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Research Article

Restoring Palmprint Biometrics: A GAN based Hybrid Framework for inpainting and deblurring

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ABSTRACT

Palmprint recognition is a reliable biometric identification technique and restoration is valuable technique for restoring and enhancing images which have been highly distorted either by some missing part or by addition of some noise to the image or the blur images. The conventional denoising algorithms struggle to handle noise whereas Generative Adversarial Networks, GAN are proved to be the efficient generative models that produces promising result and shows remarkable performance in this field. The GAN-based model is effective for denoising low-resolution palmprint images due to its ability to handle noise and retain more orientation information. Several researches are made on the restoration and various GAN models are explored but the challenge was found to be that mostly all the models focus on only single type of restoration, there is still a scope to design a GAN model that works on all types of noises with the comparatively increased efficiency. An intelligent framework/architecture is needed to generalize this complex phenomenon. This research proposes a GAN model that focuses on restoration of image damaged by several noises/factors. This study introduces a novel hybrid GAN-based model that addresses inpainting and deblurring for palmprint repair. It makes use of Transformer blocks, a PatchGAN discriminator, and a U-Net Based generator. The model learns global context and long-range dependence, downsamples, and extracts hierarchical features. The discriminator establishes if the created or real image is authentic or not. 312 subjects' 5,502 palmprint images from the CASIA palmprint library were used to train the model. Various deblurring and painting models are analysed and the proposed model is found to generate better performance. The approach can be used in real-world scenarios because it is end-to-end and doesn't require further noise localization information. Additionally, the model's scalability and processing efficiency are assessed in the article.

Keywords: Image restoration, GAN model, Generator, Discriminator, Deblurring, Inpainting

INTRODUCTION

Comprehensive and well-visualized images are necessary for computer vision tasks and are necessary for the reception and utilization of digital data. Hence image processing technology has become a crucial medium for information transmission in the digital age. Image processing involves modifying and analyzing digital images to improve quality, extract information and perform tasks. The method of preprocessing is used to improve photos and convey further analysis. Nevertheless, damage, noise and interference can taint image data, which has a detrimental effect on the completion of computer vision tasks. Noise can negatively impact image quality and efficiency in retrieval and utilization. Estimating the original image from damaged data, with a focus on corrective actions and degradation models, is the process of Image restoration. Image restoration techniques improve visual content by deblurring, repairing damaged or missing parts, eliminating extraneous items, and adding new components.

Image restoration technology is receiving attention due to growing need for high quality photographs. In the past, many methods have been introduced for image restoration, but image processing has advanced to a new level with the quick development of deep learning and computer vision technologies, in particular, GAN. In fact, many academicians have begun to look into the application of GANs in image denoising and restoration in the real world. Pan et al [1] suggested a direct GAN- based technique to deal with image restoration problems including denoising and deblurring. After undergoing end to end training, the developed model demonstrated its applicability to a range

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of picture and low-level visual issues with better performance. A Transformer-based GAN (RFormer) was presented by Deng et al. [2] to address the restoration issues with clinical fundus images. The window- based self- attention block is the main element of the suggested network. Numerous tests showed that the suggested approach was better than the others, with more efficient processing and application to clinical fundus images. Gao et al. [3] suggested a GAN- based deep learning image identification technique to fix flaws in low quality photos. GAN was used to recreate low- quality faulty images, and the VGG16 network was then used for image recognition. The findings showed that the restoration accuracy of low-quality photos had significantly improved, ranging from 95.53% to 99.62%.

To overcome the deterioration of image quality caused by distortion or hazy turbulence, Lau [4] proposed a single-frame recovery algorithm by using generative methods. To recover blurry and deformed images, the algorithm made use of a deformation corrector and a deblurring generator. Adding adversarial and perceptual loss improved image sharpness and reduced artifacts, and the findings showed that the combination provided adequate performance. Guo et al. [5] suggested a dual- stream network structure for picture inpainting. Two U-Net networks that interact extract and combine the structural and texture aspects of images are used in order to efficiently use picture information for image inpainting and to improve results. The approach is not able to more efficiently integrate the texture and structural information of the image for inpainting large missing portions, leading to a hazy inpainted image.

