Image Generation using VAE and GAN Architectures for Handwritten Signatures

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***Abstract*—This paper explores the implementation of two generative models—Variational Autoencoder (VAE) and Generative Adversarial Networks (GAN)—for the task of generating artificial handwritten signatures. The dataset consists of images of handwritten signatures, augmented with several transformation techniques to ensure variability and improve model training. The report outlines the architectures of both models, their training process, and the results achieved by generating synthetic signatures.**

I. Introduction

In recent years, the use of generative models has gained significant attention in tasks like image synthesis, where models learn to generate new images based on input data. This assignment focuses on the generation of artificial handwritten signatures using two architectures: the Variational Autoencoder (VAE) and the Generative Adversarial Network (GAN). These models were trained on a dataset of real signatures, augmented with various transformations to enhance generalization. The VAE aims to generate samples by learning latent space representations, while the GAN uses an adversarial approach to synthesize realistic-looking images.

II. Methodology

A. Dataset and Data Augmentation

The dataset used for this project consists of images of handwritten signatures. Each image was augmented to introduce variability using random horizontal flips, rotations, color jittering, and resizing. The dataset was preprocessed and normalized to ensure efficient training of both models.

- **Random Horizontal Flip**: Adds randomness by flipping images horizontally.
- **Random Rotation**: Rotates images up to 15 degrees.
- **Color Jitter**: Modifies brightness, contrast, and saturation.
- **Random Resized Crop**: Randomly crops and resizes images to 64x64 pixels.
- **Normalization**: Normalizes image pixel values to [-1, 1].

The transformations help the model generalize better, preventing overfitting on the dataset.

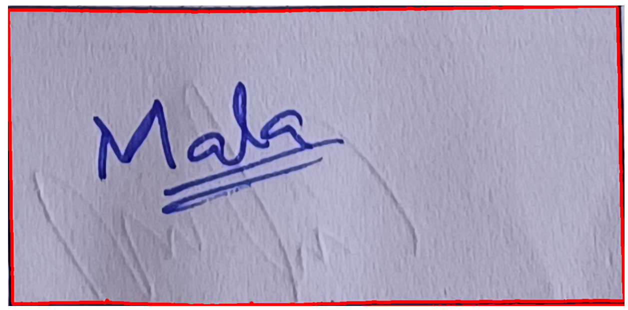

Fig. 1. Examples of original handwritten signature images from the dataset.

B. VAE Model Architecture

The VAE is a generative model that learns latent space representations to generate new samples. It consists of two main components:

- **Encoder**: Compresses the input image into a lower-dimensional latent space.
- **Decoder**: Reconstructs the image from the latent space representation.

The encoder outputs two vectors: the mean (μ) and the log-variance ($\log \sigma^2$) of the latent space. The decoder samples from this latent space to generate new images. The VAE was trained using a combination of Binary Cross Entropy (BCE) and Kullback-Leibler Divergence (KLD) losses.

C. GAN Model Architecture

The Generative Adversarial Network (GAN) consists of two competing models:

- **Generator**: Generates fake images from random noise vectors.
- **Discriminator**: Distinguishes between real and fake images.

The generator learns to produce images that resemble real handwritten signatures, while the discriminator learns to classify whether an image is real or generated. The two models are trained simultaneously, where the generator tries to fool the discriminator, and the discriminator improves its classification accuracy.

III. Results

A. VAE Generated Signatures

After training for 150 epochs, the VAE was able to generate new synthetic handwritten signatures by sampling from the learned latent space. The following figure shows examples of signatures generated by the VAE.

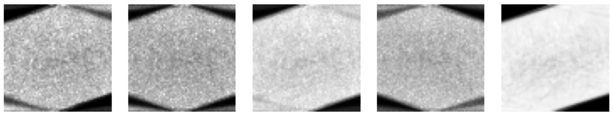

Fig. 2. Signatures generated by the VAE.

B. GAN Generated Signatures

Similarly, the GAN was trained for 150 epochs to generate realistic handwritten signatures. The generator learned to produce high-quality signatures that the discriminator could not easily distinguish from real signatures. Below are some examples of signatures generated by the GAN.

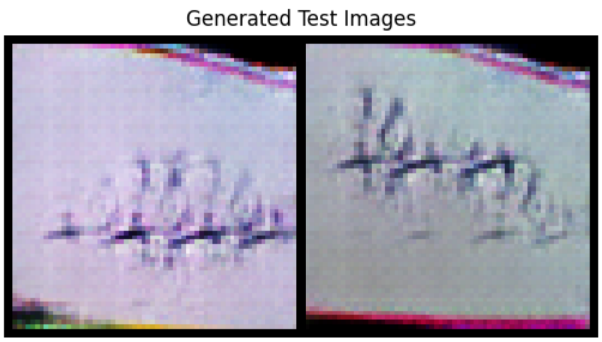

Fig. 3. Signatures generated by the GAN.

IV. Discussion

The VAE and GAN models exhibit different learning processes and results. The VAE focuses on encoding images into a latent space and reconstructing them, which led to signature generation with less variation but consistency. On the other hand, the GAN's adversarial learning allowed it to produce more diverse signatures, as it constantly improved by learning to fool the discriminator.

The main challenge encountered during training was mode collapse in GANs, which was mitigated by adjusting the noise variance throughout the epochs. The VAE occasionally struggled with producing sharp images, which may require further tuning of the latent dimensions or loss balancing.

V. Conclusion

This project successfully implemented both Variational Autoencoder and Generative Adversarial Networks for generating artificial handwritten signatures. While the VAE was able to generate new signatures by learning latent space representations, the GAN produced sharper and more realistic signatures due to its adversarial learning process. Future work could explore conditional GANs to guide the signature generation process more explicitly.