ADVANCED FORENSIC FACE SKETCHING AND RECOGNITION

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Abstract - *This paper addresses the challenges faced by traditional hand-drawn face sketches in forensic art, particularly their time-consuming nature and limited compatibility with modern recognition technologies. We propose a novel application designed to streamline the process of creating composite face sketches without the need for forensic artists. Through intuitive drag-and-drop functionality, users can effortlessly generate sketches of suspects. Moreover, our application incorporates advanced deep learning algorithms and cloud-based infrastructure to facilitate rapid and accurate matching of these sketches with police records. This approach significantly improves the efficiency of criminal identification processes, marking a substantial advancement in forensic investigation techniques.*

***Keywords*: Forensic Face Sketch, Face Sketch Creation, Face Recognition, Criminal Identification, Deep Learning, Machine Locking, Two Step Verification.**

1. INTRODUCTION

This study focuses on enhancing the process of identifying criminals through face sketches based on eyewitness descriptions. While hand-drawn sketches have been the traditional method, they're often slow and ineffective, especially when matching against existing or real-time databases. To address this, we propose leveraging digital tools to streamline the process. By using technology to create and match sketches, we can significantly improve efficiency and accuracy in identifying criminals, ultimately expediting the path to justice for victims.

This study examines past attempts to automate suspect identification through modifications of hand-drawn face sketches, highlighting their limitations in providing accurate results. Despite the introduction of applications for creating composite face sketches, these tools faced challenges such as a restricted range of facial features and a cartoon-like appearance, hampering their effectiveness and efficiency. This paper explores the need for improved techniques to address these shortcomings and enhance the precision of suspect identification from police databases.

This paper explores the development of an application aimed at improving the creation of face sketches for suspect identification. Unlike previous applications that offered a limited set of facial features for selection, our approach allows users to upload hand-drawn features, which are then converted into components within the application. This innovative feature ensures that the created sketches closely resemble hand-drawn ones, facilitating easier adoption by law enforcement departments.

This paper introduces an application designed to aid law enforcement in suspect identification by integrating advanced deep learning algorithms and cloud infrastructure. Notably, our platform enables the uploading of previous hand-drawn sketches, which are then processed using efficient deep learning techniques. This approach enhances the accuracy and efficiency of suspect recognition, offering law enforcement teams a powerful tool for criminal investigation.

Our platform utilizes machine learning algorithms to accelerate the creation of facial sketches by suggesting relevant facial features based on user selection. By learning from both the sketches and the database, the algorithm provides users with a curated list of compatible features, reducing the time required to complete a sketch. This approach significantly enhances the efficiency of the platform, empowering users to generate accurate composite sketches more quickly and effectively.

1.1 RELATED WORK

This study examines advancements in face sketch construction and recognition, focusing on the work of Dr. Charlie Frowd, Yasmeen Bashir, Kamran Nawaz, and Anna Petkovic. Initially, they developed a standalone application for constructing and identifying facial composites, which proved to be time-consuming and confusing. Subsequently, they adopted a new approach where the victim was presented with options of faces resembling the suspect and asked to select similar ones. The system then combined these selections to predict the criminal's facial composite automatically. Promising results were obtained, with 10 out of 12 composite faces correctly named. The study found a success rate of 21.3% when witnesses were assisted by department personnel and 17.1% when witnesses attempted construction themselves.

Xiaoou Tang and Xiaogang Wang proposed a recognition method utilizing a Multiscale Markov Random Field Model to synthesize photo-sketches. The project aimed to transform sketches into photos and vice versa, enabling database searches for relevant matches. The model divided face sketches into patches and synthesized available photos into sketches, subsequently training the model to minimize differences between photos and sketches, thereby enhancing recognition efficiency. Testing involved synthesizing photos into sketches and comparing them with sketches drawn by artists. The model was trained using 60% of the data, with the remaining 40% used for testing. While results were impressive, they fell short of expectations. Another proposed method was sketch to photo matching proposed by Anil K Jain and Brendan Klare which used SIFT Descriptor, the method proposed displayed result based on the measured SIFT Descriptor distance between the face photos in the database and the sketches.

