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FaceNet– A Framework for Age Variation Facial Digital Images

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Abstract

Automated face recognition plays a vital role in forensics. The most important evidence in the criminal investigation is the facial images captured from the crime scene, as they represent the identity of the people involved in crime. The role of law enforcement agencies is to identify the facial images from the suitable database. This information can be treated as strong evidence for the law enforcement agencies which becomes the most important evidence in global counter-terrorism initiatives. Contour of chin and cheek, distance between different features and shapes of facial components are some of the parameters considered by the forensic experts for manual facial identification process. This process is time consuming, and it is a tedious job. To address this issue, there is a need for developing an automated face recognition system for forensics. As a result, FaceNet – a framework for age variation facial digital images is discussed in this research work. Experiments are evaluated on CSA dataset with three age variations which provides a recognition accuracy of 86.8% and performs better than the existing algorithms.

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1. Introduction

Face sketch recognition is one of the most studied topics in forensics literature. Police can quickly narrow down and eliminate potential suspects with the use of automatic retrieval of suspect photographs from mug shot databases. But in most cases, a suspect's photographic image is not available. An eyewitness or victim's memory-based sketch recognition system is frequently the best replacement [37].

When a suspect's facial image is unavailable at the scene of the crime, facial composite sketches are frequently used to aid in the identification of suspects [23]. A forensic artist can create a sketch of the suspect's face, or facial software can generate one based on the eye-witness's details. Once the sketch is produced, the crucial next step is to identify the person depicted in the sketch. Automating this process is beneficial for identifying suspects more quickly. Automated facial recognition systems serve as tools to assist examiners in evaluating the strength of evidence, complementing traditional human-based approaches. The current and future importance of forensic face recognition prompted us to explore this new and dynamic field. This motivated us to establish a solid foundation for designing a reliable system by automating domain-specific methods for facial sketch-based recognition. Face sketches can be categorized in to six types.

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- **Viewed hand drawn sketches:** It is created by hand while looking at a certain person's digitized facial photographs. A skilled artist is therefore required to depict a person's face. These, however, cannot be utilized in law enforcement situations[4].
- **Hand-drawn forensic sketches:** These are created by forensic artists based on information provided by a victim or an eyewitness.
- **Semi-forensic sketches:** They are created based on the sketch artist's memories rather than an eyewitness or victim's description.
- **Composite sketches:** These are made using face recognition software like FACES or portrait pad. Police primarily utilize facial composite sketches to investigate crimes or identify suspects in wanted posters.
- **Caricature sketches:** These are created by hand or with the aid of specialized software that closely resembles actual photographs.

Facial composite sketch recognition (FSR) system is a query-by-sketch imaging system that may be thought of as a method of locating the image from the database that corresponds to the sketch[38].
The interactive retrieval process of FSR is carried out in two stages. Feature vectors are created for both sketch query and the facial digital images in the first stage. Then comparison is done for recognition by similarity. To improve the research findings [23], the investigator frequently engages with the FSR through a similarity indicator which is shown in Figure 1.

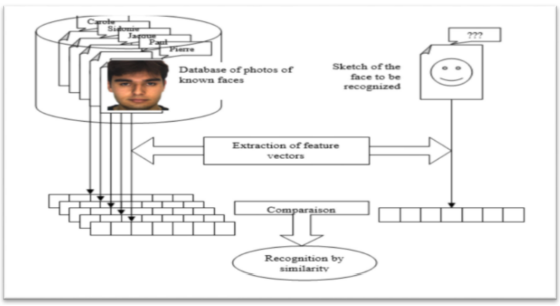

Figure 1. Face Sketch Recognition System [23]

Forensic composite sketches present a larger problem than viewed sketches because they contain incomplete information[35][36]. Research in this field is less for viewed sketches since it is more difficult. Automated face sketch recognition systems perform poorly in forensics applications, and it is unable to handle enormous variability that exists in face such as pose variations, lighting, expression, occlusion and cosmetic makeup. Several studies [5][6] have now considered composite sketches for forensic face recognition.
Once a sketch of the suspect's face is generated, the authorities believe that utilizing the sketches, someone will be able to identify the person and provide pertinent information to the investigating authorities, assisting them in quickly locating the suspects [24]. The only form of evidence available is the eyewitness or victim's description [22]. However, this method is ineffective and does not leverage. Law enforcement organizations have huge mug shot databases. Mapping of facial composite sketches to mug shots will improve the effectiveness of the system [39].
Mapping of composite sketch to facial digital images plays a significant role in forensics. The most challenging task in forensic face recognition is identifying the past crime history of a suspect having age variations such as old (between 60-80 years), same (middle, between 30-50 years) and young age (between 5-20 years). To address this issue, a framework for age variation facial digital images [8] is proposed in this research work which helps the investigating agencies for the identification of suspects effectively [32]. Figure 2 displays a sample composite sketch along with age-variation facial digital images.