Furthermore, biometric restoration technology, such as fingerprint, iris, face and palmprint has also been improved over the past ten years. Li et al. [6] introduced a generative model for face completion which contains a generator and two discriminators. Although the model's results are not very good with unaligned faces and the model does not take advantage of spatial dependencies between adjacent pixels, it is still a very good model. In the research [7], an optical blur restoration method on finger vein picture blur restoration with a modified conditional GAN is shown. Indeed, this method speeds up the training and complexity, while augments convergence, by training the deep CNN and modified conditional GAN separately. To prevent a deterministic output, dropout is removed. The study [8] presents a deep learning-based generative adversarial network (MFNN-GAN) for restoring finger-vein images with multiple degradation factors, such as non-uniform illumination and noise. The MFNN-GAN can adaptively restore to multiple degradations, even with weak or non-uniform near-infrared illuminators. Experimental results show a lower equal error rate (EER) of finger-vein recognition compared to other algorithms. The method uses a task adaptor to classify degradation factors and adaptively restores images based on these factors. The MFNN-GAN achieved the highest recognition accuracy for finger-vein recognition. Future work should focus on robust recognition methods with low illumination and strong noise and improving model inference speed. In this work, [9] generative adversarial networks (GAN) are used to improve the quality of fingerprint photos. Denoising and inpainting fingerprint images can be done simultaneously by the GAN model. The technique can fill in automatically and is resilient to background clutter and weak signals. With MSE, PSNR, and SSIM values of 0.0281, 15.62, and 0.7913, respectively, it performs better than the most advanced fingerprint denoising methods of the time. The outcomes demonstrate that the suggested technique can greatly boost fingerprint picture quality, offering important new information on fingerprint improvement.

Among biometrics palmprints are used in security systems, forensic applications and identity verification, hence its degradation under occlusions, low lighting and motion blur has to be addressed. Most of the work has been done on fingerprint and face and there is lot of scope to explore palmprints. We proposed a hybrid model for palmprint restoration is proposed, using a deblurring and inpainting approach. The model uses a U-Net Based generate, Transformer blocks, and a PatchGAN discriminator. Convolutional layers extract hierarchical features, downsamples at reduced resolution, and passes the image to a transformer for learning long-range dependence and global context. The decoder integrates skip connections from the encoder to reconstruct the image. The discriminator determines if the real or generated image is real or fake. The training objective includes GAN loss to encourage realism and L1 loss to penalize pixel-wise differences between generated and ground truth images. The CASIA palmprint database, was used for training. The model was trained for the blurred and masked input image.

RELATED WORK

Image inpainting is a pixel selection problem that selects the pixels to fill the defects or occluded areas by extracting and screening known features. However, such traditional methods like GAN are effective for images with simple texture, small missing area and low resolution, but they fail in higher level semantic features and consistency. In

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network architecture, loss function and convolution, GAN models have been improved to obtain better results. However, there are still some limits, such as inability to deal with high resolution images or images with large missing regions.

Yan and Wang [10] have developed a Deep Convolutional Generative Adversarial Network (DCGAN) for perceptual picture restoration, in particular for tasks of human face restoration. The loss function in CNN and ResNet based model preserves details and produces high quality images from degraded inputs. DCGAN was trained on the CelebA and MIT Places datasets, and PSNR with DCGAN was comparable to Non-Local Means, super resolution was better than bicubic interpolation, and facial features were better preserved during deblurring. DCGAN works well despite some points of tarnish with possible improvements in training data diversity and tweaking loss function in achieving perceptual image quality improvements.

Li [11] shows how Generative Adversarial Networks (GANs) can reduce motion blur. It is developed as a model in TensorFlow with a discriminator network of six layers and a generator network of 24 ResNet based layers. The images on the GoPRO dataset were improved with training using loss functions such as Perceptual Loss and Wasserstein Loss. The model achieved a PSNR of 29.3 dB and an SSIM of 0.72, which indicates that it may be used in real world image restoration.

The paper [12] presents an improved DeblurGAN model for blind motion deblurring, which improves image recovery quality. With three convolutional modules, 12 residual blocks (ResBlocks) and two transposed convolutional layers, the model is designed. To extract better features, additional convolutional, normalization and activation layers are inserted before and after the ResBlock structures. The discriminator is made of three convolutional models, convolutional layers, normalization layers and LeakyReLU activation layers with an additional 4X4 convolutional layer and activation layer on top of the second layer. To improve reconstruction quality, the loss function combines the perceptual and adversarial loss. The model is trained on synthetic uniform burred images and real-world motion blurred images. The experimental results show that the DeblurGAN model outperforms conventional models, and thus constitutes an advanced solution for blind motion deblurring.

The motion deblurring model DeblurGAN [13] based on deep learning uses Generative Adversarial Networks (GANs) to recover clear images from blurry inputs. It uses a conditional GAN architecture, a ResNet based generator and a PatchGN discriminator. Adversarial loss, content loss, perpetual loss are used to improve the image reconstruction quality using the GoPro dataset, and the model is trained. Training modifications enable DeblurGAN to achieve high PSNR and SSIM scores with its application in autonomous vision systems, smartphone photography and video restoration. The model is enhanced by the authors by adding more residual modules and by content specific training, leading to SSIM enhancement of 0.2 to 0.3 and more than 1.5 dB PSNR gain.

