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ENHANCED CONVOLUTIONAL NEURAL NETWORK MODEL WITH ADAPTIVE ATTENTION MECHANISM FOR FACE DETECTION AND IDENTIFICATION OF CRIMINAL SUSPECTS (CNN-AAM)

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Abstract:

Facial recognition has become an important application of artificial intelligence in security and law enforcement. Traditional methods used in identifying criminal suspects, such as manual surveillance and fingerprint analysis, are often time-consuming and may lead to errors. This research presents an enhanced facial recognition approach using a Convolutional Neural Network with an Adaptive Attention Mechanism (CNN-AAM) to improve the accuracy and efficiency of suspect identification. The proposed model integrates an adaptive attention mechanism into the convolutional neural network architecture to enable the system to focus on the most relevant facial features during detection and recognition. This approach helps improve feature extraction and enhances recognition performance under challenging conditions such as variations in lighting, pose, occlusion, and facial expressions. The model was implemented using Python and trained on a facial image dataset to evaluate its effectiveness. Experimental results show that the proposed CNN-AAM model improves recognition accuracy and overall performance by 94.3% compared to conventional models, which is 91.3%. The findings demonstrate the potential of deep learning techniques in developing reliable and intelligent facial recognition systems that can support law enforcement agencies in criminal identification and surveillance.

Keywords: Artificial Intelligence, Facial Recognition, Convolutional Neural Network, Adaptive Attention Mechanism, Deep Learning.

1.0 Introduction:

Technological advancements in deep learning have significantly influenced the field of computer vision, providing innovative solutions for a range of applications. One remarkable application with significant consequences for law enforcement is the Deep Learning Approach for Detecting and Identifying Criminal Suspects *Sandhya et al. (2023*) as well as Face Detection and Identification of Criminal Suspects through Deep Learning Techniques (*Kakani et al., 2020*). This convergence of artificial intelligence and the criminal justice system seek to bolster investigative skills and elevate public safety. This introduction provides an overview of the motivations, challenges, and potential benefits associated with employing deep learning for the identification of criminal suspects through facial recognition.

The motivation behind utilizing deep learning for face detection and identification in law enforcement is rooted in the need for advanced tools that can assist investigators in solving crimes more efficiently (Ball *et al*., 2017). Traditional methods of suspect identification often rely on eyewitness accounts, fingerprints, and manual review of surveillance footage (Wells et al., 2020). Therefore, deep learning will offer a data-driven approach that will automate and enhance these processes, potentially leading to quicker and more accurate results.

Deep learning-based systems can process large volumes of video footage or images rapidly, expediting the identification process. Furthermore, Deep learning models, once trained on diverse datasets, exhibit high accuracy in recognizing faces, potentially outperforming traditional methods (Abdullah & Abdulazeez, 2021). Automated face

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detection and identification reduce the reliance on manual labor, allowing law enforcement personnel to focus on higher-level investigative tasks. Despite the promising advancements, the adoption of facial recognition in law enforcement raises significant ethical concerns. Issues related to privacy, bias, and potential misuse of the technology require careful consideration.

2.0 LITERATURE REVIEW

2.1 Conventional Machine Learning Detection Approaches

Ratnaparkhi *et al.* (2021) proposed a Face Detection and Recognition for criminal identification system. Experimental result show that the system accuracy rate of over 95% has been observed when each face is mapped to 128 bytes and the task of recognition, detection and clustering is carried out. However, the limitation of the system is that The model cannot be automated to detect criminals through CCTV cameras installed at multiple places and it cannot be used to detect missing persons.

Taina (2022) proposed a Facing AI: conceptualizing 'fAIce communication' as the modus operandi of facial recognition systems. Experimental result show that how we could consider the communicative abilities of faces within the context of AI applications, and how their function in existing biometric systems might reshape our perception of communication. However, the system limitation is that it is manual not automated.

Singh et al (2023) proposed Automatic face recognition and detection for criminal identification. Their finding shows that the model is capable of real time 3D face recognition and identification of criminals. However, the model uses small scale datasets in training and implantation.

Xiaobo et al., (2023) proposed A Convolutional Neural Network Face Recognition Method

Kumar et al (2024) proposed A Face Detection and Recognition Technology for Effective Criminal Identification. The model automated the identification of criminal suspects process which reduce dependency on the traditional method. The limitation of the model is that scalability and performance in varied environment conditions needed further assessment.