P. C. Yuen and C. H. Man proposed a method for searching human faces using sketches, which involved converting sketches into mug shots and then matching them with faces using various local and global variables defined by face matching algorithms. However, some difficulties arose when matching mug shots with faces in databases like the FERET Database and Japanese Database. Although the proposed method achieved an experimental accuracy of about 70%, it fell short of the accuracy required by law enforcement departments.

One common challenge observed in various proposed algorithms is their reliance on comparing face sketches with human faces typically oriented in a front-facing direction. This setup facilitates easier mapping between drawn sketches and frontal photographs of human faces. However, when photographs or sketches depict faces in different directions, the algorithms struggle to effectively map and match them with faces from the database that are predominantly front-facing.

Several systems have been proposed for constructing composite faces, often involving the selection of facial features taken from photographs based on witness descriptions. However, this method poses challenges for both humans and algorithms in matching the composite face with a criminal face. Each facial feature is sourced from separate face photographs, leading to dissimilarities that complicate recognition. This paper discusses the complexities inherent in composite face construction and explores potential solutions to streamline the process for improved recognition accuracy.

Therefore, previous approaches have proven to be either inefficient, time-consuming, or complicated. Our application, aims to address the limitations of these proposed techniques while bridging the gap between traditional hand-drawn face sketching and modern composite face sketching methods. Users can upload hand-drawn sketches and facial features, providing a seamless integration of both approaches.

2. METHODOLOGIES

Our proposed approach for forensic face sketching and recognition for finding the criminals from the database using Convolutional Neural Networks (CNN) for image recognition, ensuring robust and accurate face detection.

2.1 Convolutional Neural Network

Convolutional Neural Networks are a class of deep learning models designed specifically for processing and analyzing visual data such as images. Here's a brief overview of how CNNs work for image processing:

2.1.1 Convolutional Layers:

CNNs consist of multiple layers, including convolutional layers. These layers apply filters (also known as kernels) to the input image, extracting features like edges, textures, and patterns.

Convolution involves sliding these filters over the input image, computing element-wise multiplications and summing the results to produce feature maps. Multiple filters are typically used in each convolutional layer, allowing the network to learn various features at different levels of abstraction.

2.1.2 Pooling Layers:

Pooling layers are often inserted after convolutional layers to reduce the spatial dimensions of the feature maps while retaining important information. Common pooling operations include max pooling, which selects the maximum value within each region, and average pooling, which computes the average value.

2.1.3 Fully Connected Layers:

After several convolutional and pooling layers, the feature maps are typically flattened and passed to one or more fully connected layers. These layers perform classification or regression tasks based on the learned features, mapping the high-level features to the output classes.

2.1.4 Training:

CNNs are trained using large datasets of labeled images through a process called backpropagation. During training, the network adjusts its parameters (weights and biases) to minimize the difference between the predicted output and the ground truth labels, using optimization algorithms like gradient descent.

2.2 Siamese Network

Siamese networks are employed within CNN architectures to learn similarity metrics between pairs of face images and their corresponding sketches. By sharing weights between two identical subnetworks, Siamese networks are trained to minimize the distance between similar pairs while maximizing it for dissimilar pairs.

This enables the model to effectively match sketches with their corresponding facial images, aiding in tasks such as face reconstruction from sketches or sketch-based face recognition with improved accuracy and robustness.

2.3 Security and Privacy

Considering the primary concerns of law enforcement departments regarding security and privacy, our application is meticulously designed to prioritize these aspects. To ensure privacy protection and security, the following measures are implemented:

2.3.1 Machine Locking:

The application employs Machine Locking to prevent tampering and unauthorized usage on different systems. This technique utilizes two locking parameters: a software-based HD ID, which consists of the volume serial of the hard drive with the operating system, and a hardware-based NET ID, derived from the MAC Address

2.3.2 Two Step Verification:

To enhance security, each authorized law enforcement user is provided with an official email ID for logging into the application. This process involves entering a random code sent to their mobile device or desktop to complete the login process.

