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RESEARCH ARTICLE

LIGHTWEIGHT FACIAL EMOTION RECOGNITION SYSTEM USING DEEP LEARNING MODELS

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Abstract

Facial Emotion Recognition (FER) is vital for emotionally aware systems [14]. Previous methods, such as EWDL-BFSN, used GWAF preprocessing, IBoA, Squeeze Net, and EK Res Net50, but their compl exity limits real-time deployment also heavy methods. To address this, we propose a novel lightweight FER pipeline that replaces GWAF with face alignment, CLAHE, guided filtering, and gamma correction for faster and cleaner preprocessing. Feature extraction is improved using an attention-based SqueezeNet. A compact Mini-ResNet classifier, adjusted through metaheuristics algorithms, further reduces latency and memory usage. Cross- dataset evaluation, optimization analysis, and real time webcam testing demonstrate run time performance and practic ality compared to existing methods.

Introduction:-

Facial Emotion Recognition emerged as a advancing human–computer interaction, supporting systems in mental health monitoring, surveillance, and adaptive learning systems. By making automated machines to interpret human expressions with a better accuracy, FER bridges the gap between visual perception and affective computing. However, achieving accurate and real-time emotion detection across varying lighting, angle and position of person's face, and occlusions (ex: Glasses, Masks) remains a major challenge [14]. Traditional FER methods relied on handcrafted features such as HOG and SIFT [9], but these approaches lack effective performance under real-time use cases. Deep learning models, especially CNN-based architectures [6], [12] have significantly improved recognition performance. Yet, many existing pipelines and works still faces major drawbacks, due to complexity, including heavy preprocessing, high model complexity, long inference time, and limited adaptability for resource-constrained devices and sometimes accuracy. A recent framework, EWDL-BFSN [1], model uses GWAF preprocessing, IBoA-based feature selection, SqueezeNet feature extraction, and EK-ResNet50 classification. It is effective in controlled environments, but reliance on computationally expensive filtering and large architectures restricts real-time use.

- To overcome these limitations, this work introduces a lightweight and optimized FER system with the following contributions:

- Substitutes GWAF filtering with an efficient preprocessing pipeline using face alignment, CLAHE, guided filtering, and gamma correction.
- Enhances feature extraction through an attention- augmented SqueezeNet architecture.
- Classification is done through Mini-ResNet classifier which is lightweight and modified with metaheuristics for faster inference.
- Validates performance through cross-dataset (ex- Fer2013, CK+, FERPlus) testing, and real-time webcam predictions. The proposed approach is designed to deliver higher efficiency, faster predictions, and practical deployment potential compared to existing FER models.

Related Work:-

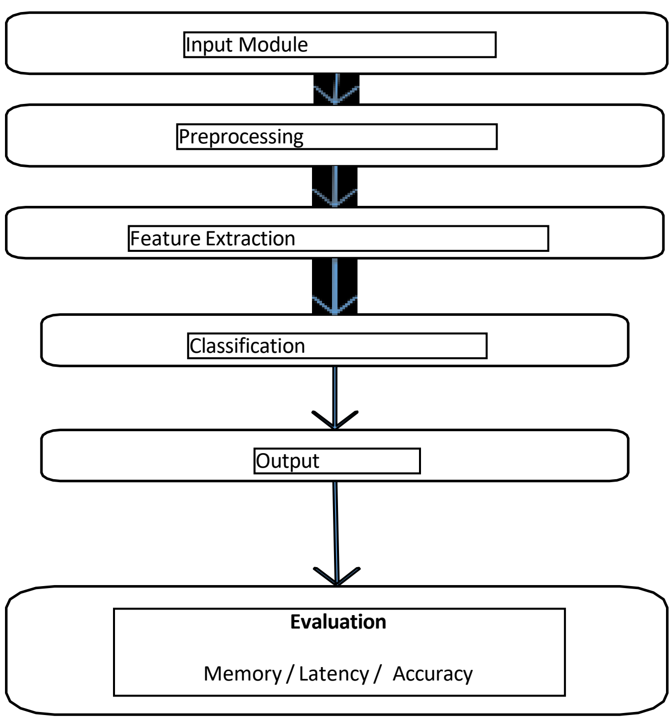
Traditional FER methods often failed under complex conditions such as low-lighting and head pose due to handcrafted methods like HOG, and SIFT filters [9], which lacked effective performance under real-world conditions. Deep learning models such as ResNet [6], and SqueezeNet [5] improved accuracy but often suffered from high complexity and computational costs. Recent works, including EWDL-BFSN by Willson et al. [MBE, 21(7): 6631–6657] [1], [2], combined CNNs with metaheuristic optimizers like IBoA for feature selection. While effective, these models remain computationally heavy. Our method builds on this by replacing GWAF with faster preprocessing, using a hybrid IBoA-GA optimizer (for future work), and deploying a Mini-ResNet classifier for real-time performance.