A new generative adversarial network (GAN) for single image motion deblurring is proposed in this paper, known as DeblurGAN-v2. [14] The key component of it is a Feature Pyramid Network (FPN) that processes images at multiple scales and performs well at extracting both coarse and fine details. It is a versatile generator that can be used with different backbone networks to strike a balance between performance and computational efficiency. The Residual Network (ResNet) backbone is used for feature extraction and multiscale representation. Furthermore, it uses Residual in Residual Densr Blocks (RRDB) from ESRGAN to further improve the feature learning and reduce the information loss. Relativistic conditional GAN with double scale approach is used by the discriminator, to provide global and local realism. Training the model is done in training with pairs of blurry and sharp images from datasets such as GoPro and RealBlur. In the GoPro and Kohler datasets, the model achieves high performance and the MoblieNet and MobileNet-DSC variants of the model outperform DeblurGAN both in terms of PSNR and SSIM.

The authors [15] present EIRGAN as their novel GAN framework in the paper "Enhanced Image Restoration by GANs using Game Theory" to enhance image restoration performance specifically for deblurring applications. The authors work to solve typical training problems in GAN models that include overfitting along with vanishing gradients. EIRGAN implements Minimax algorithms together with Nash Equilibrium through game-theoretic methods to establish equilibrium between its generator and discriminator components. The negative f-divergence loss function changes the training objective to maximize while addressing vanishing gradients to increase the generator's learning capability. The framework integrates residual dense blocks while borrowing architecture concepts from ESRGAN

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which enables deeper networks to extract superior features. The researchers evaluated EIRGAN on GoPro data which resulted in SSIM scores reaching 0.9647 and PSNR scores reaching 29.43 dB. The authors introduce a powerful image restoration method which demonstrates excellent potential for future work in GAN optimization and image processing.

A dual AU-Net network,[16] a dual-stream U-Net technique, is suggested for deblurring. This approach incorporates Least Squares GAN (LSGAN) loss to capture more content details and improve training stability, adds location code (LC) of damaged regions to assist network repair, and adds an attention mechanism to improve texture details. By integrating the dualstream AU-Net into the generator, the AU-GAN technique reconstructs the image's structural information using texture information and skip connections. The parallel three-branch discriminator design increases visual consistency, speeds up convergence, and saves time. Using the CelebA and Paris Street View datasets, the suggested approach performs better than alternative models.

The study [17] aims to develop a fast and effective image deblurring method for blind recovery of motion-blurred images using DeblurGAN (Generative Adversarial Networks). An improved model, DeblurGAN network is proposed, adjusting the input and output size to 512 × 512, while maintaining the overall network structure. Experimental results show improved quality of restored images in terms of blur removal and detail recovery. The improved network mechanism includes a convolutional layer having 3×3 kernels, a normalization layer, and an activation layer. Further research should consider the definition of the loss function, which directly affects fuzzy image restoration. Existing models exhibit color irregularities and pixel distortions also known as false textures.

To identify and reduce phony texture occurrence in the generating process, the suggested DAM-GAN [18] introduces a dynamic attention map (DAM). In the generator's decoder, the DAM blocks are integrated to apply attention masks at various sizes to refine and locate inconsistent areas. The model consists of adversarial, reconstruction and DAM specific loss functions. We demonstrate in tests on the CelebA-HQ and Places2 datasets that DAM-GAN performs notably better than current inpainting techniques in both visual and quantitative sense.

A baseline framework with a context encoder structure is the main focus of the study [19] which explores the application of GAN-based models for picture inpainting. The discriminator pics out real images from created ones and the model coherently reconstructs missing image portions. 50,000 photos from the Influencer Human Real Face Dataset are used to test the model once it has been trained o the CelebA dataset. Training time is identified as a barrier in the study and enhancements such batch normalization, GPU acceleration and the best batch size selection are recommended.

In this paper, we have proposed hybrid GAN model for palmprint restoration designed to make the image deblur and also it can be used to clean the image by removing the noise (object) from the image. It combines a U-Net generator with a transformer bottleneck and includes support for masked image inputs.

problem statement

Researchers use Generative Adversarial Networks (GANs) for image deblurring, inpainting, and restoration systems. Palmprint degradation is complex and difficult to model and palmprint image restoration uses advanced information preservation mechanisms to create high-quality, accurate images, aiming to remove degradation, enhance palm details, and retain identity. It is found through various researches that GAN models lack training and generalization capability due to the lack of high-quality, large-scale annotated datasets with realistic occlusions. In the field of image restoration, there are very few GAN models that work for multiple features restorations and also not much work has been done on palmprints. Hybrid GANs for deblurring and inpainting introduce architectural complexity and instability. GAN architectures like Transformers, ResNets, and multi-scale discriminators are computationally intensive results in restricting their use. Also, in GAN, the training process requires to ensure balance and synchronization of two adversarial networks otherwise it cannot achieve ideal performance.

PROPOSED SYSTEM

Since, palmprint restoration is the emerging and required task in maintaining security in almost every field. Our research work focuses on the use of GAN hybrid model for both image de-blurring and image inpainting, tested on palmprint. The methodology followed in work comprises of:

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a. Collection of Palmprint dataset.
b. Preprocessing of dataset to generate blurred and masked images.
c. Analysis of existing GAN models on dataset.
d. Evaluation and Validation
e. Proposed Hybrid model is trained on dataset
f. Evaluated and compared with existing models.

