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Forensic Sketch to Real Image

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Abstract

In the realm of forensic investigations, the reliance on hand-drawn sketches or verbal descriptions to identify suspects or victims is well-established. However, these traditional methods often present challenges due to their inherent subjectivity and potential inaccuracies. Recognizing the critical importance of enhancing the accuracy and efficacy of forensic identification processes, our project delves into cutting-edge techniques, particularly leveraging Deep Convolutional Generative Adversarial Networks (DCGANs). Situated at the nexus of image processing, artificial intelligence, and machine learning, these advanced algorithms offer promising avenues for transforming forensic sketches into remarkably realistic images.

Our project's primary objective is to develop a robust Forensic Sketch to Real Image Conversion System capable of generating highly authentic images from both hand-drawn and computer-generated forensic sketches. By harnessing the power of DCGANs, we aim to bridge the gap between the abstract representations provided by traditional forensic sketches and the detailed, lifelike images necessary for effective identification and investigation. This innovative system holds immense potential to revolutionize forensic practices, offering law enforcement agencies invaluable tools to aid in criminal investigations, locate missing persons, and address a myriad of forensic challenges.

Beyond its immediate applications in law enforcement and forensic science, the Forensic Sketch to Real Image Conversion System represents a significant stride towards advancing the intersection of technology and justice. By providing law enforcement agencies with the means to generate highly accurate depictions of suspects or victims from rudimentary sketches, our project seeks to bolster investigative capabilities while ensuring fairness and accuracy in criminal proceedings. Moreover, the potential societal impact extends beyond law enforcement, offering hope and closure to families of missing persons and victims of crime through improved identification methods

Keywords: DCGAN, computer vision, CNN, Sketch to image, Image processing, Face Synthesis, Generative Adversarial Networks

1. Introduction

In the ever-evolving landscape of forensic science and criminal investigations, technological advancements persist to play a pivotal function in enhancing the accuracy & efficiency of law enforcement procedures. One of the longstanding challenges investigators faces is transforming rough forensic sketches into realistic images of potential suspects. These sketches, often originating from eyewitness accounts or victims' descriptions, are crucial tools for identifying and locating individuals involved in criminal activities.

Traditionally, forensic sketch artists have been tasked with the responsibility of translating these descriptions into visual representations. While their skill and dedication are undeniable, there are inherent limitations to this manual approach. Forensic sketches may suffer from subjectivity, artistic interpretation, and variations in witness recall, potentially leading to discrepancies and missed opportunities in identifying suspects.

This opportunity lies in the intersection of artificial intelligence, deep learning, and computer vision. The emergence of deep learning algorithms, with a notable emphasis on Generative Adversarial Networks (GANs), has opened doors to unprecedented advancements in image generation and manipulation.

This system aims to surpass traditional enhancement techniques by generating highly detailed and photorealistic images from forensic data. We anticipate that such a system will expedite investigations and offer a more objective and consistent approach to visual evidence interpretation. Overall work of GAN is as the creator generates the real image in the original ages using the noise. Noise is the pixel law of the sketch given as input. During training, creator induces images using the noise and is given to the discriminator. The discriminator takes two inputs (the creator affair and the real image corresponding to the input sketch) and determines whether the generated image is fake or real grounded on the original input dataset

1.1 Contribution of the proposed system

The proposed Forensic Sketch to Real Image Conversion System offers significant contributions to forensic science and law enforcement:

- Enhanced Accuracy: By utilizing advanced techniques like Deep Convolutional Generative Adversarial Networks (DCGANs), the system improves the accuracy of forensic investigations. It generates highly realistic images from sketches, aiding in the identification of suspects or victims.

- Streamlined Processes: The system streamlines identification procedures by rapidly converting sketches into lifelike images. This efficiency reduces the time and resources needed for manual interpretation, expediting case resolutions and benefiting victims and their families.

- Support for Missing Persons Cases: It assists in cold cases and missing persons investigations by revitalizing outdated sketches, and providing new leads for law enforcement. This aspect offers hope to families seeking closure and justice for their missing loved ones.

- Technological Advancement: The system represents a significant advancement in forensic technology, showcasing the potential of interdisciplinary collaboration between computer science and forensic science to address complex investigative challenges and improve outcomes for society.

1.2 Organization of the paper

The structure of the remaining sections is illustrated in this section. Section 2 conducts a thorough exploration of relevant literature on drowsiness detection, offering essential research context and background. The article outlines the framework of the proposed system, presenting the methodology and design of our research in section 3. Section 4 provides insights into the collected data for the experiments, the experimental setup, and the outcomes, essential for validating our findings and conclusions in Section 5.