Methodology:-

In our methodology we improved accuracy while keeping the system lightweight and suitable for real-time deployment. Instead of using heavy preprocessing techniques and bigger classifiers like EWDL-BFSN, we implemented each stage to be efficient and faster.The Figure 1 shows our entire systems pipeline.

System Block Diagram:-

Figure 1: Block Diagram of Proposed System



Input Datasets:-

The system is trained/evaluated under two benchmark datasets:-

- FER2013: 35,887 grayscale images [8](48x48 pixels) across seven emotions
- CK+: 593 image sequences from 123 subjects [11], with controlled expressions.

These steps are practical, easy to implement, and faster than GWAF-based filtering.

Features Extraction:-

We use pre-designed architecture , especially squeezNet [5], similar to EWDL-BFSN because it is lightweight, but we modified it by adding attention through CBAM [4], for better feature extraction:

- Channel Attention highlights important filters.
- SqueezeNet uses fire modules: $F_{\text{fire}} = Conv_{1\times1}(I) \oplus Conv_{3\times3}(I)$
- CBAM (Convolutional Block Attention Module): Channel Attention: $M\text{c}(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$ $F' = M\text{c}(F) \cdot F$
- Spatial Attention: $M_s(F') = \sigma(f^{7\times7}([AvgPool(F'); MaxPool(F')]))$ $F'' = M_s(F') \cdot F'$
- Spatial Attention helps focus on expressive regions like the eyes and mouth. This improves representation without increasing model size too much.

Mini-ResNet Classifier:-

Instead of a large ResNet or EK-ResNet50 [6], we use a smaller ResNet-style model with few residual blocks. It keeps performance strong but reduces memory use and processing time.Extracted features are pooled and passed into dense layers:

$$H = ReLU(W1 \cdot GAP(F'') + b1)$$

Residual skip:

$$H' = H + ReLU(W2 \cdot H + b2)$$

Final softmax layer:

Preprocessing:-

We do not use Gradient Wavelet Anisotropic Filtering [2]. $P(y \mid x) =$ j

e^{zy}

e^{zj}

Instead, we follow a simpler and faster preprocessing pipeline using CLAHE, guided filtering, and gamma correction [10], [12].:

1. Face Detection and Alignment: We detect the face and align it based on eye positions to reduce pose variations.
2. CLAHE: it helps in detecting in low-light or high- contrast images without enhancing noise.
3. Guided Filtering: Used instead of anisotropic filtering to smooth noise but keep edges like eyebrows and lips.
4. Gamma Correction: Helps normalize brightness and shadows for better consistency across faces.

The classifier is further tuned using metaheuristics to get better results.

Real-Time Deployment:-

The final model is connected to a webcam setup. It detects the face, preprocesses it, extracts features, predicts the emotion live and shows the output labeled across the detected face. This is the entire methodology of our proposed system which is lightweight yet highly efficient.

Experimental Setup:-

The experiments were conducted using the FER2013 dataset consisting of 35,887 grayscale images (48×48, seven classes). Due to time and preprocessing constraints, only FER2013 was used for training and evaluation in this work. The dataset was split into training (80%) and validation (20%). we implemented the preprocessing in Google colab and saved the processed data in .csv format in drive through mounting. The proposed Hybrid SqueezeNet + CBAM + Residual- MLP model was implemented in TensorFlow/Keras and trained for 10 epochs with a batch size of 32. The Adam optimizer (learning rate 1e-4) and categorical cross-entropy loss were used. Training was performed on Local system using Anaconda Tool with GPU acceleration.