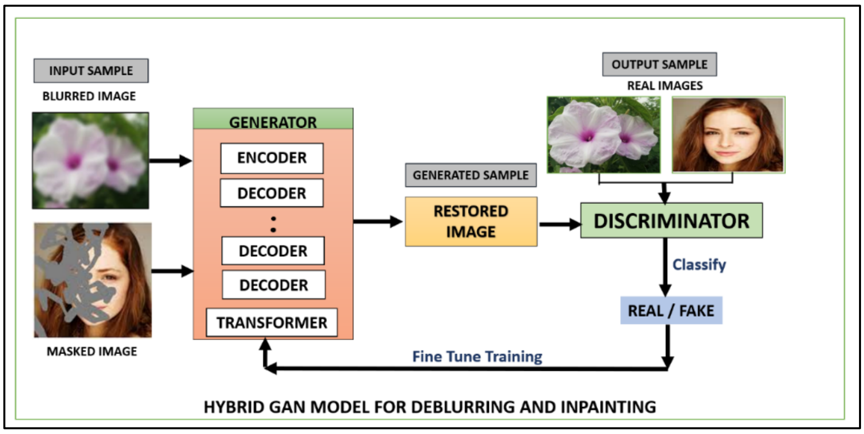

Figure 1:General Layout of Proposed Restoration Model

SYSTEM ARCHITECTURE

The basic GAN model architecture is like original GAN with discriminator and generator. The given model is a U-Net-based generator with a Transformer bottleneck. It uses a series of convolutional layers to extract hierarchical features from a degraded image and its binary mask. At the lowest resolution, features are flattened and processed using a transformer block to model global dependencies and spatial relationships more effectively than standard convolutions. The decoder uses upsampling via Conv2DTranspose layers with skip connections to recover fine details and textures. The output is generated using a final tanh-activated layer. The generator can learn contextual filling and deblurring even in masked areas due to the combined power of skip connections and the transformer. The architecture includes layer normalization, multi-head self-attention layer, and a two-layer feed-forward network with ReLU activation. The discriminator operates with a PatchGAN-style to evaluate image authenticity. The model focuses using original masked input images alongside their corresponding target images and masks as its inputs. The model design includes convolutional layers together with LeakyReLU activation and BatchNormalization followed by a single-channel sigmoid-activated output. The architecture produces realistic images while maintaining both precise restoration of masked regions and structural match to the original design.

5.1 GENERATOR ARCHITECTURE

The generator uses transformer blocks and a hybrid encoder-decoder style for image and binary mask pairs processing. It uses concatenation for inpainting and region-specific operations. The input structure consists of two tensors, one representing the mask and another one containing the deteriorated image. The model inputs a single tensor of dimensions (IMG_SIZE[0], IMG_SIZE[1], CHANNELS+1) from tensor concatenation.

The encoder consists of four convolutional blocks, each with a different activation. The sequence starts with a LeakyReLU activation, followed by a Conv2D layer with 64 filters and 4x4 kernel size. The spatial dimensions decrease by 50% after execution. The Conv2D layer has 128 filters, 256 filters, and 512 filters, with each block building hierarchical representations by increasing feature maps and reducing spatial resolution.

The encoded output from its original 4D tensor is reshaped by the Transformer Bottleneck, which is a 3D sequence for Transformer input. It has two Dense layers in a feedforward network, a second normalization layer, MultiHeadAttention for global attention learning, Layer Normalization for stability, a skip connection for residual learning, and a skip connection for input information retention. The model can track global context through this block, which makes it appropriate for jobs involving image inpainting and deblurring.

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The decoder uses Conv2DTranspose layers for image inpainting and deblurring tasks. The first block combines 256-filter Conv2DTranspose with BatchNormalization and ReLU activation, while the second block includes e2 concatenation, BatchNormalization and ReLU activation, 128 filters, and 128 filters. The third block uses e1 concatenation, 64 filters, BatchNormalization, and ReLU. The final layer produces output pixel values from -1 to 1 using the tanh activation function.

