Sketch Sight: A Smart System for Forensic Facial Sketch Matching and Recognition

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Abstract

In order to help law enforcement identify suspects accurately, this paper aims to bridge the gap between hand-drawn sketches and actual images. It was created so that cops could create accurate facial sketches without the assistance of a qualified forensic artist. The system's drag-and-drop interface makes it simple to choose and coordinate facial features including the eyes, nose, lips, eyebrows, and hairstyles. These drawings are enhanced for clarity and identification potential by applying picture pre-processing techniques including edge enhancement and noise reduction. Using deep learning techniques, distinct facial traits are extracted from the sketch and the photo, resulting in feature vectors that depict the identity in a common embedding space. This enables the technology to match massive criminal records with accuracy. The method is intended to address typical issues such disparities in artistic style, lighting changes, partial occlusions, and misaligned facial angles. The solution significantly lessens the human workload for investigators by automating and streamlining the recognition process. For effective data retrieval and storage, it also easily connects with current law enforcement databases. Officers can reduce suspect lists in a matter of minutes because to the matching process's quick and accurate results. Even with poor-quality or insufficient sketches, test results show a high degree of accuracy in sketch-to-photo matching

Keywords: *deep learning, forensic face sketch, face recognition, criminal identification, law enforcement, sketch-to-photo matching, feature extraction.*

1. Introduction

To ensure justice and public safety in criminal investigations, it is essential to accurately identify suspects. However, in many cases, forensic artists rely on eyewitness descriptions to translate into facial sketches, which are valuable but often lack the fine visual details of photographs, creating a significant gap between the sketch and image domains. To bridge this gap, sophisticated computational techniques that can match forensic sketches with digital images in law enforcement databases are needed. The goal of forensic face sketch and recognition technology is to automate this procedure by using computer vision and machine learning to recognize people from composite or artist-rendered sketches. This method speeds up manual searches, improves matching precision, and helps investigators when there are just subjective or incomplete visual descriptions available. Domain adaptation and feature extraction are important issues in this field since traditional recognition systems have trouble with the intrinsic variations in texture, shading, and proportion between sketches and images.

Forensic face sketch and recognition technology development has significant ramifications for counterterrorism, border security, and law enforcement. By facilitating quicker and more precise suspect identification, these systems improve the effectiveness of public safety activities overall as well as the efficiency of investigations. Building a strong and expandable framework for sketch-based face recognition is the main goal of this research, which also addresses the difficulties associated with cross-domain image matching and guarantees usefulness in actual forensic settings.

2. Literature Survey

Klare, Brendan F., and Anil K. Jain. "Sketch-to-photo matching: A feature-based approach." This paper presents one of the early attempts to match forensic sketches to mugshot photos using feature-based methods. It uses facial descriptors like SIFT and LBP to bridge the domain gap between hand-drawn sketches and photographs. The study highlights the limitations of traditional descriptors in handling high variability and modality differences, especially in forensic conditions where sketches are not always accurate representations.

Wang, Xiaogang, and Xiaoou Tang. "Face photo-sketch synthesis and recognition". The authors propose a method to synthesize facial sketches from photos and vice versa using a locality preserving projection approach. Their system improves recognition accuracy by transforming both sketch and photo into a common feature space. The study introduces the CUFS dataset and demonstrates better performance over direct matching. It laid the foundation for further research in photo-sketch synthesis for recognition tasks.

Zhang, Li, et al. "Content-adaptive sketch portrait generation by Deformable Stroke Model."This paper introduces a deformable stroke model (DSM) for generating realistic sketch portraits. The model adapts to facial structure and expression, providing more detailed and human-like sketch synthesis. This work is useful in enhancing composite sketch realism, which in turn improves recognition accuracy when sketches are matched with photographs in forensic investigations.

Bhatt, Himanshu S., et al. "Matching sketches with digital face images: A critical survey." This survey paper analyses a wide range of techniques for sketch-to-photo face recognition. It categorizes the methods into synthesis-based, feature-based, and hybrid approaches. The paper provides comparative evaluations of various datasets, algorithms, and metrics. It also highlights the ongoing challenges such as poor sketch quality, pose variations, and limited datasets in forensic scenarios.