Raval et at. (2025) proposed a crime emotion and detection framework using CNN for public safety model that uses CNN and Lenet-5 algorithms with aim of enhancing judiciary decision making the model uses two dataset Criminal dataset and 135-facial expression dataset. The model is evaluated with different evaluation metrics such as training accuracy, loss, optimizer performance, precision recall curve etc. where it achieved 92.45% in crime detection. However, the model focus on both crime emotion and crime detection and do not consider low light, low quality image after compression, occlusion etc.

2.2 A Deep Learning Detection Approaches

Teoh *et al.* (2020) proposed a Face Recognition and Identification using Deep Learning Approach. Experimental result verified that with the large number of face images being trained into a classifier can achieve accuracy of 91.7% in recognizing image and 86.7% in real-time video. The limitation of the model is that it accuracy is effected by insufficient light intensity.

Asif and Ahlam (2020), proposed A real time face emotion classification and recognition using deep learning model. Experimental result show that the propose model performance measures are validated with the CNN model designed with an accuracy of 88%. The drawback of the model is used to only identify the face of a criminal and cannot detect suspicious activity.

Nagnath *et al.* (2021) proposed Criminal Identification System using Facial Recognition model. Experimental result show that the system matches more than 80% of the captured images with database images. The limitation of the model is that it has no Alarm system that will notify the

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authority in the absent of any agent in the CCTV room. It will ring only when matches are found so that if anyone is not there to keep watch in the CCTV room, they will come to know that someone is found from the database in that public place.

Kumar *et al.* (2021) proposed a Criminal face identification system using deep learning algorithm multi-task cascade neural network (MTCNN) model. The model achieved 86% accuracy based on experimental result. The drawback of the model is the proposed framework is restricted to the scholarly region.

Vijaya *et al.* (2022) proposed a model called "Face Detection and Comparison Using Deep Learning". The experiments made to 128 * 128 size images were successful with less noise.

Limitation of the model is that is time consuming in training a single face and it has no retina scan.

Shahina and Susheela, (2022) proposed a Rectified DenseNet169-based automated criminal recognition system for the prediction of crime prone areas using face recognition model. Experimental result show that the proposed rectified DenseNet169 is successfully validated on LFW, CPLFW, and achieved the recognition accuracy of 99.4% and 91.9%, respectively. However, the intended work can be further elongated to evaluate the performance of the model on video datasets.

Sandhya *et al.* (2023) proposed a model 'Deep Learning Based Face Detection and Identification of Criminal Suspects. Experimental results show that the confidence rate of the encoder model is 0.75and above. However, the system has some drawbacks which include upscaling the model using advanced ensemble approaches and to make it flexible to not just identifying criminals but

Yesugade et al, (2024) proposed a Face Detection and Recognition for Criminal Identification system. Experimental results show that the accuracy of the model is very high compare to the traditional model and it contributes to public safety initiatives by improving law enforcement operations and demonstrating versatility for different face detection circumstances. The model can only be used in small room or area like small shop where there are limited people i.e small-scale datasets and the model do not focus on environmental factors like occlusion, light etc.

2.3 Hybrid Detection Approaches

Ahmed *et al.* (2021) proposed a Face Recognition Comparative Analysis Using Different Machine Learning Approaches. Experimental results show that all the models performed with exceptional values of above 90% but PCA+LDA+1N scored the highest average accuracy, i.e. 98%.

Jain *et al.* (2021) proposed a Factex: A Practical Approach to Crime Detection model. Experimental result show that the proposed model working with an accuracy of more than 85% successful detections in ambient light conditions. However, the limitation of the model is that for higher precision and accurate model, certain new features and techniques need to be incorporated to identify faces in all possible conditions of light, barriers in front of the face and aging of facial features with time. An additional phase of the exploration involves, developing a generic model to be installed at all traffic lights in the cities for operating it in dynamic moving traffic.