Table 1:The Generator Architecture

Layer	**Output Shape**	**Remark**
Input	(256,256,4)	Image+Mask
Conv2D + Leaky ReLU	(128,128,64)	
Conv2D+BinaryCrossEntropy+LeakyReLU	(64,64,128)	
Conv2D+BinaryCrossEntropy+LeakyReLU	(32,32,256)	
Conv2D+BinaryCrossEntropy+LeakyReLU	(16,16,512)	
Transformer Block	(16,16,512)	MultiHead Attention + FFN
Deconv + BinaryCrossEntropy+ReLU + Skip	(32,32,512)	Skip with Encoder Block2
Deconv + BinaryCrossEntropy+ReLU + Skip	(64,64,256)	Skip with Encoder Block2
Deconv + BinaryCrossEntropy+ReLU + Skip	(128,128,128)	Skip with Encoder Block 1
Final Output	(256,256,3)	Activation tanh

5.2 DISCRIMINATOR ARCHITECTURE

The discriminator achieves its operation through three inputs including original image and target/generated image and mask which have dimension (IMG_SIZE[0], IMG_SIZE[1], CHANNELS or 1) that merge using a Concatenate() layer on the channel axis. The first convolution block applies 64 filters through 4x4 kernels with a stride of 2 and "same" padding for spatial resolution reduction and depth enhancement. LeakyReLU activation introduces non-linearity. The second convolution block contains 128 filters along with a 4x4 kernel size and a 2x2 stride that produces additional feature map downsampling. The learning process becomes more stable because BatchNormalization performs activation normalization. Non-linear activation occurs through the application of LeakyReLU in the network. A third convolution block applies 256 filters and 4x4 kernels with a stride value of 2 to perform hierarchical feature extraction with BatchNormalization followed by LeakyReLU activation. The fourth convolution block preserves spatial resolution as it applies 512 filters with a stride value of 1. The output probability map produced by the last layer presents spatially reduced dimensions representing the likelihood of a local patch being real or fake.

5.3 LOSS FUNCTION

The loss function of the general GAN model is being modified so that it suits our model (Table 2)

5.3.1 GENERATOR LOSS

There are two components to the generator's loss: 1. The generator is encouraged to produce outputs that deceive the discriminator into believing they are real by the adversarial loss. 2. the L1 loss, which encourages visual fidelity and resemblance by penalizing pixel-by-pixel variations between the created image and the ground truth. The overall generator loss is calculated by combining these two losses using the weighting factor LAMBDA.

$$\textbf{G Loss}\ \boldsymbol{BCE(D(x,\hat{y},m),1) + \lambda \,.\, \| \, y - \hat{y} \, \|_1} \qquad \textbf{(1)}$$

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where,

Adversarial Loss: $BCE(D(x, \hat{y}, m),1)$
L1 loss: $\| y - \hat{y} \|_1$
D: Discriminator
G: Generator
BCE: BinaryCrossentropy
x: input masked image
y: ground truth sharp images
m: mask
$\hat{y}$: G (x,m) (generated image)
λ: weight for L1 loss (a scalar hyperparameter)

5.3.2 DISCRIMINATOR LOSS

The discriminator loss is computed by averaging the real loss (the ability to recognize genuine images) and fake loss (the ability to recognize created images as fake), the discriminator loss is computed. To calculate these losses, binary cross-entropy is used. The discriminator seeks to give created (false) images low probabilities and real images high probabilities.

$$\mathbf{L_D} = \frac{1}{2}[\mathcal{L}_{REAL} + \mathcal{L}_{FAKE}] \quad \mathbf{(2)}$$

where,
The Real Loss, $\mathcal{L}_{REAL}$ encourages D to classify real images as real (i.e. the output near 1) which is implemented as: BCE (D (x,y,m),1)
The Fake Loss, $\mathcal{L}_{FAKE}$ encourages D to classify fake images as fake (i.e. the output near 0, implemented as: BCE(D (x, G (x)),0)
The total Discriminator Loss over both real and fake samples to maintain balanced training.

$$\mathbf{D\ loss} = \frac{1}{2}\left[\boldsymbol{BCE}\left(\boldsymbol{D}\left(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{m}\right), \mathbf{1}\right) + \boldsymbol{BCE}\left(\boldsymbol{D}\left(\boldsymbol{x}, \hat{\boldsymbol{y}}, \boldsymbol{m}\right), \mathbf{0}\right)\right. \quad \mathbf{(3)}$$

where,
D= Discriminator
G= Generator
BCE = BinaryCrossentropy
x=input masked image
y= ground truth sharp images
$\hat{y}$: G (x,m) (generated image)
m= mask
The various loss functions of the given model are:

Table 2: Various Loss Functions of Hybrid Model

Loss Component	**Purpose**	**Function Used**	**Target**
Total Generator Loss (combined) (1) Generative Adversarial Loss + λ * Generator L1 Loss	Generator Adversarial Loss (To Fool the discriminator)	BinaryCrossEntropy	1 (Real)
	L1 Generator Loss (To encourage similarity to original image)	L1 Loss	Ground Truth
Total Discriminator Loss (combined)	Discriminator Real Loss (Correctly classify Real image as real)	BinaryCrossEntropy	1

(Mean of real and fake losses) (3)	Discriminator Fake Loss (Correctly classify Fake image as fake)	BinaryCrossEntropy	0

Experimental Results and Evaluation

6.1 DATASET

In the proposed model, for the training and testing the CASIA palmprint database has been utilized. The CASIA palmprint Image Database [20] consists of total 5,502 palmprint photos from 312 subjects, which have been taken from a self-developed palmprint identification device. The pictures were taken with a CMOS camera on a background of the same color and are 8-bit gray-level JPEG files. The gadget uses a CMOS camera to take pictures of palmprints and distributes light uniformly. Systems for real-time palmprint recognition are also being developed for mainstream PCs and PDAs.

