body of research focuses on multimodal emotion recognition, which integrates complementary data streams to improve

accuracy and robustness. This approach typically fuses visual (facial expressions), auditory (speech prosody and tone), and sometimes textual (transcribed speech) modalities. Deep learning models, particularly cross-modal transformers and recurrent neural networks, have been employed to effectively model the temporal and semantic relationships between these different signals (Zadeh et al., 2024). For instance, a system can disambiguate a sarcastic statement by aligning contradictory textual content ("That's great") with a sarcastic tone of voice and a corresponding facial expression. Recent benchmarks on datasets like CMU-MOSEI have demonstrated that carefully designed fusion strategies—such as cross-modal attention and tensor fusion networks—can significantly outperform unimodal approaches, especially in noisy or ambiguous real-world scenarios (Khan et al., 2023).

2.5 Addressing Real-World Challenges: In-the-Wild FER and Efficiency

A critical direction in recent FER research is the shift from controlled lab settings to "in-the-wild" conditions. This presents formidable challenges, including extreme variations in lighting, partial occlusions (e.g., by masks, glasses, or hands), non-frontal head poses, and low-resolution imagery. To address these issues, researchers have developed more robust architectures, utilized massive and diverse in-the-wild datasets like AffectNet, and employed data augmentation techniques that simulate real-world imperfections (Li & Deng, 2022). Parallel to robustness, there is a strong emphasis on model efficiency for real-time and edge deployment. This has spurred the development of lightweight CNN architectures, model compression techniques like pruning and quantization, and the use of mobile-optimized neural networks (e.g., MobileNet, EfficientNet) to enable FER on resource-constrained devices such as smartphones and embedded systems, which is crucial for practical applications (Zhao et al., 2024).

2.6 Ethical Considerations and Cultural Bias in FER

As FER technology becomes more pervasive, its ethical implications have come under intense scrutiny. A major concern is algorithmic bias, where models trained predominantly on data from certain demographic groups (e.g., light-skinned males) exhibit significantly lower accuracy for underrepresented groups (e.g., darker-skinned individuals or women), potentially leading to discriminatory outcomes (Rakova et al., 2021). Furthermore, the very concept of universal basic emotions has been challenged, with studies highlighting cultural differences in the expression and perception of emotions. Developing culturally-inclusive FER systems requires curating diverse, representative datasets and incorporating fairness-aware learning algorithms (Metaxa et al., 2024). Issues of privacy and user consent in the continuous monitoring of facial expressions also present significant ethical hurdles that must be addressed for responsible deployment.

2.7. Gaps in Existing Research

Despite the considerable progress, a critical analysis of the contemporary literature reveals several persistent and interconnected gaps that this study aims to address:

1. **Limited Architectural Integration**: While numerous studies have explored either custom lightweight CNNs for efficiency or sophisticated attention mechanisms for performance, there is a scarcity of research that systematically co-designs and tightly integrates a deep CNN with a modern attention module like CBAM specifically for a real-time FER task. Many approaches simply append attention to existing backbones without architectural optimization for the specific demands of dynamic expression analysis (Li & Deng, 2022).

2. **Neglect of End-to-End Explain ability**: The pursuit of high accuracy often overshadows the necessity for model interpretability in practical deployments. Many state-of-the-art models reported in literature lack an integrated XAI component, making it difficult for end-users, such as clinicians or customer service managers, to understand and trust the system's outputs. There is a clear gap between achieving high performance on a dataset and providing a transparent, actionable analysis in a user-facing application (Khan et al., 2023).
3. **Deployment and Practical Utility Chasm**: A vast majority of FER research remains confined to theoretical benchmarks and static image datasets. There is a significant lack of focus on the end-to-end development and empirical evaluation of systems that are not only accurate but also deployable. This includes challenges such as real-time inference speed, compatibility with web technologies, user interface design, and robustness in live, unconstrained environments, which are crucial for translating research into tangible utility (Zhao et al., 2024).