Figure 2. Composite Sketch with Age Variations Facial Digital Images [8]

The primary contributions of the presented research work are outlined as follows.

- FaceNet – a framework for age variation facial digital images in forensics is proposed.
- To match the composite sketch with age variation facial digital images, Face Net framework is proposed.
- In-depth examination of the proposed framework is discussed.
- The proposed framework demonstrates superior performance compared to numerous state-of-the-art face sketch recognition systems.

The organization of the research paper is as follows. A literature review on various frameworks for age variation facial digital images is discussed in section 2. FaceNet – a framework for age variation facial digital images in forensics is discussed in section 3.

The experimental results and analysis are described in section 4. The comparative study of heterogeneous face recognition approach with the existing works is discussed in section 5. The research work ends with the concluding remarks in section 6.

2. Literature Survey

Several research activities have concentrated on matching facial composite sketches with digital images. There are number of interesting methodologies [18][20] that exist to map composite sketch to facial digital images in the field of forensics.

Tang and Wang proposed an Eigenface approach to generate facial sketch images from digital images. Generation of Eigenvectors and eigenspace are the two stages involved in this approach which provide a recognition accuracy of 73%. A method based on MvDA proposed by Kan et al. [16] builds discriminant common space. The proposed method is more efficient for generalization.

Siddharth and Kisku et al. [25]. proposed an approach based on the fusion of modified local binary pattern (LBP) descriptor and multi-block LBP descriptor. The combined use of both the descriptors provides promising results and performs better than the other sketch-based algorithms. To improve the effects of synthesized images an approach based on sparse coding and dictionary learning is proposed by Zhang et al.[26]. Synthesized pseudo sketch is generated based on similarity scores computed using Nearest Neighbor algorithm. A dualscale Markov network proposed by Chen et al. [27] synthesis pseudo images by generating effective features.

The cross-modality metric learning method proposed by Huo et al. [28] uses triplet-based constraints. Experiments are evaluated on VIS-NIR facial dataset which provides promising results and performs better than the other sketch-based algorithms. Convolutional Neural Network based on Siamese network architecture is proposed by Khalil-Hani and Sung [29] uses subsampling layer for avoiding overfitting problem. Experiments are evaluated on the AT&T facial database which minimizes loss function using stochastic gradient descent.

Zhang et al.[26] proposed an approach for recognizing facial images of different modalities. Experiments are evaluated on heterogenous facial datasets which prevents overfitting problems on smaller datasets. Galea et al. [31] developed a deep learning-based architecture for composite sketch and facial digital images. The proposed framework provides a recognition accuracy of 80.7% and performs better than the existing algorithms. Schroff et al.[30] proposed triplet network model which maps facial images into Euclidean distance. Experiments are evaluated on LFW and YouTube facial dataset which provides promising results and performs better than the existing algorithms [14][15].

Most of the research [1,2,9,10] is done in matching digital images or mug shots with facial composite sketches [3,7]. The literature study reveals that there are only a few research works [21, 22] that have been reported to solve the problem of age-variation facial digital images. Therefore, the proposed framework addresses the problem of age variation facial digital images.

Limitations of existing system are the varied facial expressions, poses between composite sketches and digital images, changes in expressions and head angles which affects the accuracy of matching algorithms, leading to potential misalignments, and introducing complexities in the alignment. FaceNet – a framework is proposed for mapping composite sketch with age variation facial digital images which overcomes the limitations of existing system.

3. FaceNet – A Framework for Age Variation Facial Digital Images

Proposed framework uses DCNN for mapping age variation facial digital images with the composite sketch. It uses FaceNet, a DCNN which generates face embeddings for classification and recognition. FaceNet is chosen for the proposed framework due to following reasons which is mentioned below.

FaceNet generates face embeddings and efficiently performs classification by taking an input image, giving weights and bias to the numerous objects in the image. Deep CNN's characteristics make it simpler to adapt to the suggested framework for feature extraction, classification, and recognition[13].

The proposed framework consists of six stages: preprocessing, face detection, FaceNet, face embeddings, comparison and bounding box, face recognition with age variations. The architecture of age variation facial digital images is shown in Figure 3.

