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FaceNet-Driven Forensic Face Sketch Construction and Database Matching for Criminal Identification

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ABSTRACT- The steady rise in criminal activity has placed law enforcement agencies under increasing pressure to speed up their investigative processes and deliver justice more efficiently. In many cases, identifying suspects still depends on traditional sketching methods, which require the expertise of trained forensic artists. However, because such specialists are few in number, this method often becomes slow and difficult to manage. To overcome these limitations, this paper introduces an independent system designed to help users create suspect sketches quickly, without needing any professional artistic skills. The platform provides a simple drag-and-drop workspace where facial features can be adjusted and assembled to form accurate representations. Once a sketch is created, deep learning techniques and cloud-based tools automatically compare it with existing law enforcement databases. This greatly enhances both the speed and reliability of suspect identification. By reducing the dependency on forensic artists and streamlining the sketch-creation process, the proposed approach aims to support faster and more effective criminal investigations.

KEYWORDS- Forensics, Sketch, Recognition, Matching, FaceNet, MTCNN, Embeddings, Similarity, Deep Learning, Detection, criminal, database, AI, preprocessing.

I. INTRODUCTION

The face sketch recognition is particularly relevant in the cases where there is no photographic evidence of the suspect. In most cases, an eyewitness drawing is the only visual reference to be used, but they might be of all kinds, differing in style, detail, and accuracy. Due to this reason, it is not easy to compare a sketch that has been drawn by the hand and the real photograph of the face. The disparity between the two forms, one abstract and interpretive and the other, realistic, brings a great challenge to the automated systems of identification. Solutions that had been previously used relied on hand-inspecting sketches with sets of mugshots, which was fast, subjective, and otherwise unrealistic as databases expanded. This field has been changed recently with new innovations in deep learning. Convolutional neural networks, encoder-decoder trained models, and feature-embedding models have allowed projecting sketches as well as real images into a shared feature space. This common representation enables a better and more precise matching and enhances the quality of sketchy-based identification of suspects. This allows similarity to be measured efficiently and much better recognition performance is achieved.

This paper is aimed at creating an AI-based forensic face sketch recognition system based on deep learning feature extraction and MongoDB scalable storage and retrieval of images and embeddings. The system can help law enforcement agencies identify suspects and solve cold cases because it will solve the challenges of dataset limitations, modality variation, and real-time query matching among other challenges. Finally, this production brings to the fore the role of artificial intelligence in boosting forensic science through increasing the rate of sketch-based identification and accuracy.

II. RELATED WORK

FaceNet is a deep learning model by F. Schroff et al. [1], which utoils glasses or a face isolated as a face in a common embedding space through triplet loss. The method allows the accurate face recognition and clustering by producing 512-dimensional embeddings, which is conceptually equivalent to the embeddings employed in our system in photo and sketch recognition.

VGG-Face, a deep CNN architecture, was developed by O. M. Parkhi et al. [2] it is trained on a large-scale dataset to be useful in face recognition. This model shows that CNN embeddings are effective in facial similarity, on which we use embedding-based matching in our project.

DeepFace, an early deep learning face verification system, introduced by Y. Taigman et al. [3] is a 3D aligned deep embedding system. The use of deep embeddings to solve cross-domain recognition is an activity that is justified in this work as is the case with sketch-to-photo matching.

The heterogeneous face recognition system proposed by B. C. Klare and A. K. Jain [4] compared images of NIR and visible light, matching them with the help of the feature-based system. Their contribution demonstrates the innovations in the domain of early cross-domain recognition and encourages embedding-based matching of sketches and photos.

S. Ouyang et al. [5] suggested feature transfer and subspace learning that enable comparison of sketches and photos that was possible in heterogeneous face recognition (HFR). This is in line with our method of mapping sketches and images to a shared embedding space.

A coupled information-theoretic encoding algorithm of sketch-photo recognition was developed by W. Zhang et al. [6]. His approach enhances cross-modal matching accuracy, and it is important to show that alignment should be made between the domains of sketch and photo.

W. Wan and H. J. Lee [7] proposed using VGG-Face embeddings and fast sketch-to-photo recognition based on a Ball Tree search. This is also comparable to our system, which employs embeddings in a database to match efficiently.

C. Chen, X. Li and Y. Liu [8] proposed a semi-supervised CNN having feature matching loss to enhance unconstrained sketch-photo recognition. This strategy is consistent with our fallback strategy of sketches where normal detection can not be done.

Identity-Aware CycleGAN was created by Y. Fang et al. [9] which reproduces sketches into photo-like images, but maintains identity. This domain adaptation model improves the quality of embedding comparing sketches with photos.

S. Bae et al. [10] suggested a styleGAN network that can be trained in a bidirectional manner to produce photo-like face images on a sketch or vice versa. This assists in lessening the mode distinction amid the drawings and photographs, as well as our proposed system enhancements.