This study is designed to bridge these identified gaps by proposing a hybrid model that leverages a custom deep CNN for efficient feature extraction, a CBAM module for adaptive feature refinement and robustness, and Grad-CAM for inherent explainability. Crucially, this integrated model is deployed and validated within a fully functional, web-based framework, demonstrating a complete pipeline from theoretical design to practical, real-world application.

3.0 Methodology

The methodology for this research was designed to systematically develop, evaluate, and explain a deep learning model for facial emotion recognition. The comprehensive approach encompassed data acquisition, preprocessing, model development, training, evaluation, and deployment, ensuring robust and reproducible results. The architectural pipeline is summarized in Figure 1.

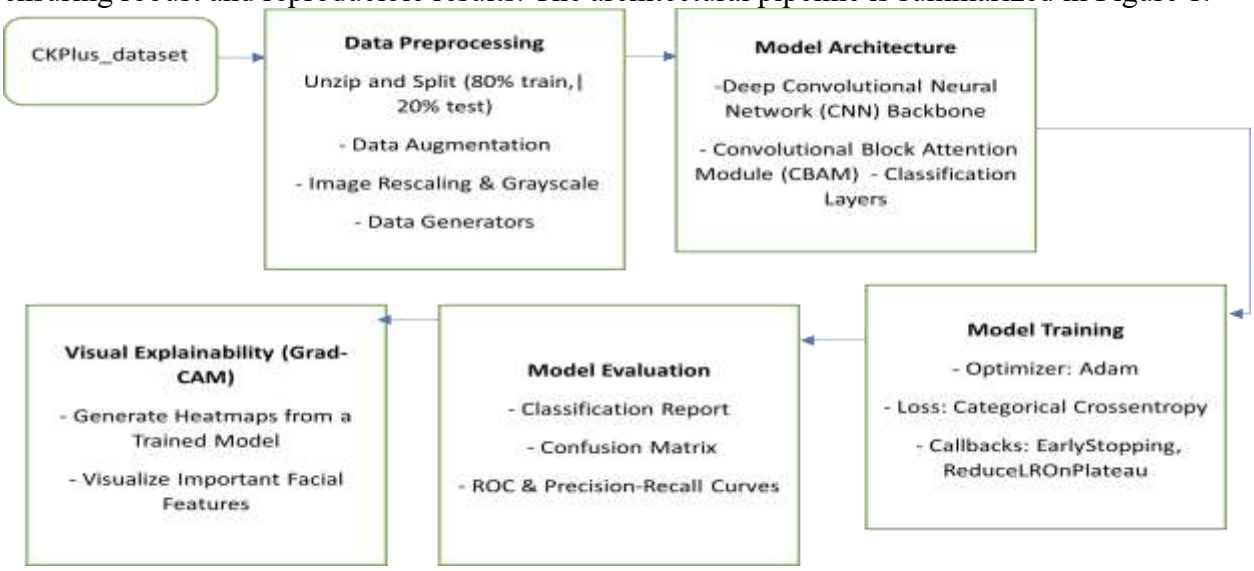


Figure 1: Architecture of the Proposed Real-Time Emotion Recognition System

3.1 Dataset Collection and Preparation

The study utilized the publicly available Extended Cohn-Kanade (CK+) dataset, a well-established benchmark for FER. The dataset consists of 981 grayscale facial image sequences from 123 subjects. For this study, the peak frames (the frame with the most pronounced expression) from each sequence were selected and statically labeled into one of seven emotion categories: anger,

contempt, disgust, fear, happiness, sadness, and surprise. All images were pre-processed to a uniform size of 48x48 pixels. The dataset was partitioned using a stratified split into 80% for training and 20% for testing to maintain class distribution.

