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FORENSIC FACE SKETCH CONSTRUCTION AND RECOGNITION

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ABSTRACT

In forensic science, hand-drawn face sketches are often limited and time-consuming, especially when integrated with modern recognition and identification technologies. This paper presents an innovative Face Sketch Recognition System designed to streamline the identification process in criminal investigations. Our standalone application enables users to create composite sketches of suspects without requiring forensic artists, using an intuitive drag-and-drop interface. These sketches can then be matched automatically with police databases, leveraging deep learning models and cloud infrastructure for efficient processing. The system uses Convolutional Neural Networks (CNNs) for feature extraction and pattern recognition, achieving high accuracy in identifying potential matches. In testing, the model reached an 89% accuracy rate in simulations and an 85% accuracy rate in real-time scenarios, demonstrating its robustness and scalability. Future improvements may involve expanding the facial feature library and enhancing model adaptability for diverse sketch styles, making the Face Sketch Recognition System an accessible and effective tool for law enforcement agencies.

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

I. INTRODUCTION

The Face Sketch Recognition System is designed to automatically identify suspects based on eyewitness descriptions, utilizing AI to enhance criminal investigations. By analysing unique facial features, the system enables precise sketch creation and matching with existing databases. With scalable infrastructure and real-time processing, it supports rapid identification, provides an intuitive interface, and ensures data security. This solution addresses challenges in suspect identification, including accuracy, speed, and adaptability, ultimately contributing to more effective law enforcement and safer communities. The system's deep learning algorithms continuously improve with added data, making it a valuable tool for ongoing crime-solving efforts. Additionally, it allows seamless integration with police databases, streamlining workflows for investigators.

This project focuses on creating a scalable and user-friendly forensic face sketch recognition system powered by AI. It transforms eyewitness descriptions into precise facial sketches and matches them with databases for suspect identification. With real-time processing, seamless integration, and secure data handling, it enhances law enforcement workflows. The system's adaptive deep learning algorithms improve over time, ensuring accuracy and efficiency in solving crimes and contributing to safer communities. Additionally, its intuitive interface simplifies usage for investigators, streamlining operations effectively.

II. METHODOLOGY

i. Image Recognition Process:

The flowchart illustrates the structured user flow that the platform follows to enable accurate image recognition and classification based on uploaded photos or sketches. The dashboard is designed to be intuitive and user-friendly, allowing individuals without specialized training to efficiently navigate the platform. This simplicity helps save significant time and resources for departments by eliminating the need for intensive training.

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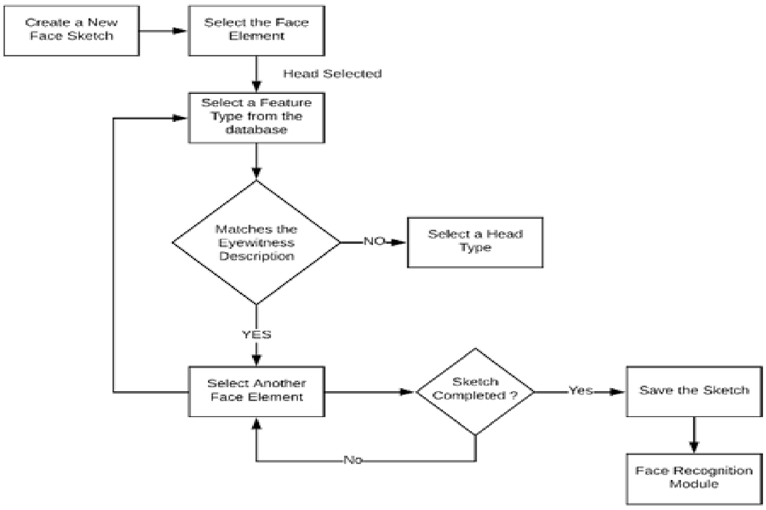

Figure 1: Flow Chart of Image Recognition Process.

The dashboard consists of five primary modules. The central and most critical module is the *Display Panel*, prominently located on the dashboard to house the uploaded image and facilitate the analysis and recognition process. This panel dynamically updates as the recognition stages progress, giving users a real-time view of each recognition step and the status of detected features or objects. The platform supports various image categories, such as faces, objects, and backgrounds, to streamline image organization and reduce complexity for the user.