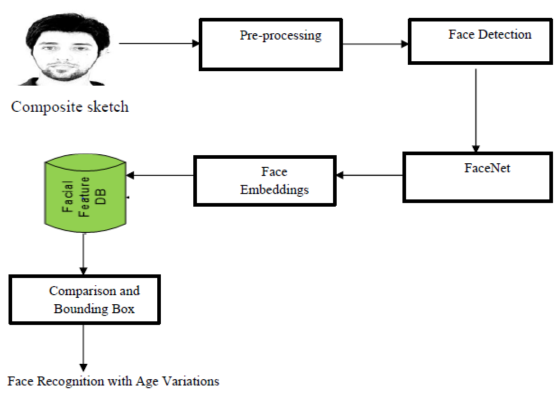

Figure 3. Architecture of Age Variation Facial Digital Images

3.1. Pre-processing

The age variations facial digital images are in RGB format [12]. The composite sketches, however, are presented in grayscale. To improve the performance of the system, all the images in the dataset must be converted in to uniform format [27][28]. Thus, all facial digital images are transformed into grayscale images which is shown in Figure 4 and 5.

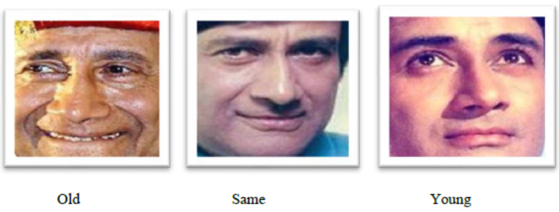

Figure 4. Age Variations Facial Digital Images: Old, Same and Young [27][28]

Figure 5. Pre-processed Age Variations Facial Digital Images

3.2. Face Detection

images are detected using Viola-Jones algorithm. It exhibits high detection accuracy, and it identifies the given input facial images regardless of their size, texture, color, mobility, position, or other characteristics [21]. It is one of the good and popular face detection algorithms as shown in Figure 6.

Algorithm for Face Detection using Viola-Jones
Input: Composite sketch
Output: Detected composite sketch
Face detection using Viola-Jones procedure begins.

Step 1: Start

Step 2: Read input image.

Step 3: Scales the entire input image with a 24×24 sub-window.

Step 4: Calculate the Haar features values of each window.

Step 5: Check the window features for classification. If yes, sub window is passed to the next location to detect face or else sub window is discarded as non-composite face.

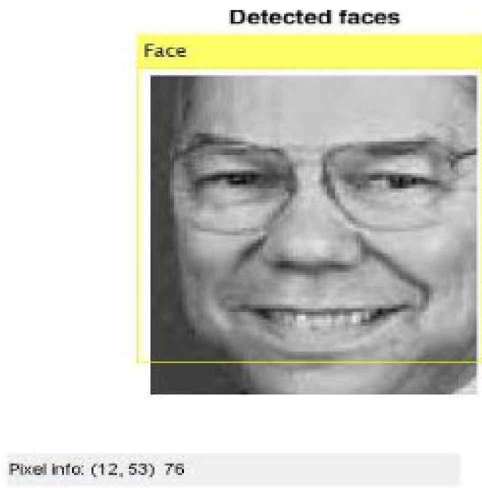

Figure 6. Face Detection using Viola Jones Algorithm

Step 6: Stop Face detection using Viola-Jones procedure ends.

3.3. FaceNet

FaceNet is a unified framework used in the proposed framework that maps each facial image into a three-dimensional space so that the distances in that space correlate to face similarity. The composite sketch of a suspect is passed to FaceNet which uses DCNN and generates face embeddings corresponding to face similarity. To quote an example, an image of person X will be placed closer to all the other images of person X as compared to images of any other person present in the dataset[11] which is shown in Figure 7.

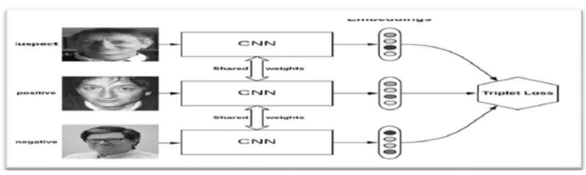

Figure 7. FaceNet Mapping Triplet Loss [11]

FaceNet uses a face image as input and produces a vector of 128 values that reflect the key facial characteristics, or "face embeddings”. Once embeddings have been produced, all subsequent activities, including verification and identification, can be carried out by representing embeddings as the feature vector.
FaceNet employs DCNN, and the network is trained to determine how similar faces are based on the squared distance between their embeddings[10]. The images that are utilized for training are resized, altered, and are tightly cropped around the face area. It uses triplet loss function and requires three images namely suspect,

positive and negative which is shown in Figure 8.

