International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Size Optimized Generative Adversarial Networks for Single Image Super-Resolution of Fingerprint Images for Big Data Applications

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Submitted: 29/01/2024 **Revised**: 07/03/2024 **Accepted**: 15/03/2024

***Abstract*:** Big data applications such as the Aadhar project necessitate the storage of large volumes of biometric data, which requires about 20,218 TB of storage space. Big data projects, which present enormous storage and processing challenges, demand large storage servers and high-end computers. This paper suggests a novel method to enhance the resolution of compressed fingerprint images using a super-resolution (SR) model that reconstructs a high-resolution (HR) image from a low-resolution (LR) image can significantly reduce the requirement for large amounts of data and costly hardware in such cases. This proposed size optimized GAN (Generative Adversarial Network) based SR model of size 2.9 MB, that enlarges a low-resolution image to a scale factor of eight times. The model was trained on the fingerprint data set FVC 2004 (Fingerprint Verification Competition) and then tested on the FVC 2004 data set. The various human visual system (HVS) parameters, such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE), were measured, and their values were found to be 35.97, 0.958, and 19.5, respectively. Perceptual loss was measured in terms of generator loss as 0.981 and discriminator loss as 0.550. The accuracy of matching between the ground-truth image and the regenerated image was measured through the SIFT (scale-invariant feature transform) method and obtained an identification accuracy of 98.7%. This approach has the potential to increase the performance of fingerprint recognition systems for latent fingerprint images.

Keywords: *Fingerprint image, Generative adversarial network, Single image super-resolution, SIFT.*

1. Introduction

High-resolution (HR) images with distinct object boundaries or detailed visual descriptions are crucial for researchers to better understand the semantics of real-world images. Big data applications that make use of image processing techniques always demand high-end machines for storage, retrieval and analysis. The technology to meet these requirements demands high-performance computing for massive computational resources and it incurs huge costs in terms of both hardware and software. [1]. So, there must be an image processing model which will reduce the complexity involved while processing and analyzing big data applications. It is difficult and costly to obtain HR images using potential hardware-based methods. For instance, one of the options such as shrinking the pixel size would reduce the quantity of light that sensors could capture resulting in an increase in shot noise. Another option enlarging the sensor slows down the charge transfer rate and substantially raises the price of imaging systems. Therefore, using algorithmic-based methods to regenerate HR images from low-resolution (LR) image is preferable than hardware-based ones. Super resolution (SR) approaches are algorithm-based techniques that aim to reconstruct an HR image from input of LR observations taken in the same scene.

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With the introduction of deep learning, big data applications seem to rely more on deep learning-based methods. In an automatic fingerprint identification system, the accuracy of identification depends on the number of minutiae points, which are contributed by the structural details of ridges and valleys in the image. Also, the storage requirement of high-resolution images is not feasible for scalable applications. Main motivation for this work was to meet the above three objectives. Major contributions are

1. Novel Model Development: This study introduces a pioneering super-resolution model developed entirely from scratch, without reliance on pre-trained models. This approach ensures that the model is tailored specifically to the task of fingerprint image enhancement, maximizing its effectiveness and adaptability.

2. Fine-Tuning with Large Dataset: We augment the robustness and generalization capabilities of our model by fine-tuning it with the extensive Socofing dataset, a significant collection of fingerprint images. This process enhances the model's ability to capture diverse fingerprint patterns and variations, improving its performance across various real-world applications.

3. Eightfold Resolution Enhancement: This model achieves an impressive eightfold enhancement in the resolution of input fingerprint images. This substantial improvement not only enhances the visual quality of the images but also enables more accurate and reliable fingerprint recognition and analysis tasks.

4. Optimized Network Parameters: We meticulously select network parameters to strike a balance between computational efficiency and storage requirements. By optimizing these parameters, our model achieves superior performance while minimizing computational overhead, making it practical for deployment in resource-constrained environments.

In this work, identification accuracy of the reconstructed image was verified using SIFT method. Number of key minutiae points in the regenerated and ground-truth image are measured and compared using publicly available algorithm fingerprint minutiae viewer (FpMV). Also, HVS (Human Visual System) parameters of the reconstructed image was measured and values are compared with the state of-the-art techniques.

The paper is organized in such a way that the related work for super-resolution methods is given in section 2 and the proposed methodology in section 3. Results and discussion explained in section 4 and section 5 deals with the conclusion of the proposed work.

2. Literature Review

Major approaches for super-resolution include classical image processing techniques and learning-based methods. In the deep learning approach, residual network-based super-resolution models, autoencoder-based super-resolution models and generative adversarial network-based super-resolution models are prominently used and are described below.

