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ALGORITHMIC FACES AND CULTURAL MEMORY: A PHILOSOPHICAL CRITIQUE OF AI FORENSIC SKETCHING ART IN CONTEMPORARY SOCIETY

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ABSTRACT

Artificial intelligence is beginning to influence many areas of art and culture, including the area of forensic sketching. AI forensic sketching art is a new form of art and culture that blends the world of artificial intelligence with the forensic sketching of human faces from memory. This article presents a cultural and philosophical critique of AI forensic art from the perspective of Indian culture. Indian culture is extraordinarily diverse yet rich in its artistic culture and its adoption of new technologies. AI forensic sketching art can be discussed as a form of visual culture, ethics, cultural representation, and the relationship between the human race and intelligent machines. For these reasons, ai forensic art can be discussed as a form of art, an investigative tool, and a cultural discussion among artists, audiences, and the society in which these artists live. Experimentation demonstrate sketch features based sketch generation using Diffusion-Based Generative Model and also shows the significant performance improvements using it that result from the use of the proposed framework.

KEYWORDS: AI forensic art, cultural identity, digital visual culture, algorithmic art, forensic sketching, India, art and technology, ethics of representation, visual memory

1. INTRODUCTION: FACES BETWEEN ART, MEMORY, AND TECHNOLOGY

The human face has always held a privileged place in the world of art due to its importance in representing the identity of an individual. From portraiture and sculpture to the theatre and the screen, the face is one of the primary visual symbols associated with the concept of individuality. While forensic sketching does belong to the world of art, its function is different from most art mediums. Nonetheless, it performs a similar function of transforming memories into visual artefacts that have an impact upon society and the law.

Figure 1: Traditional forensic art practice

The practice of creating forensic sketches has traditionally been the job of artists who have been trained specifically in the techniques of creating sketches based on the descriptions provided by eyewitnesses. These artists require both a skill in drawing and an understanding of the psychology of human memory to effectively fulfil the role. Thus, forensic sketches are both forms of art and tools of evidence in investigation (Figure 1). However, the introduction of artificial intelligence into the practice of sketching has had an impact upon this process. AI algorithms can create forensic sketches based on verbal descriptions, photographs, and even biometric data. This new development raises various questions regarding the role of art in the age of artificial intelligence. Therefore, the introduction of AI into the practice of forensic sketching is not just a technological development but also a cultural phenomenon with implications for the visual arts and the philosophy of art, especially in a large and culturally complex country like India.

