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RESEARCH ARTICLE

FA-FAS Net: Deep Learning Network for Face Recognition using Faster Region based Convolutional Neural Network

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Abstract – Face recognition (FR) has become an essential biometric technology for security, surveillance, and identity verification in modern intelligent systems. However, existing FR approaches often suffer from reduced accuracy under challenging conditions like pose variation, illumination changes, occlusion, and background noise. To address these limitations, a novel FA-FAS Net is proposed for robust and accurate face recognition. the input facial image is obtained from a face image dataset and passed through a face detection and cropping stage to isolate the facial region from the background. The detected face fed into preprocessing, it includes resizing to a standard dimension, normalization to maintain consistent pixel intensity distribution, and denoising to remove unwanted noise and enhance image quality. The pre-processed image is subsequently forwarded to the feature extraction module, where a deep convolutional neural network based on RegNet is employed to learn discriminative facial representations and generate robust feature maps. These extracted features are then utilized in the detection and recognition stage, where a backbone network inspired by VGG16 supports the object detection framework implemented using Faster R-CNN, which accurately localizes and classifies the detected face. Finally, the system outputs the recognized identity, demonstrating the efficiency of the integrated deep learning framework for reliable and high-precision FR in real-world applications. The FA-FAS Net maintains high accuracy levels of 98.87% based on the gathered dataset. The FA-FAS Net enhances the total accuracy by 0.99%, 4.07% and 4.92% better than FER, CNN, and Deep neural network respectively.

Keywords *– Face Recognition, Deep Learning, Attention Mechanism, Feature Fusion, Biometric Identification, Image Classification.*

1. INTRODUCTION

Emotions and their analysis on the human face are essential to nonverbal interaction. It promotes better oral communication and makes it more efficient and suitable in communicating the concepts [1]. It also suits to identify human attention, including behaviour, mental state, personality, tendency to commit crime, lies, etc. irrespective of gender, nationality, culture and race, the majority of people can easily identify the emotions of the face [2]. Nevertheless, one of the difficult tasks is the automation of face emotion recognition and classification. Besides this, machines should also be trained sufficiently to be able to comprehend the immediate environment particularly, the intentions of an individual [3]. One has to offer a system that is able to detect emotions of people faces with the same knowledge that human beings possess [4]. In the recent past, FER has been a newly discovered research area, especially over the past few decades [5].

The initial stage of the FER process is facing detection or the process of finding or identifying faces in a video or a single picture [6]. The pictures are not made of faces only, but rather show with complicated backgrounds. In fact, human beings can easily perform facial predictions and other facial features of an image, yet, it is a challenge to machines without superior training [7]. Face detection aims mainly at isolating face images and the non-faces (background). Others areas of face detection include gesture recognition, video surveillance system, automated cameras, gender recognition, feature recognition, face recognition, tagging and teleconferencing [8]. First, these systems must recognize faces as inputs. Everywhere there is a color sensor for image acquisition, color images are captured. As a result, the majority of existing FR methods rely on grayscale, and only a small number of methods can work with color photos. These systems either use the two primary methods of face recognition, pixel-based and window-based, which are used to increase accuracy. It takes longer to differentiate the pixel-based method a person's face from their hands. The main contribution of the research is summarized as follows,

- A novel FA-FAS Net is proposed that integrates advanced preprocessing, feature extraction, and detection modules to improve recognition accuracy.

- An efficient feature extraction mechanism based on RegNet is introduced to learn robust and discriminative facial representations, enabling improved identification performance across diverse facial datasets.
- A high-precision face detection and recognition module is developed using a combination of VGG16 as the backbone network and Faster R-CNN for accurate face localization and classification.

The remainder of this article is arranged as follows. The literature review is discussed in section two. based on face recognition, Section-3 described the proposed FA-FAS Net for the face recognition, Section-4 demonstrates the experimental analysis and Section-5 encloses with the conclusion and future work.

2. LITERATURE SURVEY

Numerous researchers have contributed significantly to the subject of face recognition.