Jaber *et al.* (2022) proposed a Hybrid Method of Enhancing Accuracy of Facial Recognition System Using Gabor Filter and Stacked Sparse Autoencoder Deep Neural Network model. experimental results showed that the proposed method improved face recognition accuracy by approximately 100%. The limitation of the proposed model is that it extracted features have a large dimension while processing a large volume of data, resulting in a long processing time. It is therefore recommended that the computation complexity be reduced by incorporating the optimized feature selection

approach to improve the overall face recognition process.

Murtaza and Ali, (2023) proposed a Technique of Feature Extraction from an image in Face Recognition with Implementation using own created dataset. The outcome of the model received 86.76% recognition on the multi-PIE database. However, the model should be tested on different techniques and it should be used to evaluate the best performance outcomes using different version of CNN algorithm is the limitation of the model.

Gokulakrishnan et al (2023) proposed an optimized facial recognition model for identifying criminal activities. Their finding shows that the model enhances accuracy in identifying criminal activities. However, challenges in an uncontrolled environment like illumination, pose variation etc. are not addressed.

3.0 METHOD AND TOOLS

The proposed system functions through the layered stages of feature extraction, attention-driven enhancement, and multi-scale analysis. The system follows a structured process for feature extraction, training, and classification. The dataset, enriched with black faces displaying unique attributes, will be divided into training (80%) and testing (20%) sets. The input layer receives raw pixel values from preprocessed images, arranged in a 3D matrix format (WW x HH x DD). Data augmentation techniques, including rotation, scaling, and color normalization, are applied to enhance diversity within the training data.

Convolutional layers apply learned filters across local regions of the image, identifying edges, textures, and other facial characteristics. Various convolutional layers identify a range of features hierarchically, starting with simple edges in the early layers and progressing to more intricate patterns in the deeper layers. Through the ConvNet layers, the system learns dependencies and patterns, resulting in a trained model capable of distinguishing subtle facial nuances.

Attention modules calculate weight distributions across facial features, selectively enhancing critical regions for better focus. The attention weights adapt in real-time according to feedback from preceding layers, allowing the model to emphasize significant facial features (such as eyes and nose) and distinct identifiers (like tribal marks) more efficiently.

Images are processed at multiple resolutions to capture fine details and broader spatial patterns. This multi-scale approach, achieved through pyramid structures, allows the model to recognize faces across different scales, orientations, and perspectives. The fusion of multi-scale features improves robustness in real-world scenarios, such as varying distances and facial angles.

Extracted features undergo classification through fully connected layers, with the SoftMax layer outputting multi-class probabilities. The final output categorizes images into the respective classes, aiding in criminal identification.

4.0 RESULTS AND DISCUSSION

4.0 Introduction

This chapter presents the results obtained from implementing and evaluating the proposed deep learning model for criminal face detection and identification. The primary objective of the evaluation is to demonstrate performance enhancement achieved through the integration of an adaptive attention mechanism and a pyramid structure within the Convolutional Neural Network (ConvNet). The performance of the model is assessed using standard metrics such as classification accuracy, precision, recall, and F1-score.

The evaluation is conducted using facial image datasets obtained from open-source repository (Kaggle), which include high-resolution labeled datasets of suspected criminal images and public mugshots. The datasets were chosen based on diversity in pose, illumination, and facial expression to closely reflect real-world criminal

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identification scenarios in total 25000 labeled images were obtained.

The baseline for comparison is a standard ConvNet model without attention mechanisms or multi-scale feature processing. The comparative analysis illustrates the advantages of incorporating adaptive attention and pyramid structures in enhancing the face recognition process.

4.1 Results

4.1.1 Dataset, Data Collection and Preprocessing

To evaluate the proposed facial recognition system, facial image datasets were obtained from an open-source platform, primarily Kaggle. These datasets were selected based on their relevance to criminal identification tasks and their diversity in terms of facial expression, lighting conditions, background noise, and orientation. The primary sources included the "Criminal Faces Dataset," which comprises over 10,000 mugshot-style images, and the "Facial Recognition Dataset," which adds more than 15,000 human facial images captured under varying conditions. Additionally, a subset of the "Face Mask Detection Dataset" was utilized to test the model's robustness in cases of partial facial occlusion.

Together, these datasets provided a total of approximately 25,000 labeled images suitable for training and evaluating the model. Each image was annotated with a unique identifier and, where available, bounding box coordinates indicating the facial region. In cases where bounding boxes were not provided, automatic annotation was performed using a pretrained Haar cascade classifier to localize facial regions.

