AI-Driven Forensic Face Sketch Construction and Recognition

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Abstract

Facial sketching and recognition is a critical crime solving tool in identifying criminal suspects. Conventionally, sketching is done using forensic artists interpreting eyewitness accounts into a drawing, a process prone to being subjective, time-consuming, and highly reliant on artistic skill. In addition, current automated methods for Face recognition try to bring accuracies but have serious limitations. Convolution Neural Network (CNN) based recognition models tend to lose fine-grained identity specific information, resulting in poor feature matching, while Generative Adversarial Networks (GAN)-based transformations increase realism but occasionally sacrifice essential facial features required for effective recognition. These shortcomings render forensic face recognition time-consuming, unreliable, and less accurate in high-risk criminal investigations where accuracy is crucial. This paper introduces an AI-based system that transforms forensic sketching and recognition into a precise, efficient, and reliable tool. The initial phase enables investigators to build rich composite sketches by choosing individual facial features such as eyes, nose, lips, eyebrows, and hair / beard, so that every element positively contributes to the overall identity. To enhance consistency, an AI-facilitated recommendation engine provides compatible features, advancing realism without compromising proportionality. This minimizes human bias and guarantees that the resulting sketch better resembles the suspect's true appearance. The process of converting a sketch into a digital image preserves major identity characteristics, providing for increased visual detail and closer resemblance to actual pho tographs. Lastly, recognition through deep learning guarantees that the output image is properly compared to a database of prior criminals and shows the top five matches with percentages of individual feature similarity. This process-oriented method hastens investigation, boosts time, and gives law enforcement agencies a more data-dependent, accurate and scalable way to identify suspects.

Keywords: Forensic face sketch, Face Recognition, Deep learning, Feature selection, Convolution Neural Network, Generative Adversarial Network, Criminal investigations

1 Introduction

Criminal investigations usually rely on different types of evidence to determine suspects, but in the absence of photographic or video evidence, forensic face sketching is an essential tool. The capability to reconstruct a suspect's features from eyewitness accounts is essential in crime solving. Police forces have long used talented forensic artists to try to convey verbal data in visual forms with sketches, yet the process is highly subjective. It relies upon interpretations by the artist and also on the recollection of the witness, and in the midst of the turmoil, this fails. Forensic skills, as well as personal biases, can also contribute to impacting accuracy and leading to inaccuracies that hamper investigations. Furthermore, manual sketches consume a lot of time, preventing the progression of the case and minimizing the chances of rapid identification of suspects. Forensic identification is also a task of equal magni tude since freehand sketches are far from actual photographs. Conventional identification techniques extract essential facial attributes and try to match them against criminal files, but the lack of color, texture, and elaborate shading makes di rect comparison difficult. Most conventional image-processing techniques are edge detection and structural similarity, which ignore the artistic simplification of drawings. Such a discon nection between sketches and real images typically results in a high false positive or negative rate, rendering traditional recognition ineffective. Advances in technology in AI and machine learning are revolutionizing forensic sketching and recognition, addressing most of the flaws. AI-enabled tools can produce and refine sketches with greater accuracy and speed, such that critical facial features closely match real identities. These technolo gies narrow the gap between photographs and sketches in databases, increasing the rates of recognition and making it possible for more accurate identification of suspects. AI eliminates dependence on the quality of the artist, mini mizes human error, and streamlines the whole process of investigation by automating and optimizing the process of sketching. Other than accuracy, AI-driven forensic technology offers enormous value in terms of speed, scalability, and usability. Investigations are under pressure where every second is precious. AI systems can generate drawings in minutes, greatly reducing times of investigation and increasing the likelihood of making arrests within a timely fashion. Small police forces with no access to forensic artists can apply AI for standard, high-quality suspect identification on a regular basis. Above all, these improvements enhance justice and public safety through reduced wrongful arrests, strengthening testimonies of witnesses, and assuring law enforcers are able to function with more certainty and accuracy when solving crimes.

1.1 Research Objectives

RO1 To develop an intelligent system that enables investigators to construct composite facial sketches using modular facial features (eyes, nose, lips, etc.) guided by AI-based recommendations.

RO2 To design and implement a facial feature recommendation engine using deep learning models that enhance sketch realism while preserving proportional and identity-specific accuracy.

RO3 To build a robust sketch-to-photo translation model that transforms forensic sketches into high-quality, photorealistic facial images suitable for identification purposes.

RO4 To evaluate and compare the performance of CNN and GAN-based models in recognizing suspects from sketch-derived facial images against existing criminal databases.