In 2024 Rostami et al., [11] proposed a unique FR and detection approach for drones to improve the identification accuracy when query photographs are obtained from far away or at a high level and do not reveal much facial information about persons. The human face is made up of numerous distinct traits that a CNN technique can use to identify faces. Utilizing the CNN structure, we apply the deep learning algorithm to attain superior face detection performance.

In 2024 Haq et al., [12] proposed a facial expression recognition (FER) by processing real time images using DL algorithm. The suggested model performed remarkably well, showing 97.9% training accuracy. These numbers show that the model successfully applied its learnings from the training dataset to the authentication dataset. It has the following restrictions: storage capacity, cost, performance, and camera quality.

In 2024 Deng et al., [13] proposed a largescale face image dataset in an effort to boost the accuracy and dependability of the DL based R system. The outcomes show that the approach is more accurate and resilient and that it is capable of meeting the real-time and security needs of FR. While the DBSCAN technique works well with medium and small sized datasets, handling large-scale datasets takes more time and computer power.

In 2024, Zhou et al., [14] proposed a FR technology, its progress process, its technical benefits, and its application scenarios. DL combined with local binary mode (LBP) features can enhance FR resilience and accuracy. Its benefits such as quick identification speed, high accuracy, and lack of interaction FR technology have become popular in numerous industries.

In 2022 Shakrani, K.V., et al., [15] recommend CNN and Open-Source Computer Vision (OpenCV) methods for real-time (live streaming video) and picture dataset-based facial mask identification. The suggested solution leverages a drone's built-in camera to take real-time pictures for CNN detection. The suggested system's classification accuracy was found to be 0.95.

In 2023 Hangaragi, S. and Singh, T., [16] suggested model uses Face Mesh to identify and detect faces. The model functions under a range of circumstances, including changing background and illumination, thanks to Face mesh. The model can also analyze images of men and women of all ages and races taken from angles other than the front. The model is trained using the deep neural network both real-time and Labeled Wild Face (LWF) dataset photos.

In 2025 Ma, J. and Wilson, A., [17] suggests a unique method for reducing the impact of adversarial perturbations by utilizing a convolutional autoencoder. Although imperceptible to the human eye, the FGSM approach produces imperceptible disturbances to input images that severely impair model performance. According to experimental findings, During FGSM attacks, the equal error rate (EER) increases, but during reconstruction, it goes from 0.36 to 0.32 (FGSM-0.1) and from 0.37 to 0.31 (FGSM-1).

3. PROPOSED METHODOLOGY

In this research, a novel FA-FAS Net for accurate face recognition. Figure 1 illustrates the proposed methodology.

3.1. Dataset Description

This study has ten images of 40 various subjects. Several subjects had their pictures taken at different times of day, under different lighting conditions, with different facial expressions (open/closed eyes, smiling/not smiling), and with different facial characteristics (glasses/no glasses). The subject matter in all of the images is presented in an upright and straightforward manner (with some side motion) against a black, uniform backdrop. The Database of Faces has a preview image. The files are in PGM format, which may be viewed on UNIX (TM) systems using the xv program. Each picture has a threshold size of 92x112 pixels with 256 grayscale levels per pixel. The images are named with the format X, where X is the topic number (1-40), and can be organized into 40 directories, one for each subject. The name of each of these directories is in the format Y.pgm, where Y is the number of the image of that subject (between 1 and 10), and each directory includes 10 images of that subject.

3.2. Pre-processing

The input facial images are resized using the closest neighbor interpolation approach to a predefined output size. This approach ensures image dimension homogeneity for consistent model input. The resizing process is suitable for face-based feature extraction applications since it uses nearest neighbor interpolation to preserve edge sharpness. The contrast and brightness of images of the same individual with the same expression might vary. Histogram equalization produces images with more closely spaced normalized mean values.