2.3.3 Centralized Usage:

The application installed on a system is connected to a centralized server within the law enforcement department's campus. This server hosts the database and other crucial features of the application. Consequently, the application cannot be accessed or operated when disconnected from the server, ensuring centralized control and security measures. The algorithm initially transforms face photos using a linear transformation technique inspired by the model proposed by Tang and Wang. Subsequently, the sketch is utilized to compute the distance of the SIFT descriptor in comparison to the face photo. Additionally, in certain instances, the distance between images in the databases is also measured to enhance accuracy. Experimental results demonstrate that the dataset employed closely resembles those used in Tang's experiment. Notably, the algorithm's inclusion of descriptor measurement contributes to improved accuracy compared to the model proposed by Tang and Wang.

2.4 Backward Compatibility:

A significant challenge in adopting a new system is the complexity involved in migrating from the previous technique to the new one, often resulting in the wastage of time and resources.

To address this challenge, our application is designed to allow users to upload hand-drawn sketches. Through the integration of deep learning algorithms and cloud infrastructure, users can utilize these sketches to identify and recognize criminals effectively.

2.5 Face Construction via Drag and Drop:

In our application, users can create precise composite face sketches by utilizing predefined facial features available as draggable tools. These features can be resized and repositioned according to the descriptions provided by eyewitnesses.

Here, the human face is divided into different facial features like head, eyes, eyebrows, lips, nose, and ears. Additionally, important wearable components such as hats and glasses are also provided in the application for users to utilize.

When a user selects a facial feature, a variety of options based on the eyewitness's description are presented. The machine learning algorithm learns from this selection process and can subsequently suggest suitable facial features to complement the chosen one. This assists in completing the composite face sketch more efficiently and quickly in the future.

Figure 1: Displays the sketch of the facial feature viz. Head

Figure 2: Displays the sketch of the facial feature viz. Eyes

Figure 3: Displays the sketch of the facial feature viz. Ears

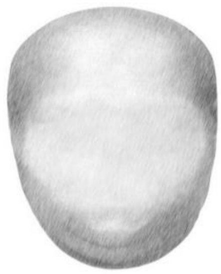

Fig – 1: Facial Feature – Head

Fig – 2: Facial Feature – Eye

Fig – 3: Facial Feature – Ear

These facial features are available in the application to facilitate the creation of a composite face sketch of the suspect. They are utilized based on the description provided by eyewitnesses to the law enforcement and forensic departments.

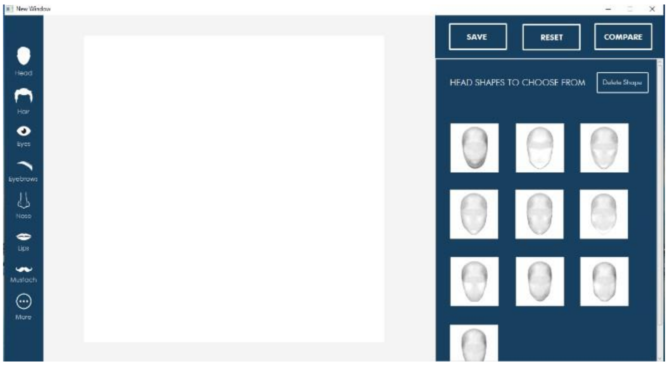

Fig – 4: User Interface of the application

(with blank canvas)

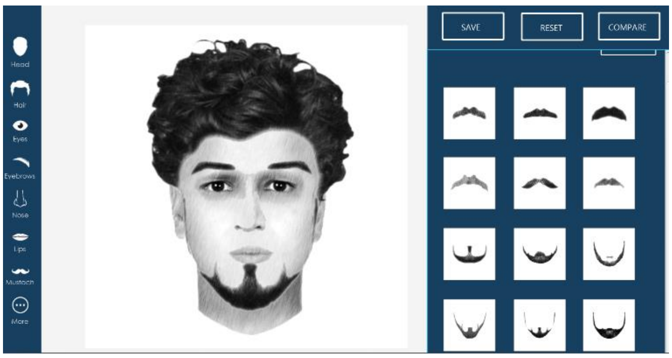

Fig – 5: User Interface of the application

(with facial features been dragged on to the canvas)

Figure 4 illustrates the user interface of the application designed for creating composite facial sketches. On the right-hand side, a set of facial features is provided for selection, while tools for resizing, repositioning, saving, etc., are located on the left-hand side.