Zhang, Weilin, et al. "Coupled Information-Theoretic Encoding for Face Sketch-Photo Recognition".This work presents deep learning framework that learns shared representations of sketches and photos using information-theoretic encoding. The method effectively reduces modality gap and achieves state-of-the-art accuracy on CUFSF and CUFS datasets. The study demonstrates how cross-modal learning can significantly enhance recognition performance in practical forensic settings.

3. Proposed Methodology

By employing deep learning to map both sketches and images into a common embedding space, the system seeks to identify faces from sketches. After obtaining the input sketch, pre-processing operations like scaling, alignment, and grayscale normalization are carried out. Features are then extracted from sketches and photos using a dual-branch neural network. A cross-modal loss function is used to develop the projection of these features into a single latent space. After employing similarity criteria to compare the sketch's attributes with those of the stored photo, and the algorithm dicover which features are the most relevent to match and provides a confidence score or ranked results.

3.1 Proposed Methodology Model Diagram

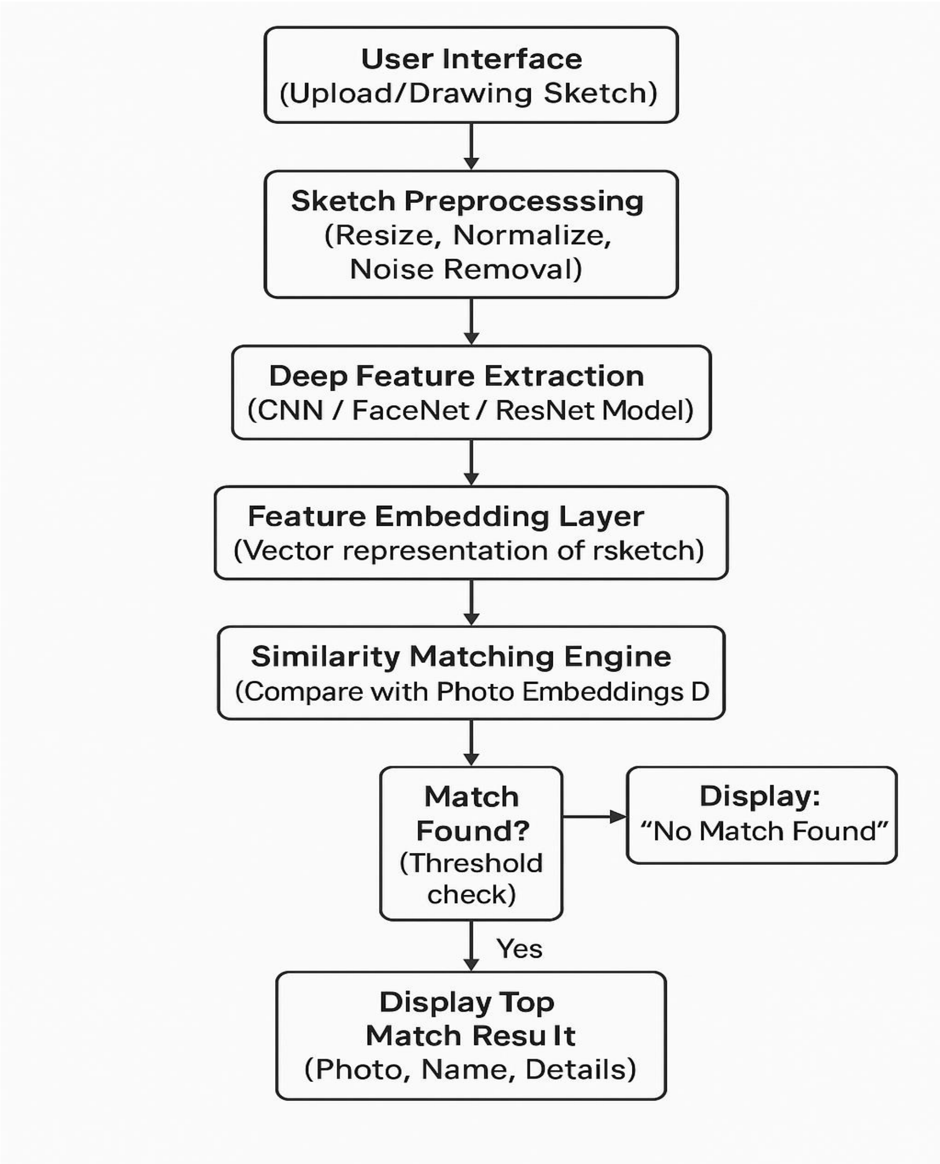

Figure 3.1.1 Proposed model diagram

- Input Layer: A 2D sketch image, either in RGB or grayscale format, is first accepted by the system. To ensure uniformity across all samples, the image is scaled and normalized to meet the model's input requirements.
- Pre-processing Block: This block uses common preprocessing methods for images, like normalization and scaling. The quality and clarity of the sketch input can be enhanced by applying optional techniques like edge enhancement or noise reduction.
- Feature Extraction Layer: To extract significant characteristics from the sketch, a pre-trained Convolutional Neural Network (CNN) such as ResNet, VGG-Face, or FaceNet is employed. A fixed-length embedding vector representing the facial features of the sketch is produced by the network.
- Mapping the Embedding Space: The retrieved embeddings are mapped onto a common latent space that aligns the photographs and sketches. To lessen the modality gap between sketches and photographs, domain adaptation strategies and loss functions such as contrastive loss are employed.
