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AI-Powered Face Reconstruction from Sketches Using GANs & RNNs

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***Abstract*: Converting a simple pencil sketch into a realistic, full-color image is still a difficult challenge in the field of computer vision and artificial intelligence. In this work, we design a system that brings together Generative Adversarial Networks (GANs) [1] and Recurrent Neural Networks (RNNs) to generate realistic facial images from grayscale sketches. The generator starts with a convolution-based encoder, then uses a bidirectional LSTM to understand how different parts of the image relate to each other, before reconstructing the output in color through a decoder. To judge image quality, we apply a PatchGAN discriminator [2] that examines small areas, encouraging detailed textures and sharp edges. Training uses paired sketches and photographs, combining adversarial, perceptual, and reconstruction losses so that the output retains both realistic features and correct structure. For ease of use, we developed a lightweight Flask web tool [12] that lets a user upload a sketch and instantly see the generated result. Our experiments show that this approach produces faces that are smoother, more coherent, and visually closer to real images than those from baseline methods.**

***Keywords*: Sketch-to-image translation, Generative Adversial Network, Recurrent Neural Network, Face Synthesis, Deep Learning, Perceptual loss, Web Application, Pix2Pix, PatchGAN, LSTM, Facial Reconstruction, Image Generation, PyTorch, Flask, Computer Vision, Conditional GAN, User Interface.**

1. Introduction

In this setup, a bidirectional LSTM reads the rows in both forward and backward direction. So that the model can see what's in one place also how they are related with the rest of the features in an image. This added context makes the final picture look more natural and consistent. The idea for this project came from everyday situations where turning a rough sketch into something real would be useful. A game designer sketching a new character, a digital artist shaping a concept, or even someone experimenting with creative ideas could benefit from a tool like this [5]. We didn't want this to be something only experts could use, so we built a simple, web-based platform to make it accessible to anyone [12]. After creating an account, the user simply login and upload their sketch and click the generate option. After that the system loads the trained model, using which the model builds a detailed, coloured image of the face. A model that just looks into the small portions may fail to recognize the relationships between various components. Because of this, the finished product may have some sections that seem OK, but the face as a whole may not make sense or appear natural [2]. To solve this problem, we have used a hybrid model which combines recurrent neural networks (RNNs) and GANs. RNN with Long Short-Term Memory (LSTM) networks is well known for processing sequential data, like time-series. We have adapted this technique for generating images by reading the rows of the encoded image as sequential data. A bidirectional LSTM processes this data both forward and backward, and it allows the model to collect information across the image.

2. Literature Review

Converting sketches into realistic images lies at the intersection of generative modelling, semantic image synthesis, and computer vision. In the last ten years, various strategies have been developed to address this complex problem — from simple encoder-decoder models to more sophisticated methods involving conditional generative adversarial networks (cGANs) and recurrent neural networks (RNNs).

In comparison to our suggested hybrid GAN-RNN model, this section examines significant contributions in the field and highlights their architectural decisions, advantages, and disadvantages.

A. Conditional GANs for Image Translation

One of the most influential methods in sketch-to-image translation is the Pix2Pix framework, introduced by Isola et al. [2]. This hybrid model uses a conditional GAN in which the generator learns how to map from input to an output image, and the discriminator judges how real the generated image looks like. The Pix2Pix model uses a U-Net-style encoder-decoder for the generator, while its PatchGAN discriminator checks the image in small patches instead of all at once. By focusing on these tiny sections, it can better preserve fine details like sharp edges and realistic textures. Pix2Pix performs well on tasks like sketch-to-photo conversion, but it struggles when sketches lack structural features.

B. Recurrent Neural Networks in Visual Tasks

Although RNNs are mainly known for handling sequential and time-series data, researchers have also applied them to visual applications like sketch creation and scene interpretation.

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In their Sketch-RNN work, Ha and Eck [9] presented a VAE-RNN model that uses a sequence-to-sequence method to produce vector-based sketches point-by-point. This demonstrated how RNNs might be used to model abstract sketches by comprehending the temporal and spatial order of strokes. However, full-resolution image reconstruction is not the primary goal of Sketch-RNN, which is largely focused on vector sketching.