A convolutional neural network-based super-resolution (SR) model was devised in [2] to enhance resolution of fingerprint images. This model showed advancements in increasing the number of minutiae points, essential for fingerprint analysis. Furthermore, the integration of nearest neighbor indexing techniques facilitated computationally feasible search operations during automatic fingerprint identification. Evaluation of the model demonstrated an identification accuracy of 85%. In reference [3], a deep convolutional neural network, integrated with noise filtering for fingerprint enhancement, was employed with adaptively updated filter sizes. This model achieved a per-pixel accuracy of 94.8%. In reference [4], Laplacian and Prewitt filters were utilized for edge sharpening, followed by a convolutional neural network to enhance the resolution of fingerprint images, yielding an accuracy of 75.6%. In [5], convolutional neural network autoencoders were employed, achieving a resolution enhancement accuracy of 95.04%. Reference [6] applied a generative adversarial network (GAN) with residual connections for fingerprint image enhancement. Additionally, ridge structure extraction was utilized to enhance resolution, with a measured Structural Similarity Index (SSIM) value of 0.937. Two GAN networks were utilized for unsupervised super-resolution of images in [7]. Moreover, in [8], a lightweight GAN with auto-encoding was employed for feature extraction and HR image generation, with FID and IS scores of 64.7 and 9.4, respectively. Reference [9] employed a conditional GAN for resolution enhancement, achieving an accuracy of 94.3% with an error rate of 0.4. In [10], a denoising autoencoder network was utilized for enhancing latent fingerprint images, resulting in an identification accuracy of 76.36%. Reference [11] introduced a deep residual network for fingerprint image enhancement, emphasizing pore detection to enhance fingerprint identification accuracy to 93.4%, with an error rate of 8.7%. Multiscale residual networks were utilized for super-resolution of natural images in [12], yielding PSNR and SSIM values of 28.7 and 0.68, respectively. Moreover, in [13], a progressive multiscale residual network was employed for natural image enhancement, integrating both pixel-wise and channel-wise attention mechanisms for relevant feature extraction. [14], a fingerprint image enhancement model combined a diffusion-coherence filter with a 2D log-Gabor filter for improved results. This model shows an error rate of 35. In [15], a GAN network was proposed, featuring an auto-encoder-based discriminator, aimed at balancing generator and discriminator losses to enhance model performance. Reference [16] introduced a GAN-based super-resolution (SR) model utilizing deep convolutional neural networks, demonstrating improved stability during training. WGAN, presented in [17], prioritized stability in parameter optimization and training processes. Furthermore, [18] enhanced WGAN performance by introducing gradient penalty in their SR model. [19] utilized a GAN-based SR model with a least square loss function in the discriminator to boost model performance. In [20], a lightweight SR model combining convolutional neural networks with edge filters was employed, albeit achieving lower accuracy in classification performance. Finally, [21] employed a convolutional neural network efficiently extracting minutiae features from fingerprint images at a low scale factor. Performance summary of super-resolution techniques are shown in table 1.

Table 1. A Summary of super-resolution techniques on fingerprint datasets

Sl No	System	Method-ology	Perfor-mance Metrics Meas-ured	Limita-tion
1	Shervin Minaee et al. -2019	Convo-lutional Neural Network	Accu-racy: 95.7 %	Com-plex Model

2	Uttam U. Deshpande et al (2020)	Convolution Neural Network	Accuracy: 80	Incomplete Feature Extraction
3	Syeda Nyma Ferdous et al. (2020)	GAN	Accuracy 94 %, Error rate 0.4 %	Model Complex
4	Ajnas Muhammed et al. (2020)	Deep CNN combined with noise filtering	PSNR: 34.05, SSIM: 98.53, MSE 0.0009	Scaled Twice only
5	Rashmi Gupta et al. (2020)	Ridge Orientation	Accuracy: 97.95	Prior data-based dictionaries are applied
6	Serigo Sapanora et al. (2021)	CNN auto-encoder	Accuracy: 95.02 %, MSE: 0.0048	Loss of true feature points in latent space
7	Sandoval Verssimo De Sousa Neto et al (2022)	Deep Convolutional Auto-Encoder	Accuracy: 94.8 %	Low scale factor, Input image size big
8	Andreea-Monica Dinca Lazarescu et al. (2022)	CNN Combined with prewet and Laplacian Filters	Accuracy: 75.6 %	Max-pooling applied after every convolutional layer
9	Subhajit Chatterjee et al (2022)	GAN	Accuracy: 99.3	Auto-encoder structure in discriminator