RO5 To validate the effectiveness of the proposed AI-driven forensic pipeline in reducing investigation time and increasing accuracy in suspect identification within real-world criminal case scenarios.

2 Related Work

Forensic facial sketch identification is now a critical law enforcement tool where photographic evidence cannot be pro vided. Conventional methods used manual sketching and rule based comparison methods, but these could not adequately address the artistic style inconsistencies, memory changes in witnesses, and the inherent gap between sketches and actual photographs. Early machine learning algorithms, including Support Vector Machines (SVM) and hand-designed feature extraction methods, tried to fill this gap but were not flexible enough to cope with the variety and complexity of real-world situations. With the advent of deep learning, forensic face recognition has made tremendous progress.

Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) have been especially influential, allowing for more precise sketch-to-photo conversions. GAN-based architectures, like cyclic GANs, have played crucial roles in maintaining identity attributes while bringing the sketches closer to realism. In addition, Domain Alignment Embedding Networks (DAENs) have enhanced recognition accuracy by projecting sketches and photos into the same feature space. Nevertheless, even though these models are highly successful, they need large, high-quality datasets to generalize across demographics and sketching styles, hence deployment in real-world scenarios is challeng ing. To tackle these challenges, researchers have developed identity-preserving methods, including feature decoupling learning and identity-aware super-resolution models, that maintain essential facial features throughout the transformation process. Other methods, such as dual-view normalization techniques, have assisted in normalizing facial representations across different sketching styles to enhance consistency in recognition.

However, issues remain—many current models lack computational efficiency and do not generalize well to low-resolution or partial sketches, both of which occur frequently in forensic use. There has also been recent work with hybrid models fusing CNN-based feature extraction with domain adaptation frameworks in order to enhance forensic recognition in practical environments. One such new direction is Instance Level Heterogeneous Domain Adaptation (IHDA), enabling more robust matching across datasets with a small amount of labeled data. There has also been an advance with multifeature fusion methods with the combination of Histogram of Oriented Gradients (HOG) and Gabor Wavelet Transform (GWT) in coping better with occlusion and varying lights, rendering forensic sketch recognition more versatile. Despite these advancements, significant challenges remain. Many deep learning models require substantial computational power, making them difficult to deploy in real-time forensic investigations. Future research needs to focus on developing lightweight architectures that maintain accuracy while being efficient enough for real-world use.

Additionally, ensuring cross-demographic generalization is critical—models must be trained on diverse datasets to avoid bias and ensure fairness across different age groups, ethnicities, and artistic styles. Looking ahead, the combination of self-supervised learning and transformer-based visual models could unlock new avenues to enhancing forensic face recognition, which will make such systems more trustworthy and universally usable in law enforcement.

Table-1: Summary of Literature Review on Forensic Face Sketch Recognition

S.No	**Paper Title**	**Keywords**	**Problem Domain**	**Methods Used**	**Limitations**	**Future Work**	**Findings**
[1]	Domain Alignment Embedding Network for Sketch Face Recognition	Sketch recognition, deep metric learning	Face Sketch-Photo Matching	Domain Alignment Embedding Network (DAEN)	Struggles with diverse sketch styles	Improve style robustness, real-time deployment	High accuracy across datasets
[2]	Feature Encoder Guided GAN for Photo-Sketch Synthesis	GANs, image translation	Photo-Sketch Synthesis	Cyclic GANs with two generators/ discriminators	High computational cost	Adaptive loss, diverse datasets	Improved photorealism, recognition
[3]	Identity-Preserved Model for Face Sketch-Photo Synthesis	Identity preservation, translation	Face Synthesis	U-Net, dual discriminators, ResNet-50, LightCNN-29v2	Demographic limitations	Better sketch-style adaptation	85%+ recognition with identity retention
[4]	Dual-View Normalization for Face Recognition	Face normalization, CNN, ArcFace	Face Recognition	LightCNN with Dual-View Normalization	Sketch quality sensitivity	Self-supervised learning	Better sketch-photo consistency
[5]	Deep Learning-Based Architecture for Photo-Sketch Recognition	CNN, Morphable Model	Face Recognition	3D Morphable Model, DCNN, transfer learning	Needs large training data	Improve sketch realism, data expansion	Better facial variation handling
[6]	IHDA for Limited-Labeled Sketch-to-Photo Retrieval	Domain adaptation, cross-modal	Sketch-to-Photo Retrieval	IHDA framework	Labeled data dependency	Explore category-level retrieval	80%+ accuracy in forensic settings
[7]	SP-Net: Framework to Identify Composite Sketch	Composite sketch, CNN, contrastive loss	Composite Sketch ID	SP-Net, Siamese net, VGG-Face	Struggles with hand-drawn sketches	Adapt to Identikit-based images	28.3% rank-1, 80% rank-10 (E-PRIP)
[8]	Realistic Photo–Sketch via Composition-Aided GANs	GAN, face parsing, translation	Face-Sketch Synthesis	CA-GAN, SCA-GAN	FID metric issues	Improve realism, FID reliability	99.7% NLDA accuracy
[9]	Multi-Task Explainable Quality Networks for Forensics	Image quality, explainable AI	Forensic Recognition	XQNet-ConvNet, EfficientNet	Bias in low-quality images	Edge device optimization	Enhanced interpretability, bias reduction