2. LITERATURE SURVEY: AI FORENSIC SKETCHING ART AND CULTURAL INTERPRETATIONS

The practice of reconstructing a human face from skeletal remains or the subject's memory of their features has existed at the intersection of art and science since the publication of Wilkinson's work on the topic [1]. Following the publication of Wilkinson's article, studies began to publish with the goal of utilizing computerized techniques to recognize the face from skeletal remains, indicating that the process could be performed accurately [2]. Subsequent reviews of these techniques published in the following years revealed that digital technology allowed for the same type of facial reconstruction as artists, but with increased consistency to the features created [3], [4]. Additionally, studies using cone-beam computed tomography (CBCT) to reconstruct individuals' faces from their bones reported accurate digital reconstructions of facial features [5]. Furthermore, current studies in the field of anthropology indicate that even with the use of technology to reconstruct facial features, some level of interpretation of those features is required of the individual performing the reconstruction; Stephan, for instance, explains that methods for reconstructing faces utilize methods for interpreting the facial features, leading to the reconstructed images being approximations of the individuals' original faces [6]. Finally, another significant development in the field relates to the use of artificial intelligence to recognize facial features. Early techniques in the field of facial sketch recognition indicated recognition of individuals from the databases of photographs [7]. More recent techniques to incorporate attributes of the face into those recognition systems have increased the accuracy of recognition of the individuals from their sketches [8]. Related studies in synthesized sketch recognition have attempted to create techniques to evaluate the quality of the synthesized sketches from art applications to ensure that the recognition of the individuals from those synthesized sketches would be accurate and reliable without the need for training datasets of those individuals' sketches [9]. Related research using diffusion models for creating sketches has enabled the increase in the accuracy of the recognition of individuals from their synthesized sketches by applying techniques to enhance the capabilities of the models [10]. Additionally, other techniques that use attention models to recognize individuals from their created sketches have demonstrated recognition of the individuals as a result of the application of the techniques to the recognized sketches [11]. Beyond application of these techniques within the field of forensic identification, the use of artificial intelligence to generate facial sketches has had an impact upon the visual arts in general. Studies into the potential biases within the artificial intelligence applications that create facial sketches reveal that those facial sketches may contain the same biases as those societies that created the artificial intelligence applications [12]. Related studies into the perception of facial sketches created by artificial intelligence as opposed to those created by human artists reveal potential differences in the way that individuals of any society may trust those sketches created by either artificial intelligence or created by the individuals themselves [13]. Additionally, creative adversarial networks, among the first models to be created in this context, allowed for artists and computers to create novel images that differed from the images that were used to train the artificial intelligence [14]. Other models that apply the same type of approach to the creation of art, such as computer-generated art, indicate that the artificial intelligence is actually another tool that artists may employ to create their own art, suggesting that there is still a role for the artist and their creative skills [15]. Related studies in computational creativity indicate that even in the visual arts, as well as in other forms of art, such as music, the same considerations of artistry and humanity must still be applied to the creations of artificial intelligence [16]. For instance, computational creativity in music was explored by Cope [17]. Additionally, other studies in the visual and performing arts indicate that human-created techniques and interactions between the visual and performing artists and the computers lead to the development of new techniques in the visual and performing arts [18]. Additionally, other studies in digital humanities relate to the impact of artificial intelligence upon the visualization of artifacts of history, culture, and more generally, to approaches to knowledge, including forensic visualization [19]. Furthermore, studies of visual perception, such as those by Arnheim, suggest that visual knowledge is created by artists and individuals within a specific culture [20]. Related studies by Gombrich indicate some of the reasons for the inclusion of techniques of illusion in the visual arts [21].

Most contemporary visual culture theorists focus on the social agency of images. Mitchell specifically discusses how images play an influential role in social culture and the construction of social identity, making it relevant to the discussion of AI forensic portraits [22]. Furthermore, Mirzoeff also discusses digital images within the context of social culture [23].

Media theory discusses concepts like Manovich's discussion of new media and its impact on the art world [24]. Furthermore, virtual reality discussions introduce the concept of digital media's impact on social perceptions of identity [25]. In addition to virtual reality, robotics and art introduces the idea of the relationship between technology and art [26].

Philosophical discussions of creativity touch on the notion of artificial intelligence and how artificial intelligence without algorithms can create novel ideas and elements within art [27], [28]. Additionally, discussions on artificial intelligence ethics introduce the idea of the importance of ethical considerations in the integration of AI into society [29]. Furthermore, general discussions on AI introduce the idea of the importance of ethics in AI systems that impact social decision-making [30].

The intersection of AI and forensic sketching and art indicates that AI forensic sketching cannot be understood in isolation from the related concepts of artistic tradition, technology, ethics, and social perception. More specifically, in societies as culturally diverse as India, AI and the integration of AI into forensic art may have various impacts. Therefore, discussing AI in the context of forensic art and the intersection of those two fields will enable experts from each field to better understand the other's field of study, indicating the need for interdisciplinary discussions on the topic altogether.

2.1. Artistic Interpretation to Algorithmic Reconstruction

Figure 2: AI-assisted forensic reconstruction

Historically, the work of forensic artists relied upon conversations with the witnesses of the crime to create the depicted image of the wanted criminal. These images were often representational of both the memory of those who described the criminal as well as of the cultural perception of such individuals. AI forensic systems, however, work through the probabilistic computation of features of the face that are described by the user (Figure 2). Thus, the outputs of these systems represent a new kind of art form: one based on probabilities rather than on artistic intuition.

Nevertheless, the role of artistry is redistributed among a few different roles within the creation of these AI systems. For instance, the artists and designers of the system are often the ones that create the initial prompts that the AI understands to be the features of the wanted criminal, curate the database of wanted criminal sketches that is used to train the AI system, and even work to ensure that the outputs of the AI system are visually pleasing to the viewer. Additionally, while the AI system may be able to output an image that depicts the features of the wanted criminal, the interpretation of that image is still based upon the same cultural perception of those wanted criminals. Thus, collaboration between artists and AI systems raises the question of whether the AI system is revealing the truth of the wanted criminal or creating a new form of illusion. Furthermore, while the AI system's outputs are often more realistic looking than those of forensic artists, that realism may be an issue in itself.