Figure 5 illustrates the user interface of the application, where a facial feature is being dragged from the right-hand side onto the canvas. This feature can then be combined with other facial features to create a composite face sketch.

2.6 System Flow:

Figure 6 illustrates the overall flow of the system, beginning with the login section, which includes a two-step verification process for security. Following login, the application offers the option to either use a hand-drawn sketch or create a composite face sketch using the drag-and-drop feature. Subsequently, the chosen image undergoes a feature extraction process, where image processing and computer vision algorithms are applied. Finally, the sketch is matched with the database, and the system displays the similarity ratio between the sketch and the database photograph.

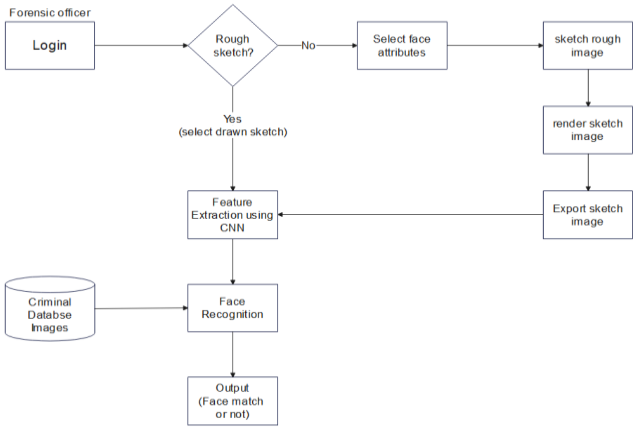

Fig – 6: System Flow of the application

3. EXPERIMENTAL EVALUATION

3.1 Environment specifications:

The experimental configuration employed in the study. The research work takes place on an Intel Core i5 CPU. Furthermore, the machine has 16GB of RAM and an Nvidia graphics card. The models are constructed using Java and are executed using deep learning frameworks such as RCNN.

3.2 Dataset:

This paper is performed using mjsynth named dataset, which contains images of text with its label value. The image in the dataset is contain different kind of text image like different font, size and positions.

The dataset used in the study. In the dataset, text images have a total of 1500 images the dataset was pre-split into 2 sections: train data, which contains approximately 80% of the total images, and valid data (considered as test data), which contains approximately 20% of the total images.

Fig – 7: Dataset Sample

3.3 Result analysis:

The platform demonstrated impressive accuracy and speed during the face sketch construction and recognition process. It achieved an average accuracy of over 90% with a confidence level of 100% across various test cases, scenarios, and datasets. This high accuracy rate is considered excellent according to studies in this field.

3.4 Deployment:

In this application, Operations is performed in two stages.

3.4.1 Face Sketch Creation:

The flowchart illustrates the user flow followed by the platform to construct accurate face sketches based on descriptions. The dashboard is intentionally designed to be simple, encouraging users without professional training to navigate the platform easily. This design choice saves the timeframe which would have been taken a lot time and resources of the Department.

