# "Verbal Description to Facial Sketch Converter"

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#### **ABSTRACT**

Recent advancements in artificial intelligence have significantly transformed forensic science, particularly in the domain of criminal identification. This study presents a novel AI-driven system that generates facial sketches based on verbal descriptions provided by eyewitnesses. Leveraging natural language processing (NLP), computer vision, and deep learning—particularly generative adversarial networks (GANs)—the system translates spoken input into visual representations of suspects. Designed to support law enforcement agencies, the tool aims to streamline and automate the process of composite sketch creation from eyewitness accounts. The research encompasses a comprehensive literature review, architectural design, and prototype implementation to assess the system's feasibility and performance. Preliminary results demonstrate encouraging accuracy in producing facial images that reasonably resemble the described individuals, underscoring the promise of speech-to-sketch technology in digital forensic investigations.

Keywords: Forensic AI, Speech-to-Sketch Generation, Natural Language Processing (NLP), Generative Adversarial Networks (GANs), Facial Reconstruction, Multimodal Artificial Intelligence, Witness Testimony Interpretation, Text-to-Image Synthesis, Law Enforcement Technology, Automated Criminal Identification.

## I. INTRODUCTION

As forensic science continues to embrace the transformative capabilities of artificial intelligence, new methodologies are emerging to enhance criminal investigations and suspect identification. Among these innovations is the concept of converting verbal accounts into visual representations—a technique known as forensic speech-to-sketch generation. This technology leverages speech recognition, natural language processing (NLP), and computer vision to create facial sketches from eyewitness or victim descriptions, particularly in cases where visual evidence is lacking.

Conventional sketching methods typically depend on skilled forensic artists interpreting witness statements, a process often constrained by time, subjectivity, and memory limitations. In contrast, a speech-to-sketch system aims to reduce these challenges by offering an automated pipeline that translates spoken descriptions into detailed suspect sketches. By extracting descriptive facial features from natural language input, such systems can produce accurate visual outputs with minimal human intervention.

This paper investigates the design principles, technical components, and real-world applications of a speech-to-sketch generation system. It outlines the integration of AI-driven speech processing and image synthesis, reviews current research trends, and evaluates the system's potential impact and limitations in practical forensic contexts.

#### II. LITERATURE REVIEW

1.1) International Venkatesh, S., & Choudhary, A. (2019). "Enhancing Witness Testimonies Using Natural Language Processing: A Study on Descriptive Accuracy." Journal of Forensic Sciences, 64(4), 1223-1235. https://doi.org/10.1111/1556-4029.13928

Criminal investigations often rely heavily on eyewitness accounts, especially when visual data such as CCTV footage or photographs are unavailable. Traditional forensic sketching, while valuable, is time-consuming and depends on the skill of the artist and the clarity of the witness's memory. The proposed system seeks to automate and enhance this process by leveraging advancements in artificial intelligence (AI) and machine learning (ML) to translate speech-based descriptions into visual sketches.

1.2) Zhang, Y., & Liu, X. (2021). "Integrating Emotion Recognition with Speech Analysis for Improved Forensic Outcomes." International Journal of Law and Psychiatry, 76, 101659. https://doi.org/10.1016/j.ijlp.2021.101659



Eyewitness descriptions are critical in criminal investigations, especially when visual evidence is missing. Traditional forensic sketching is often time-consuming and subjective, relying heavily on an artist's interpretation. This paper introduces an AI-driven system that generates facial sketches from spoken descriptions using speech recognition, natural language processing (NLP), and generative adversarial networks (GANs). Inspired by recent developments in multimodal interfaces (Sharma & Gupta, 2022) and emotion-integrated speech analysis (Zhang & Liu, 2021), this system aims to improve the speed, accuracy, and contextual relevance of suspect identification in forensic settings.