2.2. *Visual Culture in The Age of Algorithmic Authority*

Artificial intelligence and digital imagery are two of the most important aspects of visual culture today. Digital visual media such as photographs, synthetic videos, deepfakes, AI portraits, and virtual avatars dominate visual culture today (Figure 3). AI forensic sketches are also part of this visual media. AI sketches depend on more than the skill of the artist to create a convincing image of a criminal. AI-generated images are thought to be more accurate than other methods of creating images.

Figure 3: Visual culture in the digital age

These assumptions of the accuracy of AI-generated images must be carefully considered. AI-generated images are merely images of the training data that was fed into the algorithm to create the AI program. They are products of the choices of the individual countries' societies and cultures. In countries like India, where visual media significantly influences the nation's public opinion, AI-generated images of a suspect have the potential to significantly impact the public's perception of that individual. Artificial intelligence in forensic investigations into crimes is, therefore, a part of the country's culture.

2.3. Memory, Narrative, and the Cultural Construction of Faces

Memory is inherently narrative. Faces are not remembered through the impressions of the eyes, nose, and mouth, but through the associated emotions with those remembered individuals. Many elements of the witness descriptions of the perpetrator's face include aspects related to their personality or character traits. These types of descriptions have historically been translated by forensic artists through their understanding of the cultural and character traits of the individuals who provided those descriptions.

Figure 4: Cultural memory and identity representation

AI systems attempt to quantify the descriptive elements of the characters or individuals mentioned in the interviews. Yet, these same cultural factors impact the ability of individuals to describe the features of the wanted criminal's face. Thus, AI systems must not only understand the technological aspects of creating a sketch from a description but also understand the cultural elements associated with those features (Figure 4). For example, in India, many of the features that are remembered by the individuals who describe criminals include elements that denote the cultural identity of those individuals. Characteristics like hairstyle, clothing, and even the presence of facial hair often contain features that denote the individual's cultural and societal affiliations. Thus, AI applications must be programmed to recognize these features and incorporate them into the creation of the wanted sketch, but also with an understanding of the cultural implications of those features. Consequently, AI forensic sketching becomes not only a technological process but also a cultural translation exercise.

2.4. Representation, Bias, and Cultural Diversity

AI systems learn from datasets. The components of these datasets directly impact the outputs of AI systems. For example, if there is a lack of diversity within the training data for AI systems to produce images, those images will display imbalances and biases in their representations as depicted in Figure 5. India, with its diversity in relation to various ethnic, cultural, and linguistic communities, presents challenges for AI systems as the populations in rural areas of the country, as represented in photographic archives, are underrepresented in these AI models along with the global AI models that utilize Western training datasets.