6.2 TRAINING

The training process involves a discriminator that differentiates between produced and actual images, and a generator that recreates high-quality images from masked or deblurred images. A random binary mask is generated, resulting in a black rectangle on a white background, which serves as simulated damage in the image. The partial input information training model processes missing or corrupted areas by performing pixel-based multiplication. The generator uses the masked input and mask to create a fake image, and the discriminator evaluates both real and fake pairs to determine authenticity (Figure 2). The generator loss consists of adversarial loss and L1 loss, which are combined to form the total generator loss. The discriminator loss is calculated as the average of its errors in classifying real and fake images correctly. Gradients for both the generator and discriminator are computed, and their respective optimisers update model parameters.

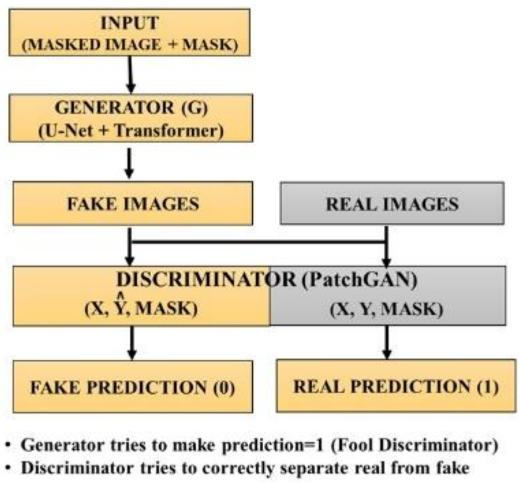

Figure 2: Working of Proposed Model

The training loop runs for a specified number of epochs, (here 170 epochs) fetching training batches from a generator that yields paired blurred and sharp images. At each step, models are trained using the step, and the generator's discriminated losses are printed for monitoring. After every epoch, the generator produces example outputs to visualize its learning over time (Figure 3). This structure offers an efficient framework for adversarial training, ensuring stable learning and aesthetically acceptable restoration outcomes.

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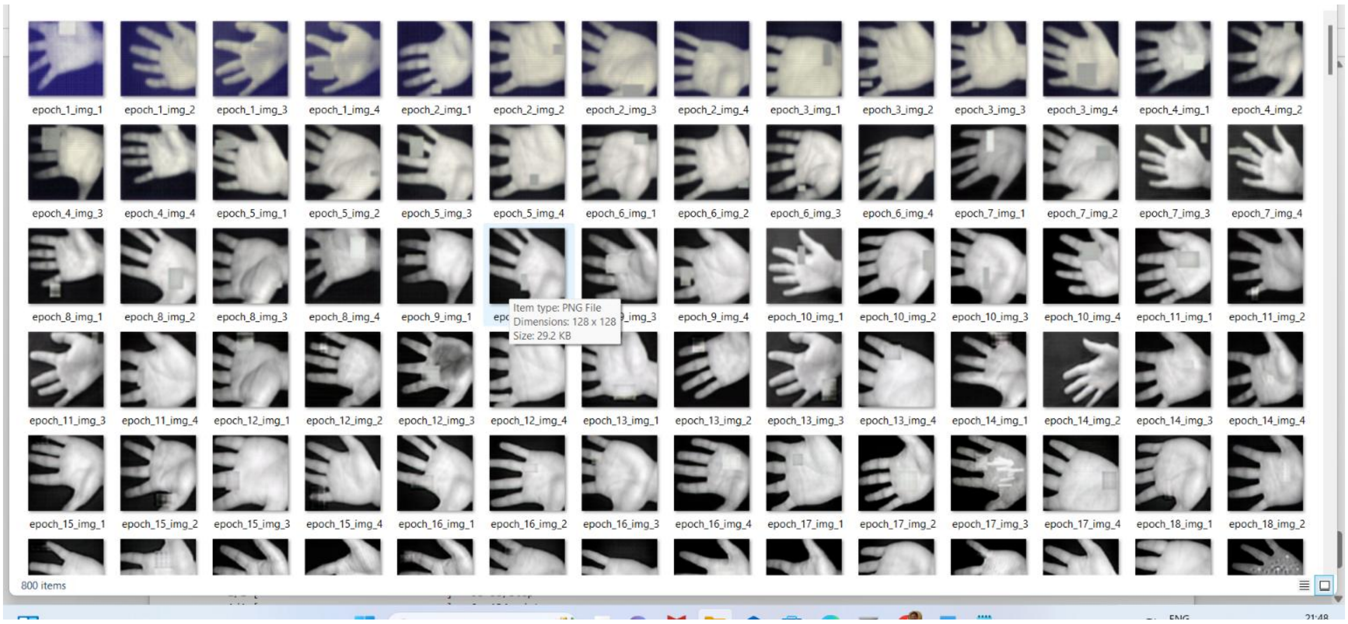

