Novel Deep Learning Technique to Improve Resolution of Low-Quality Finger Print Image for Bigdata Applications

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***Abstract*—High-resolution images are highly in demand when they are utilized for different analysis purposes and obviously due to their quality aesthetic visual impact. The objective of image super-resolution (SR) is to reconstruct a high-resolution (HR) image from a low-resolution (LR)image. Storing, transferring and processing of high-resolution (HR) images have got many practical issues in big data domain. In the case of finger print images, the data is huge because of the huge number of populations. So instead of transferring or storing these finger print images in its original form (HR images), it cost very low if we choose its low-resolution form. By using sampling technique, we can easily generate LR images, but the main problem is to regenerate HR image from these LR images. So, this paper addresses this problem, a novel method for enhancing resolution of low-resolution fingerprint images of size 50 x 50 to a high-resolution image of size 400 x 400 using convolutional neural network (CNN) architecture followed by sub pixel convolution operation for up sampling with no loss of promising features available in low-resolution image has been proposed. The proposed model contains five convolutional layers, each of which has an appropriate number of filter channels, activation functions, and optimization functions. The proposed model was trained using three publicly accessible fingerprint datasets FVC 2004 DB1, DB2, and DB3 after being validation and testing were done using 10 percent of these fingerprint data sets. In terms of performance measures like Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM) and loss functions, the quantitative and qualitative results show that the proposed model greatly outperformed existing state-of-the-art techniques like Enhanced deep residual network (EDSR), wide activation for image and video SR (WDSR), Generative adversarial network(GAN) based models and Auto-encoder-based models.**

Keywords*—*Single image super-resolution; convolution neural network; biometric; fingerprint images

I. Introduction

A biometric system is an effective tool used for personal identification in the fields of healthcare, insurance, forensics, security systems etc. In the modern computer age, among all other biometric systems, the fingerprint is one of the most widely used biometric systems. It is utilised for both personal identification and verification [1].

Now a days, in a fingerprint's rich details, such as pores and scars, can be captured using an optical fingerprint sensor at a resolution of 2000 dpi. Large scale bio metric systems are employed for personal identifications in nationally accepted identity cards and also in mobile based payment applications. For example, in India, nation-wide identity card like Aadhar, where each of the 1.3 billion citizens will have two iris pictures and all 10 of their fingerprints stored in huge database [2]. In big data system like this, it is a difficult task to meet hardware and software needed for this enormous storage and analysis for personal identification. It is challenging to compare an unknown fingerprint with this vast amount of data in personal identification. The potential of deep learning in big data allows for the analysis of very large and complex data, including images, videos or text, in the field of healthcare. Big data has security and privacy issues since acessability and process used to store, manipulate and retain data has increased [3]. In this scenario, a method for personal identification and analysis using fingerprint image with minimum computations and storage is highly in demand. Super-resolution techniques for enhancing low-resolution images in to high-resolution images with no loss of promising features used for identification is suitable in this situation, Here, we need to store low resolution images of size 50 x 50, but for fingerprint image analysis or verification, it is enhanced in to 8 times than input image so it will drastically reduce complexity involved in both hardware and software for storage as well as analysing huge volume of data.

While dealing with natural scenes and situations, the availability of high-resolution images is not always effortless. The major hurdles for the same are noise, blur, camera limitations, and limitations in acquisitions. The domains including medical diagnosis, digital surveillance, remote sensing and forensics analysis always require high-resolution images [4]. In forensics, biometric has prominent role and mostly fingerprint has vital role. For all those applications where personal identification and verification employed using fingerprint image, require high quality image and also image analysis of the same is to be performed with less space and computational complexity.

Super-Resolution (SR) is the means of reconstructing a high-quality image utilizing one or more low-quality image(s). Super-resolution techniques are divided into two categories: single image super-resolution (SISR) and multi-image super-resolution (MISR). SISR reconstructs the SR image from a low-resolution input image. SR models in the SISR and MISR categories have been constructed using either classical or deep learning methods. In the classical approach, Andrew Gilman et al. [5] observed multiple algorithms for each super-resolution category and they are given as interpolation-based, learning-based, and reconstruction-based. Bi-linear, bi-cubic, and cubic spline are the most often used interpolation algorithms. These approaches used weighted average of neighbouring LR pixels to estimate unknown HR pixels. Ledig et al. [6] observed that interpolation-based approaches are quick and easy, but they muddy the image's details and make it difficult to establish the image's precision hence blurring of features and edges in a sample image is caused. Using an external image data-set, learning-based algorithms build a link between the LR and HR image. Nasrollahi, K., and Moeslund, T.B [7] observed that in reconstruction-based methods, the details of the HR image such as edge prior, gradient prior are recovered using some prior knowledge. In classical methods, images cannot be magnified beyond the image sample resolution without losing image quality. In recent years, deep learning-based super-resolution models have superior performance over classical methods in all applications in which image analysis is required.

