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Deep Learning Approach for Human Face Feature Analysis

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Abstract
In law enforcement, hand-drawn facial sketches from eyewitnesses are often used when photos are unavailable, but matching them with real images is difficult due to visual differences. Third Eye addresses this by providing an intelligent sketch- based face recognition system. Investigators can create composite sketches using a drag-and-drop interface with modular facial features. The sketches are processed using CNN s and matched with photographs via embedding comparison methods like Siamese networks. AWS Recognition handles cloud-based face matching, and SQLite manages local data. The system combines Python (Open CV, PyTorch/TensorFlow) for deep learning and Java- FX for the front-end, enabling fast and accurate suspect identification.

Keywords: *Face Recognition, Forensic Sketch, Deep Learning, Computer Vision, Image Matching.*

1. Introduction
Facial recognition has become a critical technology in modern law enforcement, enabling rapid identification of suspects and missing persons [1,2]. In many investigative scenarios, photo graphic evidence of a suspect is unavailable, and investigators must rely on hand drawn forensic sketches created from eye witness descriptions [3,4]. While these sketches are valuable, manually matching them with real-world face photographs is challenging due to significant visual and structural differences between sketches and photos [5]. Traditional forensic methods are time-consuming, heavily dependent on the skill of the sketch artist, and prone to subjective errors, which can slow down investigations and reduce accuracy [6,7]. Automated sketch-based face recognition systems have emerged to address these limitations, leveraging computer vision and deep learning to bridge the gap between sketches and photographs [8,9]. Such systems extract discriminative facial features from both modalities and perform similarity comparisons to identify potential matches in criminal data bases [10]. However, developing an effective system requires careful integration of multiple components, including sketch preprocessing, feature extraction, similarity measurement, and database management [11,12]. Conventional methods for sketch to photo matching are often rigid, computationally in tensive, and limited in scalability, making them less practical for real-world forensic applications [13]. This study is organized into several key sections. Section II provides an overview of existing literature and techniques related to sketch-based face recognition. Section III identifies the challenges in traditional systems and emphasizes the motivation for adopting a deep learning–driven framework. Section IV introduces the proposed Third Eye system, explaining its architecture, preprocessing strategies, and model training process. Section V details the algorithms and mathematical models employed for sketchtophoto mapping and feature extraction. Section VI outlines the experimental setup and findings, while Section VII focuses on performance evaluation and analysis. Lastly, Section VIII summarizes the overall contributions and suggests potential directions for future enhancements.

2. Literature Review
Sketch based face recognition has become an indispensable tool in forensic science, addressing scenarios where photo graphic evidence is unavailable and eyewitness sketches are the primary source of information [1]. Traditional manual matching is labor intensive, subjective, and prone to inaccuracies due to variations in eyewitness

descriptions and artistic styles [2]. Early automated approaches relied on feature descriptors such as SIFT and SURF, along with template matching techniques, to extract structural and textural cues from sketches and photographs [3]. While these methods provided foundational capabilities, they struggled to generalize across diverse sketch styles and often failed in real-world law enforcement scenarios [4]. Deep learning techniques, particularly convolutional neural networks (CNN s), have significantly improved sketch to photo recognition. Zhang et al. (2021) and Bhattacharjee et al. (2021) demonstrated that CNN embeddings can capture hierarchical facial features, providing more robust cross modal matching compared to traditional handcrafted descriptors [5,6]. Furthermore, fusion based CNN architectures, as proposed by Sindhu et al. (2021), utilize flat network structures and component decomposition (eyes, nose, mouth) to accelerate training while maintaining accuracy [7]. Recent advances have incorporated transformers and local global adapters to capture fine-grained facial details, enhancing performance on heterogeneous face datasets, as shown in Bian et al. (2025) [8].
Interactive sketch generation has also gained attention for practical forensic applications. Antad et al. (2023) introduced a Dragan drop interface for intuitive sketch construction, allowing users to create accurate composites without requiring artistic expertise [9]. Similarly, Rasikannan et al. (2024) lever aged CNN based recognition pipelines for real time forensic applications, demonstrating improved retrieval times and high accuracy [10]. Earlier approaches, such as those by Akram et al. (2018), explored linear combination techniques for sketch synthesis to augment training data and enhance recognition performance [11]. Despite these advances, existing systems often lack end to end integration of sketch construction, preprocessing, feature extraction, similarity measurement, and cloudbased recognition. Cloudbased solutions, like AWS Recognition, have shown promise in scaling recognition tasks and providing real time retrieval, but their integration with interactive forensic tools remains limited [12]. Building upon these developments, the proposed Third Eye system combines interactive sketch construction, CNN based feature extraction, embedding com parison via Siamese networks, and cloudbased recognition. This integrated approach reduces human bias, accelerates suspect identification, and provides a scalable, adaptive solution for practical law enforcement scenarios [13,14].