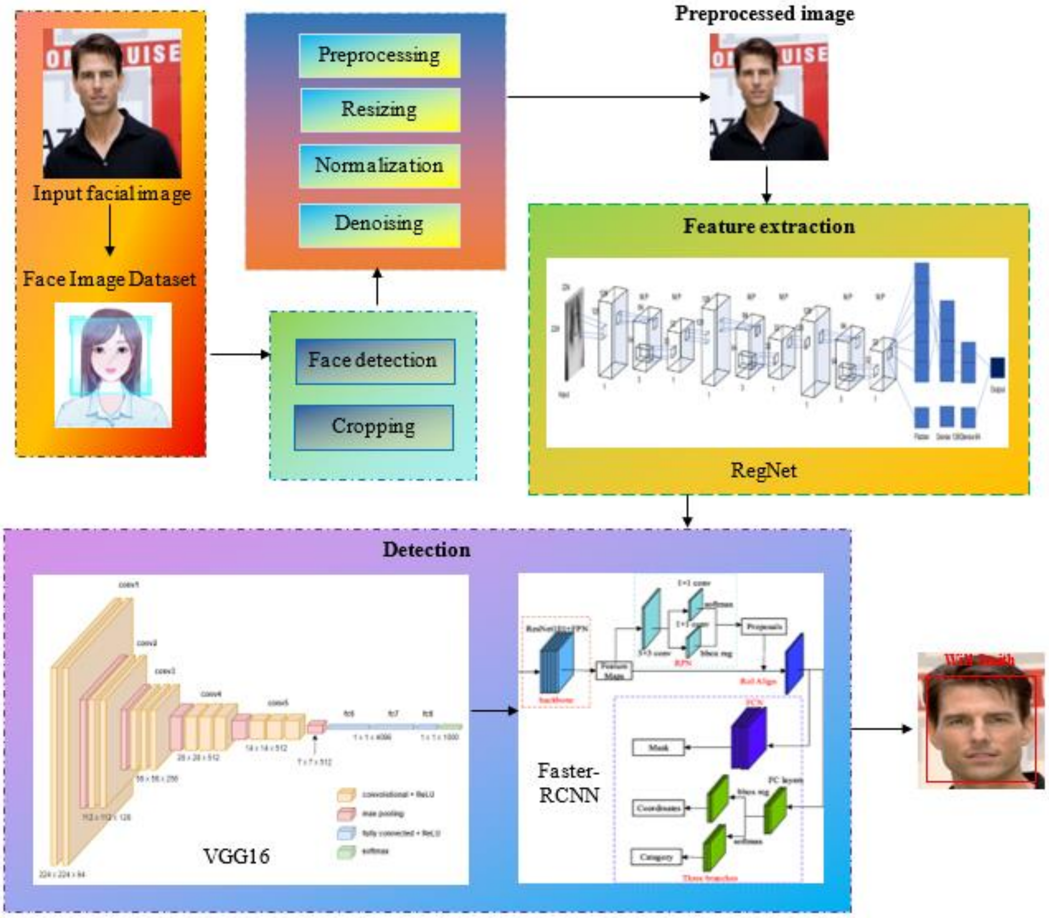

Figure 1. The workflow of the FA-FAS Net for face recognition

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

Where x' represents the new pixel value, x represents the original pixel value, σ represents the standard deviation of the pixel values in all sample images, and μ denotes the average pixel value in all sample images. Finally, a 32×32 pixel down sampled image is applied. In this stage, the input image is prepared for further processing to ensure consistent quality and format. The preprocessing steps include:

- **Resizing:** Adjusts all images to a uniform size suitable for model input.
- **Normalization:** Balances the pixel intensity values to standardize brightness and contrast.
- **Denoising:** Removes unwanted noise and improves the clarity of the image. These steps make the image cleaner, more uniform, and ready for efficient feature extraction.

