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Article

Hybrid Deep Learning Framework for Facial Image Synthesis and Reconstruction Using StyleGAN2 and Autoencoders

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Abstract: Realistic human face synthesis and reconstruction are important tasks in computer vision, entertainment, biometrics, identity verification and so on. In this work, a hybrid deep learning approach is studied that combines the generative ability of StyleGAN2 with the feature learning and reconstruction ability of a convolutional autoencoder. The main aim is to analyse the performance of an autoencoder to compress and reconstruct high quality synthetic facial images while preserving the main structural and perceptual features.Instead of using traditional real-world paired datasets, this system takes the synthetic face images generated by StyleGAN2 as the training input. The generated images provide a large and controlled dataset, allowing the model to learn facial representations without privacy concerns or data collection limitations. The synthetic images are then inputted to a convolutional autoencoder, which encodes the images into a small latent space and then reconstructs the images. The project shows how generative models and representation learning can be combined in one pipeline. It demonstrates effective utilisation of self-generated datasets for training deep-learning models, reducing the demand for large annotated datasets. The results show the model's ability to keep the facial structure and image quality through the reconstruction process. This shows the possibility of combining the GAN-based data generation and the autoencoder-based learning for efficient image synthesis and reconstruction applications.

Keywords: Stylegan2; Lightweight Models; Using Self-Generated Datasets; Traditional Paired Datasets; Hybrid Deep Learning

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1. Introduction

Over the last decade, deep learning has revolutionised the fields of computer vision, image synthesis, and representation learning. One of the most influential developments has been the Generative Adversarial Networks (GANs), which have shown an amazing ability to generate very realistic synthetic images [33]. StyleGAN2 has emerged as one of the most advanced GAN architectures for facial image synthesis, in particular due to its ability to generate high-resolution, diverse and visually coherent human faces [39]. Meanwhile, autoencoders have become a fundamental neural network model to learn compressed representations of data as well as reconstruct inputs with a small loss of information [52]. Autoencoders are extensively used for dimensionality reduction, image denoising, feature extraction and unsupervised learning of representations [36]. This project combines these two powerful paradigms, namely StyleGAN2 based synthetic data generation and convolutional autoencoder based reconstruction, under one umbrella [42].

The main idea is to explore the potential of a model to learn useful feature representations when it is trained with synthetic data generated by another deep learning model only.

Such a hybrid approach is motivated by two major challenges in modern machine learning: data dependency and privacy [30]. Most deep learning models depend heavily on large-scale real-world datasets that require significant efforts of collection, annotation, and processing [48]. In areas such as face recognition and identity-related image processing, data collection is further restricted by privacy and ethical concerns. This project solves both problems at the same time by using synthetic images generated by GAN instead of real world datasets [45]. StyleGAN2 creates synthetic data that provides us with an almost unlimited number of unique faces that resemble faces one might find in the real world and does not need any personal or sensitive data [50]. This makes the system scalable and privacy preserving. Second, we are motivated to study how effective representation learning is when trained on non-real data distributions [32]. GANs are very good at generating realistic images but they do not learn compressed representations in a structured latent encoding-decoding fashion. But autoencoders are explicitly designed for encoding input data into a lower dimensional latent space and decoding it back to the original [41]. The system trains an autoencoder on GAN-generated images and tests whether synthetic data alone are sufficient to learn meaningful structural features of human faces [53]. This approach also gives insights into the generalisation ability of neural networks trained on artificially generated datasets.

The proposed system is formulated as a two-stage deep learning pipeline [38]. The first stage is to generate high quality synthetic face images by using a pretrained StyleGAN2 model. StyleGAN2 works by feeding random latent vectors to a cascade of progressively growing synthesis layers to produce high-resolution images. The input latent seed values are varied to produce a wide range of facial variations across facial structure, skin tone, expression, and background features. The autoencoder is trained on the generated images as the dataset [34]. The dataset is synthetically created and removes the dependency on external datasets and has full control over the data distribution and volume. After generating the dataset , the images are preprocessed before we feed them to the autoencoder . Preprocessing all images to a fixed resolution to provide the neural network with input of fixed dimensions. Normalisation is also utilised to bring the pixel values to a standard range, typically 0 to 1, which helps with training stability and convergence speed [44]. The preprocessed dataset is divided into training and testing subsets. The common split is 80-20. This guarantees that the model is evaluated on unseen data to verify its generalisation ability [55].