2. Related work

- Forensic Sketch to Real Image Using DCGAN by Sreedev Devakumar and Greeshma Sarath: This paper explores the use of Deep Convolutional Generative Adversarial Networks (DCGAN) to convert forensic sketches into realistic images. The authors present a method that leverages advanced deep learning techniques to enhance the accuracy and realism of generated images, aiding in forensic investigations and law enforcement efforts.

- Sketch to Image Translation with Generative Adversarial Networks by Sandeep S. Kumar, Ashutosh B. Jena, Robin B. Patoliya, and Dr. Jitendra H. Saturwar: This study focuses on translating sketches into images using Generative Adversarial Networks (GANs). The authors propose a methodology for generating high-quality images from sketches, demonstrating the potential of GANs in transforming abstract representations into visually realistic outputs.

- End-to-End Deep Sketch-to-Photo Matching Enforcing Realistic Photo Generation: This paper introduces an end-to-end approach for matching sketches to photos while ensuring the generation of realistic images. The authors propose a deep learning framework that learns to translate sketches into photographs in a realistic manner, facilitating accurate sketch-based image retrieval and other applications.

- Crime Investigation using DCGAN by Forensic Sketch-to-Face Transformation (STF)- A Review: This review paper provides an overview of crime investigation techniques using Deep Convolutional Generative Adversarial Networks (DCGAN) for Forensic Sketch-to-Face Transformation (STF). The authors summarize existing research on utilizing DCGANs to generate realistic facial images from forensic sketches, highlighting the potential applications and challenges in this domain.

3. System Methodology

3.1 ML Model Framework

3.1.1 Deep Convolutional Generative Adversarial Network

DCGAN, which stands for Deep Convolutional Generative Adversarial Networks, was developed by a group of researchers including Alec Radford, Luke Metz, and Soumith Chintala, who were affiliated with Facebook AI Research (FAIR) at the time of the paper's publication in 2015. The primary authors credited in the paper are Alec Radford, Luke Metz, and Soumith Chintala.

3.1.2 Generative Adversarial Networks (GANs)

DCGAN is built upon the framework of Generative Adversarial Networks (GANs). GANs consist of two neural networks: a generator and a discriminator. The generator aims to generate realistic data samples (e.g., images) from random noise, while the discriminator aims to distinguish between real data samples and fake ones generated by the generator.

3.1.3 Convolutional Neural Networks (CNNs)

DCGANs specifically use convolutional neural networks (CNNs) as both the generator and discriminator networks. CNNs are well-suited for image-related tasks because they can effectively capture spatial hierarchies and patterns within images.