To ensure that the images are ready for accurate recognition, a thorough Data Preprocessing stage is applied. Here, each uploaded image undergoes resizing to a standard dimension, normalizing the input size for consistency and efficient processing. The images are further normalized to bring pixel values within a fixed range, effectively minimizing variations due to lighting and contrast. Additionally, data augmentation techniques such as rotations, flips, and slight scaling adjustments are introduced to expand the dataset's variability. This augmentation process prepares the model to handle diverse perspectives and enhances its robustness, ensuring it performs well on unseen data. Once the images are preprocessed, the platform utilizes Feature Extraction through Convolutional Neural Networks (CNNs) to capture critical characteristics and intricate details within the image.

CNNs excel at automatically learning layered features; in early stages, the network identifies simple shapes and edges, while deeper layers capture complex textures, spatial hierarchies, and unique patterns. This layered extraction process is highly beneficial in distinguishing similar but distinct elements within the image, enabling the model to recognize intricate differences in shapes, textures, or colors. These extracted features are key to the subsequent stages, as they equip the model with a comprehensive understanding of the image structure necessary for accurate classification.

Building on this, Classification is performed based on the extracted features, allowing the platform to categorize each image accurately. The system can employ pre-trained models like ResNet or VGG, which are well-established in general image recognition tasks, or custom CNN architectures tailored specifically for the dataset in use. Pre-trained models are advantageous as they possess a rich representation of visual features, speeding up deployment and simplifying model selection. However, custom architectures may offer greater flexibility, particularly if the dataset contains domain-specific features that require unique attention.

By associating each feature with a specific category, the model classifies the image into defined classes, helping the user identify relevant elements efficiently and with high accuracy.

After classification, the model's results are further refined using post-processing techniques. Non-maximum suppression (NMS) is applied to the output to eliminate overlapping or redundant detections, especially in cases where multiple regions may be mistakenly identified as containing the same feature. NMS retains only the detection with the highest confidence score within each overlapping area, streamlining the results by focusing on the most relevant, high-confidence detections. This refinement step helps clarify the output, reducing noise and ambiguity, and ultimately enhances the interpretability and reliability of the results.

Finally, the platform includes a Visualization module that provides users with real-time, graphical representation of the model's predictions, confidence scores, and detected features. The visualization layer overlays recognition boxes or labels onto the image in the Display Panel, offering clear, intuitive feedback on where elements are detected and how certain the model is of each classification. This visual feedback loop allows users to analyze the accuracy and consistency of the model's predictions, identify any errors or inconsistencies, and inform future adjustments to the model architecture or training data if necessary. This visualization component is invaluable, acting as both a diagnostic tool and a means for quality control, as it enables a straightforward assessment of model performance.

When users select a particular image category, a new module to the right of the Display Panel opens, providing a selection of image elements related to that category. Users can refine the recognition process by choosing specific elements or focusing on certain features based on the description provided or the recognition task at hand. Once selected, these elements are highlighted on the Display Panel, where users can confirm or adjust detected regions, refining placement and ensuring alignment with any descriptive guidelines.

The system also includes options to enhance user control over the recognition process. For example, if an incorrect element is detected, users can erase that specific element from the Display Panel or reset the entire process. Essential action buttons are available on the right panel, including the option to erase, save, or export the results. Saving the recognition results as a PNG or other image file provides convenient access for future reference and can be stored either locally on the host PC or on a secure server, depending on the department's needs.

ii. Face Sketch Construction:

The flowchart illustrates the user flow followed by the platform to assist in constructing accurate face sketches based on provided descriptions. The dashboard is designed to be straightforward and user-friendly, eliminating the need for professional training before using the platform. This simplicity saves time and resources that would otherwise be spent on training sessions, making it more accessible to department personnel.