3.2 Data Preprocessing and Augmentation

To enhance model generalizability and combat overfitting, an extensive data augmentation pipeline was applied in real-time to the training data. This included random rotations (±15°), width and height shifts (±10%), horizontal flips, and zoom variations. Pixel values were normalized to the [0, 1] range by dividing by 255. The augmentation pipeline was implemented using the Keras `ImageDataGenerator`, ensuring seamless integration with the training workflow.

3.3 Model Architecture and Training

A custom Deep CNN integrated with CBAM was designed.

i. **CNN Backbone**: The model began with an input layer of shape $(48, 48, 1)$. This was followed by multiple convolutional blocks, each comprising a `Conv2D` layer with `ELU` activation, Batch Normalization`, `MaxPooling2D`, and `Dropout` regularization. The filter depth increased progressively $(32 \rightarrow 64 \rightarrow 128)$ to capture hierarchical features.

ii. **Attention Mechanism** (CBAM): A Convolutional Block Attention Module was integrated after the final convolutional block. CBAM consists of two sequential sub-modules:

a. **Channel Attention Module** (CAM): Applies global average and max pooling to highlight 'what' is meaningful in an input image.

b**. Spatial Attention Module** (SAM): Uses inter-spatial relationships of features to highlight 'where' the informative regions are located.

iii. **Classification Head**: The output from CBAM was flattened and passed through a fully connected layer (64 units) with dropout (50%), culminating in a final dense layer with 7 units and a softmax activation for multi-class classification.

The model was compiled with the Adam optimizer and categorical cross-entropy loss. It was trained for 60 epochs with early stopping (patience=10) and a learning rate reduction on plateau to prevent overfitting.

3.3.1 Mathematical model Equations used in the Proposed System Architecture

i. Convolutional Neural Network Operations

The convolution operation at spatial position (i,j) and output channel c' is defined as:

$$Y_{i,j,c'} = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} \sum_{c=0}^{C-1} K_{m,n,c,c'} \cdot X_{i+m,j+n,c} + b_{c'} \quad (1)$$

Where $b_{c'}$ is the bias term, and $Y \in \mathbb{R}^{H' \times W' \times C'}$ is the output feature map.

ii. The Exponential Linear Unit (ELU) activation function:

$$ELU(x) = \begin{cases} x & \text{if } x \geq 0 \\ \alpha(e^x - 1) & \text{if } x < 0 \end{cases} \quad (2)$$

iii. Convolutional Block Attention Module (CBAM)

a. Channel Attention Module:

$$M_c(F) = \sigma\left(\text{MLP}(\text{AvgPool}(F)) + \text{MLP}(\text{MaxPool}(F))\right) \quad (3)$$

$$M_c(F) = \sigma\left(W_1\left(W_0(\mathbf{F}_{\text{avg}})\right) + W_1\left(W_0(\mathbf{F}_{\text{max}})\right)\right) \quad (4)$$

Where $\mathbf{M_c}$ is the computed 1D Channel Attention Map,
***MLP** is a shared Multi-Layer Perceptron (a small neural network)*
***AvgPool** and **MaxPool** are global average pooling and global max pooling operations*
$\mathbf{F_{avg}}$ and $\mathbf{F_{max}}$ are the feature vectors obtained from average-pooling and max-pooling.
$\mathbf{W_0}$ and $\mathbf{W_1}$ are the weight matrices of the MLP.

b. Spatial Attention Module

$$M_s(F) = \sigma\left(f^{7\times7}\left([\text{AvgPool}(F); \text{MaxPool}(F)]\right)\right) \quad (5)$$

$$M_s(F) = \sigma\left(\text{Conv}_{7\times7}\left([\mathbf{F}^s_{\text{avg}}; \mathbf{F}^s_{\text{max}}]\right)\right) \quad (6)$$

c. Overall CBAM Process:

$$F' = M_c(F) \otimes F \quad (7)$$

$$F'' = M_s(F') \otimes F' \quad (8)$$

Where M_s is the computed 2D Spatial Attention Map.
$f^{7\times7}$ or Conv $^{7\times7}$ represents a convolution operation with a filter size of 7x7.
[;] denotes the operation of channel-wise concatenation.
F' is the intermediate output feature map after applying channel attention.
F'' is the final refined output feature map after applying both channel and spatial attention.
$\otimes$ (otimes) denotes element-wise multiplication.