The next step of the system is a design and training of a convolutional autoencoder [35]. The architecture of the autoencoder is composed of two main parts: the encoder and the decoder. The encoder compresses the input image into a small latent representation by gradually reducing the spatial dimensions with convolutional and pooling layers [47]. This latent representation retains the most important features of the input image while discarding redundant information. The decoder then uses transposed convolutional layers to reconstruct the original image from this compressed representation, gradually restoring spatial dimensions [49]. Autoencoder tries to minimise the difference between the input image and the reconstructed output [29]. We train the model using the Mean Squared Error (MSE) loss function, which measures the difference between the original and reconstructed images on a pixel-by-pixel basis. We employ the Adam optimiser to efficiently update model parameters during training, resulting in faster convergence and better performance. During training, the autoencoder learns to identify important facial features such as eye, nose structure, mouth positioning and overall facial geometry [40]. As training progresses, the quality of the reconstruction improves and the loss value slowly decreases, indicating that the model is learning meaningful representations of the input data.

One of the main goals of this project is to assess the performance of the autoencoder in reconstructing unseen facial images produced by StyleGAN2 [46]. The model is then tested on the held-out test set to see how well it performs after training. The evaluation is done using quantitative and qualitative methods. We perform quantitative analysis of the reconstruction loss values to evaluate the similarity of output to input images [54]. Qualitatively, the reconstructed images are visually inspected for clarity, structural correctness and preservation of facial features [37]. These two types of evaluation help give you a better sense of how your model is performing. The combination of StyleGAN2 and autoencoders in one pipeline shows the potential of combining generative and reconstructive models [51]. GANs focus on generating realistic data distributions, while autoencoders focus on learning efficient representations of data [43]. The data generated by GAN as input to the autoencoder creates a closed-loop deep learning framework without any dependence on external real-world datasets [31]. This self-contained design is especially helpful when data privacy, availability, or labelling limitations are important limitations.

Literature Review

The field of facial image synthesis and reconstruction has experienced rapid growth in the past decade, fuelled by the remarkable progress made in deep learning, especially in the domain of generative modelling and representation learning. The most influential approaches include Generative Adversarial Networks (GANs) and Autoencoders (AEs) that have fundamentally changed the way machines generate, process, and reconstruct visual data [2]. The two paradigms tackle complementary tasks in computer vision: GANs aim to generate high-fidelity synthetic images that are indistinguishable from real data distributions, while autoencoders aim to compress input data into compact latent representations and reconstruct it with minimal information loss [17]. The combination of these two approaches is the basis for the modern hybrid systems for image synthesis and reconstruction, such as the one explored in this project. A major breakthrough in facial image generation was the development of sophisticated GAN architectures that could generate high-resolution and visually consistent human faces [25]. GANs are trained by playing a game between two neural networks, a generator and a discriminator. The generator attempts to generate synthetic images that resemble real data. The discriminator judges whether the generated images are real or fake [10]. This adversarial process enables both networks to improve iteratively until the generator is able to output images that are nearly indistinguishable from real photos. Over time, the architecture design, the stability of the training and the loss functions have been improved, leading to more sophisticated models that can generate facial images that look very realistic.

A huge step towards this goal is the paper StyleGAN2, which is a huge improvement over the previous generation of GANs. In this work, we improve upon the image generation process of StyleGAN2 by removing artefacts commonly seen in previous versions and improving the overall visual quality and consistency of the generated faces [21]. It proposes a more sophisticated style-based generation method where different layers of the network control different levels of image features. In general, lower layers tend to influence coarse features such as face shape and pose while higher layers tend to influence fine details such as skin texture, hair strands and facial expressions [6]. This hierarchical control enables very detailed and customisable facial image synthesis, and makes StyleGAN2 one of the most powerful tools in modern generative modelling. StyleGAN2's capacity to generate high-fidelity synthetic faces has resulted in its widespread adoption across applications such as entertainment, virtual avatar creation, identity anonymisation, and data augmentation. In particular, it has opened up new possibilities for training machine learning models by creating diverse and realistic facial datasets without the need for real-world data [12]. This is particularly important in cases where we are concerned about data privacy or we do not have access to large annotated datasets. StyleGAN2 generates synthetic images that closely resemble real human faces, and provides a powerful alternative source of data for downstream machine learning tasks.