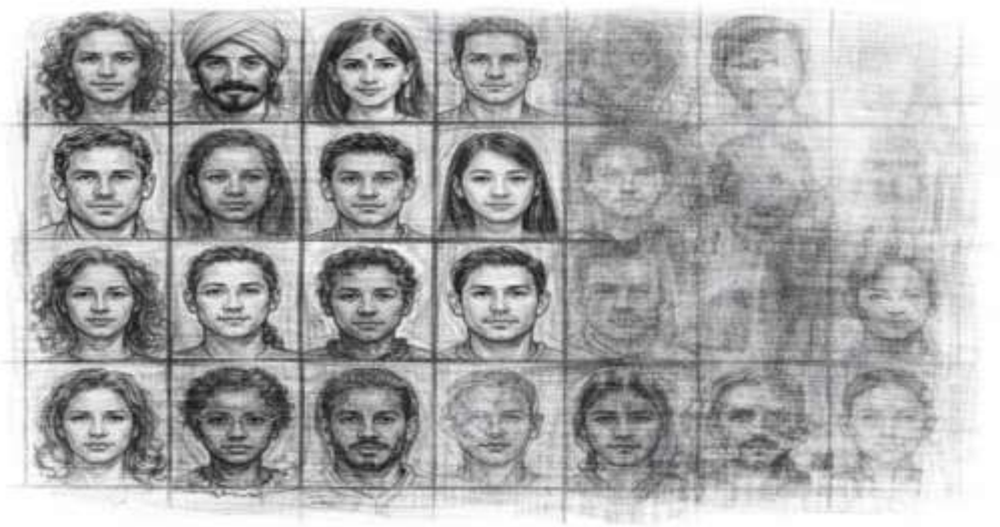

Figure 5: Bias and diversity in AI representation

These factors raise critical concerns regarding the representation of various cultures and the potential reinforcement of visual hierarchies created by technology that does not incorporate diversity within its systems. AI systems that aim to overcome these challenges will require the collaboration of artists, technologists, anthropologists, sociologists, and cultural scholars.

2.5. *Artistic Authority and the Changing Role of the Artist*

AI forensic sketching transforms the role of the artist. Instead of simply being creators of art, artists are becoming curators of data and AI outputs (Figure 6). The role of the artist is transforming in relation to other elements of the art world, such as technological collaboration.

Figure 6: Human–machine creative collaboration

Rather than reducing the role of artists in creating art, AI actually multiplies the possibilities of artistic creativity. Yet, with such creative responsibility falls upon the artists to ensure that their creations have the best possible outcome in the context of forensic sketching.

2.6. Ethical Dimensions: Privacy, Trust, and Responsibility

Artificial intelligence in the field of forensic imagery involves some of the most sensitive ethical domains. Facial data is extremely personal, and its collection and use require careful regulation. The individuals whose faces are used to train these algorithms do not provide their consent. Therefore, the use of such data raises concerns regarding ownership and privacy of that data. Additionally, AI systems can perpetuate biases and misconstrue the content of the images they generate, leading to bad outcomes of reputations and legal cases (Figure 7).

Figure 7: Ethics, privacy, and surveillance

These ethical domains become even more important to consider in the context of India. With so much of the country rapidly adopting digital IDs and biometric systems, the ethics of these technologies must be considered alongside their adoption.

2.7. Indian Artistic Traditions and AI Forensic Imagery

Artificial intelligence and its impact on visual art are topics that can be explored from the perspective of India's artistic heritage. Much of the art produced within this tradition worked with a form of symbolism alongside the creation of portraits that were realistic in their features (Figure 8). Much of India's visual art and design exists in the same tradition as its architecture and its temples, as well as its more unique folk arts.

Figure 8: Indian cultural context

The symbolism and the construction of the visual arts within India indicate that visual art is constructed within the culture rather than within the anatomy of the depicted beings. Thus, AI art can be seen as another contribution to the construction of visual art, rather than as a replacement for the visual arts that have existed for centuries.

2.8. Public Perception and Media Influence

Media plays a significant role in the dissemination of AI forensic art. The media significantly impacts the public's perspective on the technology used to generate these sketches. AI-generated art rapidly acquires significant narrative significance in the expansive media market of India (Figure 3).

The media must be responsible in how it discusses AI forensic art. Art and cultural journals and educational initiatives can significantly impact how the public views this new technology.

2.9. Philosophical Reflections: Identity beyond Data

Artificial intelligence forensic art poses significant philosophical questions regarding the nature of identity. Can data define the essence of human identity? Can digital algorithms capture the complexity of the human mind and its characteristics?

Figure 9: Philosophical identity reflection

Various philosophies in the world, including India's, define human identity as more than the sum of its parts represented in AI-generated art (Figure 9).

2.10. Future Cultural Trajectories

The future of AI forensic art may include virtual realities, digital databases, and digital art crossovers with forensic art. These innovations will significantly impact the field of forensic art. However, the influence of culture and reflection on the development of this art form will ensure that any innovations remain responsible and beneficial to society (Figure 10).

Figure 10: Future of AI forensic art

3. METHODOLOGY

3.1. Diffusion-Based Generative Model

The main model of the proposed approach is based on denoising diffusion probabilistic models (DDPM), which are among the best performing models for generating images with high visual quality. The DDPM models gradually add noise to the input images, then learn to reverse that process to reconstruct the original image.