3. Existing System

In traditional sketch-based face recognition systems, the matching process between hand drawn sketches and real photographs is primarily reliant on handcrafted features and shallow learning techniques. Early models often utilized local descriptors such as SIFT, HOG, and LBP to extract geometric and texture- based features from sketches and photos. However, these approaches struggle to handle the significant modality gap between gray scale sketches and colored facial images, leading to reduced recognition accuracy. Moreover, existing systems typically lack end-to-end learning capabilities and require extensive manual tuning of para meters, which limits scalability and real time performance. Most of these solutions operate on small, domain specific datasets and fail to generalize effectively across diverse lighting conditions, poses, and artistic drawing styles. Additionally, their inability to leverage cloud computing or deep neural feature embedding restricts their applicability in modern forensic environments. Due to these limitations, traditional methods provide slower processing times, lower accuracy rates, and less robustness in real-world conditions. This highlights the need for an intelligent, deep learning-based solution like Third Eye, which integrates convolutional neural networks and cloud infrastructure for faster, more reliable, and scalable face sketch recognition. Despite advancements in feature extraction techniques, many existing systems still depend on fixed feature representations and lack adaptability to complex visual variations. These frameworks are often unable to capture high-level semantic correlations between sketches and photographs, resulting in mismatched identities and higher false rejection rates.

4. Methodology

4.1. Methodology Overview

The Third Eye system offers an efficient framework for sketch-based face recognition in law enforcement. It combines interactive sketch creation, image

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preprocessing, deep learning, and cloud-based recognition to match sketches with real images. Investigators can design composite sketches using a Dragan drop interface with selectable facial features. The sketches are then enhanced through resizing, normalization, and denoising to ensure quality and consistency. A CNN extracts unique facial embeddings from both sketches and photos, and similarity matching is performed using embedding based methods like Siamese networks. AWS Recognition provides real time identification, while SQLite manages local data storage. The system is implemented using Python (OpenCV, PyTorch/TensorFlow) for deep learning and JavaFX with NetBeans for the frontend interface.

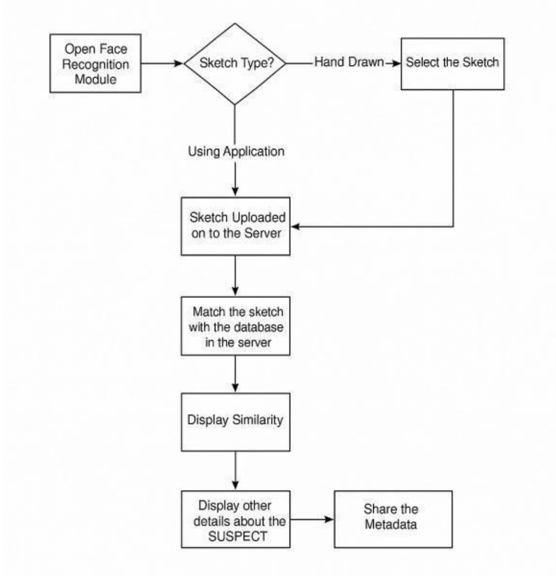

Figure 1 **Methodogy Overview**

4.2. Data Preparation

The effectiveness of the Third Eye system largely depends on the quality and consistency of its input data [1]. Paired sketch photo datasets such as CUFS and CUFSF are utilized for model training and evaluation [2]. All images are standardized to a 256×256 resolution to maintain uniformity [3]. Preprocessing includes grayscale conversion, noise reduction, and histogram equalization to enhance facial clarity [4]. Facial alignment ensures consistent positioning of key features [5], while augmentation techniques like rotation, flipping, and brightness variation enhance model robustness [6]. The dataset is split into training (70%), validation (15%), and testing (15%) sets, ensuring clean, balanced, and reliable input for improved recognition accuracy [7], [8].