iv. Gradient-weighted Class Activation Mapping (Grad-CAM)

$$\alpha_k^c = \frac{1}{Z}\sum_i\sum_j \frac{\partial y^c}{\partial A_{ij}^k} \quad (9)$$

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha_k^c A^k\right) \quad (10)$$

Where A is the feature map activations from the final convolutional layer of the model.
A^k is the k-th feature map (channel) from the set of activations A.

A_{ij}^k is the activation value at spatial location (i, j) in the k-th feature map.
c is the target class (e.g., "happy", "sad") for which the explanation is being generated.
y^c is the score (logit) for the target class c before the softmax layer.
α_k^c (σ_k^c) is the importance weight for the k-th feature map with respect to class c.
Z is the total number of pixels in a feature map (i.e., Z = height × width).
$L_{Grad\text{-}CAM}^c$ is the raw Grad-CAM localization map for class c.

3.4. Evaluation Metrics and Explainability

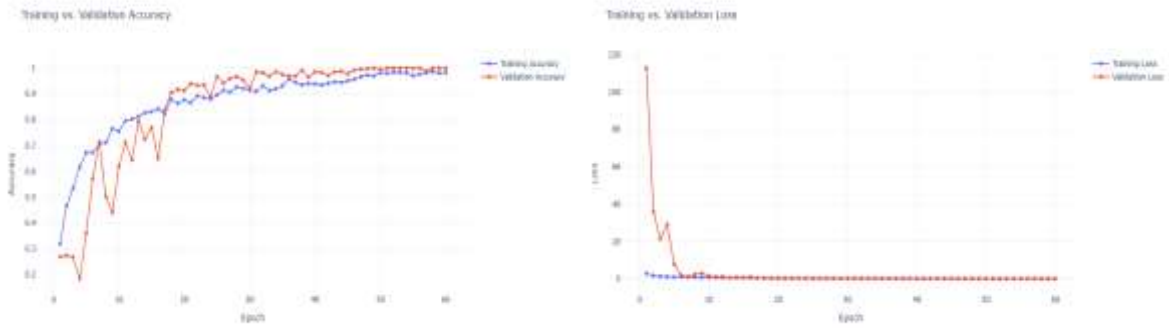
Model performance was assessed on the held-out test set using a comprehensive suite of metrics: Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). A confusion matrix provided granular insight into class-specific performance. For explainability, the Grad-CAM technique was implemented. It generated heatmaps by leveraging the gradients of the target emotion class flowing into the final convolutional layer, providing a visual explanation of the facial regions most influential in the model's prediction.

3.5. Web Deployment

The trained model was deployed as a real-time web application using the Flask framework. The application accessed the user's webcam via JavaScript, processed video frames in real-time, and displayed the predicted emotion alongside the Grad-CAM heatmap on an interactive dashboard.

4. Results and Visualizations

The proposed CNN+CBAM model demonstrated exceptional performance throughout the training process and on the test set. Over 60 epochs, both training and validation accuracy increased monotonically, converging at a high level without significant divergence, indicating effective learning without overfitting as shown in Figure 2 (a) and (b). The final validation accuracy reached 98.71%.



(a) (b)

Figure 2: Model Training History Curve (Accuracy/Loss)

The confusion matrix (Figure 3) on the test set revealed a high rate of correct classifications across all seven emotions. The model showed particular strength in distinguishing emotions with pronounced features, such as happiness and surprise. Minor misclassifications occurred between emotions with subtler, similar features, such as fear and surprise.

