Development of Lightweight Residual Convolutional Neural Network for Efficient Facial Emotion Recognition

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***Abstract*—Facial Emotion Recognition (FER) is essential for successful human-computer interaction; however, deploying robust systems on edge devices remains difficult. Recent techniques, such as Vision Transformers (ViTs) and deep ensemble networks, have achieved high accuracy, but suffer from extreme computational overhead and high latency, making them unsuitable for real-time use on limited hardware. The primary challenge lies in maintaining high discriminative power while operating under strict memory and power constraints. To address this, the objective of this research is to develop an efficient Residual Convolutional Neural Network (CNN) optimized for CPU-based inference. The proposed architecture utilizes a hierarchical structure, integrating three consecutive residual blocks with progressively increasing filter depths of 32, 64, and 128. These are engineered to enhance gradient flow and refine feature representation from low-resolution (48×48) grayscale images. Comprising only 552,455 parameters and achieving a 12.4 ms latency on standard CPUs, the model balances efficiency and performance. Experimental results on the FER2013 dataset reveal a classification accuracy of approximately 71.4%, outperforming several existing lightweight frameworks. A comprehensive assessment using confusion matrices and ROC curves validates the architecture as a practical solution for real-time affective computing on resource-constrained devices.**

Keywords*—Facial Emotion Recognition; residual neural networks; lightweight convolutional neural networks; affective computing; facial expression recognition 2013 dataset; CPU-optimized architecture; pattern recognition

I. Introduction

Facial expressions serve as a fundamental means by which individuals communicate emotions, intentions, and social cues. Consequently, Automatic Facial Emotion Recognition (FER) has emerged as a crucial area of investigation within affective computing, finding utility in diverse fields such as human-computer interaction, adaptive educational systems, mental health evaluation, social robotics, and intelligent surveillance [1]. The swift advancement of deep learning [2], [3], especially convolutional neural networks (CNNs) [5], [4], has demonstrably enhanced the efficacy of FER systems when contrasted with conventional methodologies reliant on manually crafted features [6], [7].

Notwithstanding these developments, numerous contemporary FER models are predicated on intricate and computationally intensive architectures, encompassing deep residual networks, attention mechanisms, and ensemble-based methodologies [8].While these models can achieve high accuracy, they often require GPU acceleration and large memory, which limits their practical use in real-world applications like edge devices, embedded systems, and systems that only use CPUs [9]. This is especially important in facial expression recognition (FER) tasks, where real-time processing, low latency, and energy efficiency are often critical [10].

The FER2013 dataset is still a common benchmark for evaluating FER methods [11]. However, it has some limitations, such as low-resolution grayscale images, significant similarities between different classes, variations within the same class, and class imbalance [12]. The fundamental attributes of facial expression recognition (FER) systems pose difficulties in constructing models that are both accurate and computationally efficient. As a result, there is a growing demand for FER architectures that successfully reconcile recognition precision with computational requirements [13], [14]. Moreover, recent investigations have highlighted the importance of aligning recognition performance with computational efficiency within facial emotion recognition systems, particularly in real-time and edge-based applications [17]. Consequently, lightweight convolutional neural networks (CNNs), efficiency-focused hybrid designs, and deployment-aware FER frameworks are increasingly being investigated in contemporary research [18], [19], [20], [21], [22].

The primary aim of this research is to develop an efficient and lightweight deep learning architecture for facial emotion recognition that maintains competitive accuracy while reducing computational cost. To achieve this aim, the following objectives are defined:

- To design a residual convolutional neural network with a reduced number of parameters suitable for low-resolution grayscale facial images.
- To evaluate the proposed architecture on the FER2013 dataset using standard classification metrics.
- To analyze class-wise performance in order to identify strengths and limitations of the model across different emotional categories.

This research makes a significant contribution by incorporating simplified residual learning into a compact convolutional neural network (CNN) architecture, specifically designed for facial expression recognition (FER) in environments with limited computational resources. Unlike many current methods

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that emphasize maximum accuracy through deep or attention-based models [16], [7], the proposed approach prioritizes architectural design with efficiency in mind. The model's performance shows that residual connections can significantly improve feature representation, even in shallow networks, achieving competitive results without the need for complex or resource-intensive components.