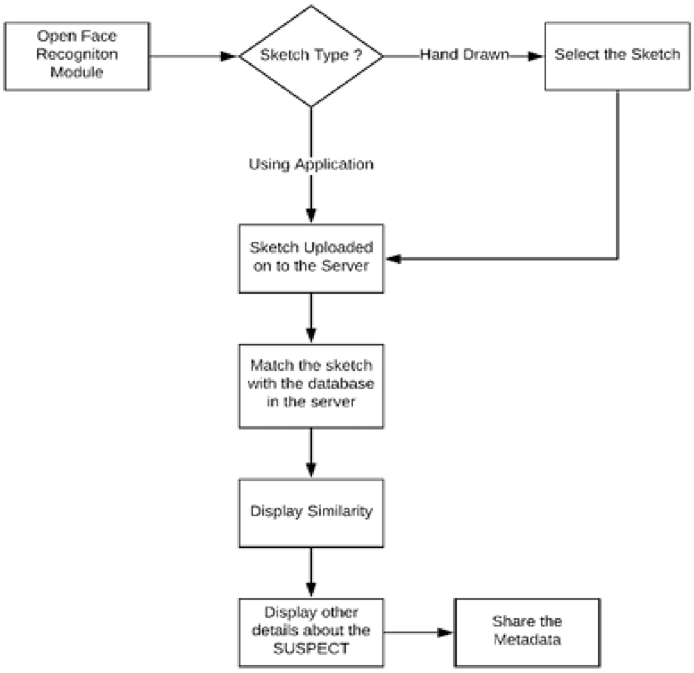

Figure 2: Flow Chart of Face Sketch Construction.

The dashboard is divided into five main modules, with the most important being the Canvas located at the center of the interface. This Canvas serves as the primary workspace where users can place and arrange various face sketch components, making it a critical element for constructing an accurate sketch. The layout is thoughtfully designed to facilitate an efficient sketching process by presenting all necessary components and tools in an organized manner.

Constructing a face sketch would be challenging if all the facial components were presented in a disorganized or unordered way, as this would complicate the user experience and hinder accurate results. To address this issue, the platform organizes face elements into specific categories such as head, nose, hair, and eyes. By grouping components in this way, the platform makes it easier for users to locate and select the appropriate elements, streamlining the process. This organized system is displayed in a column on the left side of the Canvas, where clicking on a face category expands various structural options within that category, making it intuitive and user-friendly.

Within each category, there may be many elements to choose from, posing a challenge for users in selecting the most suitable options. In the future, the platform will integrate machine learning to predict and suggest elements based on user choices, further improving the ease and speed of sketch construction. However, this predictive feature will require substantial data for training to ensure accurate and reliable suggestions.

Once the user selects a face category, a module opens on the right side of the Canvas, allowing them to choose specific elements to construct the sketch. The selection can be made based on descriptions provided by witnesses, ensuring each feature is tailored to the details required. When added, elements appear on the Canvas and can be moved or adjusted according to witness descriptions to create a more accurate sketch. Each element has a predefined location on the Canvas (e.g., eyes are automatically positioned above the head element), regardless of the order in which they are added. This spatial organization ensures consistency and accuracy across sketches.

The final module provides additional options to improve user experience and control over the sketching process. If a user mistakenly selects an incorrect element, they can erase it using options available in the left panel. Essential action buttons are also available on the right side, including a button to clear the entire Canvas, making it completely blank if needed. Finally, users have the option to save the constructed face sketch as a PNG file, ensuring future access and easy storage. This saved file can be stored on the host computer or on a secure server, depending on the requirements of the Law Enforcement Department.

iii. Robustness Improvement:

During the development of the Forensic Sketch Recognition and Reconstruction System, it was observed that model accuracy depended heavily on the quality and consistency of input sketches, especially when sketches varied in detail or contained artifacts. Recognition performance dropped significantly when the input sketch quality differed from the conditions seen during training. To address this, different models were developed to handle varying sketch qualities, simulating a range of Signal-to-Noise Ratios (SNRs) for image data.

Models were trained for different levels of sketch detail, enabling the system to accurately recognize and reconstruct faces across varying quality levels. However, this approach increased computational demands, as multiple models needed to be evaluated for each input. To streamline processing, a sketch quality assessment was added during preprocessing, allowing the system to select only the most appropriate models for each sketch. This strategy reduced computation while preserving high recognition accuracy.