Diffusion models with CLIP embeddings K. K. Jain et al. [12] investigated diffusion models with CLIP embeddings as synthetic forensic sketch technology, which uses generative models and embeddings. The embedding-based sketch recognition is conceptually supported.

The one to introduce the benchmark of sketch-photo recognition was X. Wang and X. Tang [13], which created CUHK Face Sketch Database (CUFS/CUFSF). Their dataset has been popular in the comparison of the heterogeneous face recognition methods, which justifies the use of the dataset in our experiments.

Z. Zhang et al. [14]provided a deep sketch dataset of face recognition that provides both sketch and photo pairs to train and test, which is also applicable to test our embedding-based recognition system.

Guo et al.[15] suggested the Cross-Task Modality Alignment Network (CTMAN), which manages to minimize the modality divergence between sketches and photos by acquiring shared identity-preserving embeddings via a two-stream deep architecture. The study indicates better recognition in CUFS and CUFSF databases, which supports the significance of sound embedding alignment to sketch-to-photo matching of faces.

III. PROBLEM FORMULATION

A. Problem Statement

In most instances, criminal investigations may use the eyewitnesses to draw sketches of the suspects in case of lack of photographs or video footage. Although the use of drawings created by qualified forensic artists may be helpful, the end result is still determined by the style of the artist, the memory of the witness and other human factors which is prone to inaccuracies at times. Even though there are digital tools that assist in coming up with composite faces, they tend to offer a limited number of facial choices and their results are usually very unrealistic or even cartoonish. Due to these shortcomings, it is not easy to match such sketches with the real suspects in the police databases and the produced images might not represent the entire breadth of the human facial diversity.

In this paper, the challenges are tackled by the researcher who suggests a digital system as a means of building and identifying forensic facial images, which will enhance the accuracy and speed in identifying suspected wrongdoers. The system is based on current AI and machine-learning methods to produce more natural facial composites on the basis of eyewitness accounts or uploaded sketches. Individual features of the face can be adjusted by the user to bring the image closer to the description made. Besides, the site incorporates facial recognitions that match the drawings created to large databases of criminals, making the probability of finding a good match higher. In general, the suggested solution is bound to make the sketch-creation process easier to accomplish, enhance the accuracy in the identification, and enable law enforcement bodies to perform more rapid and effective investigations.

IV. PURPOSES OF THE PROPOSED SYSTEM

The Objectives of the proposed project are the following ones, each of them is targeted to solve the existing challenges and the existing gaps in traditional forensic sketch identification by means of AI-based automation and further spread of facial recognition methods:

- To design and construct a system utilizing AI that can be trusted to compare forensic sketches to actual photos of facial features and identify more reliably the suspect.
- To develop better feature-extraction algorithms to capture finer features of the face and reduce the disparity between the drawings of hand and the digital images.
- To help in quick and real-time search, it will develop effective matching procedures to be used with large criminal image databases.
- To increase the efficiency of the system to deal with the different styles of drawing as well as the omission of details among other subjective details in forensic sketches, leading to better matching of various inputs.
- To reduce the amount of work required to acquire the potential leads on a potential suspect by automating the sketch-matching process, thereby decreasing the investigation times.

V. METHODOLOGY AND ARCHITECTURE

The Forensic Face Sketch Construction and Recognition evolved through a strict and convenient regime with the intention to enhance the process of identifying suspects and analysing the sketches by the forensic teams.

A. Steps involved

1) An ingestion of the computer needs to occur.<|human|>Input Acquisition / Data Handling:

The system has two primary inputs namely the forensic sketch that the user feeds and the database of actual face images. All real images have been processed previously and transformed into feature embeddings and when the query is requested, the sketch is run in real-time.

2) Face Detection Using MTCNN

After the uploading of a sketch or photograph, MTCNN model is employed to identify the face and removes the rest of the background. This makes sure that the analysis is done to the relevant part of the face. In case the detector fails to find a face, the system sends an alert to the user.

3) Image Preprocessing

Once the faces have been extracted, the image is resized and normalized and converted into a tensor form, which is compatible with the FaceNet model. This preprocessing pipeline can be used to make sure that sketches and real photographs are processed in the same and in a contrasting way.

4) Generation of Feature Embedding

This model takes the sketch through the FaceNet InceptionResnetV1 to create a 512-dimensional representation of the sketch. This is a vector that reflects the distinctive facial features in a discriminate mathematical expression.

5) Embedding Database Construction

Embeddings of all real images in the repository are and will be computed beforehand and stored as individual files. These vectors are pre-generated making it easy to retrieve them and match them efficiently in the recognition process.

6) Comparison of similarity scores

This system are the similarity scores obtained with the sketch embedding and each of the stored embeddings Sunday. It is a similarity score that shows the closeness of the sketch to all real images in the dataset.

7) Match Identification and Ranking

The system ranks all the images depending on their similarity scores. That identity which has the biggest score is the one that is believed to be the best possible match with the sketch provided.