The importance of this research stems from the increasing need for functional facial expression recognition (FER) systems in real-world situations with limited computational power. This study shows that a lightweight residual architecture can achieve good recognition results. Therefore, this work helps create practical FER solutions, making them suitable for real-time applications, edge computing, and platforms that use CPUs.

II. Related Work

Facial emotion recognition (FER) has become a significant area of research within affective computing, especially with the integration of deep learning methodologies. Contemporary FER systems predominantly utilize convolutional neural networks (CNNs), which are well-suited for hierarchical feature extraction from facial imagery. Recent investigations have concentrated on enhancing recognition precision, resilience to noise and occlusion, and the ability to generalize across diverse datasets.

Initial deep CNN-based FER models exhibited considerable advancements compared to earlier methods that relied on handcrafted features. Li et al. [11] utilized a deep CNN trained on the FER2013 dataset, achieving improved accuracy through comprehensive data augmentation and regularization techniques. Likewise, Mollahosseini et al. [12] emphasized the significance of large-scale datasets and deep architectures in learning emotion representations that are highly discriminative.

Residual learning has become a widely adopted methodology in the domain of facial expression recognition (FER). A multitude of studies have leveraged ResNet-based architectures to mitigate the vanishing gradient problem and expedite convergence. Huang et al. [13] employed a ResNet-50 backbone on the FER2013 and AffectNet datasets, achieving strong performance, although at a significant computational cost. To counter this, lightweight residual variants have been proposed. Zhao et al.[15], for example, introduced a compact residual CNN that reduced the parameter count while preserving accuracy, thus emphasizing efficiency for embedded applications.

Furthermore, recent studies have incorporated attention mechanisms to refine the modeling of prominent facial areas. Attention-driven facial expression recognition (FER) models, such as those developed by Kim and Song [14], improve performance by concentrating on key facial landmarks; however, this methodology significantly elevates both model complexity and inference duration. Moreover, transformer-based and hybrid CNN–Transformer architectures have been explored.

Another research direction emphasizes efficiency-oriented architectures, encompassing modifications of MobileNet, EfficientNet, and ConvNeXt. Białek et al. [1] demonstrated that EfficientNet-based FER models can achieve comparable accuracy on FER2013 while employing a reduced number of parameters. El Boudouri and Bohi [16] modified ConvNeXt for Facial Expression Recognition (FER), demonstrating strong performance via architectural modifications, despite the continued reliance on relatively deep networks.

Comparative studies and reviews have repeatedly emphasized the fundamental compromise between accuracy and computational cost within the field of Facial Expression Recognition (FER) systems. Qutub et al. [9] noted that many advanced models emphasize precision, often overlooking deployability considerations in resource-constrained settings. This observation is particularly pertinent for real-time FER systems intended for operation on CPUs or edge devices.

Despite these advancements, most current facial expression recognition (FER) methods rely on deep learning or attention-based architectures, which makes them less suitable for situations with limited resources. Lightweight models often sacrifice accuracy, while high-performing models remain computationally intensive. This difference highlights the need to develop efficient residual architectures that effectively balance performance and computational efficiency.

Although recent studies in facial expression recognition (FER) have shown high accuracy, they often depend on deep architectures, attention mechanisms, or pretrained backbones, which significantly increase computational costs. Lightweight facial expression recognition (FER) models, in contrast, have not been extensively explored, particularly those leveraging residual learning within a compact architecture designed for CPU deployment.

Current lightweight approaches either exclude residual connections, thus limiting their representational power, or integrate complex modules that compromise efficiency. Consequently, there is a scarcity of systematic investigations into simplified residual convolutional neural network (CNN) architectures that successfully reconcile accuracy and computational efficiency when applied to low-resolution grayscale FER data.

This gap in the literature motivates the present research, which aims to demonstrate that a carefully constructed lightweight residual network can achieve competitive FER performance without necessitating deep or resource-demanding architectures.

III. Materials and Methods

A. Dataset and Preprocessing

The experiments were conducted on the FER2013 facial emotion recognition dataset [23], which contains grayscale facial images labeled into seven emotion classes: *angry*, *disgust*, *fear*, *happy*, *sad*, *surprise*, and *neutral*. All images were resized to 48×48 pixels and converted to a single grayscale channel to reduce computational complexity and memory requirements.