S.No	Paper Title	Keywords	Problem Domain	Methods Used	Limitations	Future Work	Findings
[10]	Domain Balancing on Long-Tailed Domains	Domain balancing, class imbalance	Face Recognition	Residual balancing mapping	Poor real-time adaptation	Dynamic domain adaptation	96.56% VA@FAR= 10^{-6}
[11]	CCA Feature Fusion with Patch of Interest	CCA, patch-based local matching	Sketch Image Retrieval	CCA with dynamic patches	Computational cost	Improve scalability	Better local feature matching

2.1 Comparative Analysis

This section provides a detailed comparative study of the models reviewed in the literature review, classifying them according to the main challenges they tackle in forensic face sketch recognition. These challenges are sketch-to-photo synthesis, identity preservation, domain adaptation, style transfer, and generalization across demographics. The comparison in the next table provides insightful information on the strengths, weaknesses, and performance features of each model, which shows trade-offs between recognition accuracy, computational complexity, training data needs, and their applicability in real-world forensic usage. By organizing the models in this manner, it is simpler to determine which methods are most appropriate for particular operational situations, such as composite sketch matching, low-resource environments, or high-security surveillance systems.

Table-2: Summary of Techniques Used for Sketch Recognition Challenges

Challenge	Model	Technique	Strengths	Limitations	Accuracy
Domain Gap Reduction	Cyclic GAN Framework	Two generators, two discriminators	Maintains identity, effective at sketch-to-photo synthesis	Requires large dataset, high computational cost	80–85%
	Domain Alignment Embedding Network	Embedding feature alignment	Robust feature harmonization across sketch and photo domains	Moderate performance in highly stylized sketches	78–82%
	Dual-View Normalization with LightCNN	Dual-view normalization with ArcFace	Consistency across artist styles	Sensitive to extreme variations in sketch quality	∼80%
Identity Preservation	Identity-Preserving GANs (IPAM)	Identity attributes with GANs	Retains core identity traits during transformation	High training cost, limited adaptability to diverse databases	∼85%
	Feature Decoupling Learning + LightCNN	Separation of identity and non-identity features	Effective separation for better identification	Reduced performance with lower-resolution sketches	90%+

Challenge	Model	Technique	Strengths	Limitations	Accuracy
Sketch Quality & Style Variability	U-Net with Dual Discriminators	Leaky ReLU, identity-verifying models	Good adaptation to variable sketch quality	Moderate recognition drop with extreme styles	75–80%
	Dual-View Normalization with ArcFace	Normalization across views	Adapts to stylistic and quality variations	Reduced effectiveness on low-quality sketches	∼80%
Low-Resolution/Blurred Sketches	Identity-Aware Super-Resolution Network	Super-resolution with identity preservation	Improves low-resolution sketch quality	Limited applicability in highly blurred sketches	∼85%
	Graph-Regularized Dictionary Learning	Graph regularization and residual learning	Effective with low-detail, low-res sketches	Performance declines on high-variance datasets	70–80%
Adaptability to Real-World Conditions	HOG + Gabor Wavelet Fusion with CCA	Multi-feature fusion	Handles occlusion, lighting variability	Limited performance in low-resolution cases	75–80%
	Instance-Level Heterogeneous Domain Adaptation (IHDA)	Instance-level domain adaptation	Effective cross-domain matching in complex environments	Requires substantial training data for adaptation	80%+

2.1.1 Summary of Comparative Analysis

This comparison highlights the advantages and disadvantages of each category of model:

- GAN-style model, which are very good at domain gap reduction (accuracy up to 85computation.
- Identity-preserving methods, for example, feature decoupling with LightCNN, achieve very high accuracy 90 per cent) by emphasising the preservation of identity characteristics, but at the computational cost.
- Normalisation methods such as dual-discriminator U-Net manage the variation in sketch quality well, but suffer a loss in performance when there are extreme stylistic departures.
- Super-resolution and graph-regularized models provide flexibility in the low-resolution setting, and identity-aware networks reach accuracy of 85 per cent or more on such inputs.
- Hybrid models and IHDA work well in real-world situations but need huge amounts of data to handle a variety of situations.