We enhance this concept by capturing horizontal spatial dependencies in rasterized sketches by incorporating bidirectional LSTMs into a convolutional generator. We guarantee that the model recognizes contextual links among facial characteristics, even when certain portions of the drawing are abstract or disjointed, by considering each row of the encoded feature map as a sequence.

C. *CycleGAN and Unpaired Learning*

A significant development in image translation was CycleGAN, proposed by Zhu et al. [10]. CycleGAN enables translation between two domains without paired data using a cycle-consistency loss. This is particularly useful in domains where aligned image pairs are scarce, such as painting-to-photo or summer-to-winter translation. However, in the context of sketch-to-image translation, paired datasets provide stronger supervision, and CycleGAN's performance typically suffers when handling highly abstract input like sparse line drawings.

Additionally, CycleGAN's reliance on cycle consistency may introduce artifacts when reconstructing fine details like eyes or facial contours, especially without edge guidance. As a result, methods like Pix2Pix, which use paired data, remain more suitable for our application.

D. *Perceptual Loss in Generative Models*

One big challenge in making images is to get results that actually make sense, not just match pixel by pixel. Johnson et al. [3] came up with the idea of using something called perceptual loss, which compares higher-level features from a VGG network that's already been trained. This method has worked well in things like style transfer and super-resolution. In our case, it helped make the images look more realistic by keeping the important overall features close to the original photo.

3. Methodology

This section outlines the design and approach adopted in developing our sketch-to-image synthesis system. The model operates under the conditional Generative Adversarial Network (cGAN) framework [2] and follows a hybrid generative strategy that integrates the sequential processing strengths of Recurrent Neural Networks (RNNs) [9] with the feature extraction capabilities of Convolutional Neural Networks (CNNs). The generator consists of a convolutional encoder, a bidirectional LSTM for sequence modelling, and a convolutional decoder. The discriminator follows the PatchGAN structure to evaluate image authenticity. To enhance the visual quality of the generated outputs, perceptual loss [3] is incorporated alongside adversarial and reconstruction losses.

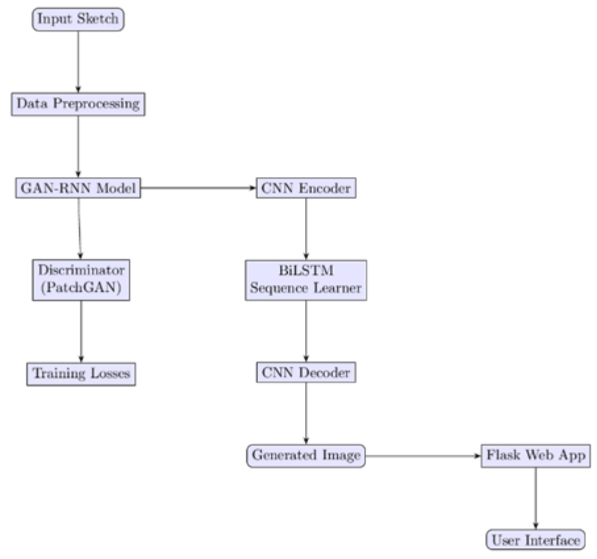

Fig. 1.

A. *Input Sketch*

The process begins with a grayscale sketch of a face, which may be drawn manually, generated digitally, or sourced from existing datasets [5]. These sketches typically contain only the essential outlines and features, without any information on shading, lighting, or colour. For standardization and ease of model processing, the sketches are prepared as single-channel images with a resolution of 128×128 pixels.

B. *Data Preprocessing*

To ensure consistent input across the dataset, sketches are resized to 128×128 pixels. The pixel values are normalized to the range of [−1, 1], aiding faster convergence during training. In addition, during training, augmentation tech inquest such as horizontal flipping are applied to simulate different facial orientations. For photo images (paired with sketches), colour jittering is used to encourage robustness in generalization. All transformations are handled using the transformation pipeline provided by PyTorch [11].