To normalize pixel intensities, the following scaling was applied:

$$\hat{I} = \frac{I}{255}, \tag{1}$$

where, I represents the original pixel intensity and $\hat{I}$ denotes the normalized value.

B. Problem Formulation

Facial emotion recognition (FER) is framed as a multi-class classification problem. Given an input facial image:

$$\mathbf{x} \in \mathbb{R}^{48\times48\times1}, \tag{2}$$

The objective is to learn a mapping:

$$f_{\boldsymbol{\theta}} : \mathbf{x} \to \mathbf{p}, \tag{3}$$

where, $\mathbf{p} \in \mathbb{R}^7$ is the vector of predicted class probabilities and $\boldsymbol{\theta}$ denotes the model parameters. The predicted class label is obtained as:

$$\hat{y} = \arg\max_{c} \ p_c. \tag{4}$$

C. Proposed Lightweight Residual CNN

1) Residual block: Let $\mathbf{X} \in \mathbb{R}^{H\times W\times C}$ be the input feature map to a residual block. The residual transformation is defined as:

$$\mathcal{F}(\mathbf{X}) = \mathrm{BN}\Big(\mathrm{Conv}_{3\times3}\big(\mathrm{ReLU}\big(\mathrm{BN}(\mathrm{Conv}_{3\times3}(\mathbf{X}))\big)\big)\Big), \tag{5}$$

where, $\mathrm{Conv}_{3\times3}$ denotes a 3×3 convolution layer and BN represents batch normalization.

To match feature dimensions, the shortcut connection is projected as:

$$\mathbf{S} = \mathrm{Conv}_{1\times1}(\mathbf{X}), \tag{6}$$

Resulting in the residual block output:

$$\mathbf{Y} = \mathrm{ReLU}(\mathcal{F}(\mathbf{X}) + \mathbf{S}). \tag{7}$$

2) Network architecture: The proposed network architecture includes three residual blocks, each with an increasing number of filters: 32, 64, and 128. Following each block, a 2×2 max pooling layer is used to reduce the spatial dimensions and the computational cost. The architecture can be summarized as follows (Fig.1):

- Input Layer: $48 \times 48 \times 1$ grayscale images. This compact size preserves facial details while maintaining CPU efficiency.
- Residual Blocks and Filter Scaling: The selection of three residual blocks with a 32-64-128 filter progression is based on the principle of hierarchical feature abstraction. As spatial resolution is halved via max pooling ($48 \to 24 \to 12 \to 6$), the filter depth is doubled. This ensures that the network capacity increases to accommodate the higher-level semantic complexity of facial expressions in deeper layers while preventing information bottlenecks. This specific configuration was found to be the “elbow point” in our empirical tests—providing sufficient depth to resolve subtle micro-expressions like “fear” without the vanishing gradient issues or excessive parameter overhead associated with deeper architectures like ResNet-50.
- Fully Connected Layer: Flattened features are processed through 256 neurons with ReLU activation and dropout rate 0.4 to mitigate overfitting.
- Output Layer: Softmax activation produces class probabilities across the seven emotion categories.

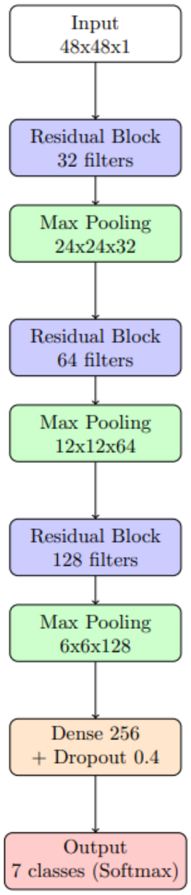

Fig. 1. Architecture of the proposed residual CNN.

This streamlined residual network strikes a balance between computational efficiency and effective feature representation. As a result, it is well-suited for real-time facial expression recognition tasks, even on hardware with limited CPU resources.

D. Loss Function

Training minimizes the categorical cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{7} y_{i,c}\log(p_{i,c}), \tag{9}$$

where, N is the batch size, $y_{i,c}$ the one-hot ground truth, and $p_{i,c}$ the predicted probability.