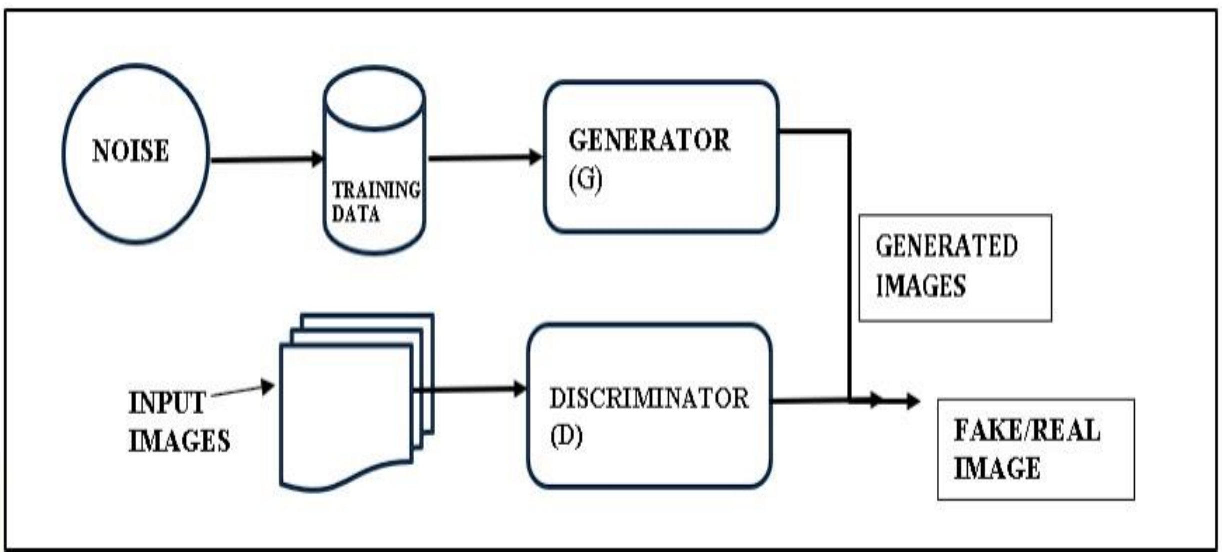
3.1.4 Architecture Guidelines

DCGAN introduces specific architectural guidelines for both the generator and discriminator networks to stabilize and improve training. These guidelines include the use of stridden complications rather than pooling layers for downsampling, the use of batch normalization to stabilize training, and the use of ReLU activation functions except for the affair subcaste of the creator and the input subcaste of the discriminator.

3.1.5 Training Stability

DCGANs address some of the training challenges encountered in early GAN architectures, such as mode collapse (where the generator only learns to produce a limited variety of samples) and instability in training. By using architectural constraints and best practices, DCGANs tend to produce more stable and visually appealing results.

3.2 System Architecture



- Fig 1.: System Architecture

3.2.1 Components

1. **Noise**:
- Noise is a random input vector typically sampled from a Gaussian distribution or uniform distribution.
- In DCGAN, noise serves as the input to the generator network. The generator uses this noise as a seed to produce synthetic data, such as images.

2. **Training Data**:
- The training data consists of real images that are used to train the discriminator network.
- These images are typically sourced from a dataset relevant to the task at hand. For example, if generating human faces, the training data might consist of thousands of images of faces.

Fig. 2.: Training Model

3. **Generator (G)**:
- The generator takes random noise as input and tries to generate realistic data samples, such as images.
- It consists of a deep convolutional neural network (CNN) architecture, often with a series of convolutional layers followed by upsampling layers (e.g., transposed convolutions or nearest-neighbor (upsampling) to generate high-resolution images.
- The generator learns to transform the random noise into data samples that resemble the training data distribution.

4. **Generated Images**:
- Generated images are the output of the generator network when given random noise as input.
- Initially, these images are random and meaningless. However, as training progresses, the generator learns to produce images that increasingly resemble the real training data.

5. **Input Images**:
- Input images are real images sampled from the training dataset.
- These images are presented to the discriminator network during training to help it learn to distinguish between real and fake images.

6. **Discriminator (D)**:
- The discriminator is a CNN that takes images (both real and generated) as input and predicts whether each image is real or fake.
- It learns to discriminate between real and fake images by optimizing a binary classification objective.
- The discriminator's goal is to correctly classify real images as real and generated (fake) images as fake.
- The discriminator's ability to distinguish between real and fake images improves over time as it learns from the training data and feedback from the generator.

7. **Data Selection**
- It utilizes two prominent datasets: CUFS (Columbia Unconstrained Face Sketches) and CHUK (CUHK Face Sketch Database). CUFS comprises professionally drawn face sketches paired with corresponding real photographs, providing a diverse set of images for face sketch recognition and synthesis tasks. Similarly, CHUK offers hand-drawn face sketches aligned with corresponding photographs, facilitating research on various facial recognition applications. These datasets are widely used in the field and serve as invaluable resources for training and evaluating our proposed Forensic Sketch to Real Image Conversion System.