Figure 3: Few Palmprints generated during Training of Proposed model

6.3 Evaluation

The performance of deblurring and inpainting is shown in the Figure 4. The generated output image from the proposed GAN model generates sharper images than before and achieve the better performance in deblurring and inpainting task. The project evaluated the performance using two metrics: PSNR and SSIM. PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise, indicating a higher quality reconstruction. SSIM measures structural similarity between the original and processed images, taking into account luminance, contrast, and structure. The project achieved an average of 33.62 PSNR and 0.925 SSIM (Table 3). However, the project provides a detailed analysis of the GAN architecture and believes that the values of PSNR and SSIM can be further improved by increasing the training epochs and number of training images, which helps optimize the performance of image deblurring using the GAN model and outperform other related works.

Table 3:Comparison on PSNR and SSIM with related works

Method	**PSNR**	**SSIM**
Ji et al [17[	31.15	0.96
Zhengdong Li.[11]	29.3	0.72
Akshat Kishore et al.[15]	29.43	0.97
Cha et al.[18]	29.49	0.96
Proposed Model	33.62	0.92

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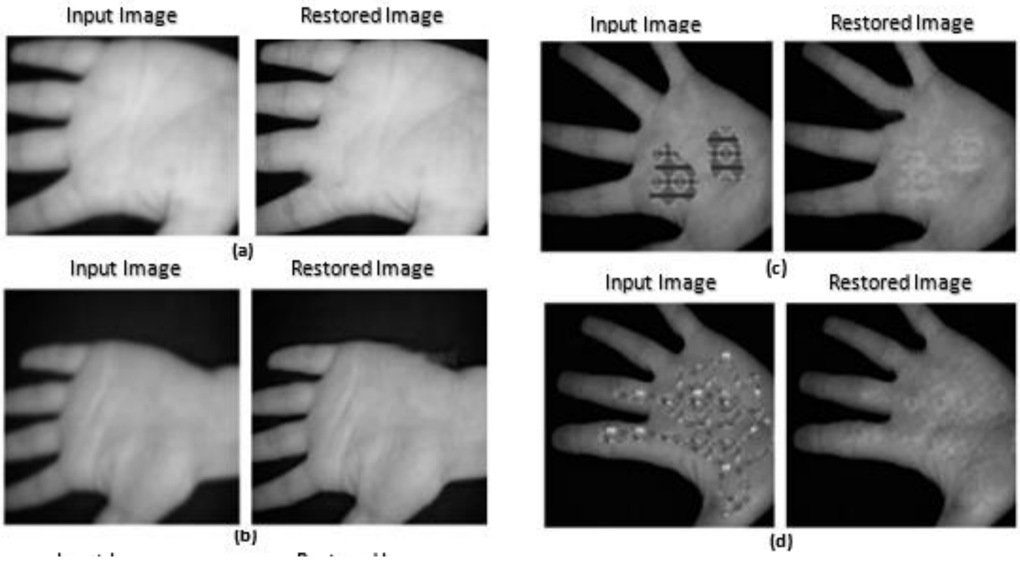

Figure 4: Ouput Images:(a) and (b) Image deblurring results of proposed model on palmprint (c) and (d) Image Inpainting results of proposed model on palmprint

7 DISCUSSION AND FUTURE WORK

GANs, a new field in deep learning, is a crucial unsupervised learning method that relies on internal confrontation between real data and models. This approach offers a glimpse into AI's self-learning ability, providing numerous opportunities for development in the field of deep learning. The proposed GAN model outcomes competitive results compared to existing models and is supposed to give better performance. It gives better results when work for generating Image inpainting or Image deblurring. The proposed approach is computationally less expensive and performs in real time. It consumes less training time and generate data that looks similar to original data. An image is input to GAN; it will generate a new version of the image which looks similar to the original image. GANs go into details of data and can easily interpret into different versions It improves the accuracy and the result is significantly better than previous results. There are many factors that can be upgraded in GAN models. The time and level of accuracy depends on the shape and dimensions of dataset and the system configuration also. This has the basis of what we saw but only the generator loss functions are improvised to provide better results. More stability of the model can be achieved and better relation with the surrounding pixels can be obtained by the generator. by making changes in layers ensuring a better quality of inpainted images.