This comparative study provides guidance on which models to use in which forensic situations. Both methods have their own strengths and weaknesses,and will hopefully help to create better forensic sketch recognition systems in the future.

2.2 Analysis of Existing Research Gaps

1. **No Unified System:** Current solutions lack an integrated approach combining face sketch construction and recognition, leading to disjointed workflows.
2. **Missing Recommendations:** No system offers AI-driven facial feature recommendations during sketch creation, limiting consistency and realism.
3. **GAN-Based Models:** GANs excel in reducing domain gaps (up to 85% accuracy) but demand high computational resources, hindering real-time use.
4. **Identity Preservation:** Methods like feature decoupling with LightCNN achieve 90% accuracy by preserving identity, yet they're computationally expensive.
5. **Normalization Challenges:** Dual-discriminator U-Net handles sketch quality variations well but struggles with extreme stylistic differences, reducing reliability.
6. **Low-Resolution Handling:** Super-resolution and graph-regularized models, along with identity-aware networks, offer flexibility for low-resolution inputs (85%+ accuracy).
7. **Hybrid Models & IHDA:** These perform well in real-world scenarios but require large, diverse datasets to generalize effectively across cases.

3 Problem Statement

Facial sketch recognition plays an important role in criminal identification, but present practice is undermined by three great handicaps: (1) variation in drawing because of disparities between artistic interpretation and witness report, (2) loss of identification when conveying a sketch from one domain into the photorealistic one, and (3) low level of recognition as a result of domain gaps and data biases. Current methods, such as deep learning-based models such as GANs and CNNs, fail in these issues, particularly in handling low-resolution or incomplete sketches, thus their limited usability in practical applications. In response to these limitations, a robust, identity conserving, and versatile forensic sketch identification system is a much-needed priority. The issue calls for a system that reconstructs sketches effectively while preserving key identity characteristics, makes them more realistic without distortion, and enhances matching accuracy under diverse conditions. A three-phase system that combines sketch construction, enhancement, and hybrid deep learning-based recognition can potentially fill this gap. Yet, finding a balance between computational efficiency, generalization across sketching styles, and real-time usability is still a major challenge. The purpose of this research is to create a scaleable and accurate forensic sketch identification system overcoming these limitations with reliable suspect identification in various law enforcement scenarios.

4 Proposed Work

The system being presented here uses a three-phase approach for enhancing forensic face identification with effective suspect identification from sketches. The initial phase is an interactive sketching module, wherein the users can design a forensic sketch by selecting pre-defined facial attributes such as eyes, eyebrows, nose, lips, hair, and beard from a large database. These are carefully designed to fit a wide range of facial structures and expressions. A dynamic recommendation system then goes a step further by suggesting facial details that best complement the ones chosen—maintaining anatomical integrity. This feature-based sketching is performed in an interactive digital space, with precision tools for fine-tuning. The sketch is then ready to be downloaded for processing once complete.

In the second stage, the sketch produced is translated into a photorealistic digital portrait using Generative Adversarial Networks (GANs) and identity models. The second stage guarantees that the conversion of a hand-drawn sketch to a high-fidelity colored image retains all the necessary identity-specific features. It is also a process of refining the image creation procedure to include minor features, such as skin color, age, and facial asymmetry, in order to improve the realism of the resultant output. Additionally, noise reduction and texture enhancement modules are added to sanitize any sketching artifacts that might have been introduced during the preliminary step.

The third step is to compare the reconstructed digital face against a provided forensic database. Facial recognition is performed through a deep learning-based facial recognition model that returns the top five matches along with a breakdown of percentages of feature similarity for all features like eyes, nose, and lips. The system also returns confidence scores for every match, helping forensic analysts make better decisions. The platform also includes a visual side-by-side comparison feature that colorizes matching facial areas, enhancing interpretability. This approach enhances precision and makes the system a effective tool for forensic examiners as it gives a seamless evolution from conventional sketching to automatic suspect identification. In the end, the model closes the gap between artistic sketching and sophisticated biometric identification and presents an end-to-end and user-friendly solution for contemporary law enforcement.