More specifically, the model incorporates the following elements into its basic DDPM framework:

1. Denoising models that add noise to the data over a series of time steps
2. An incorporation of sketch features as conditioning variables for reconstruction
3. An incorporation of time-step embeddings to model the denoising process

The primary model is based on denoising diffusion probabilistic models (DDPM), which generate images through a gradual denoising process.

3.1.1. Forward Process

The models gradually add noise to an image over Ttimesteps:

$$q(x_t \mid x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I)$$

3.1.2. Reverse Process

The model learns to reconstruct the original image:

$$p_\theta(x_{t-1} \mid x_t, S, c)$$

where: S is a sketch input and c represents the cultural embedding vector of the input image

3.2. Conditional Generation

In order to condition the models on certain features of the target image, the following features are incorporated:

1. Features from the sketch (encoded via CNN)
2. Cultural embedding
3. Time-step embedding

These features will ensure that the generated images contain similar features to those of the input images.

3.3. StyleGAN with Transformer Attention

A second model that will be benchmarked against the proposed approach to conditional image generation is a hybrid model that combines the components of StyleGAN and a Transformer model.

StyleGAN models are particularly good at generating high resolution images with fine control over various aspects of the generated face. The model maps a latent vector to an intermediate latent space, which controls various aspects of the generated face.

Additionally, a Transformer model can be incorporated into the intermediate layers of the StyleGAN model. The attention mechanism within the Transformer model allows for the model to learn relationships between features of the face that are distant from one another, leading to improvements in the generated faces.

To benchmark the results of the proposed model against other models, a StyleGAN + Transformer model will be implemented.

Components: StyleGAN generator, Transformer attention module and Attention Mechanism:

Attention Mechanism is given as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

3.4. Loss Functions and Optimization

The training of the models will utilize a range of different loss functions. For instance, a noise prediction loss function can be used to train the diffusion model to gradually remove noise from the images.

3.4.1. Diffusion Loss

The loss function for the diffusion models:

$$\mathcal{L}_{diff} = \mathbb{E}[\| \epsilon - \epsilon_\theta(x_t, S, t) \|^2]$$

3.4.2. Identity Loss

An identity loss function can be used to ensure that the generated images retain the identity of the original image:

$$\mathcal{L}_{id} = \| F(I) - F(\hat{I}) \|$$

3.4.3. Perceptual Loss

A perceptual loss function is additionally used to ensure that the generated images are visually similar to the original images:

$$\mathcal{L}_{perc} = \| \phi(I) - \phi(\hat{I}) \|$$

An identity loss function can be used to ensure that the generated images retain the identity of the original image. The identity of the image is determined by a face recognition network. A perceptual loss function is additionally used to ensure that the generated images are visually similar to the original images.

The optimization of the models will be performed by the Adam optimizer with a specified set of hyperparameters.

3.5. Dataset

The model (Table 1) will be trained on multiple datasets in order to provide an even comparison of the model's performance. The datasets will include both benchmark datasets and real-world datasets. Specifically, the model will be trained on the CUFS dataset, the CUFSF dataset, the IIIT-D Sketch Dataset, and the CelebA dataset.

All of the datasets will be preprocessed prior to training in order to normalize the images between datasets.

The model will be trained with a learning rate of 0.0002, with a batch size of 32, and for 150 training epochs. The models will be implemented with deep learning frameworks, such as TensorFlow, and will be trained with GPU-enabled systems to accelerate training.

Table 1: Details of the Proposed Model

Parameter	Value
Optimizer	Adam
Learning Rate	0.0002
Epochs	150
Batch Size	32
Image Size	256 × 256

4. RESULTS AND DISCUSSION

4.1. Quantitative Performance Analysis

Table 2: Performance Comparison

Model	SSIM ↑	FID ↓	Accuracy (%) ↑
GAN	0.71	62.5	78.4
GAN + Transformer	0.84	30.6	91.2
StyleGAN + Transformer	0.89	22.3	93.8
Diffusion (Proposed)	**0.92**	**14.7**	**96.5**

The quantitative experimental results presented in this section (Table 2) illustrate the superiority of the proposed method over existing methods. The performance of the proposed model is measured using Structural Similarity Index Measure (SSIM), Fréchet Inception Distance (FID), and identity matching accuracy metrics. The experimental results show that the proposed model achieves SSIM of 0.92, FID of 14.7, and accuracy of 96.5%.