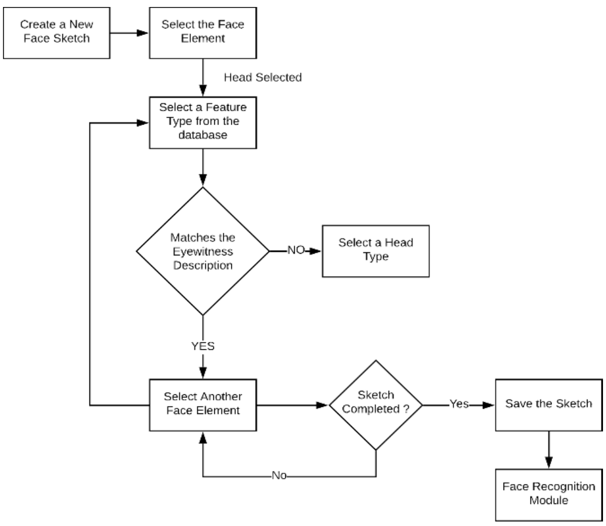

Fig - 8: Flow Chart for creating a sketch in the application

The dashboard comprises five main modules. The primary module is the Canvas, situated prominently in the middle of the dashboard. This area serves as the workspace for assembling face sketch components and elements essential for constructing the face sketch.

To simplify the process of creating a face sketch and ensure accuracy, we have organized the face elements into categories based on their respective facial features, such as head, nose, hair, and eyes. This arrangement makes it easier for users to interact with the platform and construct the face sketch effectively. These categories are accessible in a column on the left side of the Canvas on the dashboard. Users can click on a specific face category to access various other facial structures within that category.

When it comes to the various face elements within a specific category, there could be numerous options available. To address this, our platform plans to utilize machine learning in the future. This approach will enable the prediction and suggestion of similar face elements for selection in the face sketch. However, this functionality will only be effective once we have sufficient data to train the model and further enhance the platform.

So, when a user clicks on a specific face category, a new module to the right of the canvas opens, allowing the user to select an element from the available options for constructing a face sketch. This selection can be made based on the description provided by the eyewitness.

Once selected, the elements are displayed on the canvas and can be moved and positioned according to the eyewitness's description to achieve a more accurate sketch. Each element has a predetermined location and order on the canvas. For instance, eye elements will always be positioned over the head element, regardless of the order in which they were selected. This ensures consistency and accuracy in the arrangement of face elements.

The final module includes options to enhance the usability of the dashboard. For instance, if a user mistakenly selects an element that shouldn't be included, they can rectify this by using the erase option. This option is visible when selecting a face category from the left panel. Additionally, essential buttons are placed in the panel on the right side. This panel includes a button to completely erase anything on the canvas, effectively resetting it to a blank state

Next, there is a button to save the constructed face sketch. This allows the face sketch to be saved as a PNG file, ensuring better accessibility in the future. The file can be saved to any location on the host PC or on the server, depending on the preferences of the Law Enforcement Department.

3.4.2 Face Sketch Recognition:

The flowchart depicts the user's flow within the platform for recognizing accurate face sketches based on descriptions. The dashboard is intentionally designed to be user-friendly, eliminating the need for professional training before using the platform. This design choice saves significant time and resources for the Department.