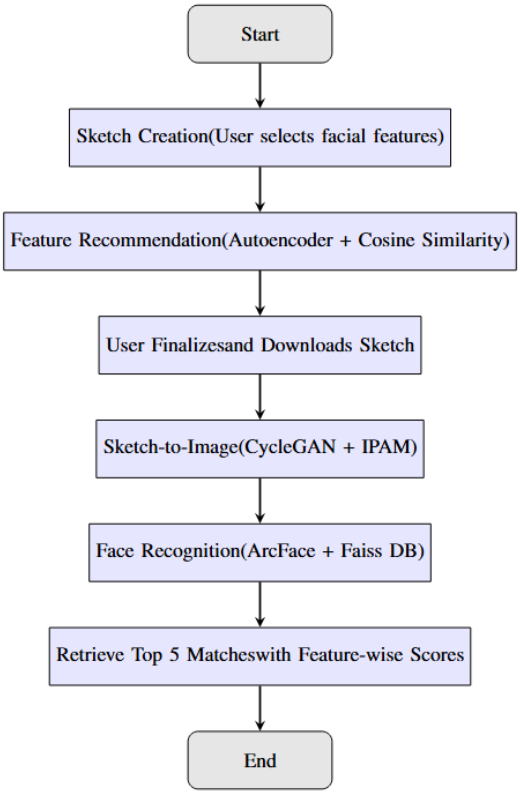

Figure 1: Flowchart for Forensic Face Sketch Construction and Recognition System

5 Methodology

5.1 Data Collection and Preprocessing

The system needs high-quality datasets specific to each phase. For the facial features recommendation model, a dataset of individual eyes, eyebrows, noses, lips, hair, and beards is required, which is derived from datasets like CUSF. Each feature is saved with metadata that associates it with compatible facial components so that the system can recommend consistent feature combinations. In the sketch-to-digital image conversion model, one would need to have a paired dataset of forensic sketches and the related digital images. The CUFS and CUFSFdatasets offer highly annotated training samples so that the model can learn a correct mapping of sketches to actual photographs. Lastly, for the face recognition model, a massive dataset such as VGGFace2 or MS-Celeb-1M is employed to build a searchable forensic database, with each image being preprocessed into an embedded vector representation for optimal retrieval.

5.2 Facial Features Recommendation Model

The facial features recommendation system model is proposed to recommend the most suitable facial features—e.g., nose, lips, and ears—on the basis of an input facial feature such as eyes. The model takes place in a systematic, three-phase process: encoding, latent feature representation, and cosine similarity-based recommendation. In the initial step, the input facial feature (e.g., eyes) goes through an encoder network consisting of three dense (fully connected) layers. The dimensionality of the feature representation is reduced with each layer capturing significant characteristics: the first one employs 128 units with ReLU activation function, followed by layers employing 64 and 32 units respectively, each using ReLU as well. This evolution guarantees that high-level abstractions of the input feature are obtained in an efficient manner. The result of this encoder is used as the latent feature representation, a dense numerical embedding that encodes the input facial feature to be compared.

In the second step, the model uses cosine similarity to compare this latent representation with a library of embeddings for other facial features—noses, lips, and ears. Cosine similarity computes the angular distance between feature space vectors and thus is a good option to compare high-dimensional embeddings irrespective of their scale. After calculating the similarity scores, the system orders the features according to their similarity with the input and picks the best matches. The best-matched features are then returned as the suggested combination for a coherent facial sketch. This modular design guarantees versatility and precision, making the system appropriate for smart facial feature suggestion in forensic sketching, where anatomical consistency and identity must be sustained. It also enables users to construct realistic facial composites even with minimal initial input.