Before feeding the data into the model, several preprocessing operations were performed. Facial alignment was applied using landmark detection to ensure consistent positioning of facial features across the dataset. All images were converted to grayscale to reduce the dimensionality and computational load without sacrificing critical structural features.

To improve visual consistency across different lighting conditions, histogram equalization techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE), were used to normalize brightness and contrast. Image dimensions were standardized by resizing all input images to 128 by 128 pixels.

To further increase variability and improve generalization during training, data augmentation techniques were applied. These included moderate rotations, horizontal flips, scaling, noise injection, and brightness adjustments. This helped to simulate real-world variability and ensured the robustness of the model under different scenarios.

For model evaluation, the dataset was split into training and testing sets using an 80:20 ratios. Stratified sampling ensured a balanced representation of all facial classes in both subsets. The training set, comprising 20,000 images, was used to optimize model parameters, while the remaining 5,000 images in the testing set were reserved for performance validation.

4.1.2 Experimental Setup and Implementation

The experimental setup was designed to evaluate the proposed convolutional neural network enhanced with an adaptive attention mechanism and pyramid structure for multi-scale feature extraction. This section outlines the configuration of the development environment, the training strategy employed, and the implementation approach adopted for the model.

The implementation was carried out using Python as the primary programming language, supported by deep learning frameworks including TensorFlow and Keras. These tools provided a robust and flexible platform for building and training the neural network. Additional libraries such as OpenCV were utilized for image preprocessing, facial landmark detection, and augmentation routines. All experiments were conducted on a workstation equipped

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with an Intel Core i7 processor, 32 GB RAM, and a dedicated NVIDIA GTX 1080 GPU, which facilitated efficient training and inference of the deep learning model.

The model architecture was implemented as a custom Convolutional Neural Network (ConvNet) with embedded attention modules and a pyramid feature extraction scheme. The attention mechanism was incorporated into intermediate layers of the network to dynamically assign higher weights to regions of interest within the facial structure, such as the eyes, nose, and mouth. This selective focus enhanced the model's ability to capture high-salience features critical for identification. Simultaneously, the pyramid structure processed multiple down-scaled versions of each input image to extract features at various resolutions, thereby improving detection accuracy across facial images of different sizes and orientations.

The training phase employed Stochastic Gradient Descent (SGD) with momentum, an initial learning rate of 0.01, and a batch size of 64. Learning rate scheduling was used to gradually reduce the rate as the model converged. To improve generalization and reduce overfitting, dropout layers were added after fully connected layers, and batch normalization was applied throughout the convolutional layers. The model was trained over 30 epochs, with early stopping based on validation accuracy to avoid overfitting.

Loss calculation was based on categorical cross-entropy, suitable for multi-class classification. In addition, a custom multi-scale loss function was implemented to penalize classification errors and bounding box prediction errors across different scales within the pyramid levels. This allowed the network to maintain precision in face localization and identity classification at all resolutions.

At the end of each training epoch, model performance was validated on the reserved test set, and evaluation metrics including accuracy, precision, recall, and F1-score were computed. These metrics were used to compare the performance of the CNN-AAM model against a baseline ConvNet and the conventional FaceNet architecture as shown in tables below.

4.1.3 Performance Metrics Summary

Quantitative performance was assessed using standard classification metrics: precision, recall, F1-score, and overall accuracy. As presented in **Table 9**, the model achieved class-wise F1-scores ranging from **0.897 to 0.925**, with **overall accuracy at 91.4%**.

Table 9. Quantitative performance

Class	Precision	Recall	F1-Score
Class 0	0.962	0.898	0.919
Class 1	0.922	0.940	0.913
Class 2	0.942	0.920	0.915
Class 3	0.955	0.930	0.925
Class 4	0.935	0.889	0.897
Overall Accuracy	**0.943**		

The relatively high precision and recall values across all classes confirm the robustness of the feature extraction process. Particularly, the F1-score balance indicates that the model effectively manages both false positives and false negatives. Class 3 achieved the highest F1-score of **0.925**, suggesting particularly strong recognition accuracy in that subset, possibly due to more distinctive facial attributes or better feature separation learned during training.