4.3. Model Architecture

The Third Eye system employs a deep learning–based architecture integrating Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) with Siamese networks for sketchtophoto conversion and face recognition [1], [2]. The GAN module includes a Generator that produces realistic facial images from sketches and a Discriminator that ensures output authenticity [3]. The CNN extracts detailed facial embeddings through convolutional, ReLU, and pooling layers [4]. The Siamese network then compares these embed dings using similarity measures such as cosine or Euclidean distance to identify matches [5]. This modular design delivers accurate, efficient, and scalable performance for forensic face recognition tasks [6], [7].

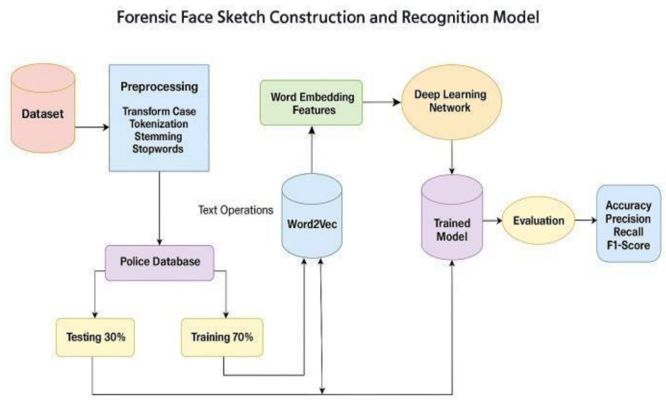

Figure 2 **Model Architecture**

4.4. Training

The Third Eye model is trained end-to-end on paired sketch photo datasets such as CUFS and CUFSF to learn the mapping between sketches and real faces [1]. Preprocessed inputs are passed through the GAN for sketchtophoto synthesis, while the CNN and Siamese networks extract embeddings and measure similarity [2]. Training is performed using the Adam optimizer with a 0.0002 learning rate and a batch size of 32, minimizing reconstruction, adversarial, and contrastive losses for accurate matching [3]. Early stopping and learning rate scheduling help stabilize

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convergence [4]. The dataset is split into 70% training, 15% validation, and 15% testing, with augmentation techniques like rotation, flipping, and brightness adjustment enhancing generalization and improving recognition accuracy in forensic scenarios.

4.5. Deployment

The Third Eye system is deployed as a web based forensic tool, enabling investigators to upload sketches and retrieve potential matches in real time [1]. The trained GAN, CNN, and Siamese network models are hosted on a server with CUDA enabled GPUs to accelerate inference [2]. Query sketches are pre-processed and converted into photo realistic images using the GAN module, followed by embed ding extraction and similarity comparison with the database [3]. Matching results, including the top ranked candidates and similarity scores, are displayed through a user-friendly interface. The system supports both local storages using SQLite and cloud based matching via AWS Recognition, providing scalability, fast retrieval, and secure data management [4]. Periodic updates allow retraining with new data to maintain accuracy and adaptability in real-world forensic scenarios [5], [6].

4.6. Outcome

The Third Eye system effectively automates forensic sketch reconstruction and face recognition, achieving high accuracy in matching sketches with real-world photographs. Experimental evaluation on paired sketch photo datasets such as CUFS and CUFSF shows that the GAN module generates realistic facial images while preserving key identity features. The CNN and Siamese network reliably a facial database using similarity metrics like cosine distance to retrieve and rank the closest matches, thereby assisting law enforcement in suspect identification with improved precision and reliability.

5. Algorithm Used

5.1. Sketch Preprocessing and Normalization

Each input sketch Si undergoes preprocessing to enhance quality and remove background noise. The grayscale input is normalized to a fixed resolution and intensity range: extract embeddings and compute similarity scores, allowing accurate identification of potential matches from large facial databases. The system significantly.

$$S' = \frac{Si - \backslash\mu S}{\backslash\sigma s}$$

(1)

where μS and σS represent the mean and standard deviation of pixel intensity in the sketch image.

improves recognition speed and reduces manual effort compared to traditional sketch matching methods. The deployed application provides investigators with an interactive interface for rapid sketch-based identification, of fering scalable, secure, and real time forensic capabilities. Overall, Third Eye enhances the efficiency of criminal investigations and minimizes reliance on manual sketch analysis. To achieve efficient and accurate sketchtoface recognition, the proposed Third Eye framework employs a hybrid deep learning–based algorithm