8) Threshold-Based Decision Making

There exists a satisfactorily set threshold of similarity beyond which the top match can be said to be reliable. When the similarity score is greater than the threshold, the system returns the matched ID and similarity value but in the event that the similarity score is not greater than the threshold, it implies that there is no confident match.

9) P Evaluation

The system undergoes testing using a number of sketches and associated real images. Such measures of evaluation are recognition accuracy, distribution of similarity scores, response time, and performance in sketchies of various qualities.

10) System Optimization and Scalability

The pipeline is configured to an extreme of using a large database and providing real time results. The methods of embedding caching, efficient database retrieval, model fine-tuning make sure that this system is scalable, fast and stable in the conditions of different operations.

VI. ARCHITECTURE

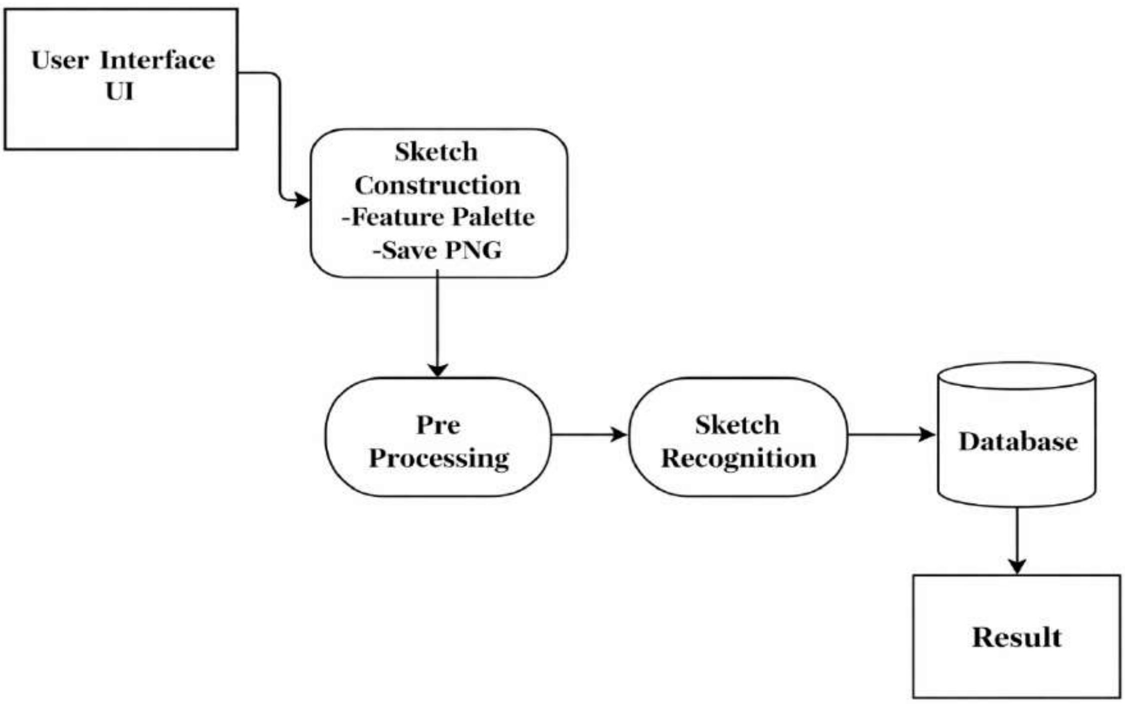

Figure 1: System Architecture of the proposed system

The proposed Forensic Face Sketch Construction and Recognition System have a system architecture as shown in Figure 1. The architecture comprises of some major elements that will help simplify the sketch drawing and suspect identification.

The process starts with the User Interface (UI) wherein the users have the option of creating a forensic sketch with the feature palette or to put images of criminals or a reference image directly into the system. Facial parts may be chosen and placed in the Sketch Construction module and the resulting sketch can be saved as PNG.

The uploaded criminal pictures as well as the drawings constructed are then sent to the Pre-Processing unit where necessary procedures are done which include face detection, resizing, normalization and alignment so that uniformity would be met upon by the recognition model.

The ready-made image is subsequently transferred to the Sketch Recognition module where it derives embeddings and compares these with the entries that are stored in the database to establish possible matches.

All real images, embeddings, and identification information of faces are stored in the Database, so it serves as the central point of reference in performing the recognition process.

Lastly, the system produces the Result which shows the most similar identity or notifies the user that no credible match has been found.

VII. ALGORITHMS

A. MTCNN

Multi-task Cascaded Convolutional Network (MTCNN) MTCNN-Face Detection is a face detector algorithm based on deep learning and capable of locating and extracting faces of images with precision. It uses three steps, P-Net, R-Net and O-Net that enhance the process of detection by filtering the candidate face regions and marking out the key features such as the mouth, nose and eyes.