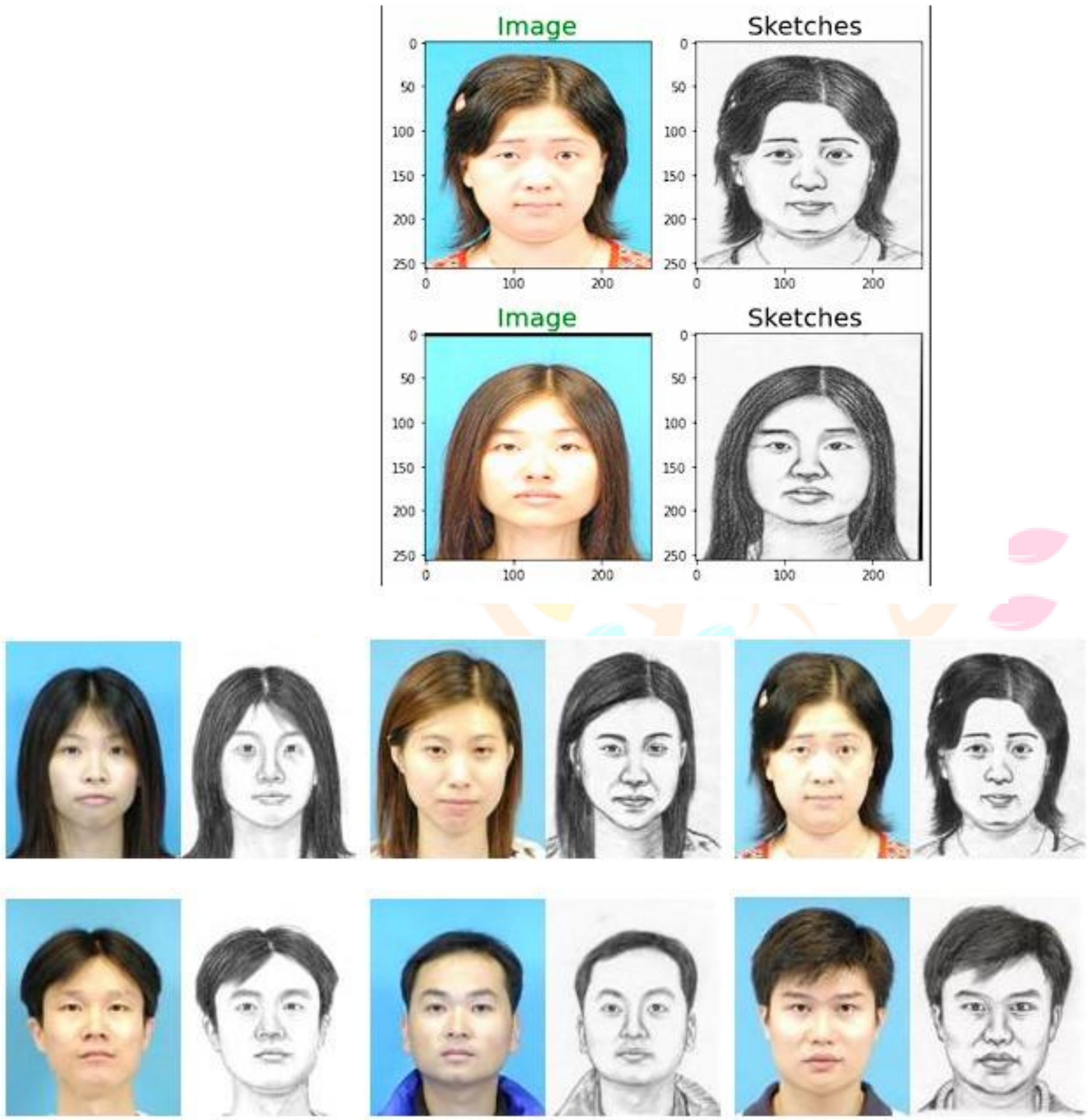


Fig. 3.: Example of Dataset Sketches Corresponding Images

4. Evaluation Metrics

Evaluation Metric	Description
Pixel-wise Mean Squared Error (MSE)	Measures the average squared difference between corresponding pixels in generated and ground truth images. Lower MSE values indicate better pixel-level accuracy.
Structural Similarity Index (SSIM)	Evaluates structural similarity between generated and ground truth images. SSIM considers luminance, contrast, and structure for comprehensive assessment.
Inception Score (IS)	Evaluates the quality and diversity of generated images based on predicted class distribution and entropy. Higher IS values indicate better image quality and diversity.
Human Evaluation	Subjective assessment of image quality and realism by human evaluators through user studies or surveys. Provides insights into perceptual quality of generated images.