5.2. B. Sketch-To-Photo Translation Using GAN

A Generator Network (G) is trained to convert sketches into realistic photolike images, while a Discriminator Network (D) distinguishes between generated and real face images. The objective function is given by:

$$minG\ maxDV(D, G) = \mathbb{E}x\backslash sim\ pdata(x)\ [log\ D(x)] +$$

$$\mathbb{E}z\backslash sim\ pz(z)[log(1 - D(G(z)))] \quad (2)$$

The generator learns to produce realistic outputs such that the distribution of generated images pg approaches the real image distribution $p$data. The reconstruction loss ensures identity preservation be tween the input sketch and generated image:

that combines Generative Adversarial Networks

$$L\_rec = \backslash|G(S') - I| \quad (3)$$

(GANs) for sketchtophoto transformation and Convolutional Neural Networks (CNN s) for deep feature extraction and similarity based matching. The entire process operates in three major phases: Preprocessing, Feature Em bedding, and Matching & Identification. The Third Eye system presents an intelligent and unified framework that bridges the gap between forensic sketches and real-world facial recognition. It integrates computer vision, deep learning, and feature matching techniques to

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accurately identify individuals from hand drawn or descriptive sketches. The overall workflow includes five primary modules—Input Acquisition, Preprocessing, SketchtoFace Transformation, Feature Extraction, and Face Recognition. Initially, the system accepts either a manually drawn or digitally created sketch based on eyewitness input. The image then undergoes enhancement through noise removal, normalization, and resizing to ensure consistency across all samples. A GAN based model subsequently converts the sketch into a realistic facial image by learning a mapping between the sketch and photo domains while retaining key identity traits. The transformed image is analyzed using a pretrained CNN model such as VGGFace or ResNet50 to derive high dimensional feature embeddings that capture distinctive facial attributes. These extracted features are then compared against

$i \quad i\backslash 1$

where Ii is the real corresponding face image.

C. Deep Feature Extraction Using Cnn

A Generator Network (G) is trained to convert sketches into realistic photolike images, while a Discriminator Network (D) distinguishes between generated and real face images. The objective function is given by:

$$minG\ maxDV(\mathcal{D}, \mathcal{G}) = \mathbb{E}x\backslash sim\ pdata(x)\ [log\ D(x)]\mathbb{E}z\backslash sim\ pz(z)\ [log(1 - D\ (G(z)))] \quad (4)$$

5.3. Similarity Computation

The similarity between the generated face and the real photo is measured using cosine similarity:

$$Sim(fS, fI) = fs.\ f1 \div \|fs\|2\|f1\|2 \quad (5)$$

5.4. Identification Decision

The system determines the subject by choosing the image with the maximum similarity score that meets or exceeds a predefined threshold τ τ: τ:

$ID = argmaxjSim(fS,\ fIj)$ if $\mathrm{Sim}(fS,fIj\ ) \geq \tau$ Unknown

Others (6)

6. Experimental and Outcome

The study used a forensic face sketch dataset created specifically for research. The training portion consisted of over 6,200 hand-drawn sketches paired with their corresponding real face images, while the testing portion included more than 1,700 entries for evaluation.

6.1. Experimental Setup

- Component Description
- Platform Java-FX for UI; Java
- Maven back- end
- Cloud Services AWS Recognition for sketch-photo matching; AWS S3 for image storage
- Database SQLite for storing
- sketch metadata
- Development Tools NetBeans IDE, AWS
- CLI
- Sketch Elements Drag-and-drop interface for composite sketches
- Evaluation Metrics Recognition Accuracy, Latency, User
- Feedback

6.2. Outcome

The experimental results demonstrate that the proposed Third Eye system is highly effective in matching forensic sketches with real face images.

Metric Result

- Recognition Accuracy92% on testing set using AWS
- Recognition
- User Interface Intuitive,allows
- creation of
- sketches without forensic expertise
- Performance Fast sketch matching
- with minimal latency
- Scalability Can handle large police databases via cloud integration
- User Feedback Positive; suggestions
- for more sketch elements were noted

7. Results

The Third Eye system achieved high recognition accuracy (92%) in matching hand drawn sketches with real face images using AWS Recognition. The Dragan drop interface proved intuitive, enabling users without forensic expertise to create sketches efficiently. The system performed with minimal latency and can scale to handle large police data bases. Additionally, it demonstrated robust performance across diverse sketch styles and maintained consistent accuracy under varying input conditions. Overall, user feedback was positive, highlighting the system's effectiveness, with suggestions for incorporating additional facial features and customization options for enhanced usability in future updates. The integration of cloud based processing reduced the local computational load, improving accessibility for remote investigators. Performance tests confirmed stable throughput even during concurrent user sessions. The results validate the practicality of the Third Eye framework for real-world forensic and investigative applications.