3. Proposed Methodology

The architecture of the proposed GAN-based SR model is depicted in Fig. 1. This study consists of two modules. The first module aims to enhance the resolution of a given low-resolution fingerprint image by a factor of eight using a GAN network. The second module identifies crucial minutiae points in the enhanced image and evaluates the quality of the image using the publicly available Fingerprint Minutiae Viewer (FpMV) algorithm and comparing it with the ground-truth image. Additionally, image matching accuracy between the enhanced image and the ground truth is measured using the Scale Invariant Feature Transform (SIFT) method. The GAN model comprises two networks: a generator and a discriminator. The input to the generator is a low-resolution image, which then generates a high-resolution image from the compressed input. The generator loss is measured in terms of adversarial loss and mean squared error. The discriminator receives inputs either of the enhanced image or the ground truth image, determining whether the regenerated image is real or fake. The generator network in this SR model is based on a convolutional neural network with residual blocks, while the discriminator part is based on convolutional operations and transposed convolution operations. Network parameters of this model are shown in table 2, and table 3 shows details of layers employed in generator and discriminator networks.

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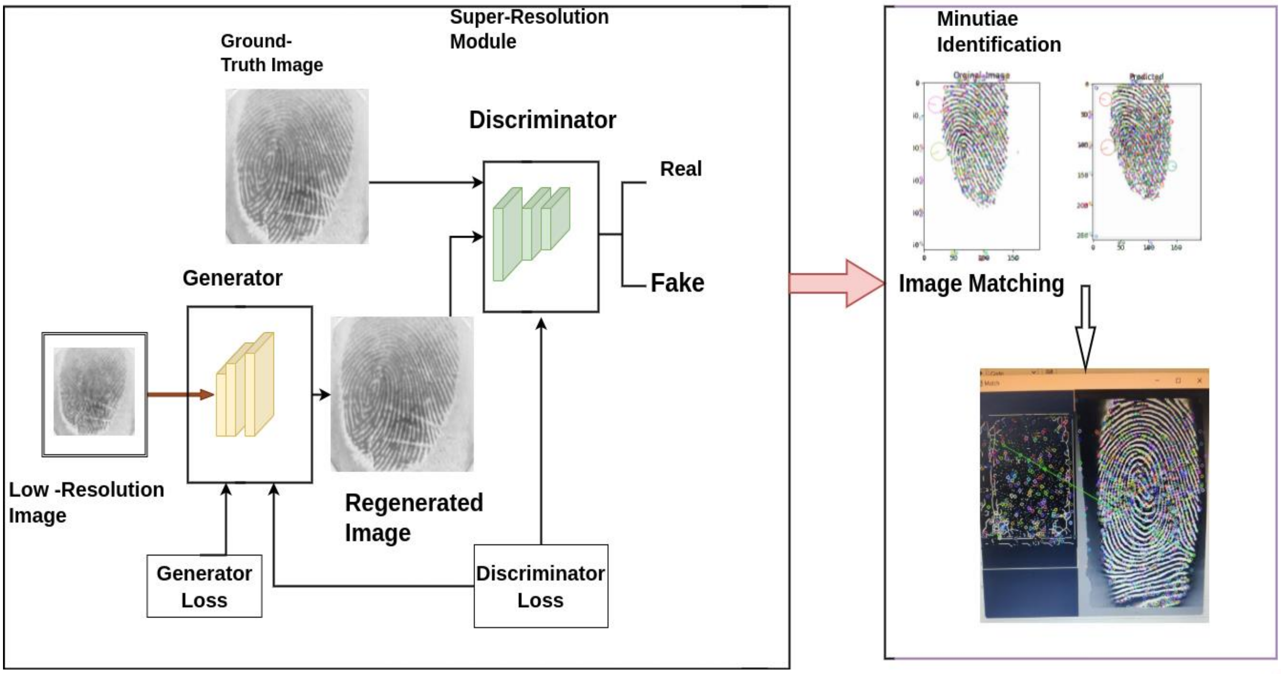