8 CONCLUSION

The objective of this study was to restore image by applying GAN (Generative Adversarial Networks) to computer vision palmprint deblurring and inpainting. The CASIA palmprint dataset was used to train the GAN model, which then produced fake images to persuade the discriminator to tell the difference between actual and false photos. Degraded and blurred photos from everyday life were then restored using the pretrained GAN model. With an average of 33.62 PSNR and 0.925 SSIM, the pretrained GAN network generated sharper pixels, as per the results. This method created visually real photos while successfully addressing image blurring and masking issues. Security implementation through biometric is very important and crucial issues now days and this model in restoring palmprint security features could benefit from the adversarial learning architecture of GAN. The model performance and the quality of the final restored image can be further enhanced by creating an appropriate loss function in the GAN architecture. Recovery is more challenging with real blurred photos because they feature more intricate backgrounds and details, more blurred kernels, an uncertain degree of blurring, and a high degree of degradation. The GAN model can be enhanced for other restoration techniques, such as super resolution, denoising, and severely degraded images with the improved image quality.

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REFERENCES

[1] Pan J, Dong J, Liu Y, Zhang J, Ren J, Tang J, & Yang M H. Physics-based generative adversarial models for image restoration and beyond. IEEE transactions on pattern analysis and machine intelligence, 43(7): 2449-2462, 2020

[2] Deng Z, Cai Y, Chen L, Gong Z, Bao Q, Yao X, & Ma L. Rformer: Transformer-based generative adversarial network for real fundus image restoration on a new clinical benchmark. IEEE Journal of Biomedical and Health Informatics, 26(9):4645-4655, 2022

[3] Gao Y, Gao L, Li X. A generative adversarial network based deep learning method for low-quality defect image reconstruction and recognition. IEEE Transactions on Industrial Informatics, 17(5): 3231-3240, 2020

[4] Lau C P, Castillo C D, Chellappa R. Atfacegan: Single face semantic aware image restoration and recognition from atmospheric turbulence. IEEE Transactions on Biometrics, Behavior, and Identity Science, 3(2): 240-251, 2021

[5] Guo, X., Yang, H., Huang, D.: Image inpainting via conditional texture and structure dual generation. In: Proceedings of the IEEE/ CVF International Conference on Computer Vision, pp. 14134– 14143, 2021

[6] Li et al, Y. Li, S. Liu, J. Yang, and M.-H. Yang, ``Generative face completion,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 3911_3919, 2017

[7] Jiho Choi, Kyoung Jun Noh, Se Woon Cho, Se Hyun Nam, Muhammad Owais, And Kang Ryoung Park, Modified Conditional Generative Adversarial Network-based Optical Blur Restoration for Finger-vein Recognition , DOI-10.1109/ACCESS.2020.2967771, IEEE Access ,VOLUME XX, 2019

[8] Jin Seong Hong, Seung Gu Kim, Jung Soo Kim, Kang Ryoung Park, Deep learning-based restoration of multi-degraded finger-vein image by non-uniform illumination and noise, Volume 133, Part A, July 2024, 108036, https://doi.org/10.1016/j.engappai.2024.108036

[9] Zhong W, Mao Li, Ning Yang, Fingerprint image denoising and inpainting using generative adversarial networks, DOI:10.1007/s12065-023-00850-2, 2023

[10] Yan Q Wang, W DCGANs for Image super-resolution, denoising and deblurring, 2017.

[11] Zhengdong Li , 'Image Deblurring using GAN', https://doi.org/10.48550/arXiv.2312.09496, 2023

[12] Wentao Ji, Xing Chen, Yihong Li, Blind motion deblurring using improved DeblurGAN, DOI: 10.1049/ipr2.12951, IET Image Processing, 2023

[13] Budzan, Mykola Mykhailych, Dmytro Mishkin, Jiˇri Matas,, DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks,Orest Kupyn, Volodymyr https://doi.org/10.48550/arXiv.1711.07064, 2017

[14] Orest Kupyn, Tetiana Martyniuk, Junru Wu, Zhangyang Wang , DeblurGAN-v2: Deblurring (Orders-of-Magnitude) Faster and Better, https://doi.org/10.48550/arXiv.1908.03826, 2019

[15] Akshat Kishore, Kumar Anupam and Nobel Dang, Enhanced Image Restoration by GANs using Game Theory, Procedia Computer Science 173:225-233, DOI:10.1016 /j.procs. January 2020

[16] Chuangchuang Dong, Huaming Liu Xiuyou Wang, Xuehui,Image inpainting method based on AU-GAN https://doi.org/10.1007/s00530-024-01290-3, 2024

[17] Wentao Ji, Xing Chen, Yihong Li, Blind motion deblurring using improved DeblurGANIET Image Processing, DOI: 10.1049/ipr2.12951, 2023

[18] Dongmin Cha Daijin Kim, DAM-GAN: Image Inpainting Using Dynamic Attention Map Based On Fake Texture Detection, arXiv:2204.09442v1 [cs.CV] 20 Apr 2022

[19] Zhengyang Hana, Zehao Jiangb, Yuan Ju*c, AN-based Algorithm for Efficient Image Inpainting., arXiv paper 2309.07293:,2023

[20] Zhenan Sun, Tieniu Tan, Yunhong Wang, Stan Z. Li, "Ordinal Palmprint Representation for Personal Identification", Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition, Vol.1, pp.279-284., Orlando, USA.,2005