Gaussian noise is often present in images due to sensor limitations and brightness variances. Pixel-based filtering methods are used to reduce this background noise. The Low Pass Filter (LPF) is a popular technique that smooths images by reducing high-frequency elements (such noise and fine texture details) while maintaining low-frequency information that depicts the image's overall structure. The averaging filter, which has the following mathematical definition, is a common use of an LPF:

$$LPF(i,j) = \frac{1}{m \times n} \sum_{x=-a}^{a} \sum_{y=-b}^{b} I(i+x, j+y) \tag{2}$$

where $I(i,j)$ is the intensity of the pixel at position (i,j), $m \times n$ is the size of the filter kernel $(e.g., 3 \times 3\ or\ 5 \times 5)$, and $a = \frac{m-1}{2}$, $b = \frac{n-1}{2}$. This operation effectively averages the neighboring pixel values within the kernel window to produce a smoothed output image.

3.3 Feature Extraction

RegNet effectively converts raw facial images into condensed, highlevel representations for the detection of facial features. RegNet, an effective CNN, was created to automatically produce efficient network topologies by modifying key network parameters and applying a set of predictable design rules. The process begins with a main convolutional layer that captures lowlevel characteristics such as skin texture, facial contours, and early expression details. According to a quantized linear rule, RegNet is divided into four main stages, each of which increases the number of channels.

$$x_k = quantize(x_i + x_j \cdot k, q) \tag{3}$$

`The network can gradually capture increasingly complex and abstract properties, such as skin textures, facial contours, and expression variations associated with identity, thanks to this architecture. To allow the network to learn several complementing patterns at once, each stage consists of grouped convolutional blocks, also known as bottleneck blocks, which divide feature maps into smaller groups. In faces, this feature is especially helpful for identifying fine-grained details such as wrinkles, moles, or subtle expression changes.

$$D(k) = quantize(D_i + k \cdot \Delta) \quad (4)$$

Batch normalization and non-linear activation functions like ReLU or Swish are utilized to further stabilize the learning process and preserve small visual variations in facial textures. As the data moves deeper into the network, the semantic richness increases while the spatial resolution decreases.

The most important information extracted from the facial image is captured in a one-dimensional vector by compressing the spatial features at the end of the feature extraction process using a global average pooling (GAP) layer. This vector is then sent to a classification head, which uses the learned features to assign an identity label. As a result, it is ideally suited for real-time and edge-based FR applications.

$$x_k = x_i + l \cdot k \quad (5)$$

where $w_i$is the width at stage i, $w_0$is the initial width, and w_a(or k) is the slope that determines how much the width increases. The width result is then adjusted using a predetermined factor q.

$$x_k = round\_to\_multiple(x_i + l \cdot k, q) \quad (6)$$

This quantized width scaling allows the network to grow methodically while maintaining compatibility with modern GPU/TPU hardware.

$$x'_k = quantize(x_k, q) \quad (7)$$

$$x_q(k) = q \cdot \lfloor x(k) \rfloor \quad (8)$$

RegNet uses bottleneck blocks with group convolutions in each stage, which divide the feature maps into smaller groups and process them simultaneously. This group-oriented architecture helps the network effectively learn a range of local facial patterns, including skin textures, facial landmarks, and subtle expression variations, which are essential for accurate recognition. As the facial image passes through multiple stages of the network, RegNet captures increasingly abstract features progressing from simple patterns like edges and textures in the early layers to complex identity-specific representations in the deeper layers.

$$N = | \{w_q(i) \mid i = 0,1, \ldots, D-1\} | \quad (9)$$

A feature vector is created from the high-dimensional feature maps using GAP, which captures the overall spatial information of the face. This feature vector is passed to a FCL, which Res-Net the final face classification or identification.

3.4 Face Detection

The VGG-16 is used to fine-tune a pre-trained model for face detection in a Siamese architecture (SA). Once each VGG-16 FCL has been eliminated, the network is expanded to include all three FCL, contains 512 neurons and the ReLU activation function. The VGG-16 convolutional layers (CL), including three CL and one pooling layer (PL), are then frozen to avoid weight changes during training. The only weight that may be changed is the FCL, which is added later. The architecture of VGG16 is displayed in figure 2.