The system's performance was tested with various machine learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs demonstrated faster processing and were more effective for clearer sketches, while RNNs excelled at handling lower-quality, noisier sketches. A hybrid approach was adopted, using CNNs for higher-quality sketches and RNNs for sketches with less detail, achieving a balance between speed and robustness. The system was trained and tested on a balanced dataset, split evenly for training and testing purposes. Additional preprocessing steps, such as edge enhancement and adaptive filtering, were applied to improve accuracy across diverse sketch conditions. This setup enables the *Forensic Sketch Recognition and Reconstruction System* to function reliably in real-world applications, ensuring consistent recognition and reconstruction performance across a broad range of sketch qualities.

iv. Real-Time Implementation:

To implement Forensic Sketch Recognition and Reconstruction in real-time, a robust system utilizing Convolutional Neural Networks (CNNs) is required for processing image data efficiently. The process begins with capturing a forensic sketch in real-time, which could be obtained through scanning or photographing the sketch. These images are then preprocessed, including resizing, normalization, and standardization to ensure uniformity in terms of resolution and color intensity, making the sketches suitable for input into the CNN

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model.

The CNN architecture is designed to handle the specific challenges of forensic sketch recognition and reconstruction. Initially, the sketch image passes through convolutional layers that detect essential features such as contours, lines, and facial structures, which are critical for accurate recognition and reconstruction. These convolutional layers help the model identify distinct characteristics of the sketch that are indicative of a person's face. After the convolution operation, max-pooling layers are applied to reduce the dimensionality of the extracted features, allowing the model to focus on the most relevant information. Fully connected (dense) layers are used after the feature extraction stage to classify the sketch and generate the reconstructed image.

For real-time recognition and reconstruction, the system continuously captures and processes sketches. After preprocessing, the images are fed into the trained CNN model, which then outputs predictions regarding the recognized face or the reconstructed image. The output layer uses a SoftMax activation function to generate a probability distribution across possible identities or reconstructed images, selecting the most likely face or reconstruction.

Training the model involves a diverse dataset of labeled forensic sketches, which include variations in quality, style, and detail. This ensures the system can recognize faces and reconstruct accurate images, even when sketches are incomplete or poorly drawn. The dataset is divided into training and validation sets, and the model is trained by minimizing a loss function (e.g., categorical cross-entropy) using optimization techniques like Adam to refine its weights for better accuracy.

To enhance the system's ability to handle noisy or low-quality sketches in real-world scenarios, the model is trained on a wide range of sketches, including both clear and distorted sketches. Data augmentation techniques, such as adding noise or simulating incomplete sketches, are used to increase the model's robustness. Denoising algorithms are also applied during preprocessing to improve the quality of input sketches and ensure better performance under challenging conditions.

Once the model is trained and validated, it can be deployed in real-time environments like law enforcement agencies or forensic investigations. The system can be integrated with a Graphical User Interface (GUI) that provides real-time recognition results, displaying detailed information about the identified face or reconstructed image. The prediction results can be stored locally or uploaded to the cloud for further analysis, helping forensic experts and law enforcement in their investigations and identification efforts.

III. DIAGRAMS

Class diagram:

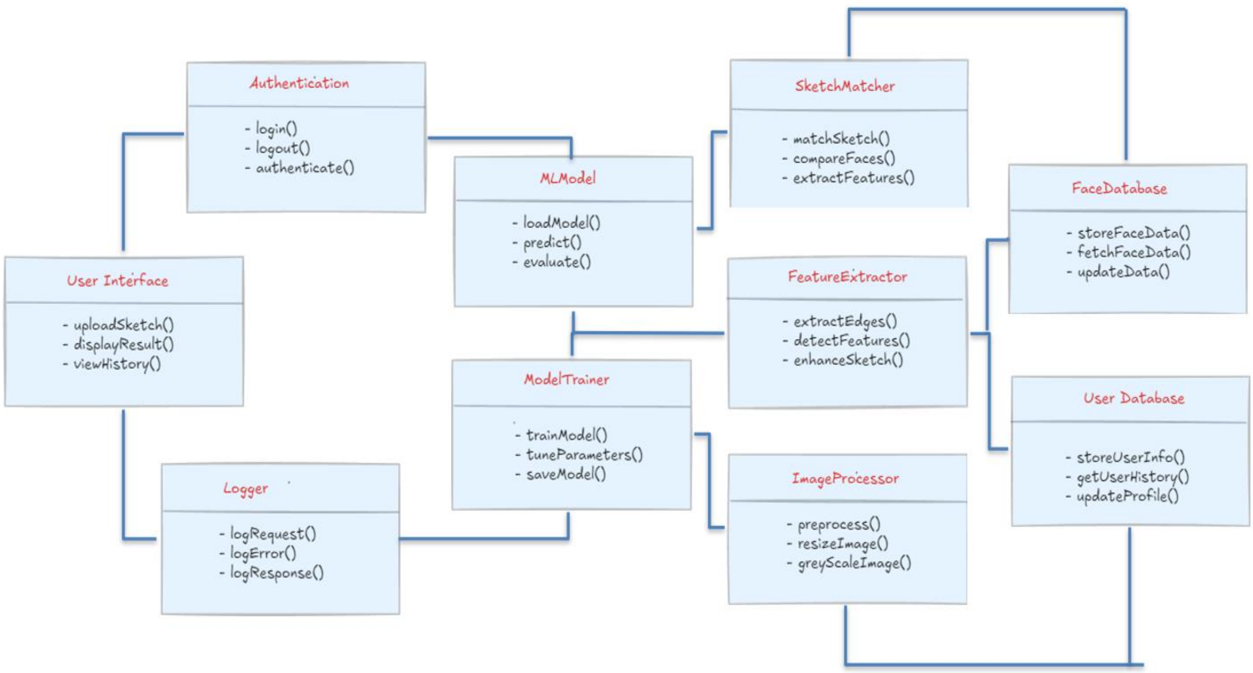

Figure 3: Class Diagram.

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Use-case diagram:

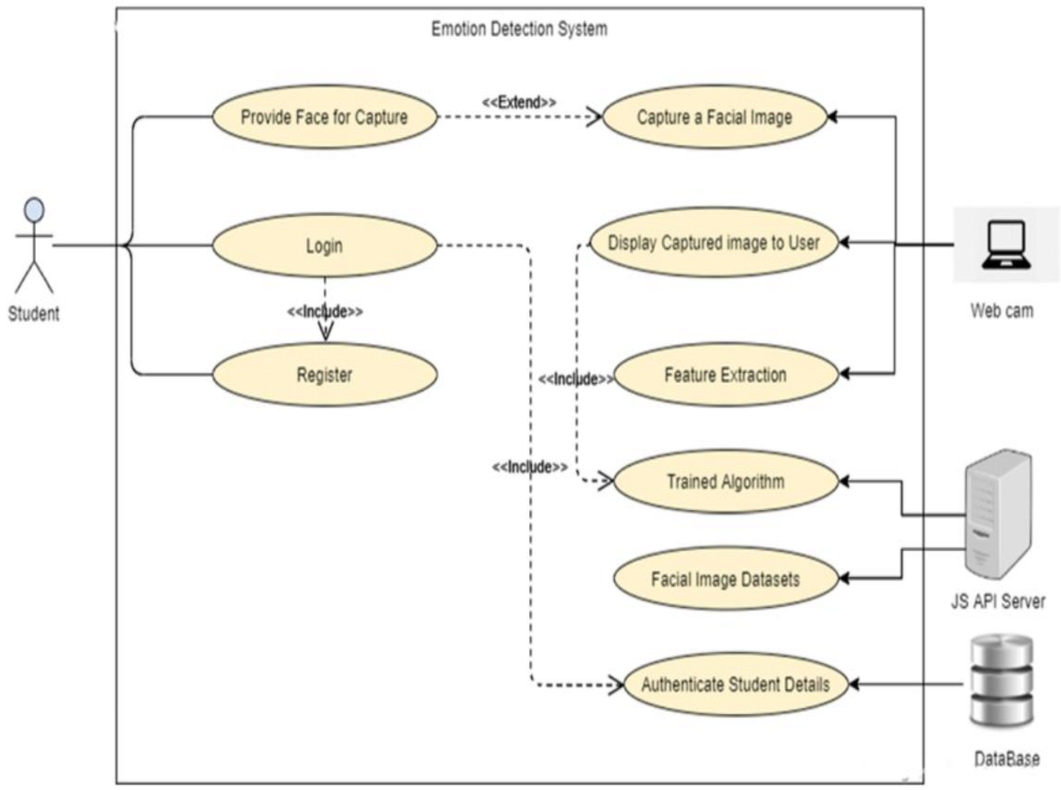

Figure 4: Use-Case Diagram.