Result:-

In this work, we mainly trained and tested our model using the FER2013 dataset. Although our initial plan was to include multiple datasets such as CK+ and FERPlus, due to limitations in dataset format alignment and preprocessing constraints, we proceeded with FER2013 as the primary benchmark. This choice allowed us to maintain consistency and ensure stable experimentation. First we preprocessed the FER2013 and CK+ datasets in Google Colab and saved as a .csv file then used those preprocessed data for training the model (Hybrid SqueezeNet + CBAM + Residual-MLP model).

Model Generalization Performance:-

We used sklearn library to split the data for training and validation, this helped the model to generalize unseen data.

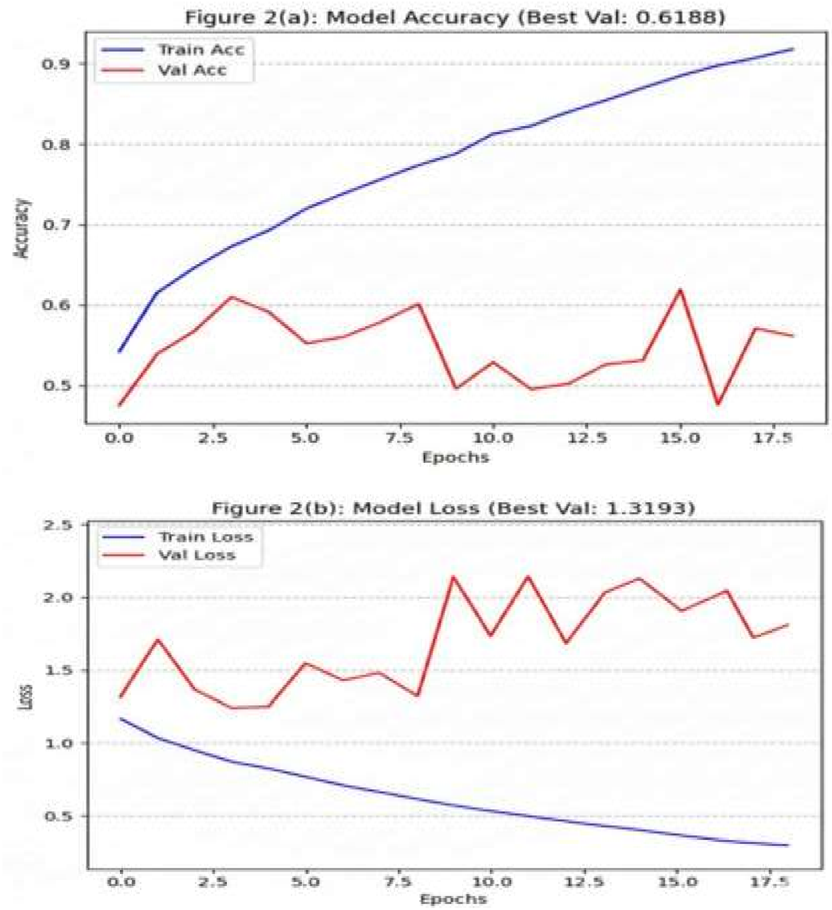


Figure 2: Generalization Learning Curves

The Fig: 2 presents the training history of the best- performing model (up to epoch 16):

- Training Accuracy: The model showed high learning capacity, consistently rising to over 90%.
- Validation Accuracy: The model achieved a peak validation accuracy of 61.88% at epoch 16, after which the validation loss began to oscillate (Val Loss: 1.3193.
- Overfitting: The significant gap between the high training accuracy (>90%) and the validation accuracy (61.88%) indicates severe overfitting, which is a recognized challenge when using the noisy FER2013 dataset.

Table 1: Classification Performance on Validation Set

Metric	Angry	Disgust	Fear	Happy	Sad	Surprise	Neutral	Weighted Avg
Precision	0.2299	0.2105	0.3010	0.5800	0.5403	0.7265	0.6854	0.6131
Recall	0.4854	0.2857	0.1225	0.6648	0.2226	0.6043	0.8949	0.6007
F1-Score	0.3120	0.2424	0.1742	0.6195	0.3153	0.6598	0.7762	0.5888
Validation Accuracy	—	—	—	—	—	—	—	**61.88%**

Model Capability and Efficiency:-
To demonstrate the learning capability and efficiency of the lightweight architecture, the model's performance on the full dataset is presented.