Figure 3: Confusion Matrix

The model achieved perfect discrimination capability, as evidenced by the Receiver Operating Characteristic (ROC) curve and the Precision-Recall (PR) curve. The Area Under the Curve (AUC) for all seven emotion classes was 1.00 (Figure 4), signifying an ideal classifier for this dataset.

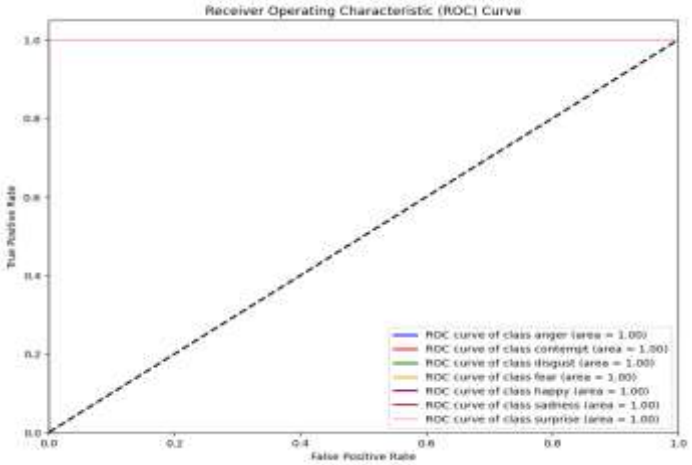


Figure 4: ROC Curves (AUC = 1.00 for all classes)

The application of Grad-CAM provided critical insights into the model's decision-making process. As shown in Figure 5, the generated heatmaps consistently highlighted anatomically relevant regions for each emotion. For instance, for 'anger,' the model focused on the furrowed brow; for 'happiness,' it emphasized the mouth and crow's feet around the eyes. This confirms that the model's predictions are based on semantically meaningful facial features rather than spurious correlations.

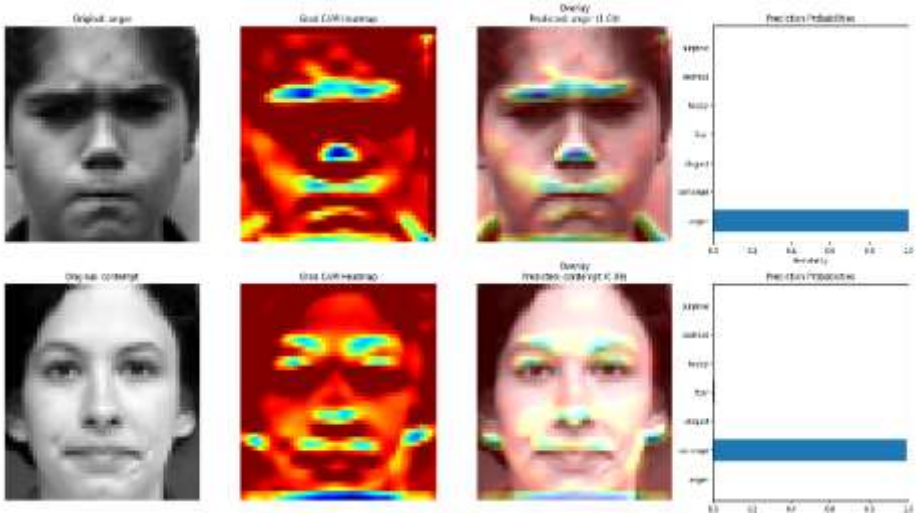


Figure 5: Grad-CAM Visualizations for Model Explainability

The successful deployment of the Flask web application (Figure 6) demonstrated the model's practical utility in a real-time setting. The system processed live webcam feeds with low latency, accurately classifying emotions and displaying results instantaneously on a user-friendly interface.