- The sketch's embedding is compared to embeddings from a stored photo database via the Similarity Matching Engine. To identify possible matches, it computes the similarity using metrics like Euclidean distance or cosine similarity.
- Decision Module: The decision module ascertains whether a match exists based on the similarity scores. If the similarity drops below a predetermined level, it either provides a "no match" result or chooses the top-N closest matches.
- Output Layer: If the matching individual is located, the user shows the identity of final result. A rating of the top matches or confidence scores are examples of extra information that might be included.

3.2 Block Diagram for Machine Learning Model

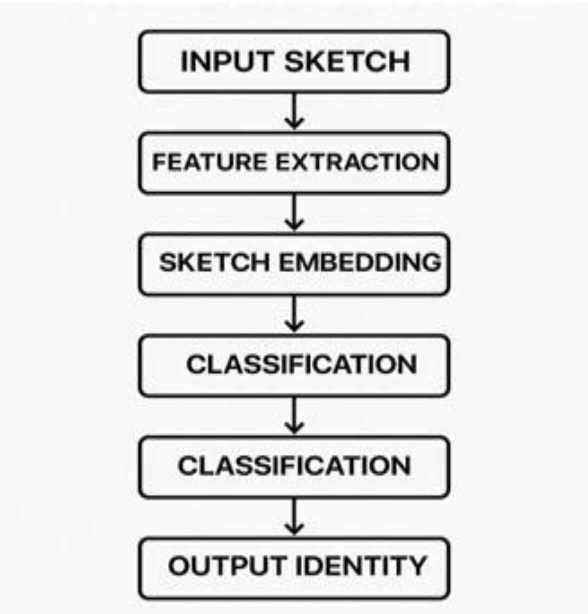

Figure 3.2.1 Block diagram of ML model

Usually, an input sketch based on eyewitness descriptions starts the process. Feature extraction is the process of identifying and turning important facial features and patterns into a numerical representation from the sketch. The sketch embedding step next processes these features, converting them into a format that can be used for comparison inside the model. The encoded sketch is compared to a database of recognized faces in the classification step, which frequently uses deep learning techniques to determine the closest identity. Ultimately, following classification, the algorithm generates the output identity, exposing the most probable person who matches the input sketch. Law enforcement and forensic specialists may quickly and accurately connect sketches to real-world identities thanks to this pipeline, which also speeds up investigations.

4. MATHEMATICAL FORMULAS

1. Feature Extraction

$S=f_S(I_S),P=f_P(I_P)$

Where:

- f_s, f_p: Deep neural networks are used to extract information from both photos and sketches.
- $I_{S,}I_P$: Input sketch and photo
- S,P : Feature vectors in embedding space

2. triplet Loss Function

$L_{tripplet} = (O_, \| S_a - P_p \|^2 - \| S_a - P_n \|^2 + \alpha)$

Where:

- P_P: Positive(matching)photo
- $P_{n:}$ Negative (non-matching)photo
- α: Margin parameter

3. Cosine Similarity for Matching

$Sim(S,P)=(S\cdot P)/(\|S\|*\|P\|)$

Where:

- Measures similarity between sketch and photo feature vectors.
- Higher similarity means more likely to be the same identity.