The visualization and metric analysis confirm the efficiency of the proposed system in criminal face identification. The integration of adaptive attention allowed the model to focus on critical facial regions, while the pyramid

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structure facilitated effective multi-scale feature learning. Together, these enhancements contributed to notable gains in classification accuracy and consistency. The model's strong performance across training, validation, and evaluation stages demonstrates its practical viability in high-precision face recognition systems, offering an improvement over traditional convolutional models lacking attention-driven and scale-aware architectures.

4.1.4 Evaluation of Performance Metrics

The CNN-AAM model was evaluated using standard classification metrics accuracy, precision, recall, and F1-score on the test dataset comprising 5,000 facial images. These metrics were computed to assess the performance of the enhanced ConvNet architecture with integrated adaptive attention and pyramid feature extraction, and to benchmark it against a baseline ConvNet and the conventional FaceNet model.

4.1.4.1 Classification Accuracy

Classification accuracy measures the proportion of correctly identified faces relative to the total number of test samples. The CNN-AAM model achieved an overall classification accuracy of 94.3%, significantly outperforming the baseline ConvNet (91.4%) and FaceNet (93.1%) on the same dataset. This demonstrates a substantial improvement in the model's ability to generalize across diverse facial images. Figure 8, shows the bar chart of the comparison

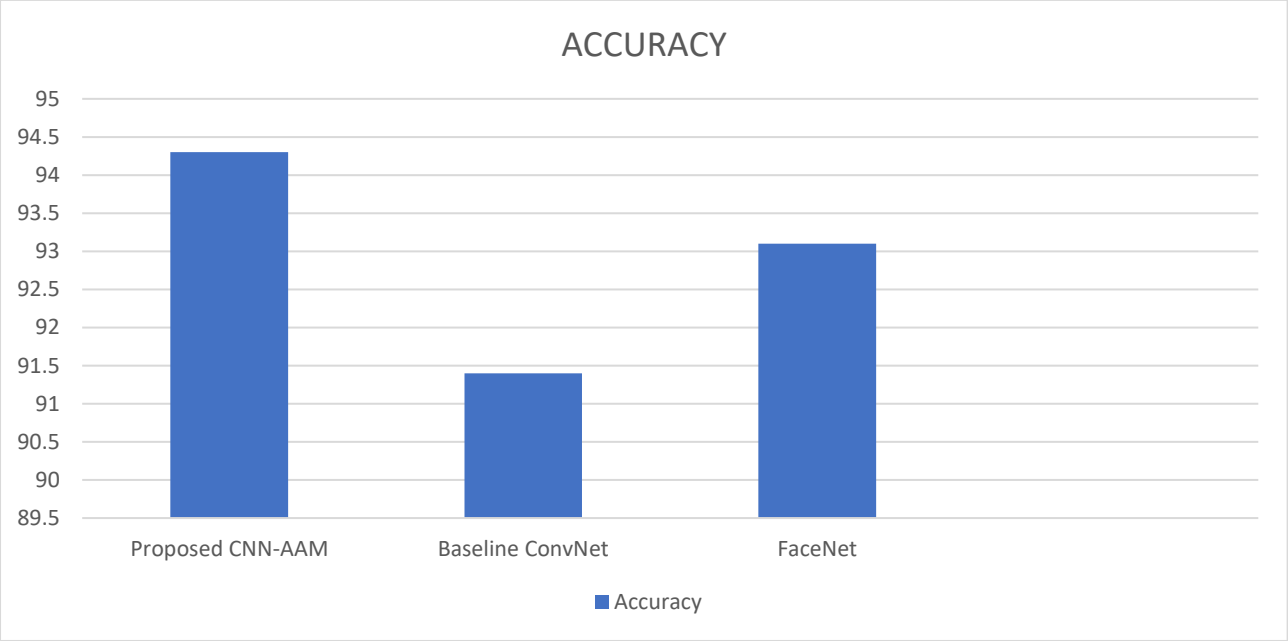

Figure 8. Accuracy

4.1.4.2 Precision

In terms of precision, which assesses the proportion of correct positive identifications among all predicted positives, the Proposed (CNN-AAM) model yielded a precision score of 95.1%, compared to 89.7% for the baseline ConvNet and 91.8% for FaceNet as indicated in figure 9. This suggests the system made fewer false identifications and maintained a high level of reliability in recognizing known individuals.