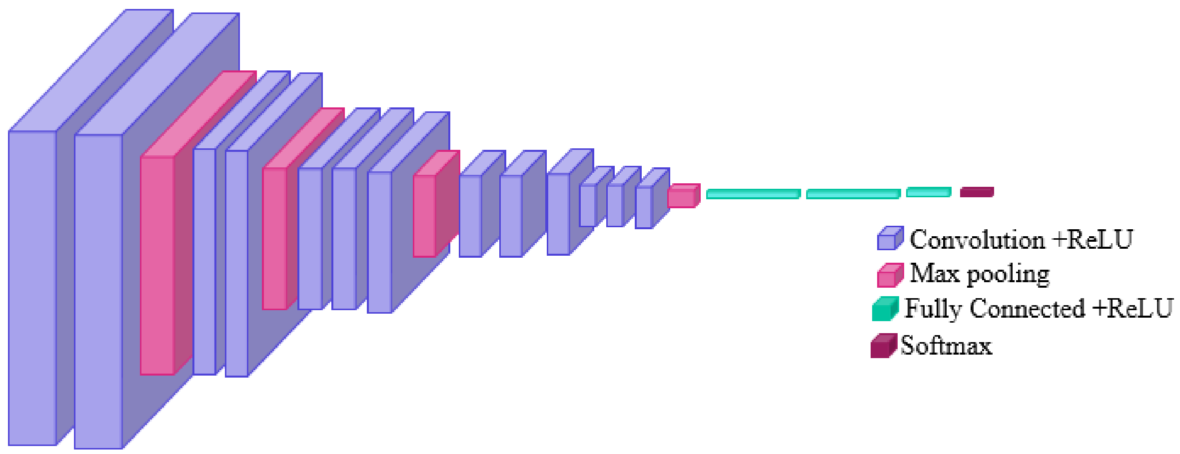

Figure 2. Architecture of VGG16

$$M = (1-z)(E)^2 + z\left[maz\left((n-E),0\right)\right]^2 \quad (8)$$

where y is the binary label indicates whether two input images are similar ($z = 0$) or dissimilar ($z = 1$). The value of the margin, m is greater than zero. The margin existence indicates $n = 1$ and that pairs outside of it have no effect on the loss function. For both CNN available in SA, E is the output vectors and it is computed as follows:

$$d = \|f(x_0) - f(x_1)\|_2 \quad (9)$$

Each of the model's outputs, $f(x_0)\ and\ f(x_1)$, comprises a feature vector with 512 parameters, and E is the Euclidean distance between the two pictures (inputs), x_0 and x_1. The model's predicted values of 0 or 1 allow for a more complete and accurate comparison of expected and actual values, as each image pair's labels are initialized to either 0 or 1.

$$E = \begin{cases} 0, & d < 0.5 \\ 1, & d \geq 0.5 \end{cases} \quad (10)$$

The Faster R-CNN recognizes and separates several faces in an image using pixel-level detection. The Region Proposal Network (RPN) rapidly generates the Region of Interest (RoI) on the FM after the ResNet-101 backbone collects the face features from the input image. Additionally, to accurately maintain precise spatial coordinates and output the FM to a predetermined size, they employ the Region of Interest Align (RoI Align). The detection branch locates and classifies the bounding box at the network's end, and the Fully Convolution Network (FCN) in the segmentation branch creates the matching face Faster for the image. Traditional region-based approaches, such as RoI Pool, are typically effective for extracting a small FM from ROIs due to two quantization procedures that induce misalignment between the extracted features and the ROI. This may have no effect on classification and localization using traditional detection methods, but it has a significant impact on face identification and pixel-accurate Faster prediction when employing this technique.