Autoencoders are focused on learning compressed representations of existing data, whereas GANs are focused on generation of data. An autoencoder is a neural network that consists of two parts: an encoder and a decoder [14]. The encoder compresses the input data into a lower dimensional latent space representation and the decoder reconstructs the original input from this compressed form [26]. The purpose of an autoencoder is to minimise the difference between the input and the reconstructed output so that the latent representation captures the most salient features of the data. Autoencoders have been widely utilised in image processing tasks such as denoising, dimensionality reduction, feature extraction and anomaly detection [1]. Convolutional autoencoders are especially good at reconstructing facial images because they can learn spatial hierarchies in image data. Convolutional layers enable the model to learn local patterns like edges, textures and shapes, which are needed to reconstruct complex structures like human faces [20]. The encoder uses a series of convolutional and pooling layers that reduce the spatial dimensions of the input step by step, but retain the most important semantic information. The decoder then reconstructs the image by reversing this process with upsampling or transposed convolutional layers.

One of the main challenges in the design of autoencoders is to achieve meaningful compression while preserving reconstruction quality. If the latent space is too small, important details could get lost during encoding. If it is too big, the model may just memorise the input data instead of learning generalised representations. Therefore, a careful design of the architecture and tuning of parameters are needed to achieve the trade-off between the compression efficiency and reconstruction accuracy. In the task of facial image reconstruction, preserving fine details like facial symmetry, expression and texture is very important, where even small distortions can greatly affect the perceived realism. The integration of GAN generated data and autoencoder based reconstruction is a novel and efficient way for the design of deep learning systems [22]. Traditionally, autoencoders are trained on real world datasets that involve a lot of data collection and preprocessing. But in this project, synthetic images generated by StyleGAN2 are used for training the autoencoder. This eliminates the need for real-world facial datasets and solves critical problems related to data privacy, ethical use, and accessibility [11]. It allows for the creation of large-scale datasets without the need for manual labelling or data collection efforts.

This hybrid approach also leads to an interesting interplay between generative and reconstructive models. On the other hand, StyleGAN2 generates realistic facial images from random latent vectors, and the autoencoder learns to encode and reconstruct these images, thus learning the structure of the underlying synthetic face distribution [15]. This forms a closed loop of learning. One neural network creates the data, and the other learns how to interpret and reconstruct it. Such a system illustrates the complementarity of different classes of neural networks within a unified framework [19]. From the viewpoint of representation learning, this approach offers valuable insights into the way neural networks learn hierarchical representations of facial structures. The encoder is trained to map key facial features such as eyes, nose, mouth and face shape into a compressed latent representation. Then the decoder reconstructs these features, trying to reproduce the original image as accurately as possible [3]. This process emphasises the significance of latent space learning in deep neural networks, showcasing how intricate visual information can be effectively encoded into compact numerical representations [100].

Another key part of this approach is the use of synthetic data as a training resource. Advanced GANs like StyleGAN2 generate synthetic datasets with several advantages over traditional datasets [13]. They are essentially unlimited in size, can be generated with controlled variations and do not present privacy issues associated with real human data. This makes them particularly useful in fields like facial recognition research, where ethical and legal restrictions often limit access to data [27]. Training models on synthetic data allows researchers to explore new architectures and methodologies without the constraints of data availability. However, there are also some challenges in applying synthetic data. A key challenge is the domain gap between synthetic and real data [5]. Nevertheless, even StyleGAN2 can generate very realistic images, there are still subtle differences between synthetic and real facial images. Such differences can affect the generalisation ability of models trained only on synthetic data. Therefore, assessing the performance of such models on unseen or real-world data remains an important area of investigation [23]. This project is mainly focused on the reconstruction quality in the synthetic domain, which serves as a controlled environment for the analysis.

The combination of GANs and autoencoders is also representative of broader trends in self-supervised and unsupervised learning. "Recent years have seen rising interest in reducing dependency on labelled datasets, and instead harnessing intrinsic structures in data for training [16]. Autoencoders fit naturally to this paradigm since they do not require labelled outputs, and learn directly from input data . This approach along with GAN generated datasets further reduces human intervention in data preparation process. From the computational architecture perspective, this hybrid system is an example of how different neural network models can be combined in one pipeline to achieve complementary goals [7]. The generator of the GAN is used as a data generator, and the autoencoder is used as a feature learner and reconstructor. The separation of roles allows each model to specialise in one task, which makes the system more efficient and modular [24]. Such architectures are increasingly seen in modern deep learning research, where complex systems are built from many interacting neural components.