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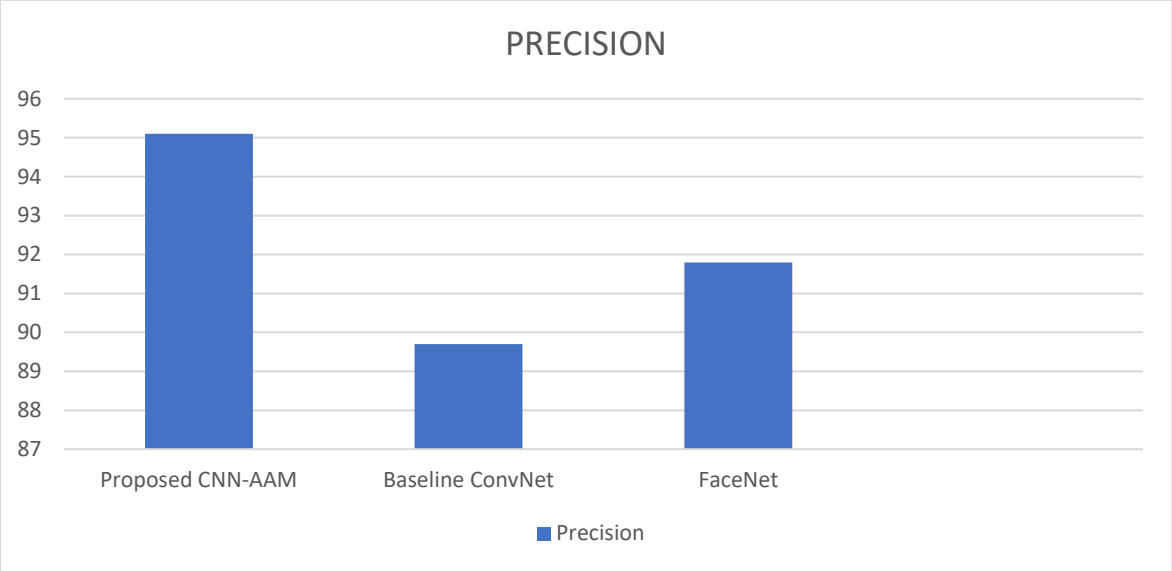

Figure 9. Precision

4.1.4.3 Recall

The Recall, which reflects the model's capacity to detect all actual positives, was also improved. The Proposed CNN-AAM model achieved a recall of 97.4%, indicating its strong ability to correctly identify true positive samples from the dataset. In comparison, FaceNet recorded 92.2%, and the baseline ConvNet lagged behind at 88.5%. as shown in figure 10