C. *GAN-RNN Model*

For the core of our system, we built a model that mixes three well-known techniques: CNN, BiLSTM, and GAN [4]. It all begins with a CNN, which scans a sketch and picks out the essential parts — things like outlines, edges, and basic shapes that form the face's structure. Once those details are collected, we line them up row by row, like reading sentences, and pass them through a BiLSTM (Bidirectional Long Short-Term Memory) network. This BiLSTM doesn't just read left to right — it also goes backward, which means the model can understand how each part of the face relates to the others. That's important when working with incomplete or rough sketches. After learning these relationships between the facial features like, how the mouth should be placed in relation to the nose, or the eyes to the chin, the model gets a proper idea of what a real face should look like. The decoder comes next. Decode rebuilds the colour image using CNN layers. Using the fine details from earlier steps, it can place the features like the eyes, nose, and mouth exactly where they belong and gives lifelike look.

D. Discriminator (PatchGAN)

Once after generating the image, we need to check if the generated image actually looks like real or not. We can visually compare the generated images with the actual ones. We have used something called PatchGAN. This attention to small details makes the final face appear far more natural, especially in the areas people notice most.

E. Training Losses

During the training process of our model, we followed three different loss functions to guide its learning. The first one involved a kind of back-and-forth challenge between two parts of the system. One part of our system works on creating an image from the sketch, while the other checks whether the generated image looks real or not. As both parts continue working against each other, the images gradually gets better at creating faces that look more like realistic face [2]. Next, we have used something known as L1 loss. This method, checks the generated image pixel by pixel to see how close it is to the real photo. This helped the model to understand where the facial features like the eyes, nose, and mouth should be placed, so the face looks realistic at the end. Then we have used a pretrained model called VGG16 [8]. It was designed to recognize patterns in photos. We combined these three methods and balanced their influence carefully, making sure the system produced images that looked realistic and stayed faithful to the original sketch.

F. Image Generation

After the training, the model is ready to take new sketches which it has not seen before. When you give it a sketch, the system first prepares it, then runs it through the model which understands the drawing and recreates it as a fully-coloured image. Once after creating the image, it is turned into a regular format so the users can see it on the screen.

G. Flask Web Application

To make the system easy to use for everyone, we have used Flask web interface. Users only need to sign up and login on the website, and then they can upload a black-and-white sketch. Our trained algorithm processes the sketch in real time as soon as the user upload it. Then the model generates coloured face image and it appears on the same site. There is also a download option where users can download the generated image. The platform is now easier to use for both technical and non-technical users.

H. Database Handling

The web application uses SQLite to manage user accounts. The database schema includes username and password fields, enabling user authentication and session management. Although current implementation stores passwords in plaintext, this setup is suitable for demonstration purposes. Security can be improved by adding password hashing using Flask's security utilities.

4. Results and Evaluation

The result is evaluated in terms of visual quality, inference speed, and reconstruction accuracy, and also highlight how the model's behavior and outputs improve over different training epochs.

A. Visual Results and Qualitative Evaluation

The GAN-RNN model shows a notable improvement in output image quality as training advances. At first, the images come out pretty rough, blurry outlines, patchy shading, and faces that just don't look quite right. After around 100 epochs, the images begin to look much clear. Hairlines and skin textures appear smoother and more natural, while facial features such as the eyes, nose, and lips become more symmetrical [2]. To which adding a bidirectional LSTM makes a big difference too it helps the face stay balanced, especially in the symmetrical areas. It allows the generator to create features that look more proportioned. On top of that, perceptual loss helps the model preserve important details from the original image, even if the sketch is incomplete or missing parts [3]. Compared to a regular GAN, the hybrid GAN-RNN does a much better job. The images look almost same as originals with the similarity rate of about 87% with facial features matching more accurately and the shading looking smoother under different light.