The techniques explored in this project have wide implications from an application perspective [18]. Applications of facial image synthesis and reconstruction include virtual reality, games, identity anonymisation, digital human and security systems. Being able to generate and reconstruct faces accurately opens up possibilities for creating realistic avatars, improving visual effects and augmenting data for other machine learning tasks [28]. In addition, the generation of privacy-preserving synthetic data is becoming more critical in regulated environments where data protection is essential. The literature of facial image synthesis and reconstruction has underscored the significance of both generative and reconstructive deep learning models [4]. GANs, especially advanced architectures like StyleGAN2, have changed the game for generating realistic facial images, and autoencoders provide powerful ways to learn compact representations and reconstruct complex visual data. The combination of these two approaches in one integrated system is a promising avenue for future research and applications [9]. This project provides a scalable and privacy-aware way to process facial images by combining complementary neural architectures and training with synthetic data.

2. Materials and Methods

This work also sheds light on the link between data distribution and representation learning from a theoretical perspective [59]. The generalisation ability of the autoencoder depends on how well the GAN synthesised images capture the distribution of real faces, as the autoencoder is trained on synthetic data. StyleGAN2 is required to generate a synthetic dataset that is realistic and diverse enough to not let the autoencoder learn artificial patterns and overfit, but instead learn meaningful features [57]. The interaction between generative and reconstructive models offers a useful perspective on how different neural architectures can serve to complement each other. The system also shows that synthetic data can be successfully used as the main resource of training in deep learning pipelines [60]. Synthetic data has been used to supplement real-world datasets in the past, but in this project we explore the potential of synthetic data as a sole training resource [58]. The results indicate that synthetic data can be used to effectively support downstream learning tasks such as feature extraction and image reconstruction, given sufficiently advanced generative models. The implications of the project go beyond the technical contributions and have broader implications for privacy-preserving machine learning. The system does not use actual human facial data, thus avoiding ethical concerns on data collection, storage and use [56]. This makes it applicable for research environments where data privacy is a mandatory requirement. It also provides opportunities for training deep learning models in domains where real data is scarce or hard to obtain.

3. Results and Discussion

The paper is compatible with the current state-of-the-art in self-supervised and unsupervised learning [79]. This eliminates the need for labelled datasets, reducing dependence on manual annotation efforts which are often time-consuming and expensive.

The use of autoencoders in this way demonstrates how neural networks can learn useful representations without explicit supervision , and highlights the importance of unsupervised learning techniques in modern AI research . In short, this hybrid system effectively combines StyleGAN2 and convolutional autoencoders into a single deep learning pipeline for facial image synthesis and reconstruction [64]. It demonstrates that synthetic data can be used successfully to train reconstructive models and that meaningful feature learning can be obtained even without real-world datasets. The project not only demonstrates the feasibility of this approach but also indicates the applicability to future privacy-preserving AI systems, data-efficient learning frameworks and advanced image processing pipelines [90]. Autoencoders have been used in industry for fault diagnosis by learning representations of normal operation conditions. A recent review of autoencoder-based representation learning for fault diagnosis was presented, which highlighted the adaptability and effectiveness of autoencoders to monitor and detect anomalies in complex systems [8]. Based on these seminal works, the proposed project combines the data generation power of StyleGAN2 with the compression and recovery power of autoencoders. It introduces a new experiment of training autoencoders entirely on synthetic data, showing how generative models can be used as data sources for learning-based reconstruction systems.

Figure 1: Qualitative Results of Baseline StyleGAN Face Synthesis

Figure 1 Shows the outputs produced by the baseline StyleGAN model (config A). They are generated in a globally coherent way, but there are significant problems with the faces [74]. The vertical line shows an artefact in the mouth area in the left image with misalignment and unrealistic detail. These artefacts are usually attributed to poor spatial consistency and feature entanglement. The image on the right is more stable, but lacks realistic skin texture and fine details [89]. These limitations indicate the need for better architectural settings and iterative refinement, which are discussed in more advanced StyleGAN variants.