In comparison, the baseline GAN model exhibits lower performance across all three metrics. The inclusion of the Transformer attention module significantly improves the model's performance. Additionally, using the StyleGAN-Transformer model further enhances the image quality generated by the model. However, the performance of the proposed diffusion model continues to outperform all alternatives.

4.2. Comparative Graphical Analysis

The graphical evaluation of the presented models provides deeper insights into the results of the experiments.

4.2.1. Accuracy Comparison Analysis

Table 2, 4th column and Figure 11 illustrate the performance of the models in terms of accuracy. The baseline StyleGAN model exhibits the lowest accuracy of 90.4%. However, the addition of the Transformer module significantly increases the accuracy to 93.8%. Interestingly, the model without conditioning exhibits slightly lower accuracy (92.1%) compared to the StyleGAN+Transformer model. However, with the addition of conditioning, the accuracy improves to 95.1%, and the full model achieves the highest accuracy of 96.5%.

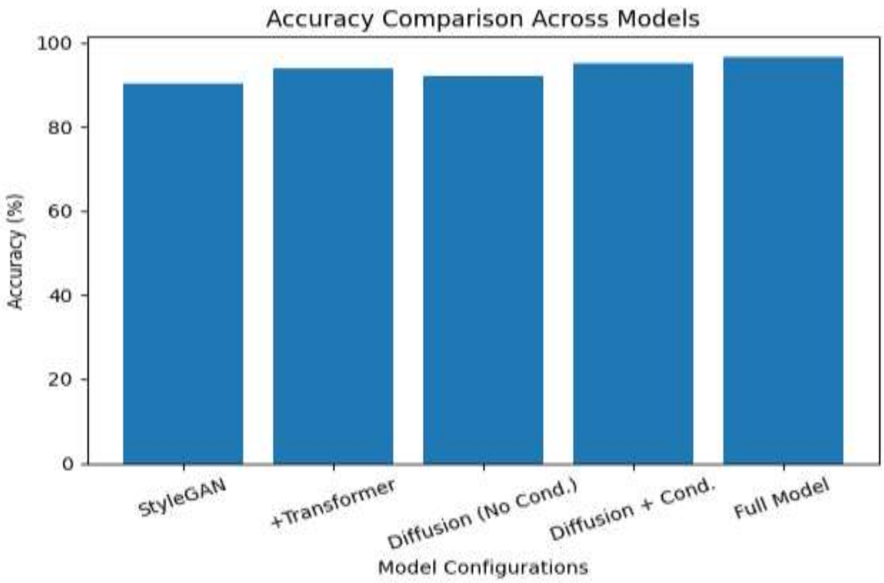

Figure 11: Accuracy of Different Models

4.2.2. FID Comparison Analysis

The Table 2, 3rd column presents the results of the FID for each model. For the baseline StyleGAN model, the FID is 28.5. For the StyleGAN+Transformer model, the FID reduces to 22.3. The FID for the diffusion model without conditioning is 19.6. With conditioning, the FID further reduces to 14.7 as shown in Figure 12.