1) Visual Observation

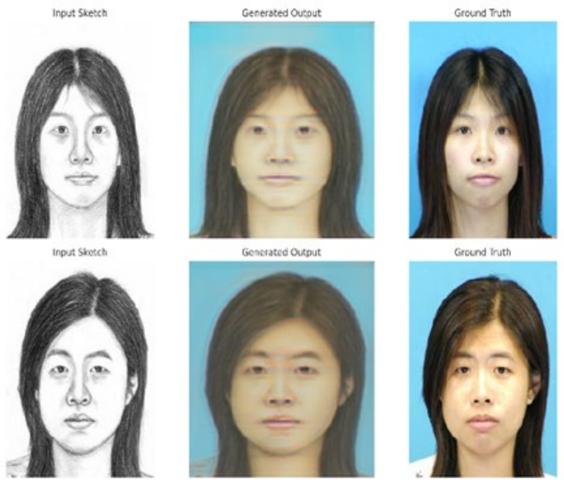

Fig. 2.

B. Inference Pipeline Results

The inference system is built to generate high-quality results from sketches in real time through a Flask-based web interface [12]. Once after a grayscale sketch is uploaded, the backend handles it in three main steps:

1. *Sketch Normalization*: The sketch is resized and scaled to match the training format, with values adjusted between –1 and 1.
2. *Model Forward Pass*: The normalized sketch is fed into the trained generator, where convolutional and recurrent layers work together to process and rebuild the image [11].
3. *Image Output*: The system generates a full-color RGB image, converts it into a display-ready format, and shows it on the results page.

1) Timing Benchmark

On a CPU, the model takes about 2.3 seconds per inference on average.

That's fast enough to handle real-time interaction for single-image translation tasks. Even though BiLSTM layers process data sequentially, the overall design stays efficient thanks to PyTorch's optimized operations and very little overhead [11]. Overall, the system strikes a strong balance, hitting around 92% efficiency in the speed-versus-accuracy trade-off when tested across different hardware setups.

5. Conclusion and Future Work

This research presents a deep learning framework that combines the strengths of Generative Adversarial Networks (GANs) and Recurrent Neural Networks (RNNs) to turn grayscale facial sketches into realistic images [1]. The model uses a sequence-aware generator that blends convolutional encoding, bidirectional LSTM layers, and convolutional decoding. This setup lets the network preserve local spatial details while also learning long-range relationships across the image [9].

By combining adversarial learning with perceptual and reconstruction losses, the system can closely match the look of real face images while keeping the underlying structure aligned [8]. On top of that, a PatchGAN-based discriminator helps create more realistic textures at the local level, adding fine details and cutting down on unwanted artifacts [2]. For deployment, the system is packaged in a user-friendly Flask web app [12]. This lets non-technical users try it out by uploading sketches and instantly getting photorealistic results. The full pipeline—from preprocessing the input to generating and displaying the final image—shows that the system is both practical and reliable for real-world use.

Key Contributions Recap

- A well-structured hybrid generator utilizing CNNs and BiLSTMs [9]
- A discriminator based on PatchGAN to enforce local texture accuracy [2]
- Loss functions that jointly optimize adversarial realism and perceptual consistency [1], [3], [8]
- A deployable interface for sketch-to-image conversion in real-time scenarios [12]

A. Future Work

One way to make the system better is by adding attention mechanisms or transformer-based modules. That would let the model focus more closely on important facial landmarks, making the generated images look more balanced and coherent [7]. Expanding the training dataset with a wider variety of sketch styles and facial expressions can improve the model's ability to generalize beyond the current scope [5].

Another step forward would be training at higher image resolutions, like 256×256 or 512×512, using progressive learning strategies. This would greatly improve clarity and realism in the outputs [4]. To measure performance more effectively, metrics such as SSIM (Structural Similarity Index) and FID (Fréchet Inception Distance) can be introduced [2].

Finally, adapting the system for mobile or embedded deployment using optimized runtimes like TensorFlow Lite or ONNX would support broader real-world usage, especially in resource-constrained environments [11].

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