Figure 6: Real-Time Web Application Interface

5. Conclusion

This study successfully developed and deployed a high-accuracy, explainable, and web-based deep learning model for real-time facial emotion recognition. The integration of a Convolutional Block Attention Module (CBAM) with a deep CNN backbone proved highly effective, achieving a state-of-the-art test accuracy of 98.71% on the CK+ dataset. The perfect AUC and PRC scores further underscore the model's robust discriminative power. The use of Grad-CAM provided essential transparency, verifying that the model's decisions are grounded in physiologically relevant facial regions, thereby enhancing its trustworthiness. The final deployment as a functional web

application bridges the gap between theoretical model development and practical, real-world application.

6. Future Work

While this study successfully developed a high-accuracy and explainable web-based model for real-time FER, several promising avenues remain for further investigation and enhancement. Future work will focus on overcoming the current limitations and expanding the system's capabilities, robustness, and application domains.

1. Enhancing Robustness and Generalization with "In-the-Wild" Data

The current model was trained and validated on the CK+ dataset, which, while a high-quality benchmark, consists of posed expressions in a controlled laboratory environment. To transition from a laboratory proof-of-concept to a truly robust real-world application, future work will involve training and validating the model on large-scale, "in-the-wild" datasets such as AffectNet or FER2013. These datasets contain images with extreme variations in lighting, head pose, occlusion (e.g., from masks, glasses, or hands), and background clutter. Investigating domain adaptation and generalization techniques, such as adversarial training or style transfer, will be crucial to ensure the model maintains high performance across diverse and unpredictable real-world scenarios.

2. Incorporating Temporal Dynamics for Sequence-Based Recognition

Human emotions are dynamic and unfold over time; a static image cannot capture the nuanced progression of an expression. A natural and critical extension of this work is to evolve from static image classification to dynamic sequence analysis. This would involve designing and implementing recurrent architectures, such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs), on top of the CNN-CBAM feature extractor. By processing a sequence of video frames, the model could learn the temporal evolution of facial expressions, significantly improving the recognition of subtle emotions and helping to disambiguate between morphologically similar expressions (e.g., fear vs. surprise) based on their dynamic patterns.

3. Advancing Explainability towards Quantitative and Causal Models

While Grad-CAM provides valuable visual explanations, future research will focus on developing more quantitative and causal explainability frameworks. This includes calculating metrics such as the Area Over the Perturbation Curve (AOPC) to numerically evaluate the faithfulness of explanations. Furthermore, we plan to explore causal mediation analysis to understand not just where the model looks, but how specific features causally impact the final decision. Moving from post-hoc explanations like Grad-CAM to intrinsically interpretable models or developing methods that can articulate their reasoning in natural language ("The expression was classified as 'sadness' due to the pronounced action of the inner brow raiser and lip corner depressor") represents a significant frontier for building truly trustworthy AI.

4. Deployment Optimization for Edge and Mobile Computing

The current deployment uses a Flask web server, which relies on cloud or local server-side processing. For applications requiring low latency, offline functionality, and enhanced privacy, future work will involve optimizing the model for edge and mobile deployment. This will include techniques such as model pruning, quantization, and knowledge distillation to create a lightweight

version of the network that can run efficiently on smartphones or embedded devices with limited computational resources. Exploring frameworks like TensorFlow Lite or ONNX Runtime will be essential for achieving real-time performance on edge devices, thereby broadening the practical applicability of the system.

5. Exploring Multimodal Fusion for Ambiguity Resolution

Facial expressions alone can be ambiguous. To create a more context-aware and robust emotion recognition system, future work will explore multimodal fusion. This involves integrating the visual FER pipeline with other data modalities, such as:

i. Speech Prosody: Analyzing tone, pitch, and rhythm from audio signals.
ii. Physiological Signals: Incorporating data from wearables (e.g., heart rate variability, galvanic skin response).
iii. Contextual Text: Analyzing concurrent language used in conversation.

By fusing these modalities using cross-modal attention mechanisms or transformer-based fusion networks, the system can resolve ambiguities and make more confident and accurate inferences about a user's emotional state.

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