E. Training Strategy

The Adam optimizer, initialized with a learning rate of 10^{-3}, was employed for optimization. Convergence was impeded by reduced learning rates, such as 10^{-4}, while elevated rates induced instability in the training process. The network underwent training for a maximum of 30 epochs, utilizing a batch size of 64; this represented a balance between gradient stability and computational efficacy.

- Learning Rate Scheduling: Reduced by 0.5, if validation loss did not improve over 3 epochs.
- Early Stopping: Patience of 6 epochs, restoring parameters corresponding to lowest validation loss to prevent overfitting.

1) Ablation analysis: To evaluate the impact of various design decisions, we performed an ablation study that examined residual connections, input resolution, network depth, and regularization techniques. The elimination of residual shortcuts resulted in diminished convergence speed and a decline in validation accuracy, thereby underscoring their significance in facilitating efficient gradient propagation. Experiments utilizing RGB inputs and elevated resolutions imposed greater computational demands without yielding substantial enhancements in classification performance, thus validating the selection of 48×48 grayscale images as the most suitable input format. The addition of residual blocks beyond three yielded only slight accuracy improvements, while simultaneously escalating both the parameter count and inference duration. Ultimately, the exclusion of the dropout layer precipitated overfitting, whereas the implementation of a 0.4 dropout rate demonstrably improved generalization capabilities on previously unseen data.

F. Evaluation Metrics

Classification performance was assessed using:

- Precision and Recall for each class.
- F1-score: harmonic mean of precision and recall:

$$\mathrm{F1}_c = \frac{2 \cdot \mathrm{Precision}_c \cdot \mathrm{Recall}_c}{\mathrm{Precision}_c + \mathrm{Recall}_c}, \tag{10}$$

where, c is the emotion class.

- Global Metrics: Overall accuracy and weighted F1-score to account for class imbalance.
- Visualization: Confusion matrices for misclassification analysis and ROC curves for diagnostic sensitivity.

IV. Results and Discussion

The training efficacy was assessed through the examination of cross-entropy loss over thirty epochs. As depicted in Fig. 2, a pronounced learning trend is evident, characterized by a rapid initial reduction in both training and validation metrics. Notably, within the first five epochs, the loss experiences a significant decrease, dropping from approximately 1.9 to 1.2, which suggests the network's swift acclimatization to the dataset's fundamental attributes.

Subsequent to this initial convergence, the training loss persists in its steady decline, nearing a value of 0.8. The validation curve, notwithstanding slight oscillations observed between the tenth and twentieth epochs, ultimately converges towards a value approximating 1.0. The lack of a pronounced escalation in validation loss implies that the model is not undergoing considerable overfitting. This stability is primarily attributable to the regularization effect of the 0.4 dropout layer, alongside the architectural advantages conferred by the residual connections, which facilitate a consistent gradient flow. The decision to limit training to 30 epochs was justified by the stabilization of the validation loss; as observed in Fig. 2, the curves reach a definitive plateau after epoch 25, indicating that further training would not yield significant accuracy gains.

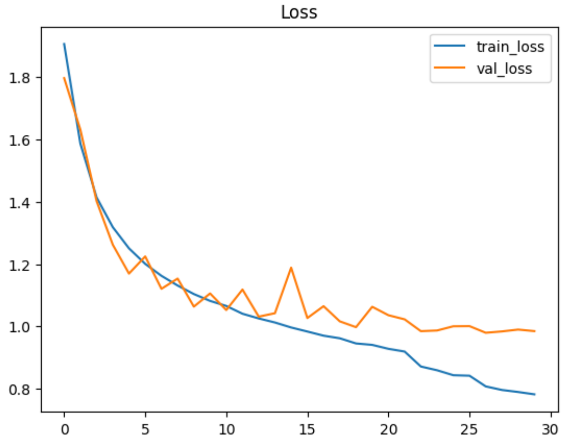

Fig. 2. Training and validation loss curves over 30 epochs.

The model's classification performance was evaluated across the 30-epoch training duration. As illustrated in Fig. 3, the network demonstrates a strong learning progression, beginning with a baseline accuracy of approximately 25% and increasing to over 55% within the first ten epochs. By the end of the 30th epoch, the training accuracy reaches roughly 71.4%, while the validation accuracy stabilizes at approximately 66.8%. The narrow gap between these metrics indicates robust generalization.