In this paper a novel method for generating high-resolution fingerprint image from a low-resolution fingerprint image is proposed in which resolution enhanced eight times than input image using convolution neural network architecture and sub pixel convolution operation.

The paper is organized in such a way that the related work for SISR approaches is offered in Section II, the framework for the proposed model is explained in Section III, Experiment part is described in Section IV, results and evaluation metrics are reviewed in Section V, and the conclusion is presented in Section VI.

II. Related Work

Major approaches for super resolution of fingerprint images includes classical image processing techniques, Residual networks-based SR models, Auto-encoder based SR, Convolutional neural network-based SR and Generative adversarial network-based SR models as described below.

A. Classical Image Processing Techniques for SR

Ganchimeg G and Leopold H developed a model for fingerprint enhancement based on classical image processing techniques [8]. They employed filtering methods for noise removal followed by edge detection methods and thinning process for enhancement, but their result gets blurred for higher magnification orders. Nouf Saeed and Alotaibi [9] applied Gabor filter for denoising and after that deep boltzmann method is applied for ridge enhancement. Dinca Lazarescu Andreea-Monica et al.[10] applied convolutional layers for feature extraction and also for mapping low-resolution fingerprint image in to high-resolution images, but in their method, initially low-resolution image is enhanced using Laplacian filters and thereafter convolutional operations are employed. Major limitation of classical image processing techniques is artifacts or blurring occurs for large magnification orders.

B. Residual Network based SR Models

Zhenzhen Yang et al. [11] applied residual network for enhancing personal identifying features pores and ridges available in low resolution images. In their model, they applied 32 residual blocks in which each block contains 3 convolutional layers and relu activation functions. Finally resultant features extracted using residual blocks are combined with pixel shuffling blocks and regenerated output image. Since model is complex, it is computationally intensive. Seonjae K [12] employed two CNN (Convolutional neural network) based network for feature extraction and enhancement. First network employed for feature extraction of low-resolution images using dense layer with local skip connections. After that input image upscaled using interpolation technique and passed in to second network, which composed of many dense layers with local and global skip connections. Finally output from first and second network concatenated to regenerate enhanced image. Here, since second network performs feature extraction on interpolated image, computational requirement is considerably more and also dense network processing on features of interpolated image rather than original image. Yongliang Zhang et al. [13] employed convolutional residual network for fingerprint liveness detection.

C. Autoencoder based SR Models

Sandoval Veríssimo de Sousa Neto et al. [14] applied deep convolutional auto-encoder for feature extraction and applied Gabor filtering and Gaussian filtering for enhancement. But major limitation of auto-encoders is while encoding input image in to latent vectors, information loss may occur. Sergio Saponara et al. [15] applied convolutional auto-encoders for fingerprint image enhancement. In their model they employed convolutional layers for feature extraction, max-pooling layer used for down sampling and up sampling by deconvolution layer. Major drawback of auto-encoder based models are, while encoding input image, all promising features may not be represented in latent form hence during decoding and regenerating phase information loss takes place.

D. Convolutional Neural Network (CNN) based SR Models

Ajnas muhammed and Alwyn roshan [16] employed deep convolutional network (20 layers) for image enhancement. Since their network is deeper, it is computationally expensive. Ayushi Tamrakar and Neetesh Gupta [17] proposed SR model based on convolutional neural network (CNN) and long short-term memory (LSTM). In their model, they first applied CNN for both feature extraction and enhancement, thereafter LSTM applied on this feature map to classify images based on ridges in output image so that personal identification is employed using these ridges information. Fandong Zhang and Jufu Feng developed a model based on CNN and joint KNN-Triplet embedding. [18]