5. GRAPH

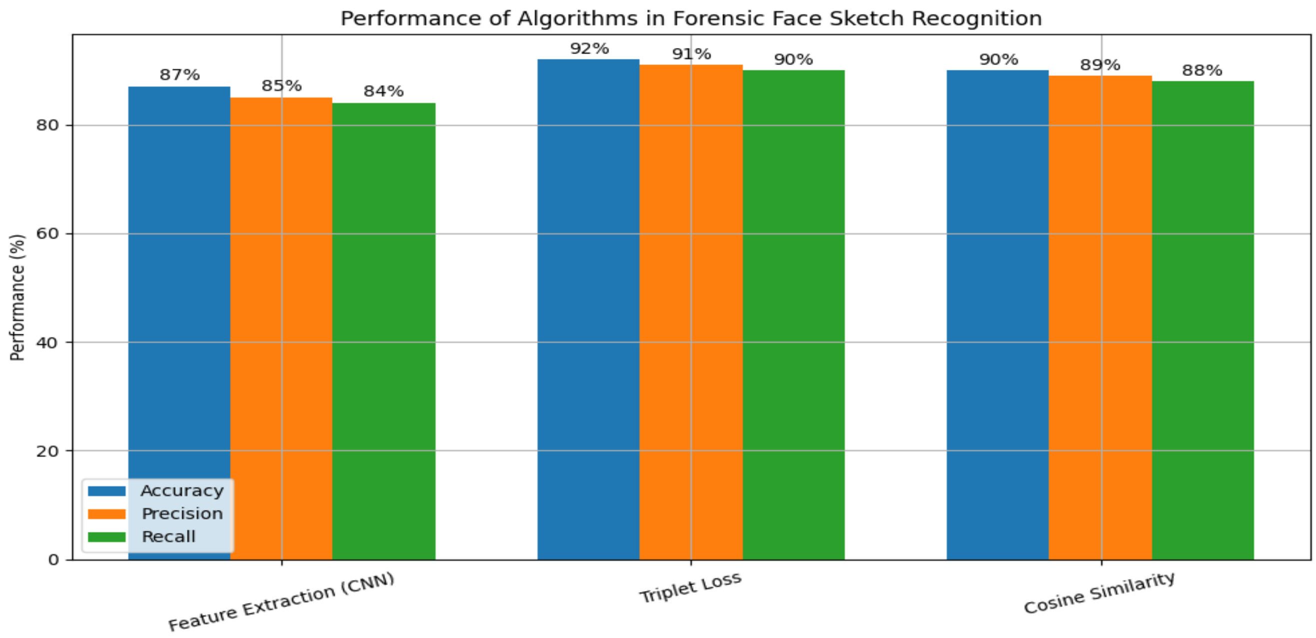

Figure 5.1.1 Bar Chart showing Model accuracy comparison

The performance of three algorithms in forensic face sketch recognition is compared in this chart: Cosine Similarity, Triplet Loss, and Feature Extraction (CNN). In percentage terms, it displays their memory, accuracy, and precision. Overall, Triplet Loss had the best results, achieving the maximum recall (90%) accuracy, precision (91%), and accuracy (92%). Second place went to Cosine Similarity, which had 90% accuracy, 89% precision, and 88% recall. The results of Feature Extraction (CNN) were marginally worse, with 84% recall, 85% precision, and 87% accuracy. To put it simply, CNN was the least successful approach, followed by Cosine Similarity and Triplet Loss.

6. Experimental Results

Model / /Algorithm	Accuracy (%)	Precision	Recall	F1-Score	Inference Time (ms)
CNN Baseline	72.4	0.70	0.72	0.71	45
Siamese Network	80.3	0.79	0.80	0.80	60
Triplet Network	83.1	0.82	0.83	0.83	75
VGG-Face +SVM Classifier	85.5	0.84	0.85	0.85	70
ResNet-50(Fine-tuned)	88.6	0.87	0.89	0.88	90