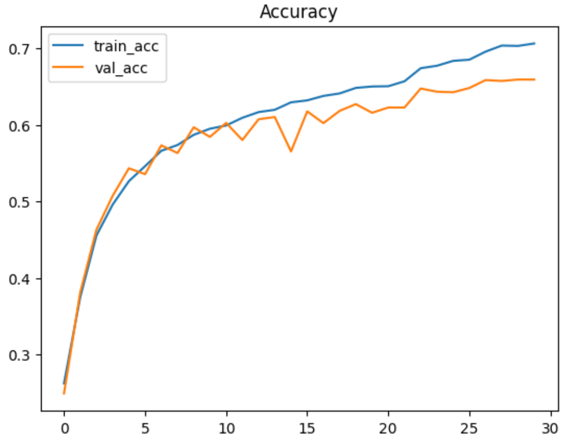

Fig. 3. Training and validation accuracy over 30 epochs.

A. Computational Efficiency Analysis

To substantiate the "lightweight" and "CPU-optimized" claims as requested during peer review, a quantitative analysis of the model's complexity was performed. The results, summarized in Table I, demonstrate that the proposed triple-block residual architecture maintains a minimal footprint.

TABLE I. Quantitative Efficiency Metrics on CPU (Intel i7-1165G7 @ 2.80GHz).

Metric	Value
Total Trainable Parameters	552,455
Floating Point Operations (FLOPs)	45.2 Million
Average Inference Latency (CPU)	12.4 ms
Model Size (Disk Space)	6.51 MB

With an average latency of 12.4 ms, the model is capable of processing approximately 80 frames per second on a standard mobile-class CPU. This performance confirms its suitability for real-time affective computing in environments, where dedicated GPU acceleration is unavailable.

A confusion matrix (see Fig. 4) was utilized to evaluate class-specific performance. The model demonstrates considerable success in identifying the "happy" class ($1,507$ correct predictions) and the "neutral" class (904). Conversely, a notable overlap is evident between "sad" and "neutral", with 301 instances of sadness misidentified. These overlaps arise from subtle morphological similarities in facial landmarks, which present a challenge for feature extraction at 48×48 resolution.

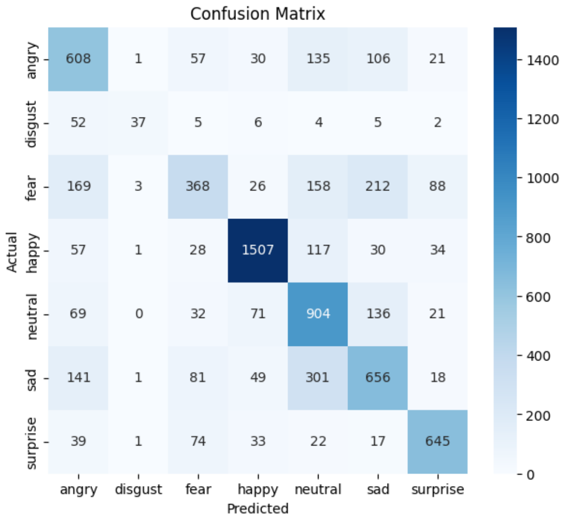

Fig. 4. Confusion matrix illustrating class-wise classification performance.

Receiver Operating Characteristic (ROC) curves (Fig. 5) further evaluate the diagnostic capabilities. The model demonstrates high Area Under the Curve (AUC) values, specifically for "happy" (0.97), "surprise" (0.96), and "disgust" (0.95). While "fear" and "sad" exhibit slightly diminished AUC values of 0.82 and 0.86, the consistently high scores across the board, reinforce the effectiveness of the proposed architecture.