Fig.1.Proposed Model Architecture

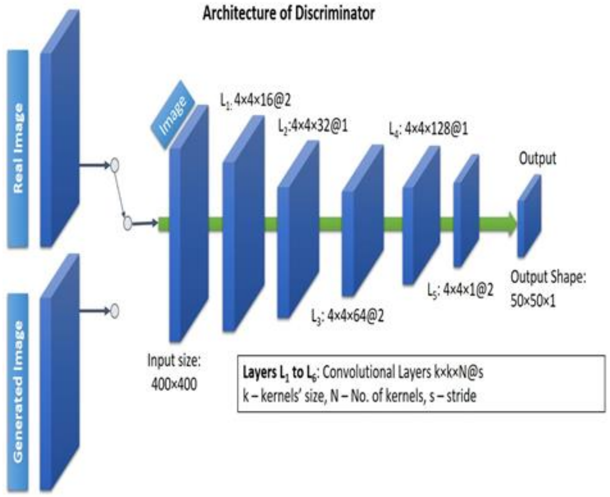


Fig.2. Discriminator Network in Proposed Model

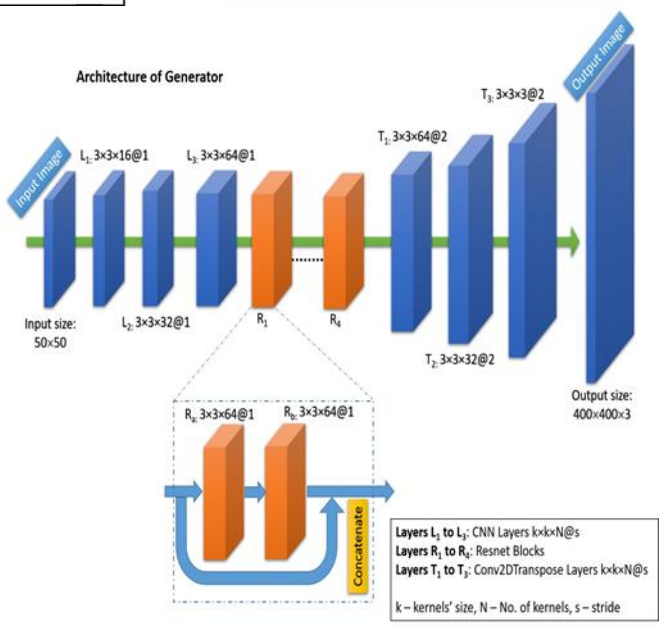


Fig.3. Generator Network in Proposed Model

3.1. Generator

The generator part of the proposed model is shown in fig3. Our architecture comprises three convolutional layers followed by four ResNet blocks and four transposed convolution layers for deconvolution operations. Notably, we maintain consistency in input and output image sizes through strategic padding and a uniform stride value of 1 across all layers. Additionally, we introduce innovative features such as concatenating outputs from ResNet blocks to enhance performance. LeakyReLU activation functions are applied consistently to promote non-linearity and feature extraction. Furthermore, our deliberate choice of a stride value of 2 for deconvolution operations optimizes spatial fidelity during upscaling.

3.2. Discriminator

The discriminator component of our model, depicted in Fig. 2, plays a pivotal role in guiding the generator towards producing high-quality images. Comprising six convolutional layers, its architecture is carefully crafted to discern and provide feedback on image fidelity. Initially, the first convolutional layer employs 16 filters with a kernel size of 4x4, followed by the second layer with 32 filters of the same size. Subsequently, the third and fourth layers escalate in complexity, featuring 64 and 128 filters, respectively, each with a 4x4 kernel size. Notably, the LeakyReLU activation function is chosen for all layers except the final one, where Softmax is applied. A crucial design choice lies in the strategic utilization of a stride value of 2 in every layer, facilitating broader discrimination capabilities across features. By orchestrating this discriminator architecture, we aim to leverage its feedback loop to steer the generator towards producing images of superior quality, thereby enhancing overall model performance.

Table 2. Network Parameters in proposed model

Network	Architecture	Loss Functions	Optimization function	Activation Function	Training Batch size and Epoch
Generator	Convolutional layers and ResNet Blocks	Pixel loss and Discriminator loss	Adam with learning rate 0.001	Leaky ReLU in all layers	16 & 200
Discriminator	Convolutional layers and Transposed convolutional layers	Binary Cross Entropy loss	Adam with learning rate 0.001	Leaky ReLU in every layer except last layer. Soft max applied in last layer	16 & 200