Figure 8. Triplet Loss Function [10]

The idea behind triplet loss function is that the suspect image must be closer to positive images as compared to negative images. In other words, the distance between the embeddings of suspect image and the embeddings of positive images must be lesser than the distance between embeddings of suspect image and embeddings of negative images.
AdaGrad algorithm and SGD are used for two different purposes inresearch work. AdaGrad adjusts the learning rate for each parameter according to the accumulated gradient information, which can be advantageous when working with sparse data. Stochastic Gradient Descent updates parameters using a constant learning rate and optimizes the loss function. In Figure 9, the third axis (z) shows the loss with regard to the two weights, and the two axes (x and y) represent the weights[11].
The reasons for choosing ReLu activation function are described as follows.

- It preserves nonlinearity by passing only relevant features to the next subsequent layers in CNN.
- ReLu will not activate the neurons at the same time, and it is computationally inexpensive.

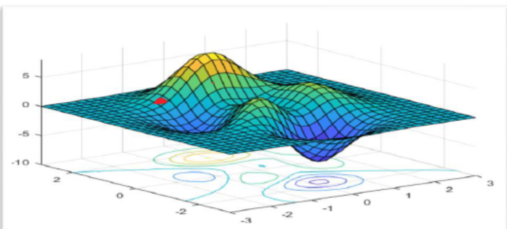

Figure 9. Stochastic Gradient Descent [11]

FaceNet uses GoogLeNet style inception model[5]. The proposed framework make use of inception network architecture with several filters of varying sizes used simultaneously which is shown in Figure 10. CNNs are a subcategory of deep neural networks that are made up of numerous hidden layers that convolve to produce a dot result[11]. The three basic building blocks of CNN are convolutional layer, pooling layer and fully connected layer. In the proposed framework, CNNs

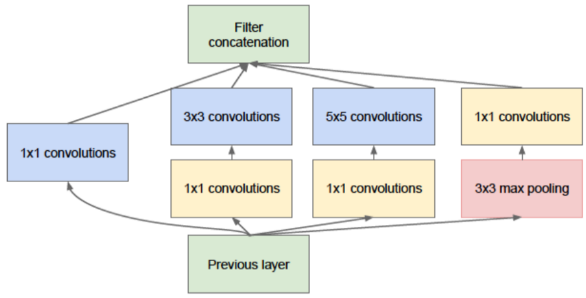

Figure 10. Representation of Inception Model [5]

are trained using FaceNet which uses GoogLeNet style inception model for generating the filters.
The convolutional layer, which is the first layer of the CNN[32], receives input from composite sketches during the training phase. Convolution, ReLU and max pooling operations are carried out by each convolution layer. The squashing (tanh) function connects the convolution and pooling layers, allowing a pooling layer to pass output with additive bias b_{mn} as indicated in Equation 1.

$$x_{nm} = \tanh\left(\text{pooling}\left(\sigma_{xn}^{m-1} * k_{mn}\right) + b_{mn}\right) \qquad \text{(Equation 1)}$$

Here x denotes the result of convolution and pooling layers, b_{mn} denotes additive bias, k indicates kernel which is the result of convolutional layer after applying the convolution operations such as ReLU and max pool process. Feature maps are produced after going through the convolutional layer.

3.4. Face Embeddings

The generated feature maps are passed to the fully connected layer which generates face embeddings outputting a vector of 128 numbers and it is stored in the database.
Algorithm for Computation of Face Embeddings using FaceNet
Input: Detected facial grayscale facial image
Output: Face embeddings with a vector of 128 numbers

- **Step 1**: Triplet loss function is used to generate face embeddings which is represented by the function $f(y)$ such that $y \in \mathbb{R}$ The embeddings are normalized in such a way that

$$\|f(y)\|_2^2 = 1$$

- **Step 2**: Suspect image must be closer to positive image as compared to negative image such that

$$\|f(y_i^s) - f(y_i^p)\|_2^2 + \alpha\langle\|f(y_i^s) - f(y_i^n)\|_2^2\rangle$$

$$\forall (f(y_i^s), f(y_i^p), f(y_i^n)) \in T$$

The symbol α is the origin between positive and negative pairs, T represent image space, s represents suspect image, p represents positive image and n represents negative image.