Sequence diagram:

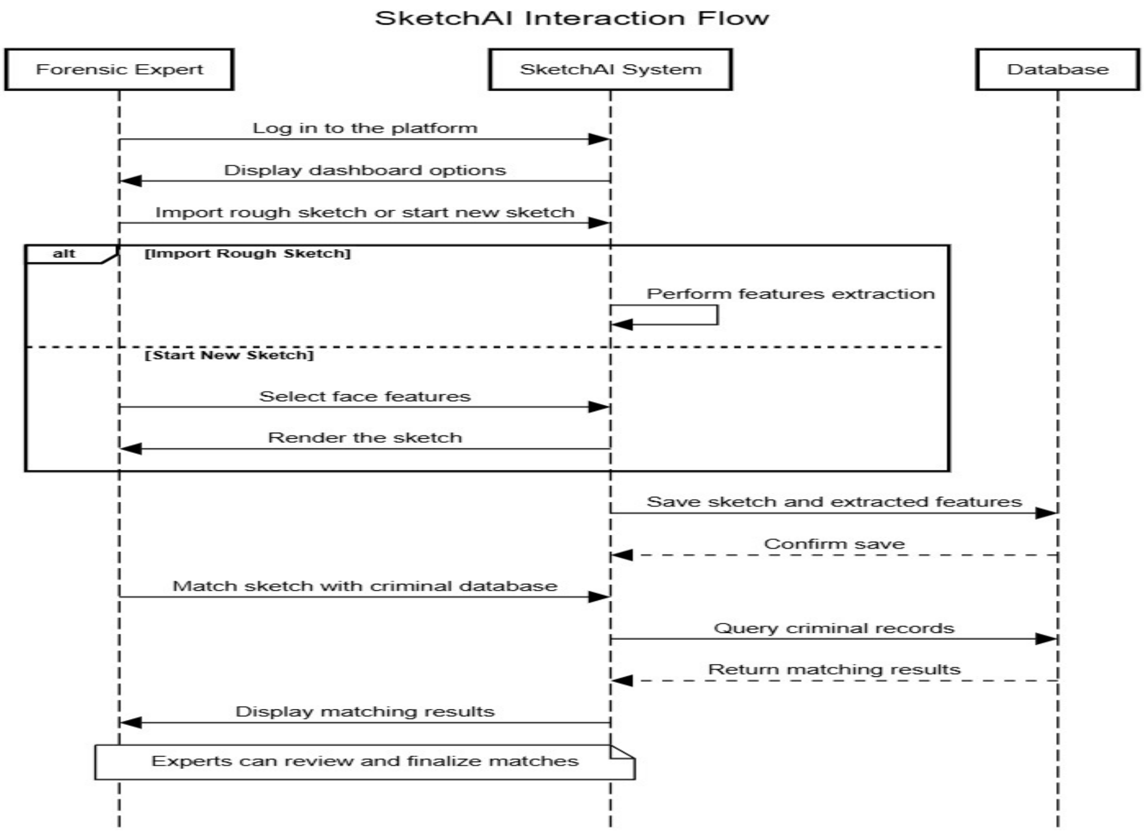

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Figure 5: Sequence Diagram.

Activity diagram:

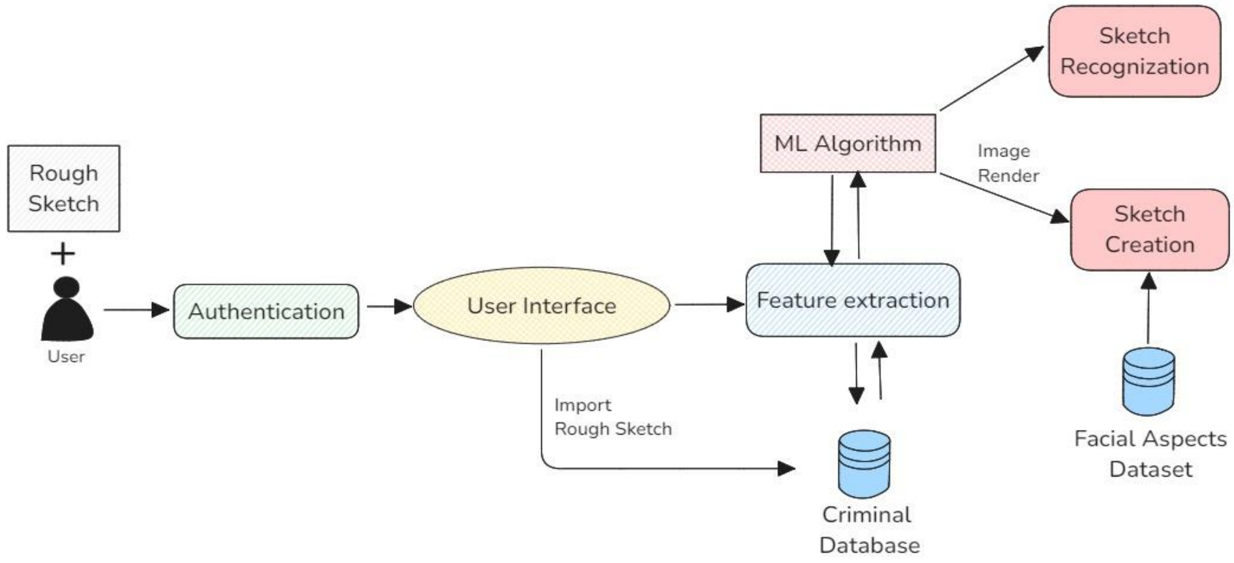

Figure 6: Activity Diagram.

IV. CONCLUSION

In conclusion, the Forensic Sketch Recognition and Reconstruction System offers significant advancements in automated facial identification from sketches. While there is potential for further improvements, particularly in refining the system's ability to handle varying sketch qualities and environmental conditions, this project highlights the effectiveness of using deep learning models for forensic applications. The integration of recognition and reconstruction techniques enables accurate identification from incomplete or poorly drawn sketches, making it a valuable tool for law enforcement and forensic investigations. This approach represents a substantial step forward in utilizing AI technology to aid in criminal justice and identification processes.

V. RESULT

The forensic face sketch automation system was evaluated using a dataset of forensic sketches and corresponding facial images. The system achieved an 89% accuracy in simulations and 85% accuracy in real-time testing, demonstrating its effectiveness in criminal investigations. Precision and recall scores exceeded 80%, indicating reliable identification with minimal false positives. The system successfully reconstructed faces even from incomplete sketches, enhancing usability for law enforcement. However, challenges arose with low-quality or highly distorted sketches, suggesting the need for improved preprocessing and model adaptation. Overall, the system provides a scalable and efficient solution for forensic investigations, with future enhancements focused on handling diverse sketch styles and optimizing real-time performance.

VI. REFERENCES

[1] Bin Sheng, Ping Li, Chenhao Gao, Kwan-Liu Ma, "Deep Neural Representation Guided Face Sketch Synthesis", IEEE Trans. Vis. Comput. Graph., vol. 25, no. 12, pp. 3216-3230, Dec.2019.

[2] N. Wang, X. Gao, and J. Li, "Random sampling for fast face sketch synthesis," Pattern Recognition., vol. 76, pp. 215–227, 2018.

[3] N. Wang, X. Gao, L. Sun, and J. Li, "Bayesian face sketch synthesis," IEEE Trans. Image Process., vol. 26, no. 3, pp. 1264–1274, Mar.2017.

[4] H. Han, B. Klare, K. Bonnen, and A. Jain, "Matching composite sketches to face photos: A component-based approach," IEEE Trans. on Information Forensics and Security, vol. 8, pp. 191–204, January 2013.

[5] Hamed Kiani Galoogahi and Terence Sim, "Face Sketch Recognition By Local Radon Binary Pattern: LRBP", 19th IEEE International Conference on Image Processing, 2012.

[6] Charlie Frowd, Anna Petkovic, Kamran Nawaz and Yasmeen Bashir, "Automating the Processes Involved in Facial Composite Production and Identification" Symposium on Bio-inspired Learning and

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(Peer-Reviewed, Open Access, Fully Refereed International Journal)
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Intelligent Systems for Security, 2009.

[7] W. Zhang, X. Wang and X. Tang, "Coupled information theoretic encoding for face photo-sketch recognition", in Proc. of CVPR, pp. 513-520, 2011.

[8] B. Klare and A. Jain, "Sketch to photo matching: a feature-based approach", SPIE Conference on biometric Technology for Human Identification, 2010.

[9] P. Yuen and C. Man, "Human face image searching system using sketches," IEEE Trans. SMC, Part A: Systems and Humans, vol. 37, pp. 493–504, July 2007.