Table 3. Layer Parameters in Generator and Discriminator Networks

Block	Layer Details	No of Channels	Kernel Size	Stride	Padding
Conv 1	Convolution Layer, Leaky ReLU	16	3 X 3	1	1
Conv 2	Convolution Layer, Leaky ReLU	32	3 X 3	1	1
Conv 3	Convolution Layer, Leaky ReLU	64	3 X 3	1	1
Res-Net Block	Convolution Layer, Leaky ReLU	64	3 X 3	1	1
De-con-volu-tion	Conv2DTranspose Layer	64	3 X 3	2	1
De-con-volu-tion	Conv2DTranspose Layer	32	3 X 3	2	1
De-con-volu-tion	Conv2DTranspose Layer	16	3 X 3	2	1
Conv 4	Convolution Layer, Leaky ReLU	16	4x4	2	1
Conv 5	Convolution Layer, Leaky ReLU	32	4x4	1	1
Conv 6	Convolution Layer, Leaky ReLU	64	4x4	2	1
Conv 7	Convolution Layer, Leaky ReLU	128	4x4	1	1
Conv 8	Convolution Layer,Soft-max	1	4x4	2	1

3.3. Experimental Set-Up and Training procedure

In this study, the dataset was meticulously prepared using Python with TensorFlow technology, leveraging the computational power of an Intel Xeon 64-bit 2.60 GHz CPU and Nvidia Quadro T1000 4GB GPU. The dataset creation process involved resizing original images to a standardized 400x400 resolution to obtain high-resolution (HR) images. These HR images were then down sampled to generate corresponding low-resolution (LR) images, forming the training and testing datasets. In the training phase, the generator received the first LR image as input to produce a generated image of size 400x400. Subsequently, either the generated HR image or the original HR image was randomly fed into the discriminator. The discriminator's output indicated whether the input was real (original HR image) or fake (generated HR image), marked respectively as 1 and 0. With the known ground truth of the discriminator's input, the discriminator loss was calculated to update its weights, aiming to enhance its accuracy in

discriminating between real and fake images. Meanwhile, the generator loss was determined by combining the discriminator loss (negated) and the pixel loss (mean squared error), guiding weight updates in the generator layer. Through this iterative process, the discriminator continually refined its ability to distinguish real from fake images, while the generator learned to produce high-quality images closely resembling real ones. Training progressed until the discriminator's discrimination capabilities were significantly challenged, indicating the generator's success in generating authentic-looking images. At this point, the training process halted, marking the convergence of the coupled discriminator-generator training.

3.4. Details of Dataset Employed

The proposed model was trained on publicly available standard data-set FVC-2004. The data-set FVC2004 has 3 sets of finger print images with different resolutions and applied in such a way that 90 % of the images are used for training and 10 % of the images are used for testing purpose. The dataset details are shown below in Table 4.

Table 4. Details of dataset employed in proposed model. [24]

Data-Set	Number of Images	Image Size
FVC 2004, Database 1	240	640 X 480
FVC 2004, Database 2	240	328 X 364
FVC 2004, Database 3	240	300 X 480

3.5. Performance Evaluation metrics [25].

Structural Similarity Index Measure (SSIM): Structural analysis of the regenerated image with ground-truth image is measured using SSIM. It compares structural similarity with respect to luminance, contrast and structural features of both images. The SSIM value varies from -1 to 1. The SSIM expressed between two images x and y is given as in equation (1).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c1)(2\sigma_{xy}+c2)}{(\mu_x 2+\mu_y 2+c1)(\mu_x 2+\mu_y 2+c2)} \quad (1)$$

Where x and y are ground-truth image and reconstructed images being compared.

μ_x , μ_y : Average luminescence values of x, y

σ_{xy} : Covariance of x and y

$\sigma_x^{2,}$ σ_y^2 : Variances of x and y

Peak signal-to-noise ratio (PSNR): The PSNR value indicates how similar two images are. PSNR is used to measure the quality between ground-truth image and the reconstructed image. It is given as in equation (2).

$$PSNR = 10log_{10}\, 10(2^n - 1)/\sqrt{MSE} \quad (2)$$

Mean Squared Error (MSE): MSE value shows amount of error in the reconstructed image. It is calculated using equation (3)

$$MSE = \sum_1^M \sum_1^N \left(X_{(i,j)} - Y_{(i,j)}\right)^2 \quad (3)$$

Where X(i,j) , Y(i,j) represents pixe1l value at (i ,j) in ground

truth image and reconstructed image.

3.6. Tools Used

Details of tools applied are described in table 5.

Table 5. Details of Tools employed

Sl. No	Tool Used	Functions	Developed By
1	SIFT (Scale Invariant Feature Transform).	Tool to find similarity between images.	David Lowe 1999. [27]
2	FpMV(Fingerprint Minutiae Viewer)	1. Displays the dimension of an image. 2. Displays the total minutiae detected by" mindtct". 43 Displays the minutiae based on user selected quality value.	National Institute of Standards and Technology (NIST). [26]

4. Results and Discussion

The performance of this model was evaluated across three different behaviours of the proposed architecture, as depicted in Table 6. It is evident from the table that the second case exhibits superior performance compared to the other two cases, demonstrating higher values for key HVS parameters such as SSIM, PSNR, and MSE, alongside a reduced number of parameters and computational complexity. Consequently, the model was configured based on these parameters.