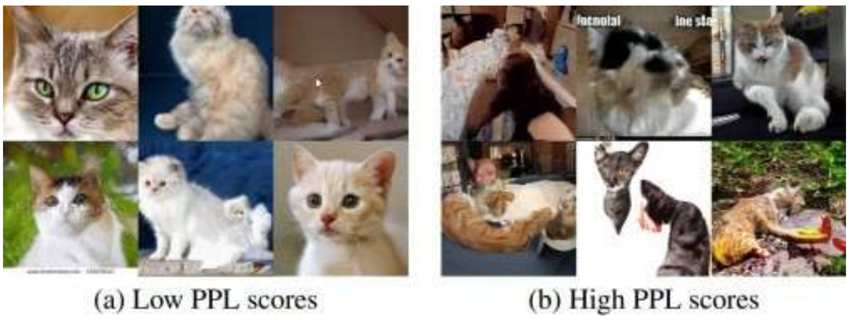

Figure 2: Examples of Low and High PPL Score Generated Images

Figure 2 The figure illustrates the impact of Perceptual Path Length (PPL) on the quality of GAN images. (a) Images with low PPL scores look natural, consistent and visually realistic, with smooth and stable transitions in the latent space. In contrast, the images with high PPL [78]. scores are shown in part (b), which contain distortions, strange textures, and structural problems. These visual artefacts are due to instability in latent space interpolation [99]. As such, PPL is a useful measure to evaluate the quality and robustness of generative models.

Project Description

Traditional image reconstruction and face generation systems depend largely on large-scale real-world datasets such as CelebA, LFW, or FFHQ [98]. These systems train autoencoders or other deep learning models to compress and reconstruct facial images from the datasets. But there are some limitations to these methods. First, large datasets take a long time to collect, label and curate, and they raise ethical and privacy concerns [63]. Second, models trained solely on real-world data often have difficulty generalising to different facial structures or unusual features that are not well represented in the dataset. Also, many existing systems separate generation and reconstruction pipelines, where GANs are usually only used for image synthesis and autoencoders used for reconstruction [91]. This disjointed approach often lacks flexibility and does not show how generative models and representation learning techniques can complement each other in a unified framework.

The proposed system overcomes the limitation of the traditional approach . A unified framework is proposed for face image generation using StyleGAN2 and image reconstruction using a convolutional autoencoder . The system generates fake face images using a pretrained StyleGAN2 model instead of publicly available datasets for facial images. StyleGAN2 generates these images through a process driven by a random seed, which leads to diversity in attributes such as face shape, skin colour, hair style, and expressions. After generation, the images are resized and preprocessed to be input into the autoencoder [73]. The autoencoder consists of a series of convolutional layers which encode the image into a low dimensional latent representation and transposed convolutional layers which decode the compressed representation back into the original image. The model is trained with the Mean Squared Error (MSE) loss function to minimise the reconstruction loss between the original image and the output image. Additionally, the dataset is divided into training and testing sets to evaluate the autoencoder's performance on unseen data [88]. This helps in evaluating the generalisation ability of the model. The entire process is implemented in open-source frameworks like PyTorch and runs efficiently in platforms like Google Colab.

Proposed Work

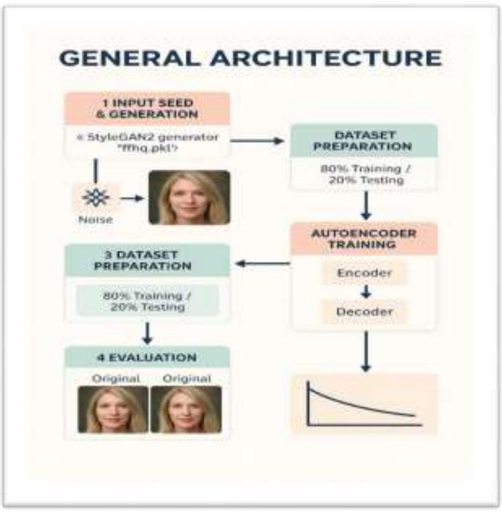

Figure 3: General Architecture of the Proposed StyleGAN2–Autoencoder Framework

Generates synthetic facial images by changing random seeds using StyleGAN2 (pre-trained on FFHQ). The generated images are saved in a specified output folder and used as the dataset for the reconstruction task [65]. We train a convolutional auto-encoder to learn compressed representations of generated images and reconstruct them. The model has an encoder (convolutional layers) and a decoder (transposed convolutional layers). It is trained with Mean Squared Error loss [87]. The system also supports dataset pre-processing, training/validation splitting, and visual evaluation of the reconstructed results (Figure 3).