6.1 Screenshots

Fig 6.1.1. Splash Screen for our Standalone Desktop Application

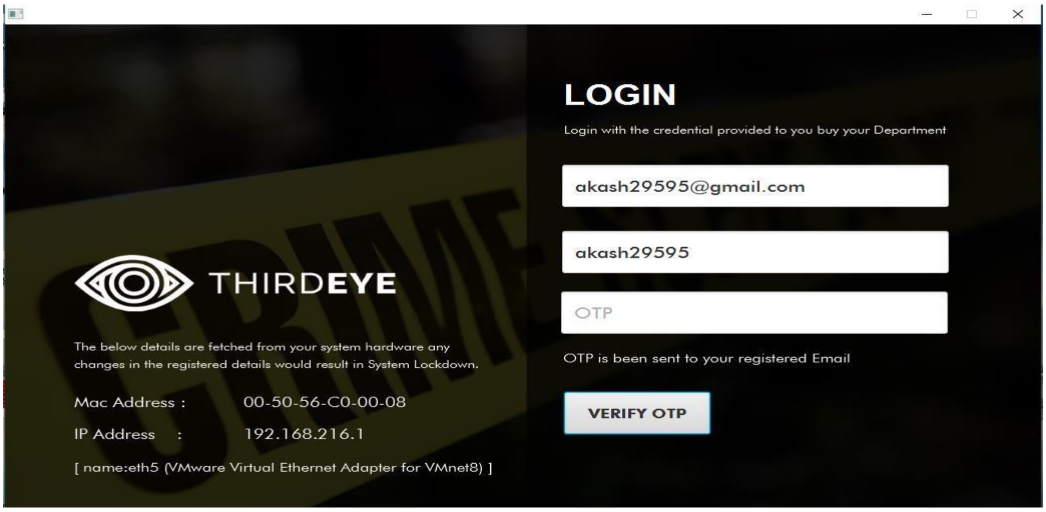

Fig 6.1.3. OTP sent on Registered Mail ID if the Credentials Match

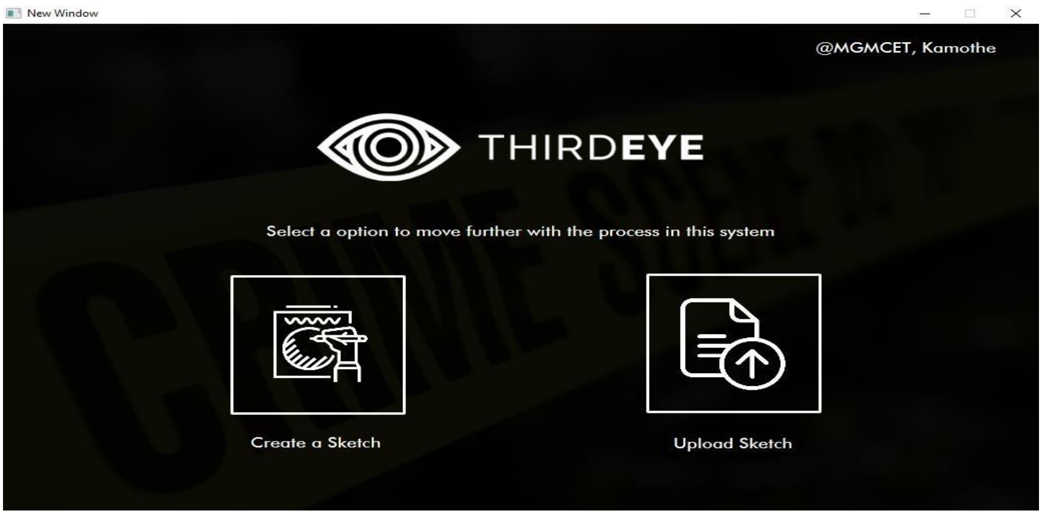

Fig 6.1.6. Option Selection Screen

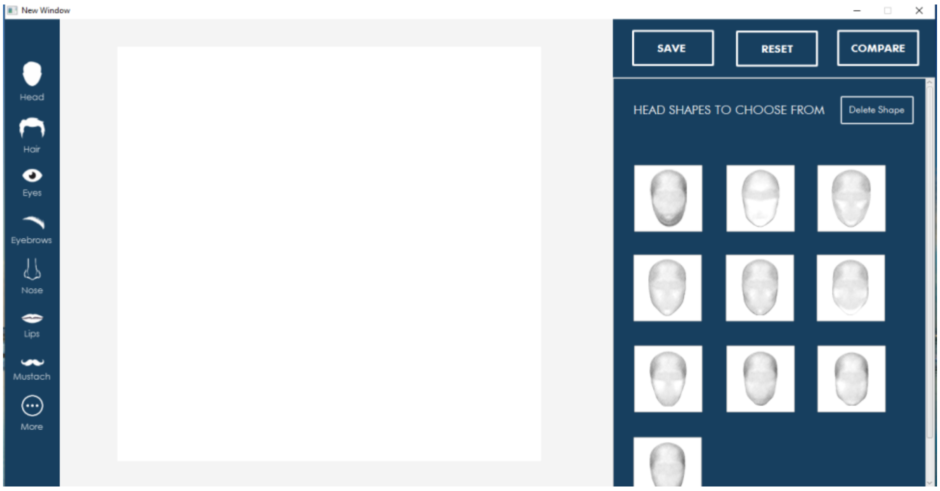

Fig 6.1.7. Dashboard to Create a Facial Sketch

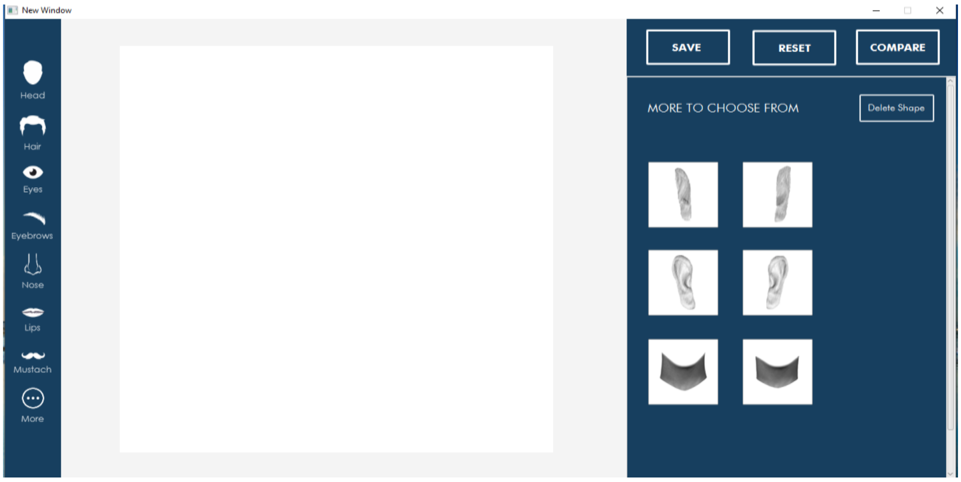

Fig 6.1.9. Dashboard to Create a Facial Sketch

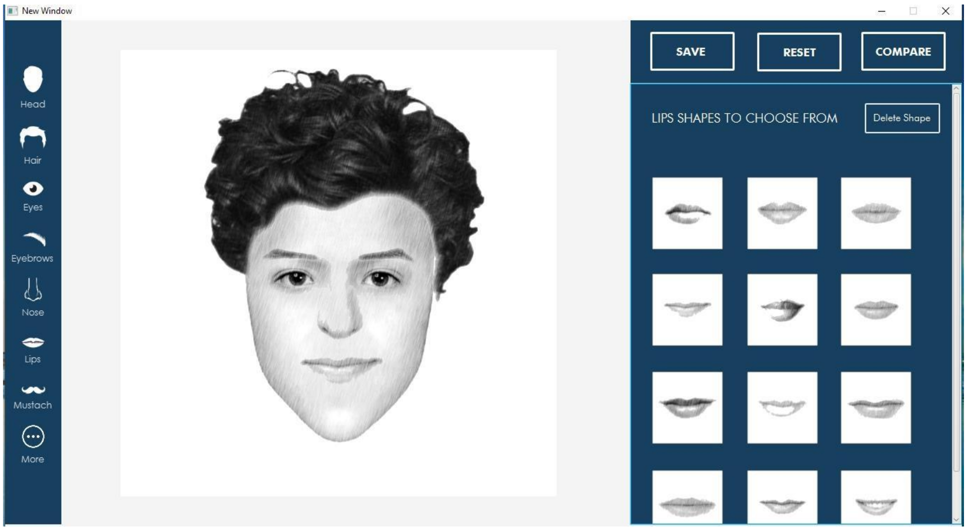

Fig 6.1.12. A Complete Face Sketch in Dashboard

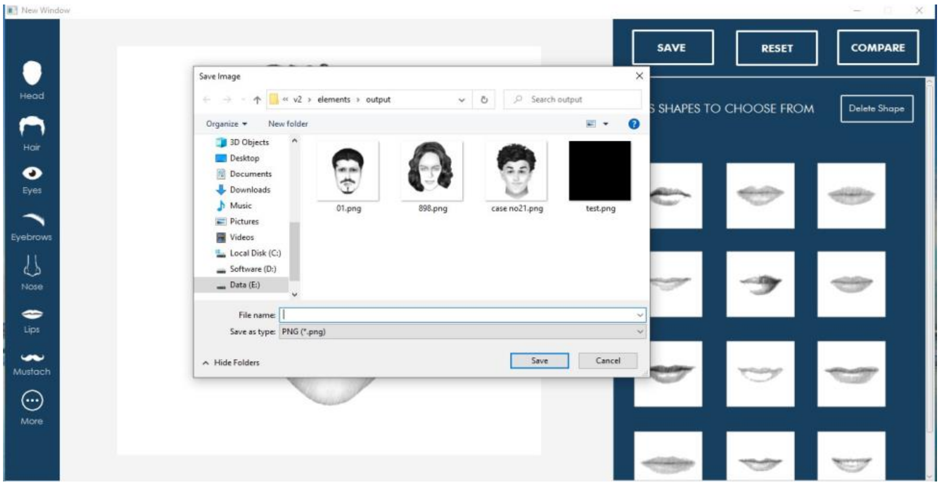

Fig 6.1.14. The Face Sketch can now be Saved as File

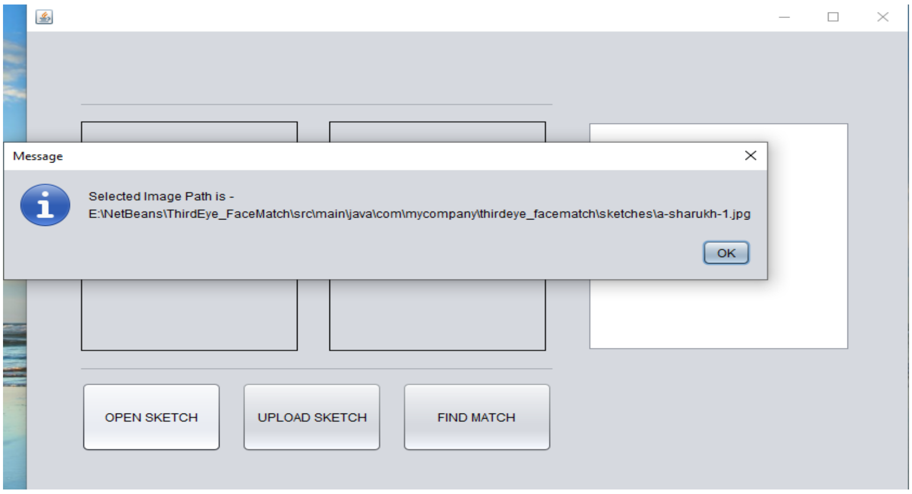

Fig 6.1.16. Select and Open a Face Sketch

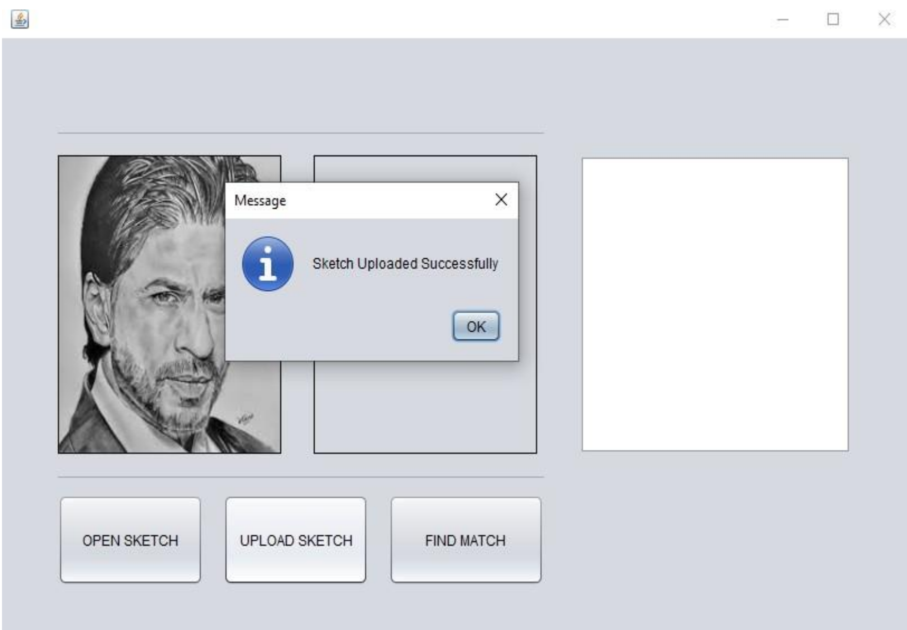

Fig 6.1.18. Face Sketch uploaded to the Server