Table 6. Kernel Behavior and result obtained in Proposed model.

Sl No	Author & Year of Publish-ing	Meth-odology	Identifi-cation Accu-racy in %
1	Uttam U. Deshpande et al, 2020 [2]	Convo-lution Neural Network	80
2	Rasmi Gupta et al. 2020 [23]	Orien-tation and Phase Recon-struction	97.7

3	Sergio Saponara et al. 2021 [5]	Convolution Auto-Encoder	95.02
4	Sandoval Verssimo de Sousa Neto et al. 2022 [24]	Convolution Deep Auto-Encoder	94.1
5	Andreea-Monica et al. 2022 [21]	CNN Combined with Edge features	94.1
6	Konakanchi Anusha and P. V. Siva Kumar et al. 2023 [22]	CNN combined with filtering and Edge detection	99, Scale Factor 2
7	**Proposed SR Model**	**Size Optimized GAN**	**98.7, Scale factor 8**

4.1. Model Size Comparison

Fig.4. illustrates that the generator size in our proposed GAN architecture is measured at 2.9 million parameters, whereas the discriminator consists of 0.724 million parameters. A comparison is made with state-of-the-art methods utilizing GANs for enhancing the resolution of fingerprint images. This figure demonstrates that our model achieves eightfold resolution enhancement of low-resolution images with an optimal size in comparison to state-of-the-art methods.

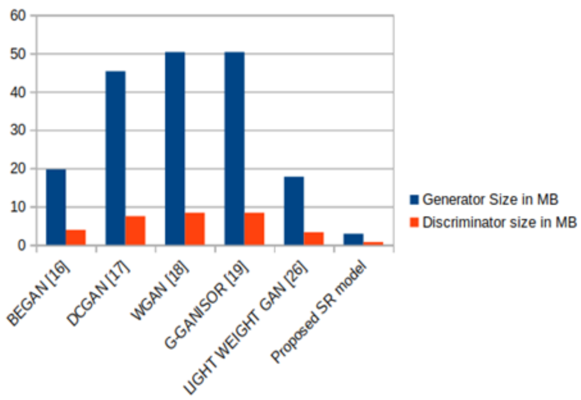


Fig.4. Proposed model size comparison with state-of-the-art methods

Table 7. Accuracy Comparison with state-of-the-art methods

Case #	Number of Kernels	Number of Parameters	PSNR	SSIM	MSE	Model Size	FPS(Frames/second)
1	8-16-32-ResNet_Block-32-16-8	5,41,065	26.145	0.7458	24.12	2.18 MB	379
2	16-32-64-ResNet_Block-64-32-16	5,53,417	35.974	0.9584	19.45	2.99 MB	346
3	32-64-128-ResNet_Block-128-64-32	13,02,537	34.567	0.9571	20.698	5.09 MB	207

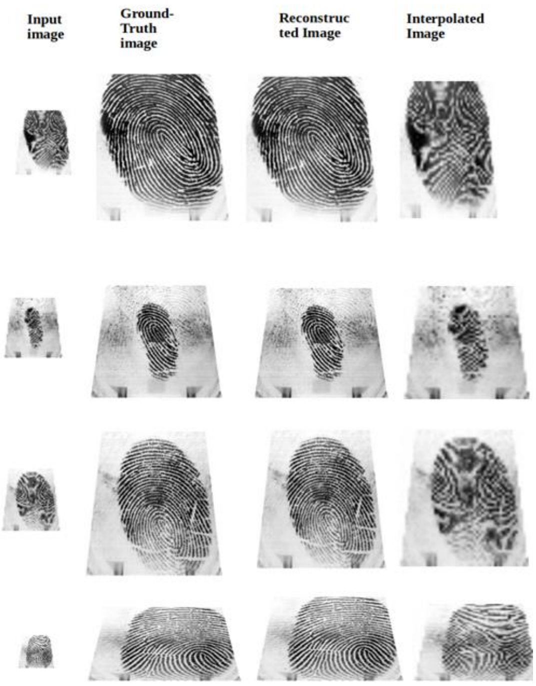
4.2. Identification Accuracy Measurement using SIFT algorithm and comparison with state-of-the-art methods.