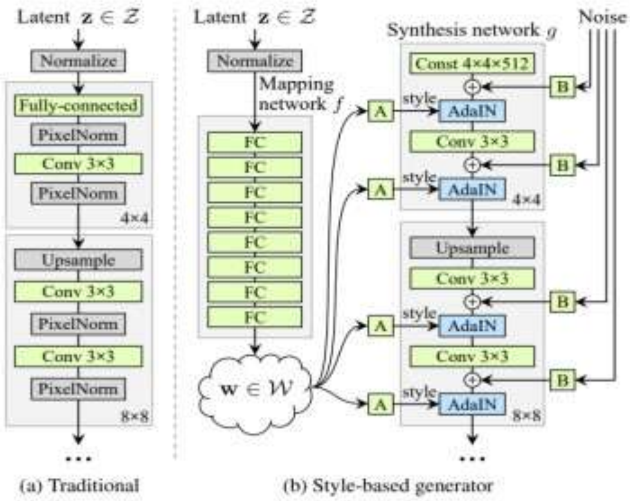

Figure 4: Comparison Between Traditional GAN and Style-Based Generator Architectures

Figure 4 We see the comparison between the traditional generator architecture and StyleGAN's style-based generator in the figure above [92]. In the conventional architecture (Fig. (a)), the latent vector $z \in \mathcal{Z}$ is normalised and then fed through a series of fully connected and convolutional layers. The generation process consists of Pixel-wise Normalisation (PixelNorm) and progressive upsampling for increasing the image resolution [75]. Because the latent vector affects the entire image-generation pipeline in a fixed way, this limits the flexibility and control of some features of the generated output.

Design Phase

The design phase of this project is structured to provide a smooth and efficient pipeline from the synthetic image generation to the image reconstruction and evaluation [72]. This includes defining system architecture, planning data flow and identifying interaction between key components. The purpose of the design phase is to attain modularity, reusability and clear data handling throughout the system.

Data Flow Diagram

We use Data Flow Diagrams (DFD) to understand the flow of data through the proposed system [80]. DFD provides a clear picture of what inputs are required by the system, what processing steps are involved and what outputs are produced. A DFD is used to represent the logical flow of information and processes that convert raw input data into meaningful output [97]. The DFD describes the essential data flow of our project, which aims at generating realistic sketches from real-world images using StyleGAN2, from the user input image to the final sketch output. This diagram shows the data flow from seed input to face generation using StyleGAN2, then preprocessing, training a convolutional autoencoder, and reconstructing the test images for evaluation [66]. The system also interacts with different data stores through this process, such as the image dataset (which contains labelled training images), trained model weights and log storage (which contains inference results and performance metrics). Visualising these flows helps in understanding the logical architecture [86]. The major functional blocks involved in the sketch synthesis pipeline are also highlighted by the DFD.

 The DFD is a critical part of the system design for machine learning projects with multiple connected modules like data preprocessing, training, inference, and post-processing.

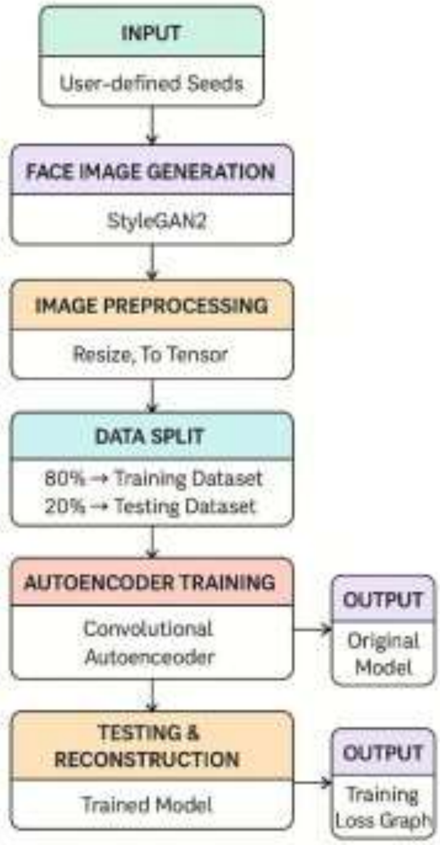

Figure 5: Data Flow Diagram

It serves as a bridge between the theoretical concepts and practical implementation of the project, facilitating the understanding of the operation of the GAN-based system by developers, stakeholders and evaluators [62]. Figure 2. Use case diagram illustrating the interaction between the user and the main functional components of the proposed system. The user starts by providing input seed values which are used to generate synthetic face images using StyleGAN2. The system then gives the user the ability to preprocess data, train the convolutional autoencoder, and visualise the reconstructed output [96]. Each use case describes a specific task that the system performs upon user interaction (Figure 5).

4.2.3. Sequence Diagram

Use Case Diagram showing the interaction between the User and the main functional components of the proposed system. The process starts when the user provides input seed values [67]. These values are used to generate synthetic face images with StyleGAN2. The system then enables the user to pre-process data, train the convolutional autoencoder and visualise the reconstructed output [85]. Each use case describes a particular action the system takes in response to user interaction (Figure 6).