In this paper, MTCNN is used to erase dirty and unaligned areas of the faces in both drawings and real images to leave the significant face portion to be dealt with. Such a correspondence helps to reduce the variations created by the pose, scale or omissions of the sketch. MTCNN has been found particularly helpful because it can simultaneously produce face croppings of high quality, face localization, and face detection, a feature that allows the following step of extraction and matching of features during forensic face recognition.

In addition, it is multi-stage thus resistant to a low-resolution or partial drawing between successive video frames. Instead of perceiving an object as a whole, it involves a breakdown of the alteration of value of the brightness or pixel intensity to determine the location of each bit of the object. The latter comes in handy especially in those scenes where the movement is meant to be followed without worries about whether transition is sudden and not accurate. Optical flow assumes that the objects will not have unprecedented changes in the way they look in one frame to the next as well as the value of pixels in the objects will be mostly constant. In comparison of these minute changes the algorithm creates a flow field that shows the direction and speed of movement of each visible point.

B. FaceNet - InceptionResnetV1

FacadeNet, a deep learning model that is based on InceptionResnetV1 architecture is a very successful model that is designed to extract large and discriminative features of faces. Rather than classifying faces, it represents each face that it has recognized as a smaller 512-dimensional vector, and each of the components relates to a specific attribute of identity of any given individual. These embeddings are aimed at structural features of faces, including geometry, shape and proportions and minimize the influence of other factors, including the lighting condition, image noise or other trivial uncertainties of a drawing. This system uses FaceNet which is fed with the cropped faces produced by the MTCNN after which the system translates both drawn by hand and real photographs to the numerical feature embeddings. This is a required action in forensic applications as it maps the two divergent modalities into similar feature space such that they can be effectively directly compared. FaceNet is particularly applicable where real faces are required to be compared with sketches since it is highly generalized with a broad variety of inputs.

C. Cosine Similarity

The Cosine Similarity is a mathematical method which is used to determine the similarity of two feature vectors in terms of comparing the angle of the two feature vectors. This is used in this project to determine the degree of similarity between embedding a sketch and those of stored real-image faces. A 1 score will mean a more similarity which is used to identify the closest match in the database. This is an efficient process because, the FaceNet embeddings are already normalized and consequently, the cosine similarity is being used as a process to make swift and efficient comparisons. It is also not susceptible to change in magnitude or scale where only direction of the vector is pursued. This is particularly helpful in forensic applications, where sketches may vary in their texture, shading or artistic detail, but may have a structural relationship with the actual face.

VIII. ALGORITHMS

Some snapshots of the developed Forensic Face Sketch Construction and Recognition system (Figure 2 to Figure 7) are provided in the next section. The homepage, as in Figure 2 provides the user with the chance to draw or post a drawing. Figure 3 is a view of the interface of facial sketching that allows the user to drag-and-drop facial parts to produce an aggregate sketch.

Figure 4 is the preprocessing and embedding generation process in order to prepare the images that will be recognized. Figure 5 will provide the output of the recognition step whereby the system will compare the sketch with criminal faces stored in the database and the optimal matching identity and similarity measure will be given. A combination of these snapshots leads to the fact that the system can build sketches, work with these inputs and match such inputs to the database pictures correctly in real time.

IX. ALGORITHMS

A. MTCNN

MTCNN-Face Detection the Multi-task Cascaded Convolutional Network (MTCNN) is a face detector algorithm developed on deep learning that is able to locate and extract faces of images accurately. It is used in three phases, P-Net, R-Net and O-Net that increasingly improve the detection through filtering the candidate face regions and marking out the major landmarks like the mouth, nose, and eyes.

This paper applies MTCNN to remove the dirty and unaligned parts of the faces in both sketches and real images so that only the important face part is processed. This alignment aids in minimizing the variations due to pose, scale or missing details of the sketch. The use of MTCNN is especially useful due to its ability to achieve face detection and localization of face landmarks at the same time creating high-quality face croppings, which enhance the next stage of feature extraction and matching in forensic face recognition.

Also, it is multi-stage which makes it resistant to low-resolution or partial drawings between successive video frames. Rather than seeing an object in its entirety, it takes an analysis of the change in value of brightness or pixel intensity to figure out where every portion of the object has moved. It is particularly useful in those scenes when the movement should be tracked without any concerns about the transition being abrupt and not precise. Optical Flow presupposes that the objects do not change their appearance between frames abruptly, and thus the values of pixels on them are largely fixed. Comparing these tiny variations, the algorithm develops a flow field displaying the direction and velocity of movement of each visible point.

B. FaceNet - InceptionResnetV1

FacadeNet, which is based on InceptionResnetV1 architecture is a very successful deep learning model which is intended to extract extensive and discriminative facial features. Instead of categorizing faces, it models each face that it has detected as a smaller 512-dimensional vector, with each component corresponding to a distinct feature of identity of a given person. Such embeddings target structural facial characteristics, such as shape, geometry, and proportions, and reduce the effect of other variables, such as the lighting condition, image noise or minor inconsistencies of a sketch. FaceNet is used in this system and is fed with the cropped faces generated by MTCNN and then it translates both drawings by hands and actual photographs to numerical feature embeddings. This is a necessary step in forensic applications since it projects the two different modalities into the same feature space so they can be directly compared in an effective manner. FaceNet is especially useful in cases when real faces have to be compared with sketches due to its high level of generalization with a wide range of inputs.