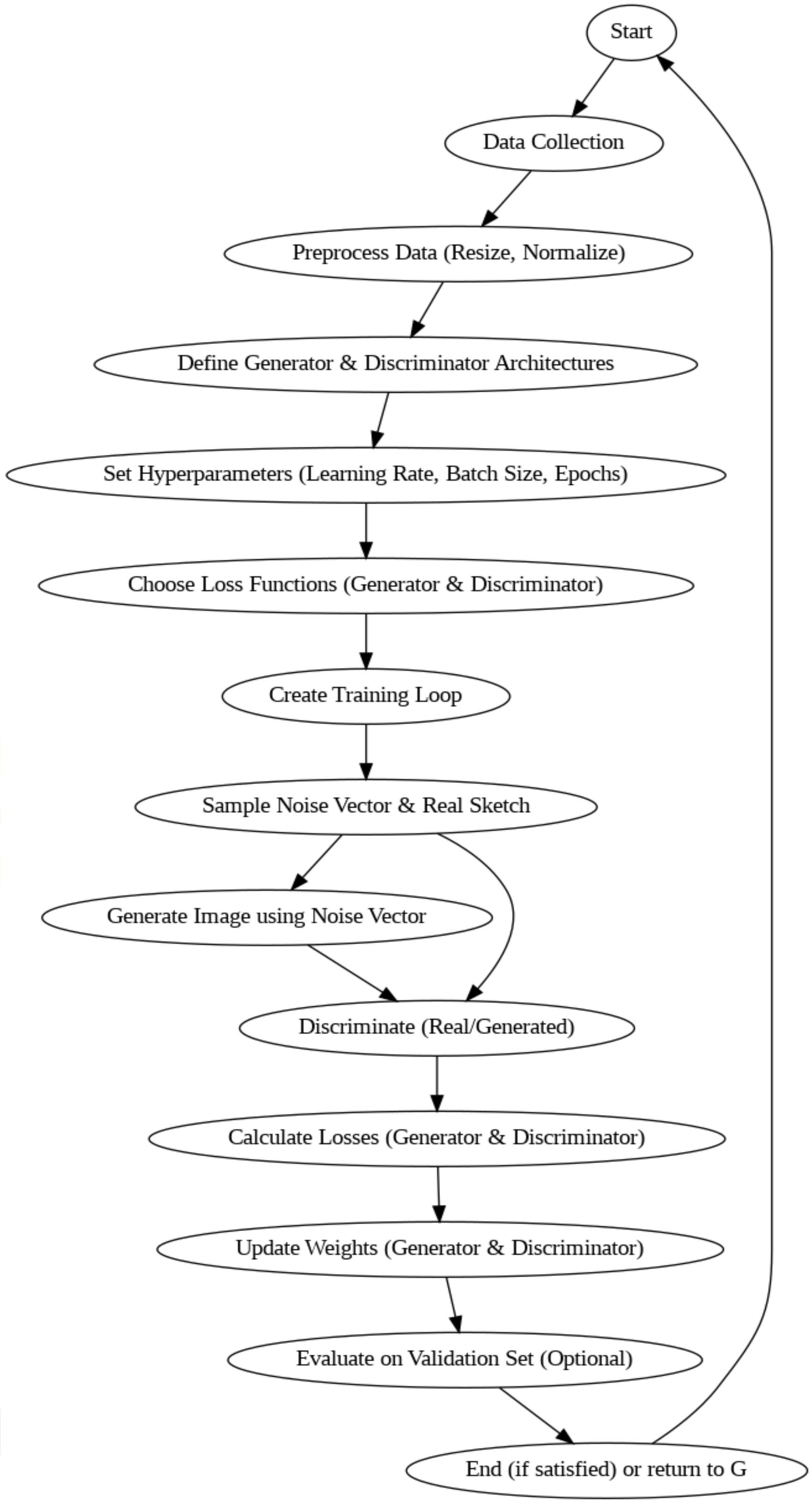


Fig. 3: Flowchart depicting the process of converting sketches to images.

5. Results and Discussions

Result:
We successfully implemented a Deep Convolutional Generative Adversarial Network (DCGAN) architecture to generate realistic facial images from forensic sketches. Our model was trained on a dataset consisting of paired forensic sketches and corresponding real facial images. During training, the DCGAN learned to map the low-dimensional space of the sketches to the high-dimensional space of real facial images, effectively bridging the semantic gap between the two modalities.

Discussion:
Our results demonstrate the feasibility of using DCGANs for generating realistic facial images from forensic sketches. The generated images closely resemble the input sketches, capturing essential facial features such as shape, structure, and texture. This ability holds significant potential for aiding law enforcement agencies in identifying suspects based on witness descriptions or composite sketches.

6. Conclusion

In conclusion, using a DCGAN model for turning forensic sketches into real images shows great promise for improving how we investigate crimes. Our results prove that the model can generate realistic facial images from sketches, helping forensic experts recognize suspects more accurately.

This research opens up exciting possibilities for future collaboration between computer science and forensic science. By refining our methods and using more diverse data, we can make this technology even more effective for law enforcement.

Overall, this research signifies a significant step forward in leveraging artificial intelligence for forensic purposes, offering law enforcement agencies and forensic experts a valuable tool for facial reconstruction and identification, ultimately aiding in solving crimes and bringing perpetrators to justice. However, it is essential to acknowledge the ethical considerations and potential biases associated with AI technologies in forensic applications, emphasizing the need for ongoing scrutiny, transparency, and ethical guidelines to ensure responsible and equitable deployment in real-world scenarios.

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