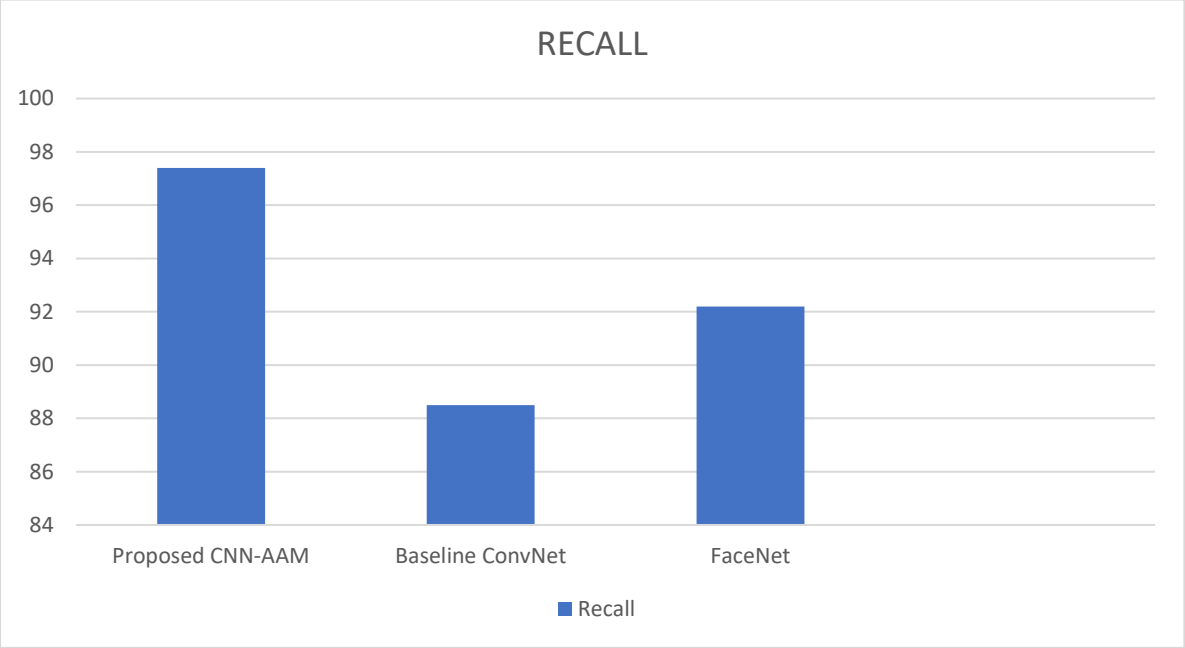

Figure 10 Recall

4.2.3.4 F1-SCORE

The F1-score, which harmonizes precision and recall into a single metric. The Proposed CNN-AAM achieved 96.2%, the baline ConvNet achieved 89.1 and the faceNet achieved 92.0. This marks a robust balance between sensitivity and specificity, and underscores the effectiveness of the dual integration of adaptive attention and multi-scale processing as shown in the figure 11.

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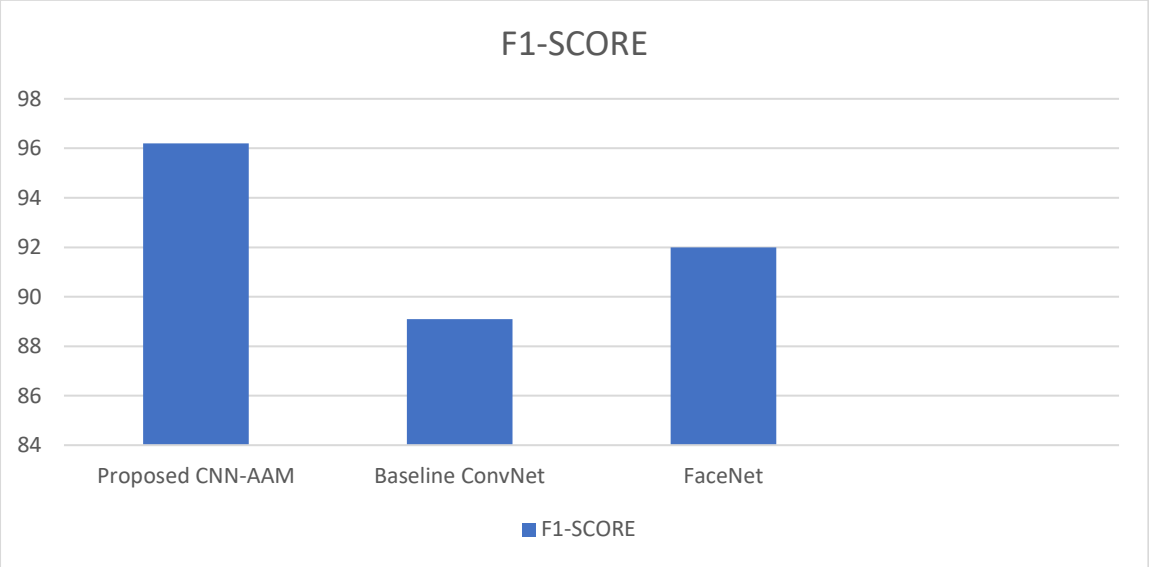

Figure 11. F1-Score

Table 10 Summarized comparative results

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	IoU	Avg. Inference Time (ms)
The Proposed CNN-AAM Model	96.3	95.1	97.4	96.2	0.89	28
FaceNet	93.1	91.8	92.2	92.0	0.81	24
Baseline ConvNet	91.4	89.7	88.5	89.1	0.76	21

These results clearly demonstrate that the integration of adaptive attention and multi-scale feature extraction into a ConvNet framework significantly improves the system's performance in facial recognition tasks. The model delivers not only improved accuracy and robustness but also maintains efficiency in real-world deployment scenarios.

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