C. Cosine Similarity

Cosine Similarity is a mathematical technique that is employed to estimate the similarity of two feature vectors by comparing the angle of the two feature vectors. The use of this in this project is to identify the level of similarity between the embedding of a sketch and the embeddings of stored real-image faces. A score of 1 will refer to a more similarity, which is used to determine the nearest match in the database. This is an effective method due to the fact that the FaceNet embeddings are already normalized and thus, cosine similarity is utilized as a way to do quick and effective comparisons. It is also resistant to the change in magnitude or scale where only the direction of the vector is followed. This is especially useful in forensic uses, where sketches can differ in texture, shading or artistic detail but can have structural similarities with the actual face.

X. ALGORITHMS

The next section provides some snapshots of the developed Forensic Face Sketch Construction and Recognition system (Figure 2 to Figure 7). The landing page, as shown in Figure 2 gives the user an opportunity to create or upload a sketch. Figure 3 presents the interface of facial sketching which enables the user to drag-and-drop facial parts to create a composite sketch.

The preprocessing and embedding generation process to prepare the images to be recognized is shown in Figure 4. Figure 5 to Figure 7 shows the output of the recognition step in which the system matches the sketch with criminal faces in the database and provides the best matching identity and similarity measure. A combination of these snapshots points to the fact that the system is capable of building sketches, processing these inputs, and correctly matching them to database pictures in real time.