The identification accuracy of regenerated image was measured using the scale-invariant feature transform (SIFT) method. It begins by identifying key points in the image that are invariant to changes in scale and rotation, ensuring that these points can be reliably recognized regardless of their appearance in different contexts. These key points are then refined to precisely localize their positions and orientations within the image. Next, descriptors are generated for each key point, capturing unique characteristics of the surrounding image region such as gradients and textures. These descriptors serve as compact representations of the key points and are used for matching similar features between images. By comparing descriptors, SIFT can find corresponding points across different images. The proposed model shows identification accuracy of 98.7%. Fig. 5 shows matching procedure using SIFT method which find matching accuracy between regenerated image and ground-truth image. Table 7 shows comparison of our model with state-of-the-art methods on accuracy in fingerprint identification.

Fig.5. Image similarity checking using SIFT method

4.3. Reconstructed images Obtained for randomly selected images from FVC 2004 and comparison with state-of-the-art methods.

The model's performance is evaluated using both performance metrics and visual assessment of output images generated from randomly selected images in the FVC 2004 dataset. Fig. 6 depict the low-resolution input image, ground-truth image, reconstructed image produced by the proposed model, and the output image obtained through bicubic interpolation. The comparison reveals that the reconstructed image from the proposed model closely resembles the original image, whereas the image from bicubic interpolation appears blurred. This visual evidence underscores the effectiveness of the proposed model in achieving high-fidelity image reconstruction compared to traditional interpolation methods.



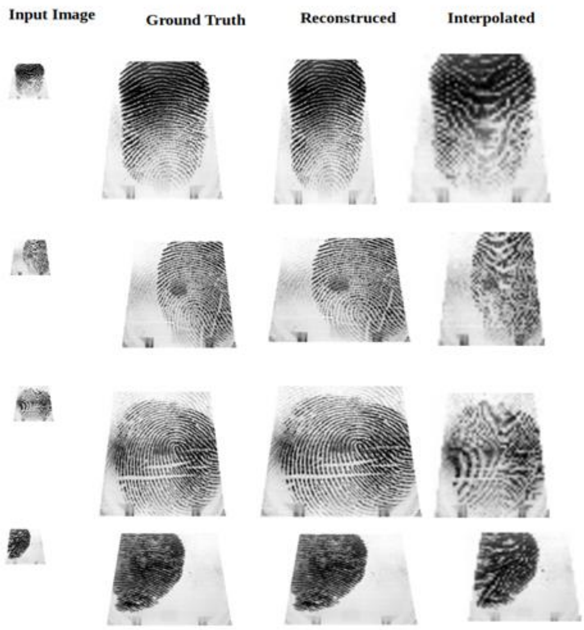


Fig.6. Result obtained in proposed model: Input image, Ground-Truth image, Reconstructed Image, Interpolated image for randomly selected image from FVC 2004 Dataset

4.4. Minutiae points extracted using FpMV(Fingerprint Minutiae Viewer) Method.

The Fingerprint Minutiae Viewer (FpMV) distribution is developed by the National Institute of Standards and Technology (NIST). The goal of this software is to provide researchers a tool to view a fingerprint image with minutiae points overlaid on top of the fingerprint. The minutiae detection is based on "mindtct" application from the NIST Biometric Image Software (NBIS). It displays minutiae points and quality of the image. In fig.7, top figure represents minutiae points and quality of reconstructed image for a sample image from the dataset and bottom figure shows minutiae points and quality of ground-truth image of same sample image from the dataset. Here red and green dots represent ridge endings and bifurcations. Fig. 8 shows key minutiae points detected in the ground-truth image(top) and reconstructed image(bottom) using FpMV algorithm for a sample image from the dataset and also number of key minutiae points in the reconstructed image is more than that of ground-truth image.