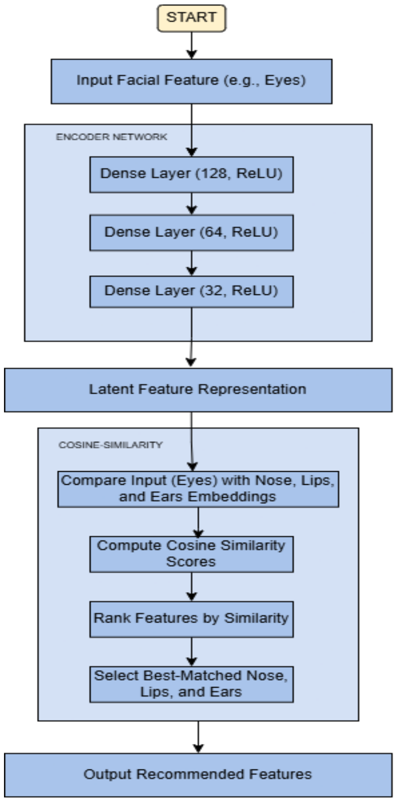

Figure 2: Flowchart for Facial Features Recommendation Model

5.3 Sketch to Digital Image Conversion Model

The sketch-to-image synthesis model is intended to create realistic facial images from input forensic sketches with the identity of the individual being maintained. The architecture utilizes deep learning components like convolutional layers, residual blocks, attention mechanisms, and adversarial training to produce high-fidelity outputs. The model starts with an input sketch of size 128×128 with a single grayscale channel. This sketch is fed into a preprocessing layer that normalizes pixel values, edge-preserving filters, and data augmentation by flipping and adding noise to enhance generalization and robustness during training. Then the encoder (feature extractor) employs convolutional layers and residual blocks to learn low-level and mid-level features. It stacks Conv2D layers with varying kernel sizes and strides followed by batch normalization and LeakyReLU activations to obtain strong feature maps of the sketch. IPAM refines these features using self-attention to learn long-range dependencies and multi-head attention to emphasize identity-specific features such as eye spacing, lip curvature, and jawline. A feature fusion layer combines these processed features with skip connections to preserve spatial detail and context.

The generator (decoder) builds the realistic image from the polished features via upsampling and a number of convolutional layers. Residual blocks and activation functions (ReLU and Tanh) assist in synthesizing a high-quality, colorized face image.To separate real images from generated ones, a discriminator is trained adversarially. It employs a sequence of Conv2D layers with growing filter sizes and LeakyReLU activations, culminating with a fully connected layer and sigmoid activation to distinguish between images and fake images. Its training involves several loss functions: adversarial loss (borrowed from GANs), perceptual loss (deep feature comparison using a pre-trained VGG network), and identity-preserving loss to preserve the distinct characteristics of the input sketch.