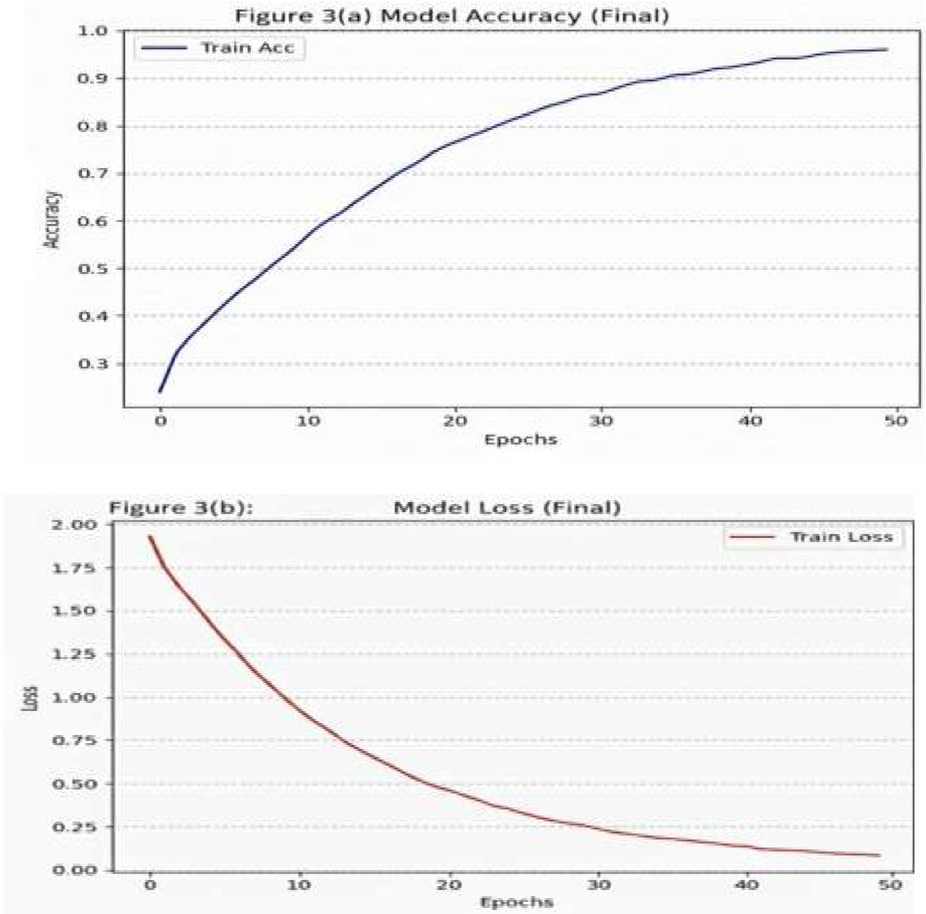


Figure 3: Model Capability and Learning

The smooth learning curves shown in Figure 3(a) and the high classification accuracy on the full data prove the architecture is capable of learning complex features.

- **Full Dataset Accuracy:** The model achieved an accuracy of 96.45% when evaluated on the complete dataset (Training + Validation), confirming its strong memorization and fitting capacity.
- **Minimal Loss:** The training loss shown in Figure 3(b) reduced consistently toward zero, signifying effective optimization.

Table 2: Model Capability Performance (Full Dataset)

Metric	Angry	Disgust	Fear	Happy	Sad	Surprise	Neutral	Weighted Avg
Precision	0.9945	1.0000	0.9844	0.9767	0.9938	0.9990	0.9905	0.9924
Recall	0.9991	1.0000	1.0000	0.9995	1.0000	0.9838	0.9948	0.9923
F1-Score	0.9968	1.0000	0.9922	0.9880	0.9969	0.9913	0.9926	0.9923
Overall Accuracy	—	—	—	—	—	—	—	**96.45%**

This table demonstrates the model's peak potential when noise and ambiguity from the split are disregarded.