The Faster RCNN model has two phases that are comparable to the conventional region-based approach. The RPN provides possibly bounding boxes (BBs) for the object face. The Fast RCNN architecture extracts the features of each candidate box before classifying and localizing the BB. In addition, a Faster branch was introduced parallel to the classification and BB placement branches, similar to the Faster R-CNN. Therefore, we define a multitasking objective function, which includes classification loss L_{cls}, BB location loss L_{box}, and segmentation loss L_{mask}.

$$L = L_{cls} + L_{box} + L_{faster} \quad (11)$$

$$L_{cls}(p_i, p_i^*) = -p_i^* log p_i - (1 - p_i^*) log(1 - p_i) \quad (12)$$

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \frac{\lambda}{N_{box}} \sum_i p_i^* . L_1^{smooth}(t_i, t_i^*) \quad (13)$$

Where, $p_i, and\ p_i^*$ is anticipated probability of anchor, λ was a balancing parameter, $t_i\ and\ t_i^*$ is predicted coordinate and ground truth coordinated and $N_{cls}\ and\ N_{box}$ normalization term set to be mini-batch size and the number of anchor locations.

$$L_{faster} = -\frac{1}{m^2} \sum_{1 \leq i,j \leq m} \left[y_{ij} \log \hat{y}_{ij}^k + (1 - y_{ij}) \log(1 - \hat{y}_{ij}^k) \right] \quad (14)$$

where L_{mask} is the average binary cross-entropy loss computed over the region of size $m \times m$. The K[th] Faster corresponding to a specific ground-truth class, each pixel location (i, j) within this region is evaluated. Let y_{ij} denote the true binary label of the pixel at location (i, j) in the ground-truth Faster, and $\hat{y}_{ij}^k$ represent the predicted probability for the same pixel in the predicted Faster associated with class k. The binary cross-entropy loss is averaged across all pixels in the area to make sure the predicted Faster closely matches the target for detecting each face class.

4. RESULT AND DISCUSSION

In this section, the experimental set up of the proposed model was implemented by MATLAB 2020b. The proposed model to evaluate the approach of the collected facial images, a number of measures were employed.

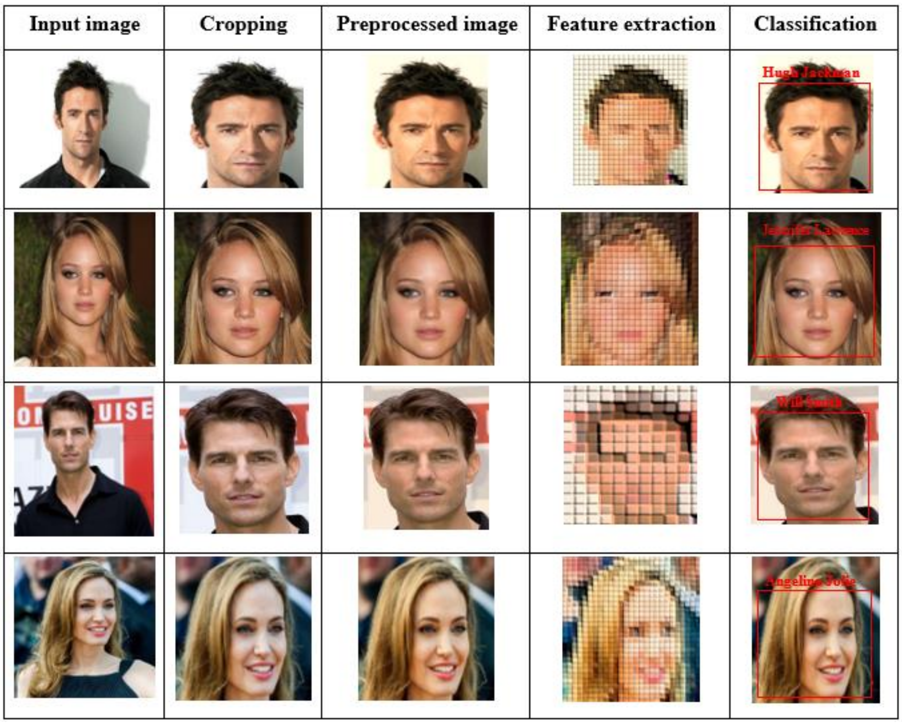

Figure 3. Experimental result of the proposed model

Figure 3 shows the experimental outcomes of the proposed model for face recognition. The column 1 shows the facial images are first collected from a dataset. In the cropping stage, the facial region is detected and isolated from the background to focus on the relevant area of interest. The preprocessed image stage then standardizes the cropped face through operations such as normalization, resizing, and noise reduction to improve image quality and consistency for model processing. Next, during feature extraction, distinctive facial characteristics are converted into numerical feature maps or embeddings, which capture unique patterns such as facial structure and texture. Finally, in the classification stage, the extracted features are analyzed by a trained recognition model to identify the individual by matching the features.