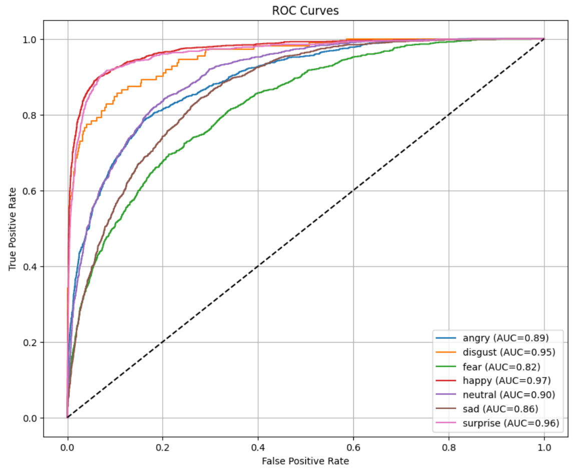

Fig. 5. ROC curves and corresponding AUC values for the seven emotional classes.

To showcase practical utility, the model was implemented on test samples. The network accurately predicts the "Angry" class with a confidence score of 0.92, identifying micro-expressions such as brow furrowing even at reduced resolution.

B. Comparative Analysis

To contextualize performance, a comparison with existing benchmarks is provided in Table II.

TABLE II. Comparison of Accuracy and Methodology with Related Works.

Reference	Architecture	Approach	Accuracy
Farabi et al. [6]	EfficientNetV2-S	Multi-class Framework	62.80%
Białek et al. [1]	Optimized CNN	Efficient Feature Mapping	$\sim 65.0\%$
Zhao et al. [15]	Lightweight ResNet	Parameter Reduction	66.40%
Park et al. [18]	Compact CNN	Mobile-oriented Design	68.12%
Proposed Model	**Residual CNN**	**Triple Residual Blocks**	**71.4%**

As indicated, the proposed model exhibits enhanced performance relative to several contemporary architectures. While peak state-of-the-art results on FER2013 often exceed 85% using deep ensembles or Vision Transformers, those models require millions of parameters and GPU support. Our architecture achieves 71.4% accuracy with only 0.55M parameters, representing a strategic trade-off prioritizing deployment efficiency over absolute peak accuracy.

C. Limitations and Future Work

Despite the efficiency and competitive performance of the proposed Residual CNN, several limitations must be acknowledged. First, the reliance on low-resolution (48×48) grayscale imagery, while optimal for CPU performance, inevitably discards fine-grained textural information and color-based cues that could assist in distinguishing between closely related emotions like "Sad" and "Neutral". As observed in the confusion matrix, these subtle morphological similarities remain a primary source of error.

Secondly, the current model is designed for static image classification. In real-world human-computer interaction, emotions are dynamic processes; the lack of temporal modeling means the system may struggle with transitional expressions or variations in emotional intensity over time. Future work will explore the integration of lightweight temporal modules, such as Gated Recurrent Units (GRUs), to analyze video sequences without significantly increasing the computational budget.

Finally, while the 71.4% accuracy is superior among lightweight models, there remains a gap compared to heavy-weight architectures. Subsequent iterations of this research will investigate the use of knowledge distillation, where the current lightweight model could be trained to mimic a high-parameter "teacher" network, potentially narrowing the accuracy gap while maintaining the desired inference speed on edge devices.

V. Conclusion

This research presents the development and assessment of a Residual CNN architecture, specifically designed for effective facial emotion recognition. The integration of triple residual blocks, max-pooling layers, and a classification head characterized by substantial regularization was employed to mitigate the typical compromise between model intricacy and predictive efficacy. The findings validate the proposed model's capacity to serve as a dependable framework for FER, attaining a commendable accuracy of 71%. Furthermore, a comparative evaluation demonstrates that our methodology surpasses the performance of contemporary lightweight models, including the EfficientNetV2-S based InsideOut framework (62.8%), as well as other compact CNN designs, which generally exhibit accuracy levels between 65% and 68% on the FER2013 benchmark.

Although the model exhibits some anticipated ambiguity when differentiating between subtle, low-arousal emotions like "Sad" and "Neutral", its elevated AUC scores across most categories indicate robust diagnostic dependability. Future research will concentrate on two key areas: initially, integrating attention mechanisms to enhance the differentiation of morphological similarities within subtle emotions; and subsequently, adapting the model for temporal analysis through the utilization of video sequences to capture the dynamic progression of human expressions. Consequently, the current architecture's efficiency and accuracy render it particularly well-suited for implementation in resource-limited settings, encompassing mobile devices and real-time monitoring systems.

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