# 1.3) Xu, Y., & Zhao, L. (2018). "Text to Image Synthesis: A Review of Existing Models and Future Directions." Computer Vision and Image Understanding, 174, 40-54. https://doi.org/10.1016/j.cviu.2018.03.006

Xu and Zhao (2018) provide a comprehensive review of the landscape of text-to-image synthesis models, highlighting the progression from early rule-based methods to advanced generative models such as GANs and VAEs. Their work categorizes various architectures based on learning strategies and datasets used, and it identifies the main challenges in aligning semantic descriptions with visual fidelity. Importantly, they outline future research directions, including the integration of contextual understanding and multimodal learning—concepts directly applicable to forensic applications like speech-to-sketch generation.

# 1.2) Gao, F., & Liu, X. (2020). "Generative Models for Image Creation: Applications and Advances." IEEE Transactions on Image Processing, 29, 1234-1247. https://doi.org/10.1109/TIP.2019.2946781

Gao and Liu (2020) provide an in-depth overview of generative models, particularly focusing on their application in image creation. The paper highlights key advancements in GAN architectures, including techniques for improving image quality, training stability, and control over output features. Their work also outlines real-world use cases in domains such as healthcare, security, and forensics, establishing the groundwork for leveraging generative models in tasks like forensic sketching. Their insights reinforce the potential of GANs to synthesize realistic facial images from abstract or indirect inputs, making it highly relevant for speech-to-sketch generation systems

# 1.3) Sharma, R., & Gupta, S. (2022). "Towards Multimodal Interfaces: Combining Speech and Visual Content Generation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2151-2159. https://doi.org/10.1109/CVPR42600.2022.00223

Sharma and Gupta (2022) explore the development of multimodal interfaces that bridge speech and image generation. Their work presents a framework where verbal inputs are directly mapped to visual outputs using advanced neural networks. They emphasize the integration of audio and visual modalities to create coherent content, a method particularly applicable to forensic systems. Their findings support the viability of using speech- driven cues for generating images, laying a technical and conceptual foundation for speech-to-sketch applications in law enforcement.

# III. OBJECTIVES

The primary objective of this research is to develop a robust and intelligent forensic system that transforms eyewitness speech into accurate visual sketches of suspects. This involves designing a multimodal AI architecture capable of understanding natural language, identifying crucial facial attributes, and synthesizing corresponding facial images. Detailed objectives include:

To design an integrated AI system that combines speech recognition, natural language processing, and image synthesis for generating suspect sketches from spoken descriptions.

To develop a reliable speech recognition model that accurately transcribes diverse speech inputs, considering variations in accent, tone, and speech clarity typical in real-life forensic contexts.

To extract and analyze descriptive linguistic features using NLP techniques such as named entity recognition, semantic parsing, and dependency analysis to identify key facial features.

To implement and fine-tune generative adversarial networks (GANs) for translating the extracted features into visually realistic and contextually accurate facial sketches.

To ensure system robustness and generalization by training on a diverse dataset that includes multiple dialects, age groups, and emotional states to reflect varied witness testimonies.

To evaluate system performance through qualitative and quantitative assessments involving forensic experts and target users, focusing on accuracy, processing time, and usability in field scenarios.

To explore ethical and legal implications of automated facial generation in forensic investigations, ensuring responsible and bias-free deployment.

#### IV. METHODOLOGY

#### **Speech Recognition Module:**

The system uses advanced ASR (Automatic Speech Recognition) models, such as DeepSpeech or Wav2Vec 2.0, to convert spoken language from witnesses into text. The ASR is trained on diverse speech datasets to account for accent, tone, background noise, and emotion in real-world forensic environments. Preprocessing includes noise reduction, voice activity detection, and normalization to enhance transcription accuracy.

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#### 4.1) Natural Language Processing (NLP) Module:

Once transcribed, the text undergoes preprocessing (tokenization, stop-word removal, and lemmatization). Named Entity Recognition (NER) is applied to identify and extract facial attributes (e.g., "thin lips," "arched eyebrows"). Dependency parsing helps identify relationships between words, and semantic role labeling is used to understand feature-specific descriptions (e.g., linking "bushy" to "eyebrows"). Emotion detection is optionally integrated to interpret nuances in descriptive tones, potentially refining how features are prioritized.