- **Step 3**: Triplet loss function L is expressed as

$$L = \sum_{i=1}^{N} \left[\|f(y_i^s) - f(y_i^p)\|_2^2 - \|f(y_i^s) - f(y_i^n)\|_2^2 + \alpha \right]$$

- **Step 4**: Triplets are selected such that $\|f(y_i^s) - f(y_i^p)\|_2^2$ is maximum and $\|f(y_i^s) - f(y_i^n)\|_2^2$ is minimum.
- **Step 5**: Face embeddings outputting a vector of 128 numbers is generated.

3.5. Comparison and Bounding Box

A composite sketch is provided as input to the proposed framework during the testing phase. Face embeddings are generated, and they are compared to the embeddings that have already been saved in the database. If a match is made, bounding boxes are created for the detected matching facial digital images of various ages, including young, same-age, and old.

3.6. Face Recognition with Age Variations

The facial digital images with age variations[33][34] such as young, old and same for the corresponding composite sketch are recognized.

4. Results and Discussion

The datasets considered for the experimentation and the various performance measures of the proposed framework are discussed in this section.
Experiments are evaluated on CSA dataset [27, 28] consists of age variations facial digital images. The total number of samples considered for experimentation is 640.
The dataset is divided into a training set and testing set, with the ratio of each set being 75:25. The training set comprises of 480 digital face photos total, divided into 160 digital face photos representing three different ages young, old, and the same. The testing set consists of 160 composite sketches. The statistics of samples for CSA dataset are shown in Table 1.

Here, a composite sketch is used as input to the proposed framework, which categorizes the provided input image and presents matching facial digital images of three age variations for the corresponding composite sketches as illustrated in Figure 11. The confusion matrix for the proposed framework is tabulated in Table 2.

Figure 11. Sample 1– Age Variations Facial Digital Images with Composite Sketch

A total of 160 testing samples were used in the experiments, 134 of which showed perfect matching of facial digital photos with the three different ages, while the other 26 samples showed wrong matching. The results of different performance measures for the proposed framework obtained on CSA dataset is tabulated in Table 3.
Figure 12 depicts the graphical representation of various performance measures for the proposed framework based on FaceNet. In this plot, values in X-axis denote different performance measures and values in Y-axis denote the results of various measures in percentage.

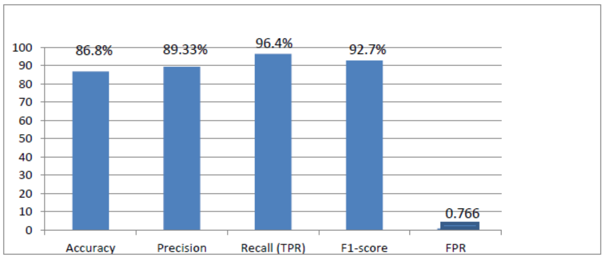

Figure 12. Graphical Representation of Various Performance Measures for Proposed Framework based on FaceNet

Figure 13 depicts the graphical representation of various performance measures for the proposed framework with the existing works. In this plot, values in X-axis denote different performance measures, values in Y-axis denote the results of various measures in terms of percentage for the proposed framework with the existing works. The results of different performance measures for the proposed framework with the existing works is tabulated in Table 4.

Table 1. Statistics of Samples for CSA dataset

DatasetName	*CompositeSketch*	*DigitalImages*	*Challenges*	*Source*	*Size*
Composite Sketch with Age Variations (CSA)	160	480 with 160 digital face photos three different age variations	Each subject's digital images consist of three groups: young, same and old	Image Analysis and Biometrics Lab, IIIT Delhi	Min-200×200 dimensions to Max-1000×2000 dimensions Sample–jpeg format

Table 2. Confusion Matrix

	TruePositive	*FalsePositive*	*TrueNegative*	*FalseNegative*	*Accuracy*
Results	134	16	5	5	86.8%

Table 3. Various Performance Measures of Proposed Framework

ProposedFramework	*PerformanceMeasures*	*Results*
Face Embeddings using FaceNet	Accuracy	86.8 %
	Precision	89.33%
	Recall(TPR)	96.4%
	F1score	92.7%
	FPR	0.766

Table 4. Various Performance Measures of Proposed Framework with the Existing Works

SL.No	*Methodology*	*Accuracy*	*Precision*	*Recall*	*F1 – Score*
1	Deep Belief Network [19]	58	71.3	83.4	91.1
2	Adaptive Sparse Representations [40]	85.1	87.4	89.2	89.8
3	Artificial Neural Networks [6]	81.2	93.2	93	85.5
4	{**Proposed Framework**	**86.8**	**89.33**	**96.4**	**92.7**