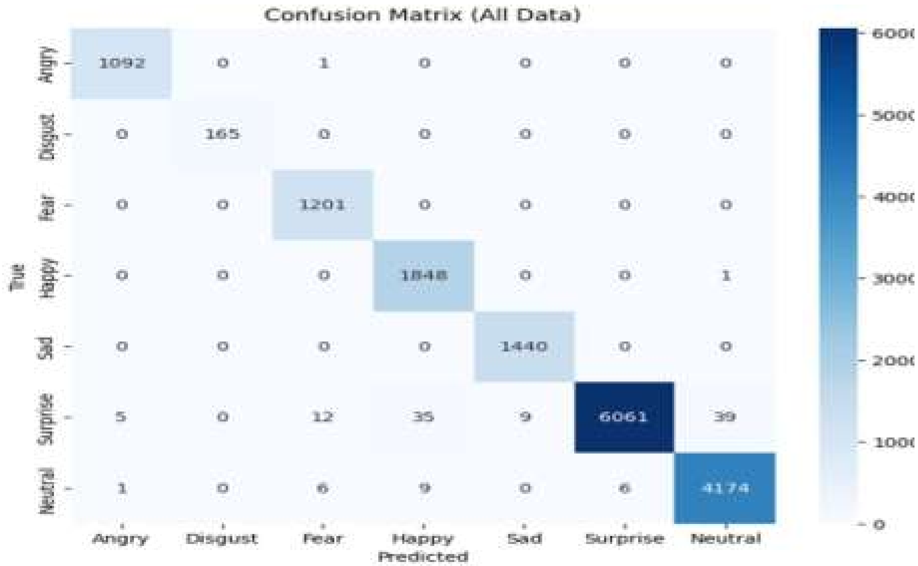


Figure 3: Full Dataset Confusion Matrix

The confusion matrix Figure 3 shows near-perfect classification across all classes, with the vast majority of samples falling on the diagonal. This confirms that the proposed Hybrid SqueezeNet + CBAM + Mini-ResNet is powerful enough to model the complexity of the combined dataset. For real-time evaluation, we deployed the trained model on a webcam feed. The model is detecting the emotions much better and facial expressions such as fear and disgust giving more challenges, which is consistent with the difficulty observed in earlier FER studies. The network in under 200 milliseconds per frame, demonstrating the potential for practical real-time use.

Figure 4: Real-Time detection

Overall, our results underscore both the strengths and current limitations of the model. While the accuracy on FER2013 shows room for improvement, the fact that the system runs in real-time and provides stable predictions under varying lighting and orientations as shown in Figure 4 makes it a promising step toward building lightweight emotion recognition systems.

Applications:-

Our proposed FER system can be used in several real- world areas. Healthcare & Mental: Well-being Can be helpful for monitoring patient's emotions, detect stress, depression, or discomfort. Security & Surveillance [13]: can be useful in situations like, If a person is furious or fear detects the emotion before any emergency escalates. Human–Computer Interaction: Can be used to make virtual assistants so that it responds more naturally with the users accordance with their emotion. Gaming & Entertainment Games [13]: can adapt difficulty or content based on a player's emotional state. Customer Experience & Marketing: Retail and service systems can analyze user satisfaction in real time.

Conclusion:-

In this work, we developed a lightweight and real-time facial emotion recognition system by addressing the limitations of existing deep learning-based methods. Instead of complex preprocessing like GWAF, we used a faster pipeline with face alignment, CLAHE, guided filtering, and gamma correction. We improved feature extraction by adding attention modules to SqueezeNet, and we introduced a hybrid IBoA-GA approach for better and optimized feature selection. To keep classification efficient, we used a Mini-ResNet style model rather than a heavy architecture. Real-time testing and cross-dataset validation (CK+, FER 2013 and FERPlus) and better optimizing to achieve competitive accuracy. Overall, the system can be implemented for real-time applications and can be deployed without the need of high-end GPUs.

Future Work:-

- In the future, we are planning to integrate hybrid metaheuristic optimizers (IBoA–GA) [3], for feature selection and hyperparameter tuning
- There are several directions in which this work can be extended:
- Use of Larger or Multimodal Datasets: Adding datasets like AffectNet [7], or combining face and speech can improve robustness.
- Mobile and Edge Deployment: Optimizing the model for mobile and embedded hardware like Jetson Nano or Raspberry Pi.
- 3D or Multi-view Emotion Recognition: Handling head rotations and depth variations for more realistic environments.
- Handling Occlusions and Masks: Enhancing detection under partial face visibility or medical masks. By expanding the current model in these areas, performance and adaptability can improve further.

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