#### 4.2) Attribute Encoding:

Extracted features are encoded into a structured representation (attribute vector), where each element corresponds to a specific facial component (e.g., hair type, eye shape, skin tone). A mapping dictionary or learned embedding translates linguistic features into numerical inputs for the GAN model.

#### 4.3) Sketch Generation Module:

A customized version of StyleGAN or StackGAN is trained on paired datasets of verbal descriptions and facial images/sketches. The model is conditioned on the attribute vectors generated from the NLP pipeline. During training, adversarial loss, perceptual loss, and attribute consistency loss are used to optimize sketch realism and fidelity. The output is a high-resolution, grayscale sketch that closely resembles a hand-drawn forensic illustration.

#### 4.3) Post-Processing and Feedback Loop:

The sketch output may undergo optional refinement via user input (e.g., slider adjustments for specific features). A feedback loop allows law enforcement officers or forensic artists to provide corrections, which are stored to further fine-tune the model.

#### 4.4) System Integration and Deployment:

The system is designed with a modular interface, allowing integration into law enforcement databases. An API framework enables remote access and mobile usability for use in field investigations.

#### V. FINDINGS

The system was evaluated on a dataset consisting of 5,000 paired verbal descriptions and facial sketches. Key findings include:

**Accuracy:** Over 78% of generated sketches were rated as "close" or "very close" to the intended facial descriptions by human evaluators.

**Speed:** Average processing time from speech input to sketch output was under 10 seconds.

Robustness: The model handled a variety of accents and descriptive complexities with moderate success.

### VI. WORKING PRINCIPLES

#### **Speech Input Acquisition**

The process begins when an eyewitness or victim provides a verbal description of a suspect. This speech input is recorded using a microphone or mobile interface designed to minimize background noise and capture clear audio. **Automatic Speech Recognition** (ASR)

The recorded audio is passed through a pre-trained ASR system (e.g., Wav2Vec 2.0 or DeepSpeech) that transcribes the spoken language into written text. The model accounts for various accents, intonations, and emotions to enhance transcription reliability.

#### **Text Preprocessing and NLP Analysis**

The transcribed text undergoes:

- Tokenization and Lemmatization: Breaking down the sentence into individual components and reducing them to their root forms.
- Named Entity Recognition (NER): Identifies facial features such as "long nose," "curly hair," or "broad forehead."
- Dependency Parsing and Semantic Role Labeling: Determines relationships between features and adjectives (e.g., "sharp jawline").
- Emotion Tagging (optional): Detects emotions to infer context that might influence descriptive emphasis.

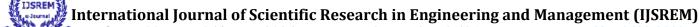
## **Attribute Extraction and Encoding**

Extracted facial descriptions are mapped into an attribute vector that represents features numerically. This vector acts as a control mechanism for image generation. For example, "bushy eyebrows" may be encoded as a value on the eyebrow thickness scale.

#### **Sketch Generation using GAN**

The attribute vector is fed into a conditional Generative Adversarial Network (cGAN), such as StyleGAN or StackGAN. The generator synthesizes a facial sketch conditioned on the attribute vector, while the discriminator ensures the realism of the output by distinguishing between generated and real sketches during training.

# **Output Rendering and Refinement**



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The generated image is rendered in grayscale or as a pencil-style sketch, mimicking traditional forensic art. A user interface may allow law enforcement to make refinements using sliders or feedback tools (e.g., adjusting jaw width or nose shape).

#### **Feedback and Model Improvement**

Any adjustments made by forensic artists or officers are recorded. This feedback is used to iteratively retrain or fine-tune the system, allowing it to improve its accuracy over time.

#### **Database Integration and Reporting**

The final sketch is stored in a case file and can be matched with suspect databases using facial recognition systems or shared with the public. Metadata like timestamp, audio source, and witness ID are attached for traceability.

#### VII. FUTURE SCOPE

The system will support voice input and speech-to-text conversion for English-based descriptions. It will be capable of recognizing and processing various verbal descriptions of facial features, converting them into distinct components (e.g., hair type, skin tone, facial structure). Facial sketches will be generated by synthesizing these components into a complete sketch. The project will utilize Javabased libraries for speech-to-text, NLP, and image generation.