4.1 Performance Analysis

This section assessed the proposed model approach using a number of measurements from the collected dataset, include recall (RE), specificity (SP), F1 score (F1), accuracy (AC), and precision (PR).

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (15)$$

$$Specificity = \frac{TN}{TN+FP} \quad (16)$$

$$Precision = \frac{TP}{TP+FP} \quad (17)$$

$$recall = \frac{TP}{TP+FN} \quad (18)$$

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \quad (19)$$

where T_{pos} and T_{neg} indicates the true positive and negative of the provided images, F_{pos} and F_{neg} display the sample images false positives and negatives.

4.2 Comparative Analysis

The proposed methods accuracy and efficiency were demonstrated by comparing it to other existing methods. The RegNet and Faster RCNN is used to enhance the accuracy of face recognition. A comparison is performed between the FA-FAS Net approach and current approaches such as RCNN, Mask RCNN, Fast RCNN.

Table 1. Comparison of the existing methods and proposed method

Techniques	AC	SP	PR	RE	F1
RCNN	88.45	89.85	87.10	85.96	86.52
Mask RCNN	91.32	92.29	90.47	89.26	89.86
Fast RCNN	95.74	94.62	94.84	91.57	88.28
Proposed	98.87	96.48	95.27	94.87	95.04

Table 1 demonstrates the superior performance of the FA-FAS Net over traditional methods such as RCNN, Mask RCNN, and Fast RCNN across all evaluation metrics. The proposed approach achieves the highest AC of 98.87%, indicating its effectiveness in correctly identifying facial features. Additionally, it records improved SP (96.48%), which reflects its ability to correctly identify negative cases, and higher PR (95.27%), showing reduced false positives. The RE value of 94.87% highlights the model's capability to detect true positive instances efficiently, while the F1 of 95.04% confirms a balanced performance among PR and RE. These improvements are mainly due to the integration of RegNet for robust feature extraction and Faster R-CNN with Siamese architecture for precise detection and matching, making the proposed method more reliable and accurate compared to existing techniques.

Table 2. Accuracy comparison of the current approach and FA-FAS Net approach

Authors	Method	Accuracy
Haq et al., (2024)	FER	97.9%
Shakrani, K.V., et al., (2022)	CNN	95%
Hangaragi, S. (2023)	Deep Neural Network	94.23%
Proposed	FA-FAS Net	98.87%

Table 2 illustrates an accuracy comparison of current approaches and the FA-FAS Net. The proposed FA-FAS Net maintains high accuracy levels of 98.87%. The proposed FA-FAS Net enhances the total accuracy by 0.99%, 4.07% and 4.92% better than FER, CNN, and Deep neural network respectively. According to the above comparison, the proposed approach is more accurate than the existing models.

5. CONCLUSION

The proposed FR system presents an effective and reliable DL-based framework for accurate identification of individuals from facial images. By integrating advanced preprocessing techniques, robust feature extraction using RegNet, and precise detection and classification through the combined capabilities of VGG16 and Faster R-CNN, the system successfully enhances recognition accuracy and detection reliability. Overall, the proposed framework offers a practical and scalable biometric authentication method for use in the actual world surveillance, and security applications, and it offers a strong foundation for future enhancements such as real-time deployment, multimodal integration, and improved recognition under challenging scenarios. The proposed FA-FAS Net maintains high accuracy levels of 98.87% based on the gathered dataset. The proposed FA-FAS Net enhances the total accuracy by 0.99%, 4.07% and 4.92% better than FER, CNN, and Deep neural network respectively.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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