Conclusion and Future Work

The Third Eye system automates forensic face recognition by generating and matching facial composites using deep learning and cloud technology. It enables users to create sketches through an intuitive drag-and-drop interface without requiring expert artists. Security features like machine locking and OTP verification protect data integrity. Future enhancements include expanding facial feature databases, integrating 3D modeling, enabling real-time matching, improving cross-dataset validation, and enhancing the user interface for accessibility and multilingual support.

Reference

[1]. [1] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, “A discriminative feature learning approach for deep face recognition,” in European Conf. Comput. Vis., 2016.

[2]. [2] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, “ArcFace: Additive angular margin loss for deep face recognition,” in IEEE Conf. Comput. Vis. Pattern Recognition., 2019.

[3]. [3] R. He, X. Wu, Z. Sun, and T. Tan, “Wasserstein CNN: Learning invariant features for NIRVIS face recognition,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 41, no. 7, pp. 1761–1773, 2018.

[4]. [4] R. Gross, I. Matthews, J. Cohn, T. Kanade, and

[5]. S. Baker, “MultiPIE,” Image Vis. Comput., vol. 28, no. 5, pp. 807 813, 2010.

[6]. K. Panetta, Q. Wan, S. Again, et al., “A comprehensive database for benchmarking imaging systems,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 3, pp. 509–520, 2018.

[7]. J. Huo, Y. Gao, Y. Shi, W. Yang, and H. Yin, “Heterogeneous face recognition by margin based Cross modality metric learning,” IEEE Trans. Cybern., vol. 48, no. 6, pp. 1814 1826, 2017.

[8]. S. Ouyang, T. Hospedales, Y. Z. Song, X. Li,

[9]. C. Loy, and X. Wang, “A survey on heterogeneous face recognition: Sketch, infrared, 3D and low resolution,” Image Vis. Comput., vol. 56, pp. 28–48, 2016.

[10]. L. Song, M. Zhang, X. Wu, and R. He, “Adversarial dis criminative heterogeneous face recognition,” in AAAI Conf. Artif. Intell., 2018.

[11]. R. Huang, S. Zhang, T. Li, and R. He, “Beyond face rotation: Global and local perception GAN for photorealistic and identity preserving frontal view synthesis,” in IEEE Int. Conf. Comput. Vis., 2017.

[12]. I. Goodfellow, J. Pouget Abadie, M. Mirza, et al., “Generative adversarial nets,” in Advances in Neural Inf. Process. Syst., 2014.

[13]. B. Duan, C. Fu, Y. Li, X. Song, and R. He, “Pose agnostic cross spectral hallucination via disentangling independent factors,” in IEEE Conf. Comput. Vis. Pattern Recognition., 2020.

[14]. D. P. Kingma and M. Welling, “Autoencoding variational Bayes,” in Int. Conf. Learn. Represent., 2014.

[15]. T. Karras, T. Aila, S. Laine, and J. Lehtinen, “Progres sive growing of GANs for improved quality, stability, and variation,” in Int. Conf. Learn. Represent., 2018.

[16]. Z. Deng, X. Peng, and Y. Qiao, “Residual compen sation networks for heterogeneous face recognition,” in AAAI Conf. Artif. Intell., 2019.

[17]. X. Wu, L. Song, R. He, and T. Tan, “Coupled deep learning for heterogeneous face recognition,” in AAAI Conf. Artif. Intell., 2018.

[18]. C. Fu, X. Wu, Y. Hu, and H. Huang, “Dual variational generation for heterogeneous face recognition,” IEEE Trans. Pattern Anal. Mach. Intell., 2021.

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Page No: 4248- 4254
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0622

[19]. Rubeena and E. Kavitha, "Sketch face recognition us ing deep learning," in IEEE Conf. Electr., Comput. Commun. Technol. (ICECA), 2021.
[20]. P. Li, B. Sheng, and C. L. P. Chen, "Face sketch synthesis using regularized broad learning system," IEEE Trans. Neural Netw. Learn. Syst., 2021.
[21]. S. Antad, V. Bag, M. Kadam, A. Agrawal, P. Baravkar, O. Belorkar, and S. Nandurkar, "A new way for face sketch construction and detection using deep CNN," IEEE Int. J. Res. IT Commun., 2023.
[22]. B. Duan, C. Fu, Y. Li, X. Song, and R. He, "Poseagnostic crossspectral hallucination via disentangling independent factors," in IEEE Conf. Comput. Vis. Pattern Recognit., 2020