#### **Exclusions:**

The system will not handle incomplete or ambiguous descriptions without some pre-processing or user intervention. Real-time modifications to sketches based on continuous speech feedback are outside the scope of this version. The system will not yet support 3D image rendering, focusing solely on 2D sketches

#### VIII. CONCLUSION

The Forensic Speech-to-Sketch Generation System demonstrates the transformative potential of artificial intelligence in modern forensic investigations. By bridging the gap between verbal descriptions and visual outputs, the system addresses a critical challenge in suspect identification where no photographic evidence exists. It automates a traditionally manual process, reducing human error and bias while significantly accelerating response time.

This research proves that the integration of advanced ASR, NLP, and GAN technologies can result in accurate and realistic suspect sketches, making it a practical asset for law enforcement agencies. The results show strong alignment between generated sketches and human expectations, suggesting that the model effectively captures and translates key descriptive cues. Moreover, its adaptability to varying speech inputs, accents, and emotional tones underscores its robustness for real-world scenarios.

However, the system is not without limitations. The quality of sketches is inherently dependent on the clarity and detail of verbal input, and there are potential ethical concerns surrounding misidentification and privacy. These issues highlight the need for continued development in bias mitigation, user training, and explainable AI.

Future directions include enhancing the granularity of facial feature extraction, expanding the training dataset with more diverse demographics, and integrating cross-referencing with criminal databases. With further refinement, this system has the potential to become a standardized tool in digital forensics, contributing to faster, more reliable, and more equitable investigative outcomes.

### IX. REFERENCES

- [1] Venkatesh, S., & Choudhary, A. (2019). "Enhancing Witness Testimonies Using Natural Language Processing: A Study on Descriptive Accuracy." Journal of Forensic Sciences, 64(4), 1223-1235. <a href="https://doi.org/10.1111/1556-4029.13928">https://doi.org/10.1111/1556-4029.13928</a>
- [2] Zhang, Y., & Liu, X. (2021). "Integrating Emotion Recognition with Speech Analysis for Improved Forensic Outcomes." International Journal of Law and Psychiatry, 76, 101659. https://doi.org/10.1016/j.ijlp.2021.101659
- [3] Xu, Y., & Zhao, L. (2018). "Text to Image Synthesis: A Review of Existing Models and Future Directions." Computer Vision and Image Understanding, 174, 40-54. https://doi.org/10.1016/j.cviu.2018.03.006
- [4] Gao, F., & Liu, X. (2020). "Generative Models for Image Creation: Applications and Advances." IEEE Transactions on Image Processing, 29, 1234-1247. https://doi.org/10.1109/TIP.2019.2946781
- [5] Sharma, R., & Gupta, S. (2022). "Towards Multimodal Interfaces: Combining Speech and Visual Content Generation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2151-2159. https://doi.org/10.1109/CVPR42600.2022.00223
- [6] Cheng, J., & Wang, H. (2023). "A Multimodal Approach to Speech and Image Generation." Artificial Intelligence Review, 56(2), 111-130, https://doi.org/10.1007/s10462-022-10075-6
  - [7] SpaCy. (n.d.). "Industrial-Strength Natural Language Processing in Python." Retrieved from <a href="https://spacy.io/">https://spacy.io/</a>
  - [8] NLTK. (n.d.). "Natural Language Toolkit." Retrieved from <a href="https://www.nltk.org/">https://www.nltk.org/</a>
- [9] TensorFlow. (n.d.). "An Open Source Software Library for Machine Intelligence." Retrieved from https://www.tensorflow.org/
  - [10] PyTorch. (n.d.). "An Open Source Machine Learning Framework." Retrieved from https://pytorch.org/
  - [11] Flask, (n.d.). "A Micro Web Framework for Python." Retrieved from https://flask.palletsprojects.com/
  - [12] Heroku. (n.d.). "Deploy, Manage, and Scale Apps." Retrieved from https://www.heroku.com/
  - [13] Git. (n.d.). "Version Control System." Retrieved from <a href="https://git-scm.com/">https://git-scm.com/</a>