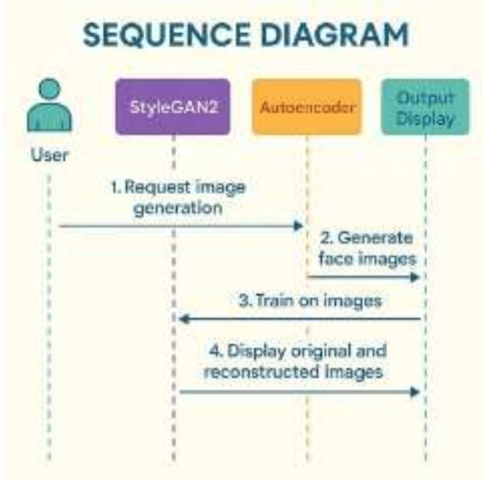

Figure 6: Sequence Diagram

Module Description

The proposed system is composed of five main modules [76]. The generated face images are preprocessed, used for training, and efficiently reconstructed and evaluated. Each module is a critical piece in that process.

Module 1: Image Generation

This module is responsible for creating the dataset to train the autoencoder. It uses a pretrained StyleGAN2 model trained by NVIDIA, which is known for generating high-fidelity face images [71]. The model takes a set of seed values as input, and outputs a range of synthetic faces, each with a different expression, facial structure, hairstyle, and other features. The images are saved in a specified directory in .png format [81]. The variance within the dataset ensures that the autoencoder is exposed to a wide range of facial features during training.

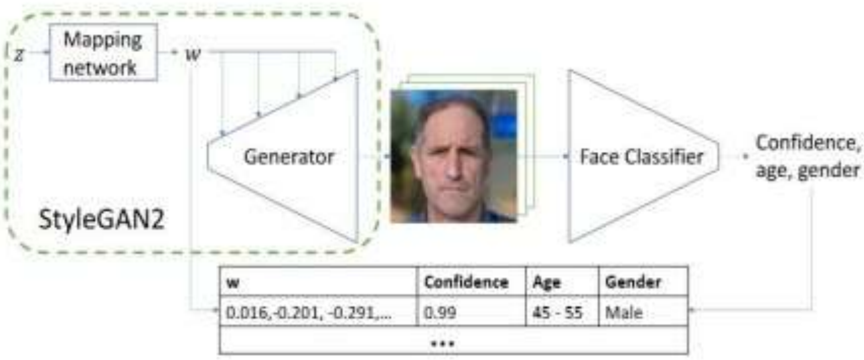

Figure 7: Block diagram of the synthetic face generation and evaluation pipeline

Figure 7 This diagram shows how StyleGAN2 generates a synthetic face from a latent vector zzz, which is first mapped to www through a mapping network [82]. The generated image is then analyzed by a face classifier to predict attributes like age, gender, and confidence. The output is presented in a table format for easy interpretation.

Data Preprocessing

After the synthetic images are generated, they are resized and normalised before being fed to the model [95]. This module takes care of the image transformation using the transformation utilities of pytorch. To decrease the computational load, each image is resized to 64x64 pixels maintaining the facial structure. Images are converted to tensors and normalised to bring pixel values into a range for the autoencoder to process efficiently [68]. This module also checks for corrupted images and skips any invalid files on loading.

Module 3: Data Splitting

To objectively evaluate the performance of the autoencoder, the dataset is divided into two parts: 80% for training and 20% for testing [93]. This is implemented using the PyTorch random_split() function. In order to train the model to compress and reconstruct facial images, we use the training set, and we test images the model has never seen before using the testing set [77]. This makes sure that the reconstruction quality is not biased and provides an honest account of how the model performs on unseen data (Figure 8).

Figure 8: Dataset taken for testing

Module 4: Auto Encoder Model

This module builds the core convolutional autoencoder. It consists of two parts:

Encoder: A series of convolutional layers that reduce the spatial dimensions of the input image while extracting high-level features [83]. It compresses the 64×64 image into a lower dimensional latent space.

Decoder: A set of transposed convolutional layers that reconstruct the image back to its original dimensions from the latent space.

The autoencoder is trained using the Mean Squared Error (MSE) loss function, which measures the average squared difference between the original and reconstructed pixel values [69]. The Adam optimizer is used to update model weights and minimize reconstruction error over time (Figure 9).