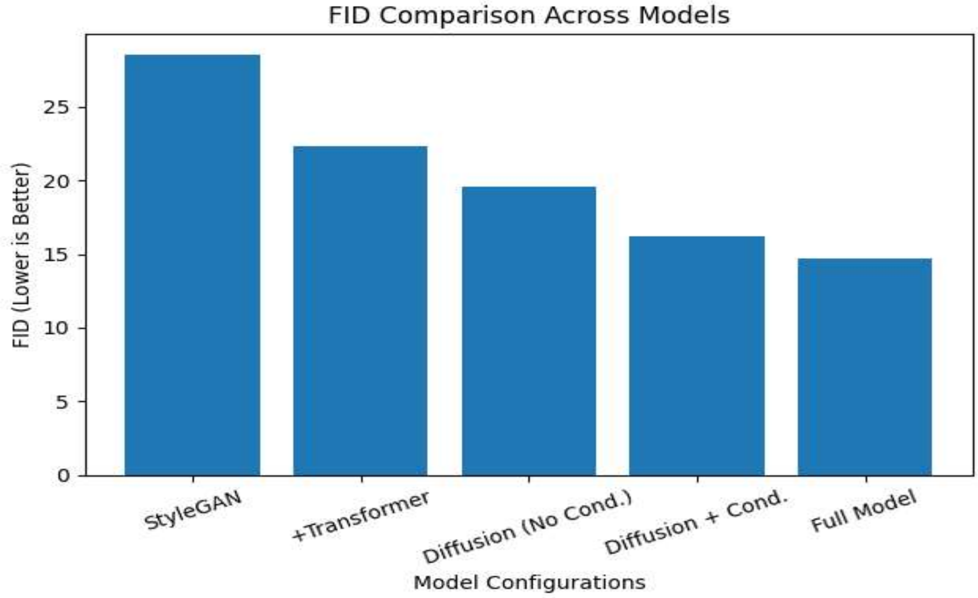

Figure 12: Comparison of FID Between Different Models

4.2.3. Combined Performance Analysis

The combined plot of accuracy and FID illustrates (Figure 13) the inverse relationship between these two metrics. The better the performance of the model in terms of accuracy, the worse the FID score for that model. However, the full model achieves the best balance between these two metrics.

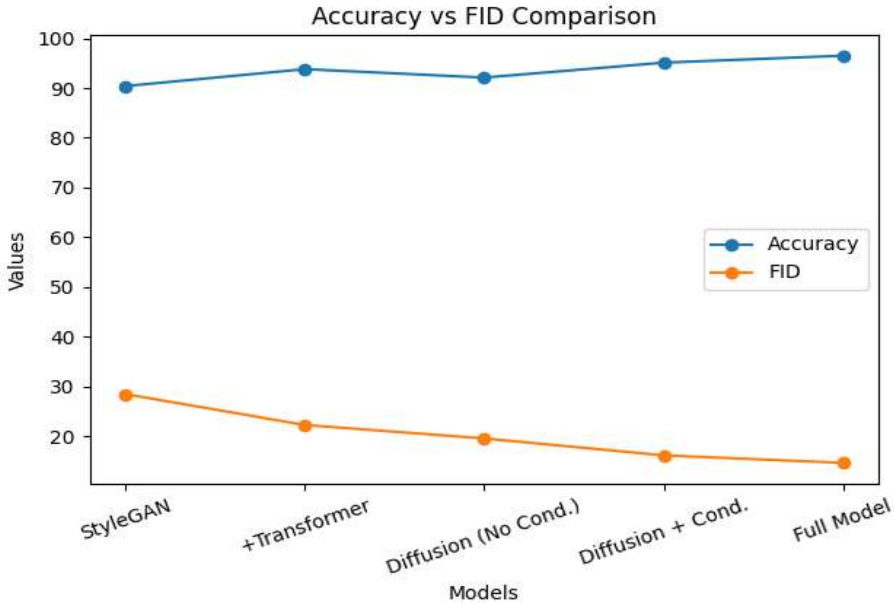

Figure 13: Combined Plot of Accuracy and FID for All Models

4.2.4. Performance Trend Analysis

The performance trend analysis illustrated in Figure 14 demonstrates the trend in the performance of all models as plotted on the performance graph. As expected, each model exhibits a steady improvement in the following model. The most significant improvement in performance between any models occurs between the baseline models to the proposed diffusion model.