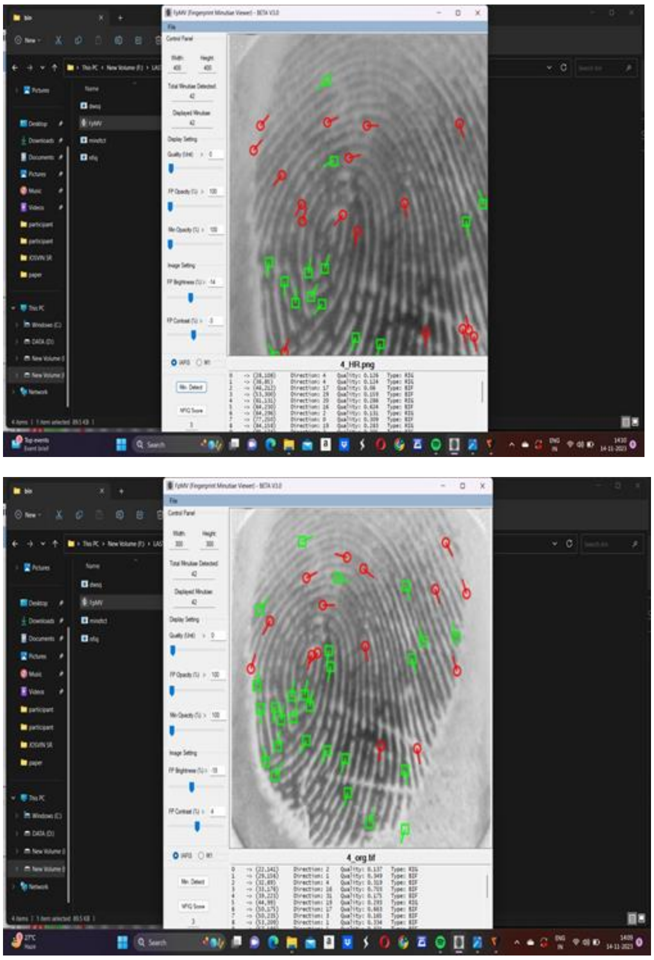
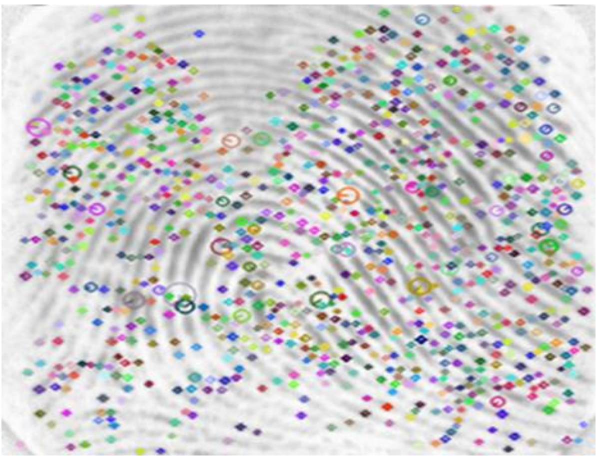


Fig.7. Number of minutiae points and quality of reconstructed image (top) and ground-truth image (bottom) for a sample image from FVC 2004 dataset using FpMV method



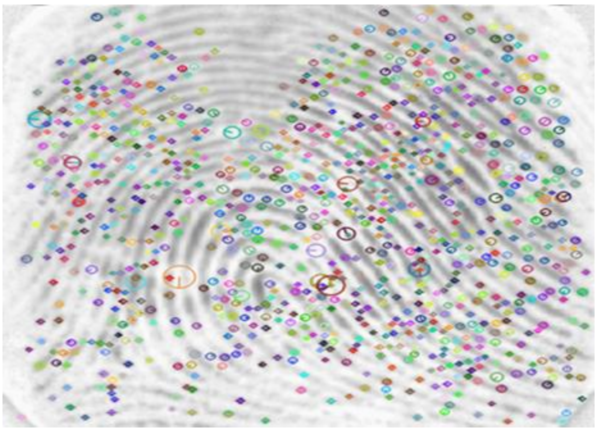


Fig.8. Number of minutiae points identified in the reconstructed image(top) and in ground-truth image using(bottom) for a sample image from FVC 2004 dataset using FpMV method.

5. Conclusion

This study focused on single-image super-resolution of fingerprint images, enlarging a low-resolution image of size 50x50 by a factor of eight using size-optimized GAN SR model. The resulting reconstructed output image shows superior performance compared to state-of-the-art methods. Evaluation metrics including SSIM, PSNR, MSE demonstrated the enhanced quality of reconstructed image. Furthermore, employing the FpMV algorithm, the number of minutiae points in both the original and reconstructed images were measured indicating the fidelity in reserving details during super-resolution process further validate the accuracy of the reconstructed image, image similarity was verified using SIFT algorithm, revealing an impressive identification accuracy of 98.7 %. These findings underscore the efficacy of the proposed model, showcasing its capability to outperform existing methods in single-image super-resolution of fingerprint images. Future research directions include extending this approach to enhance resolution in latent fingerprint images obtained from crime scenes, thereby contributing to advancements in forensic science.

Author Contributions

This methodology developed by **Ms.Lisha P P** under the supervision of **Ms. Jayasree V K**

Conflicts of Interest

There is no conflict of interest on this work.

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