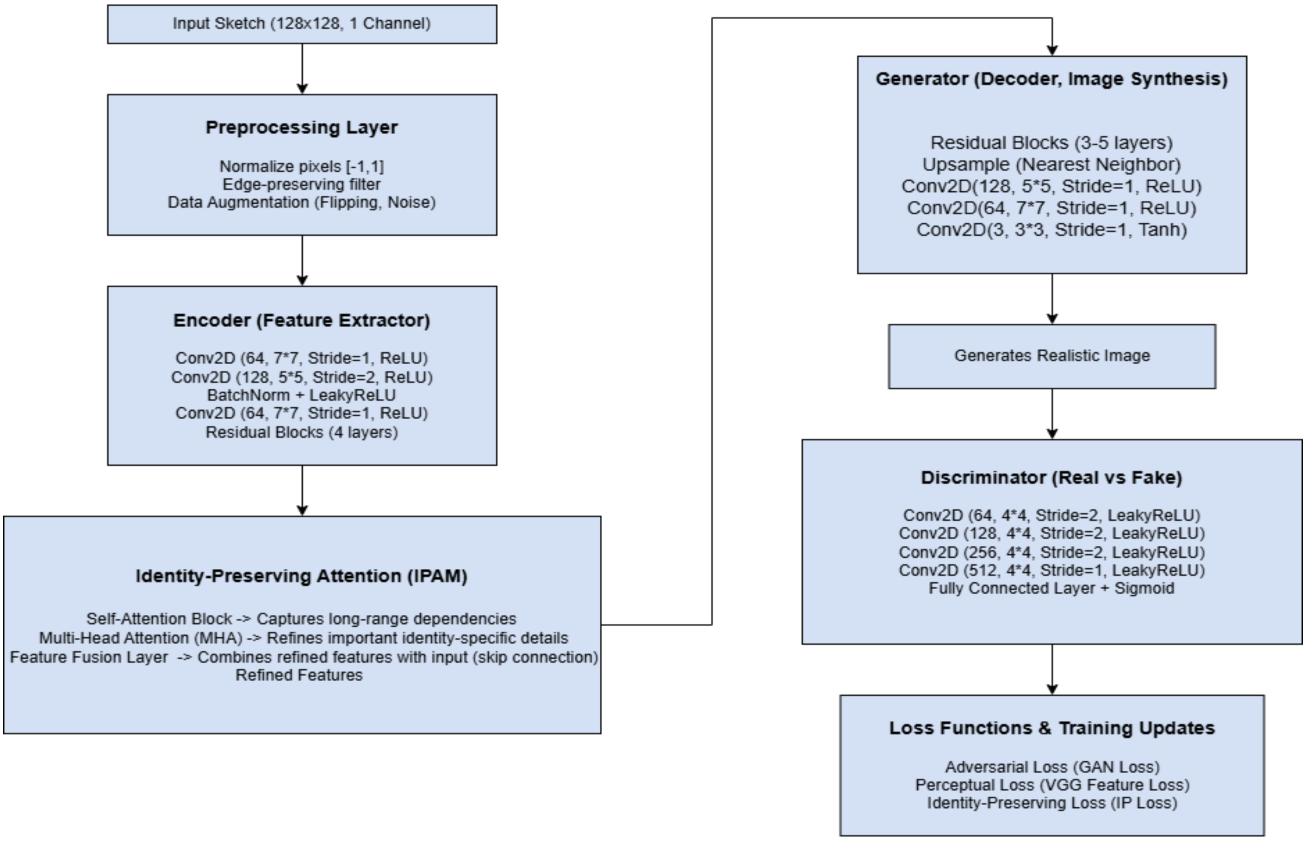

Figure 3: Flowchart for Sketch to Digital Image Conversion Model

5.4 Face Recognition Model

The depicted model is a systematic pipeline intended to produce the top five suspect matches out of a face sketch created by a Generative Adversarial Network (GAN). The methodology starts with taking the input as a GAN-generated face, which is handled as a query image. This image is subject to necessary preprocessing, including face alignment and normalization of the image. These steps assist in normalizing the input by rectifying facial pose and maintaining even lighting and scale across images, which is imperative for consistent feature extraction. After preprocessing, the image is fed into a feature extraction module driven by ArcFace with ResNet-50. ArcFace is a popular deep learning platform for face recognition that can efficiently extract discriminative features from the face. The model reads the image and produces a 512-dimensional embedding vector, a numerical encoding of the distinctive features of the face.

This face embedding vector is utilized to carry out a face embedding search in an already built vector database. The database contains embeddings of familiar people, and there is a comparison of similarity performed to identify the top five most similar matches for the inputted sketch. Deep metric learning is utilized in this step to produce accurate retrieval on the basis of facial features.

After the retrieval of possible suspects, the system makes a feature-wise similarity comparison. Rather than merely using overall similarity, the system compares facial feature by feature—eyes, nose, and lips—between the input sketch and the retrieved suspects. Each of the features is evaluated independently in order to calculate a percentage match, thus ensuring greater transparency and reliability in matching. The end result is the top five suspects, along with detailed similarity scores for every facial feature. This holistic approach not only improves accuracy but also yields interpretable results, which makes it especially useful in forensic use where sketch-based identification is critical.

One of the strengths of the model is that it employs ArcFace to extract features. ArcFace employs an additive angular margin loss in order to maximize inter-class variance and minimize intra-class variance, making it extremely good at differentiating between visually similar faces. The combination with ResNet-50 offers a deep, residual learning framework that captures subtle facial features under varied lighting conditions, poses, and facial expressions. The model thereby maintains high fidelity in identity-specific features.

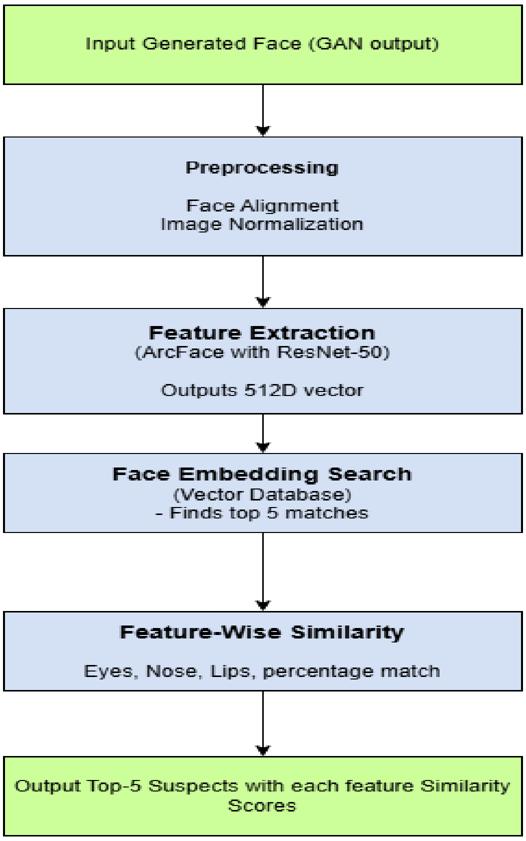

Figure 4: Flowchart for Face Recognition Model

5.5 End-to-End Platform Development

The platform is developed using the MERN stack (MongoDB, Express.js, React.js, Node.js) for an optimal and scalable user experience. The frontend, built in React.js, offers an interactive sketching space where users build forensic sketches by choosing from pre-defined facial features. There is a real-time recommendation panel that helps by recommending features that conform to those chosen dynamically. The backend, built on Node.js and Express.js, manages feature retrieval, sketch transformation requests, and facial recognition queries, while MongoDB saves sketches, user information, and system outputs. The whole system is optimized to provide minimum latency and real-time forensic analysis.