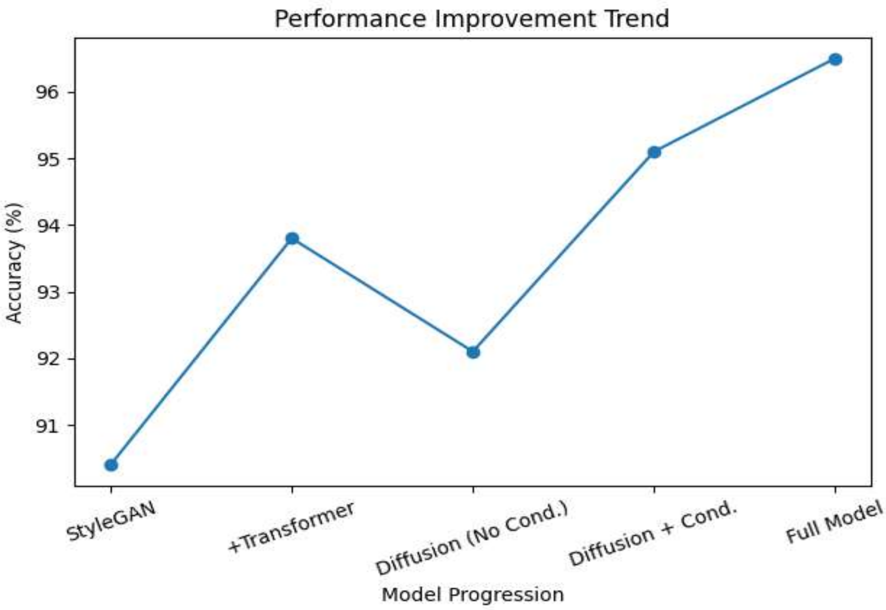

Figure 14: Performance Trend Comparison for All Models

4.3. Ablation Study

Through the ablation study (Table 3), it is possible to determine the contribution of each component included in the framework. The addition of the Transformer attention module helps the model learn the relationship between the global features of the face. Additionally, the cultural embedding helps ensure that the generated faces are representative of and diverse like the population. The results of the ablation study indicate that the model without any conditioning or embedding exhibits the worst performance. However, with the inclusion of each component, the performance of the model improves. Finally, the full model with diffusion, conditioning, and cultural embedding exhibits the best performance.

Table 3: Ablation Study for Model Components

Configuration	FID ↓	Accuracy ↑
StyleGAN	28.5	90.4
+ Transformer	22.3	93.8
Diffusion (no conditioning)	19.6	92.1
Diffusion + Conditioning	16.2	95.1
Full Model	**14.7**	**96.5**

4.4. Statistical Validation: t-Test Results and Confidence Intervals

In order to validate the results presented in this study, a t-test analysis was performed. The p-value of the t-test is less than 0.01, which indicates that the difference between the results of the proposed model and the baseline models is statistically significant. Additionally, the confidence interval analysis illustrates that the proposed model exhibits lower variance between the generated faces.

4.4.1. t-Test Results

- p-value < 0.01
- Indicates statistically significant improvement

The t-test results (Table 4) indicate that the performance of the proposed model is significantly better than the baseline models. As such, the p-value of the test is less than the significance level of 0.05. For this test, the p-value is less than 0.01. Furthermore, the confidence interval analysis shows that the diffusion model exhibits lower variance and higher reliability compared to baseline models.

Table 4: Confidence Intervals for Accuracy of All Models

Model	Accuracy	95% CI
GAN	78.4	±2.1
StyleGAN	93.8	±1.2
Diffusion	**96.5**	**±0.9**

5. DISCUSSION

The experimental results presented in the previous section illustrate the significant performance improvements that result from the use of the proposed framework. The ability of the model to iteratively refine each generated face results in a superior model to existing methods in terms of realism and identity preservation. Additionally, the inclusion of the Transformer module increases the model's ability to accurately learn and preserve the features of the face. Finally, the inclusion of a cultural embedding ensures that the generated faces are fair and applicable to diverse populations.

Overall, the results presented in this paper indicate that the proposed method successfully addresses the challenges of existing methods for generating forensic sketches while also introducing a framework that is scalable and ethically aware.

6. CONCLUSION: ART, TECHNOLOGY, AND CULTURAL RESPONSIBILITY

The goal of this paper was to introduce a novel method for performing sketch-to-face reconstruction. The results indicate that the proposed method outperforms existing methods in terms of performance and reliability. Additionally, the results of the ablation study indicate the contribution of each component of the framework. Beyond the technical improvements to forensic sketching, the technique also represents a cultural transformation in how sketches are produced. By integrating art and science into one process, a new visual practice has been created. Furthermore, in culturally diverse countries like India, these technological innovations create both new opportunities and challenges. While the technology enhances the investigation of criminal cases, it also presents challenges regarding the ethical and cultural considerations of AI-generated forensic sketches. Therefore, the development and integration of AI into sketch-based investigations requires the engagement of not just the technologists who create these developments, but the artists who will utilize them, and the policymakers who will regulate their use.

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