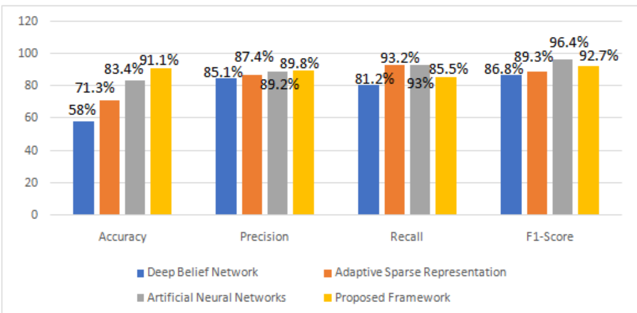

Figure 13. Graphical Representation of Various Performance Measures for Proposed Framework based on FaceNet with the Existing Works

The ROC curve for proposed framework based on FaceNet is shown in Figure 14. In this plot, a value in X-axis indicates FPR and a value in Y-axis indicates TPR. The AUC values for proposed approach based on FaceNet are 0.873 which is 0.127 less than best value for ROC. It indicates that the model has an ability up to 0.873 to distinguish between positive and negative class.

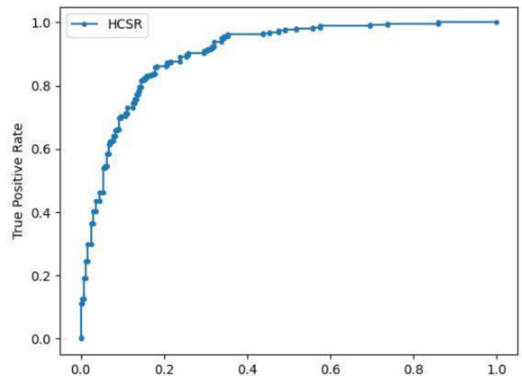

Figure 14. ROC Curve for Proposed Approach based on FaceNet

Table 5. Performance Analysis of Proposed Framework with the Existing Works

SL.No	*Authors*	*Methodology*	*Accuracy*
1	Mittal et al.(2015)[19]	Deep Belief Network	58%
2	Peng et al.(2019)[23]	Sparse Graphical Representation based Discriminant Analysis	70 %
3	Iranmanesh et al.(2018)[17]	Coupled Deep Neural Network	76.4%
4	**Proposed Approach**	**Face Embeddings using FaceNet**	**86.8%**

5. Performance Analysis of Proposed Framework with the Existing Works

The performance analysis of proposed framework with the existing works in terms of recognition accuracy is tabulated in Table 5 and same is represented in Figure 15. The proposed framework uses FaceNet which employs the deep learning architecture of GoogLeNet, renowned for its exceptional accuracy in face sketch recognition. Hence it is observed from the comparative study that proposed framework provides a recognition

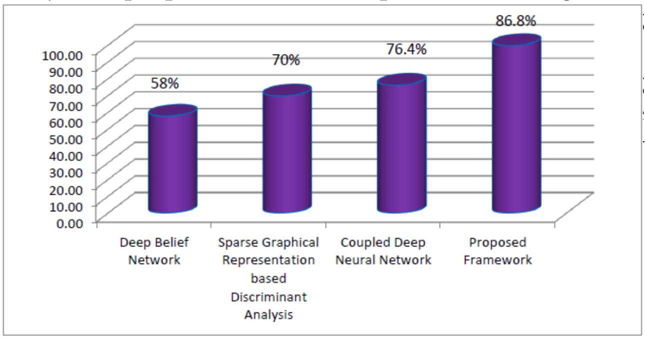

Figure 15. Performance Analysis of Proposed Framework with the Existing Works

6. Conclusion

Mapping facial digital images of different age variations from a given composite sketch helps to identify the suspects in an efficient way. FaceNet, a framework for age variations facial digital images is developed in this research work. Experiments are evaluated on CSA dataset with three age variations which provides a recognition accuracy of 86.8%. The proposed framework provides promising results and performs better compared with other existing sketch-based algorithms. Various deep learning models can be explored for sketch-based recognition across different age variations and system can be made scalable for large database. scope for enhancement in this research work lies in refining the performance of the proposed model. Consequently, supplying a greater volume of images to the network could potentially enhance the model's performance. However, due to the scarcity of available images, the proposed model could not undergo testing on larger datasets.

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