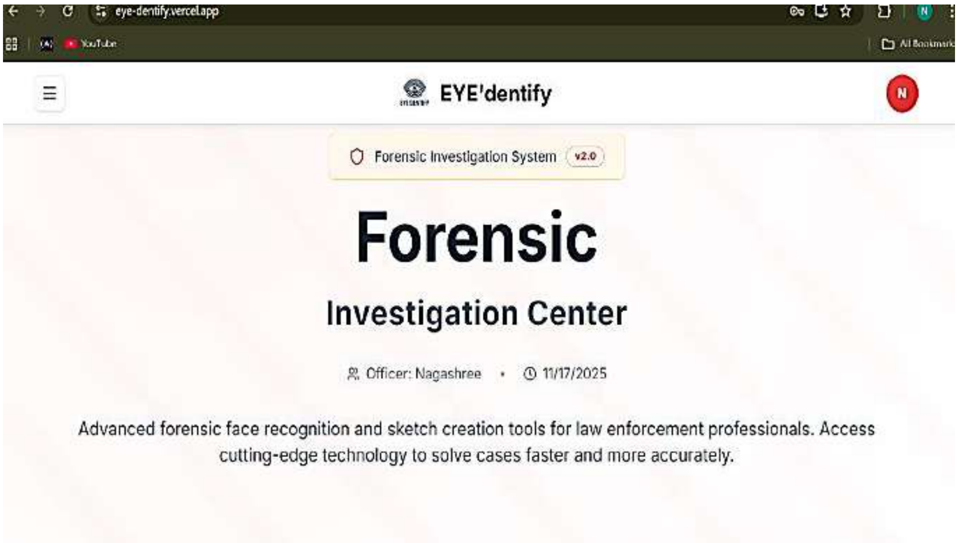

Figure 2: Landing Page

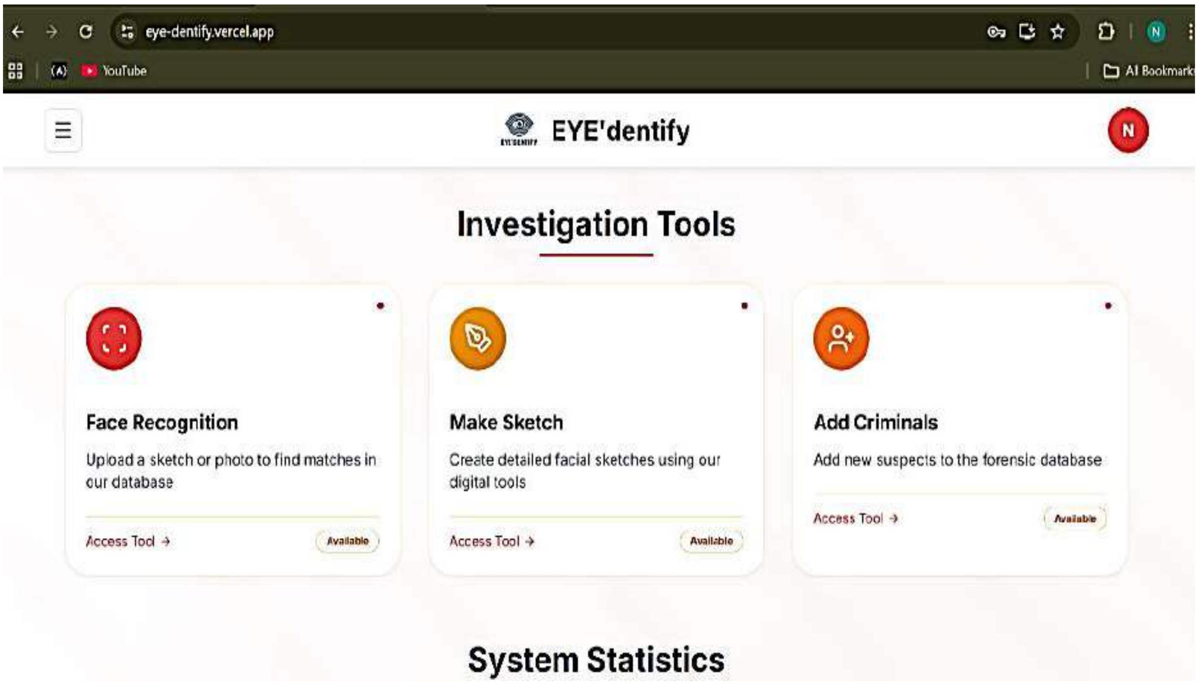

Figure 3: Facial Sketching dashboard

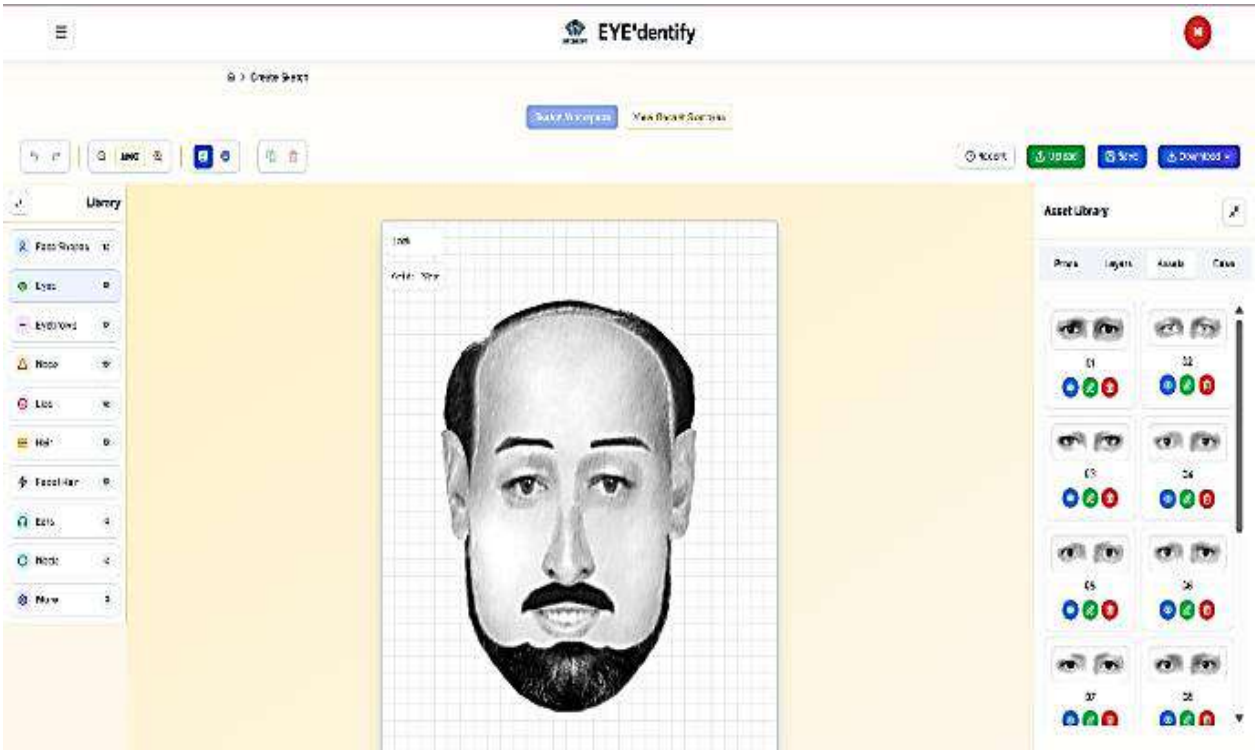

Figure 4: Sketch Page

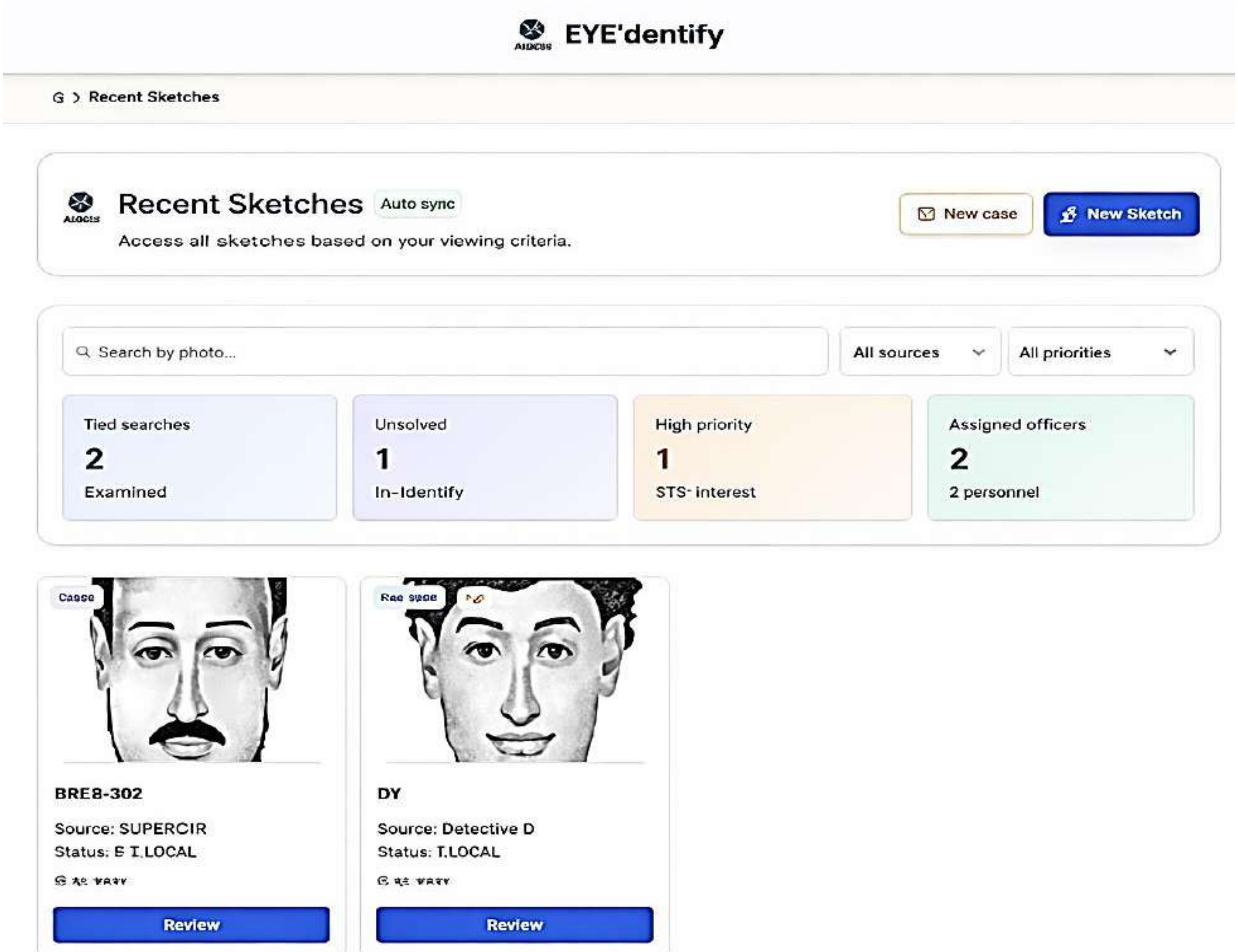

Figure 5: Recent Sketched page

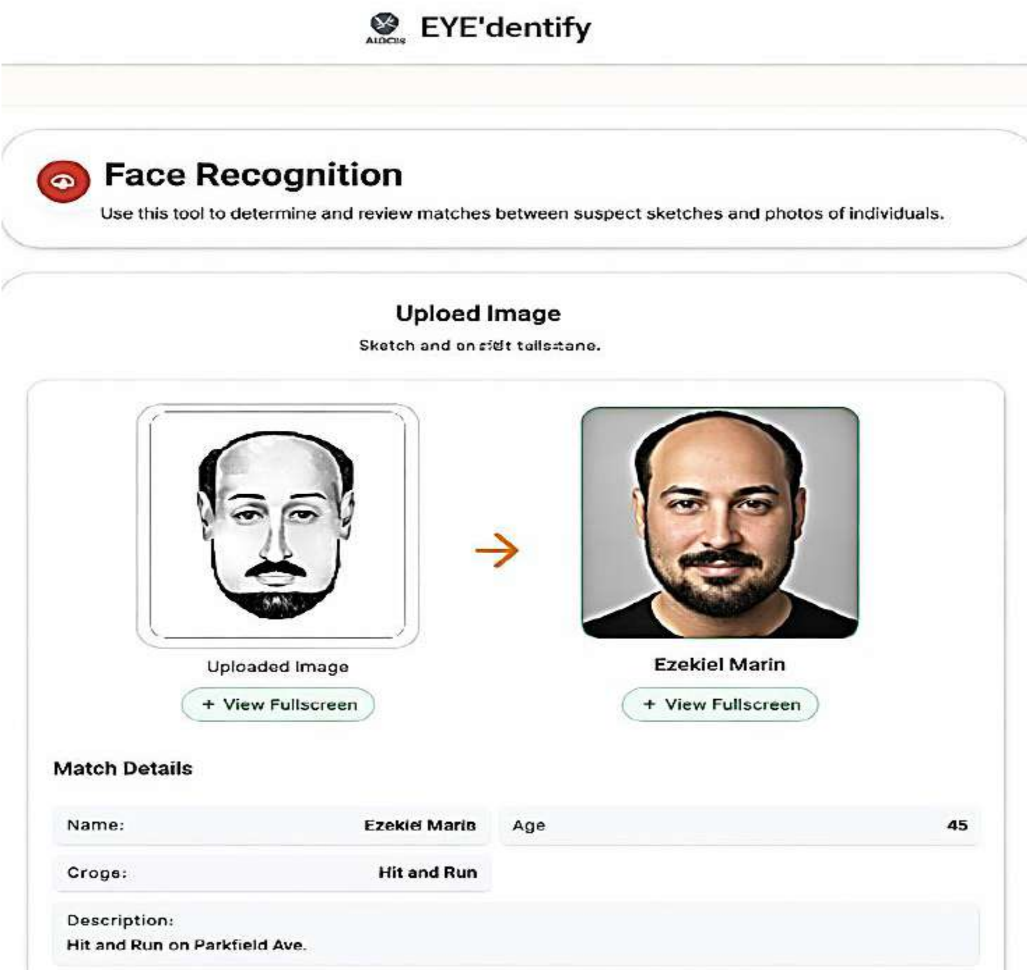

Figure 6: Demonstrates how to add criminal

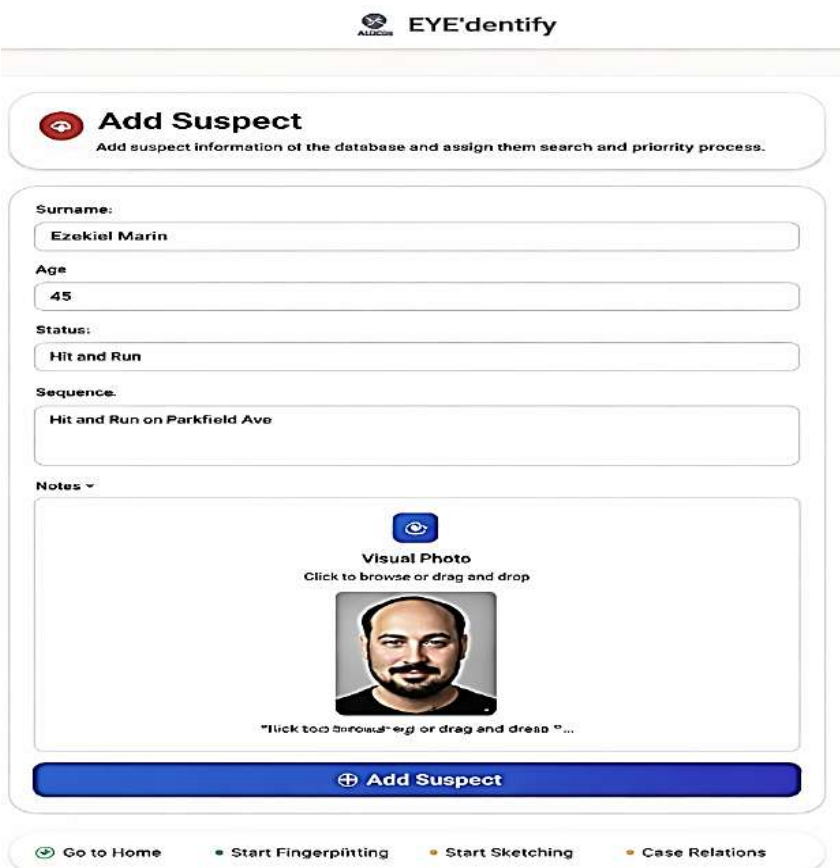

Figure 7: Face recognition result

XI. CONCLUSIONS

This article summarizes the progress of AI-based forensic sketch-to-face recognition and demonstrates how deep learning analyses face-to-face recognitions, such as FaceNet, VGG-Face, patch-based CNNs, among others, can enhance suspect recognition using hand-drawn sketches. In spite of the problematic aspects, including scarce datasets, sketch-photo modality gaps, and computational requirements, when incorporated with scalable databases and rapid similarity search, AI recognition is useful to the efficient and practical application of forensic techniques. The system complements the human judgment by aiding investigators with credible automated matching to increase faster and more accurate identification. Further enhancements might involve biometric or metadata support, better retrieval and partial or low-quality sketch support. Comprehensively, the project is making a significant stride towards effective and usable forensic recognition tools by the police force.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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