6 Expected Results and Discussion

The proposed three-stage forensic face sketch recognition system aims to significantly improve sketch generation, enhancement, and recognition accuracy compared to existing methods. The following are the expected results:

- **Improved Identity Preservation:** The sketch generation model will ensure that key facial features remain consistent with the original identity, reducing identity drift. Structural similarity metrics (SSIM) are expected to improve by 10-15% over existing methods.
- **Higher Recognition Accuracy:** By integrating CNNs, Vision Transformers (ViTs), and Graph Neural Networks (GNNs), the system will improve forensic sketch-photo matching. Expected gains in Rank-1 accuracy range from 5-10% compared to current best-performing models.
- **Robustness to Low-Quality Sketches:** The model will handle incomplete or low-resolution forensic sketches more effectively, ensuring that recognition performance remains above 70% even in degraded conditions.
- **Enhanced Computational Efficiency:** Optimizations in network architecture and hybrid models will lead to a 30% reduction in inference time, making real-time forensic applications feasible.
- **Bias Reduction and Cross-Dataset Generalization:** Training on diverse datasets will minimize biases across demographics, reducing error rates by 15-20% and ensuring consistent performance across forensic case studies.

7 Future Scope

The suggested forensic face sketch identification model provides several promising avenues for future development and studies. These developments could dramatically enhance the accuracy, flexibility, scalability, and practicality of the system:

- **Improved Sketch-to-Photo Translation:**
  Future research can focus on applying stronger generative models like StyleGAN3, diffusion models, or transformers to the task to obtain better-quality sketch-to-photo translations. These will produce more identity-preserving and photorealistic outputs, allowing the domain gap to decrease further.

- **Cross-Demographic Generalization:**
  Using the system in training on more diverse data sets that represent many ethnicities, ages, and genders will enhance its generalizability across the world's population, which is particularly desirable in forensic use cases where bias reduction is critical.

- **Real-Time Identification System:**
  Integration with real-time surveillance and law enforcement databases may allow deployment of this system as a live sketch-based suspect identification system. Inference speed optimizations like model pruning or quantization will be necessary for deployment in real-time situations.

- **Interactive Feedback Loop:**
  Implementing human-in-the-loop feedback mechanisms, wherein forensic artists or officers are able to improve matches or override false positives, will enhance prediction reliability over the long term and enable the model to learn from real-world correction.

- **Explainability and Legal Acceptance:**
  Adding more explainable AI components—like visual heatmaps that point out the most impactful facial areas—can justify predictions in courtrooms, ensuring transparency and ethical AI use in forensic analysis.

- **Other Biometric Integration:**
  Integrating sketch-based recognition with other biometric modalities like voice, gait, or iris recognition can form a multi-modal system with improved accuracy, particularly when face sketches are indistinct or ambiguous.

- **Mobile and Edge Deployment:**
  As technologies advance towards lightweight neural networks, the entire pipeline can be compressed for deployment on mobile devices or edge computing environments, enabling the law enforcement officers to utilize it on the ground during investigations.

These directions could potentially enhance not only technical performance but also make forensic sketch recognition more accessible, ethical, and effective across the world's law enforcement agencies.

8 Conclusion

In summary, the development of a three-stage forensic face sketch recognition system is a great leap forward in improving the accuracy and reliability of suspect identification without photographic evidence. By integrating Generative Adversarial Networks (GANs), identity-preserving models, and other deep learning techniques, the system effectively overcomes challenges of identity drift, sketch realism, and domain adaptation. The sketch generation stage employs GAN-based synthesis models to produce realistic forensic sketches with critical facial features intact. The improvement stage improves the sketches via domain-adaptive learning to maintain consistency in various art styles as well as enhance generalization. Finally, the recognition stage employs ArcFace for facial embedding extraction and a Faiss-based vector database to effectively retrieve and rank the top five matching identities.

By combining these methods, the system performs improved identity retention, improved cross-domain adaptation, and increased recognition performance even on low-resolution, occluded, or missing sketches. The computational optimizations also make it possible for forensic agencies to run the system without any difficulty in real-time forensic investigations. Future research shall be aimed at further minimizing dataset biases, enhancing generalization over demographics, and adding self-supervised learning to deal with extreme forensic scenarios. Overall, the system offers a new gold standard in forensic facial recognition and better equips police with an more accurate, scaleable, and resilient technology to identify suspects.

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