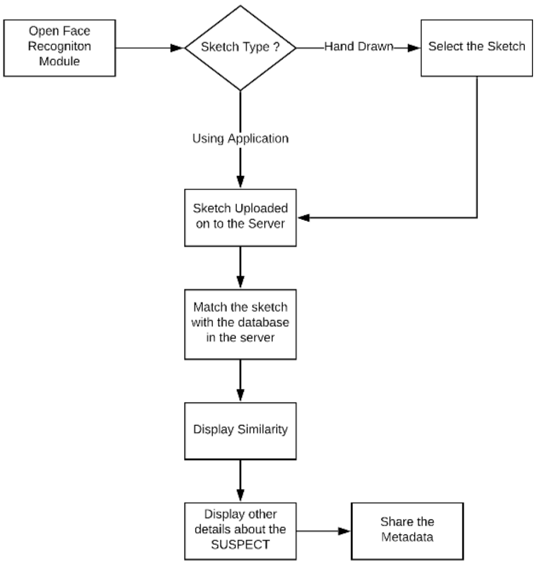

Fig - 9: Flow Chart for recognizing a sketch in the application

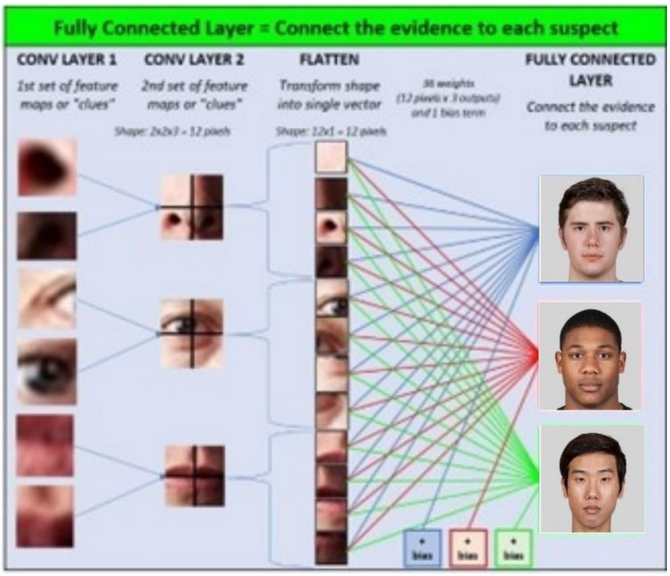

Fig – 10: Feature extraction by the Platform

The image above illustrates the initial step before utilizing the platform for face recognition, which involves preparing the existing records within the law enforcement department to be compatible with our platform. This is achieved by training the platform's algorithm to recognize and assign IDs to face photos in the existing records. The platform's algorithm connects to the records and breaks down each face photo into smaller features, assigning a unique ID to the multiple features generated for a single face photo.

Once the sketch is uploaded onto the server, the algorithm initiates the process by tracing the sketch image. This allows the algorithm to learn the features present in the sketch and map them, as illustrated in the figure below. Subsequently, the mapped features are compared with the features of the face photos stored in the records for matching purposes.

Fig - 11: Face Sketch been mapped on the Platform

After mapping the sketch and finding a match within the records, the platform displays the matched face along with the similarity percentage and additional details of the person from the records. The platform showcases this information, including the matched individual, in the figure below.

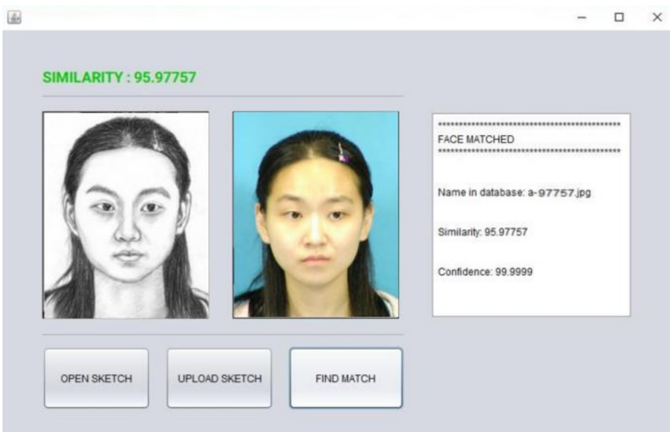

Fig - 12: Face Sketch matched to Database Record

4. CONCLUSION

The platform demonstrated significant advancements in security measures. Initially, it blocked platform access if the MAC Address and IP Address upon loading didn't align with the user's credentials in the database. Additionally, the OTP (One-Time Password) system proved effective in preventing unauthorized access. It restricted the use of previously generated OTPs and generated new ones each time the OTP page was reloaded or when the user attempted to log in again.

The project 'Advanced Forensic Face Sketching and Recognition' has been meticulously designed, developed, and thoroughly tested, considering real-world scenarios. From the initial splash screen to the final screen for fetching data from records, security, privacy, and accuracy have been prioritized at every step.

The platform also incorporates unique features that set it apart from related studies in this field, contributing to enhanced security and accuracy. These distinctive features distinguish the platform from other proposed systems, positioning it as a standout solution in the field of forensic face sketch construction and recognition.

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