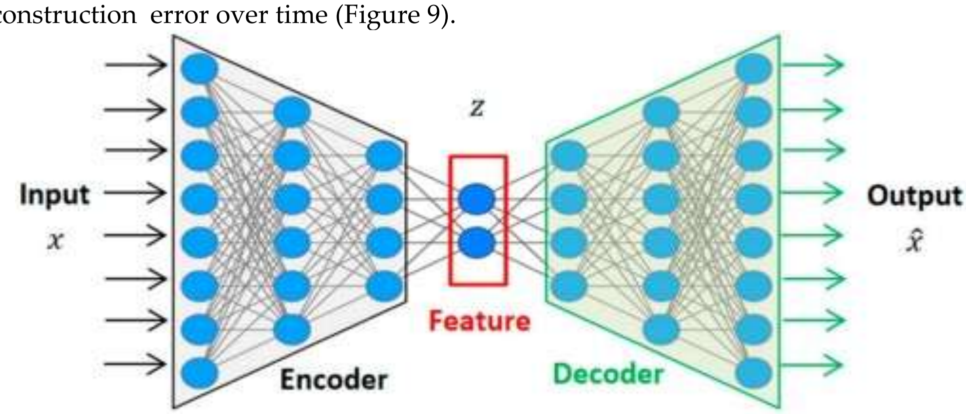

Figure 9: Auto Encoder Diagram

Step:3 Visualization and Evaluation

This module covers the evaluation of the trained autoencoder [94]. The trained model is then tested on unseen data from the test set. The reconstructions are then compared side by side with the original inputs to see whether the model can learn to reproduce facial features [61]. The system also displays the training loss curve over epochs to visualise the learning progress. This module helps to validate the good generalisation of the autoencoder or if architectural improvements are needed.

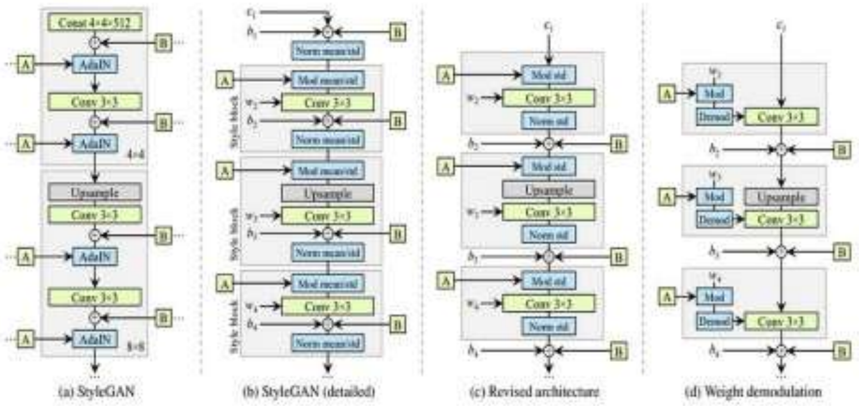

Figure 10: Architectural revisions leading to weight demodulation

Figure 10 StyleGAN starts from a learned constant input and uses Adaptive Instance Normalisation (AdaIN) to inject style information at each layer. (b) Detailed StyleGAN shows style application via AdaIN after each convolution. (c) Updated Architecture (StyleGAN2) Removes AdaIN and adds weight scaling and normalisation before convolution to improve image quality and reduce artefacts. (d) Weight Demodulation takes this a step further by modulating and demodulating the convolution weights, which helps stabilise training and ensure consistent style transfer [84]. The system proposed in present generates high quality images with optimisation of resources like computation time, GPU memory and energy. It consists of aspects such as the speed of image generation, the scalability for larger batches, the tolerance against errors, and a tradeoff between resource consumption and the image quality [70]. These metrics are useful to evaluate the performance of the system and identify areas of improvement.

4. Conclusion

Our project is a successful demonstration of the state-of-the-art capabilities of generative adversarial networks in generating high quality realistic images. The proposed system takes advantage of the advancements in previous systems, such as artefact removal, improved representation of latent space, and improved computational efficiency, to balance the output quality and resource utilisation. This work demonstrates the robustness and scalability of StyleGAN2 for applications such as image synthesis and creative exploration, and marks a significant advance in generative model technology. Future work will include generating higher resolution outputs for use cases such as digital art and virtual environments, integrating custom datasets for tailored use cases such as medical imaging or fashion, and implementing interactive features for real-time control of latent variables. Furthermore, efficiency optimisation by means of model pruning or distillation may allow for deployment on edge devices, and investigation of multi-modal generation from text and image inputs may increase the scope of applications. The integration of explainable AI tools will make the generation process more transparent and broaden the reach of the system in industries and research fields.

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