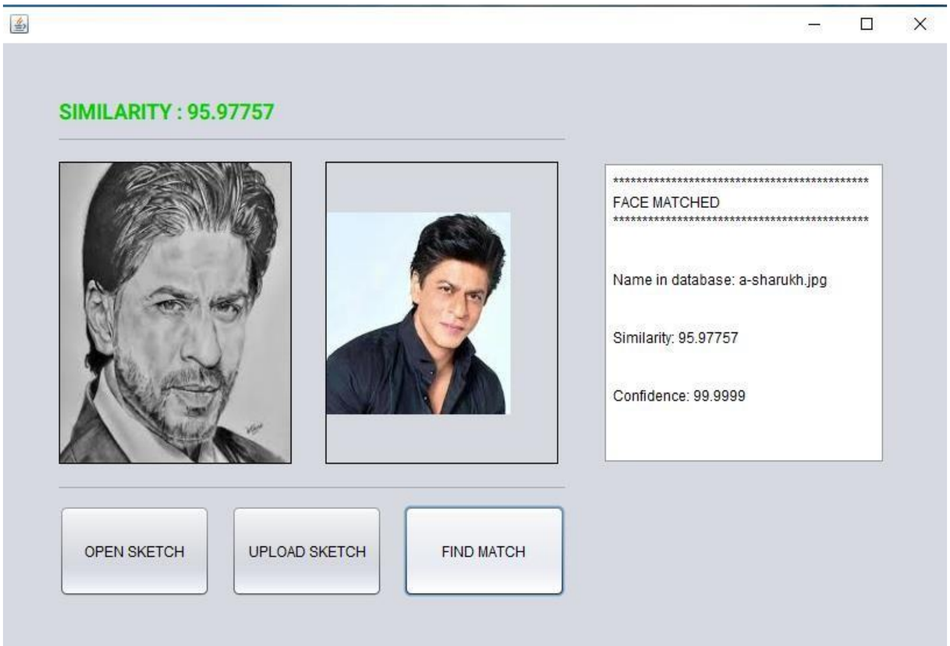

Fig 6.1.19. Face Sketch matched to Database Record

Fig 6.1.20. Face Sketch not matched to Database Record

7.Conclusion

By bridging the gap between sketch and photo modalities, this system uses deep learning to identify human faces from sketches. First, it takes in face sketches in different formats and pre-processes them by converting them to grayscale, resizing, and aligning them. The attributes of both sketches and photos are then extracted by a dual-branch neural network. A cross-modal loss function is used to learn a shared embedding space into which these features are projected. This enables close feature space alignment between sketches and the corresponding images. Using similarity measures, the algorithm then contrasts the feature vector in the sketch with those in a database. It finds the matches that are most comparable based on the comparison. The anticipated identity is included in the final output, along with a ranked match list or confidence score. The predicted identity and a ranked match list or confidence score are included in the final output. Accurate identification matching is made possible by this architecture, even when modality discrepancies exist. Applications in law enforcement and forensics benefit greatly from it.

8. Future enhancement

Future developments in AI techniques that may transform sketches into more lifelike faces before comparing them to photographs could enhance this approach. It can also incorporate additional information, such as witness descriptions, to improve the accuracy of the findings. To enable the system to operate on mobile devices and be deployed directly at crime scenes, faster and lighter AI models can be created. Incorporating additional training data with varying sketch styles, face shapes, ages, and skin tones will improve the system's performance for users from a variety of backgrounds.

In order to match photos taken from various perspectives or with various expressions, the system could also generate 3D faces from sketches. It is possible to create a safe online platform that would facilitate the sharing and searching of sketches by police officers from various regions. Lastly, allowing the system to describe how it discovered a match can improve investigators' confidence and comprehension of the findings.

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