E. Generative Adversarial Network (GAN) based SR Model

Syeda Nyma Ferdous et al.[19] employed SRGAN for extracting features for detecting minutiae, ridge and pores to be enhanced so that personal identification is possible in all challenging situations but major hurdles of applying GAN model is computational complexity. Chi-En Huang et al. [20] employed residual GAN for enhancement. In their model, they employed residual network with attention module as generator and classification module will act as discriminator. Rafael Bouzaglo and Yosi Kellerc [22] developed generative adversarial network with Resnet 50 as encoder, and convolutional decoder used for reconstruction. Masud An Nur Islam Fahim and Ho Yub Jungy [23] employed GAN based model for reconstructing good quality fingerprint image by applying skip connections on denoising auto-encoders and thereafter convolutional layers are appled for decoding. Amol S Joshi et al. [24] employed conditional GAN for deblurring input image followed by multiple discriminators. Gan based SR model requires training for both generator and discriminator separately and it takes longer time for reconstructing a better-quality image compared to other models, hence it is practically not feasible for employing to realtime applications. Mingzheng Hou et al.[25] employed GAN based network for generating good quality image. They applied SRResnet for upsampling the input image of appropriate size. Then, upsampled image was fed into an attention-based network for regenerating good quality image. Multiple discriminators were then applied to determine how well the regenerated image matched with ground-truth image. Since their model too complex, it is computationally expensive.

It is clear from the analysis of the previously mentioned SR models that there are a range of models for producing high-quality images from low-resolution data. All image processing applications require high-quality images in various scales to be supplied with less computations and minimal complexity in training and testing. Success rate of deep learning-based applications rely on learning strategy, availability of data-set, architecture of the model employed. Hence convolutional neural network architecture, a light weight neural network architecture with suitable number of layers, activation functions and optimizing functions is suitable to reconstruct images with higher PSNR and SSIM values with minimal training and testing computations.

III. Proposed Methodology

A. Model Architecture

In this model, initial step is pre-processing of input image (low-resolution image). In pre-processing stage, the gray scale finger print raw image is converted into unit 8 bit image. Then its pixel values are normalized to values between 0 and 1 by dividing pixel values by 255.

The preprocessed data is given to the deep learning model for training and testing. Architecture of proposed model shown in Fig. 1. In order to build a suitable model for enhancement of fingerprint images, we developed and tested 5 different behaviours of this architecture from scratch by changing number of filter (see Section V-A). Model details are explained in the Fig. 1. The input size of model is kept as 50×50 and the model predicted an output image of size 400×400. So, a resolution increasing factor of 8 times is achieved by this proposed system. The quality of generated HR image is verified and analysed using various standard techniques (see section V).

All five convolutional layers employed Relu as activation function and Adam as optimizing function with stride value as 1. After feature extraction and image reconstruction process, sub pixel convolution layer applied for up sampling LR image in to 8 times. Sub pixel convolution operates on 3 channels (3 sub pixels) of every pixel and combines 3 values for up sampling and regenerated image is very similar to ground truth image. Fig. 1 shows proposed SR model architecture with CNN and sub-pixel convolution operation.

B. Pixel Loss

During model training, the model weights are updated based on the custom pixel loss functions L_{pixel}. It is computed as per (1). In (1), GT represents ground truth image and SR image represents reconstructed image.

$$L_{pixel}(GT, SR) = \frac{1}{hcw}||GT - SR||_2^2 \tag{1}$$

Where h, c and w are the height, number of channels and width of the image.

IV. Experiment

A. Dataset

Proposed model trained from scratch using DIV2k data-set (https://data.vision.ee.ethz.ch/cv/DIV2K) and fine-tuned with publicly available standard fingerprint dataset - FVC2004 (http://bias.csr.unibo.it/fvc2004/databases.asp). This dataset is provided by the Biometric Systems Lab (University of Bologna), the Pattern Recognition and Image Processing Laboratory (Michigan State University) and the Biometric Test Center (San Jose State University). They provide three sets of finger print images with different resolutions and types. Table I shows the details of finger print dataset.

TABLE I. Dataset Details with Number of Images and Resolution

Data set	Number of images	Image size	Resolution
FVC 2004 DB1	240	640x480 (307K pixels)	500 dpi
FVC 2004 DB2	240	328x364 (11K pixels)	500 dpi
FVC 2004 DB3	240	300x480 (144K pixels)	500 dpi

B. Performance Evaluation

Well-known objective evaluation methods for measuring image quality include peak signal-to-noise ratio (PSNR), mean squared error (MSE), and structural similarity index (SSIM)[21]. This metric is defined as

$$MSE = \frac{1}{MN}\sum_{1}^{M}\sum_{1}^{N}(x_{i,j} - y_{i,j})^2 \tag{2}$$

Where $x_{(i,j)}$ represents original reference image and $y_{(i,j)}$ represents generated image and i and j are pixel positions of M N size image.

Peak signal-to-noise ratio (PSNR): PSNR is evaluated in decibels and is inversely proportional the Mean Squared Error. It is given as

$$PSNR = \frac{10log_{10}(2^n - 1)}{\sqrt{MSE}} \tag{3}$$

The higher values of PSNR denote the better quality of the reconstructed image.

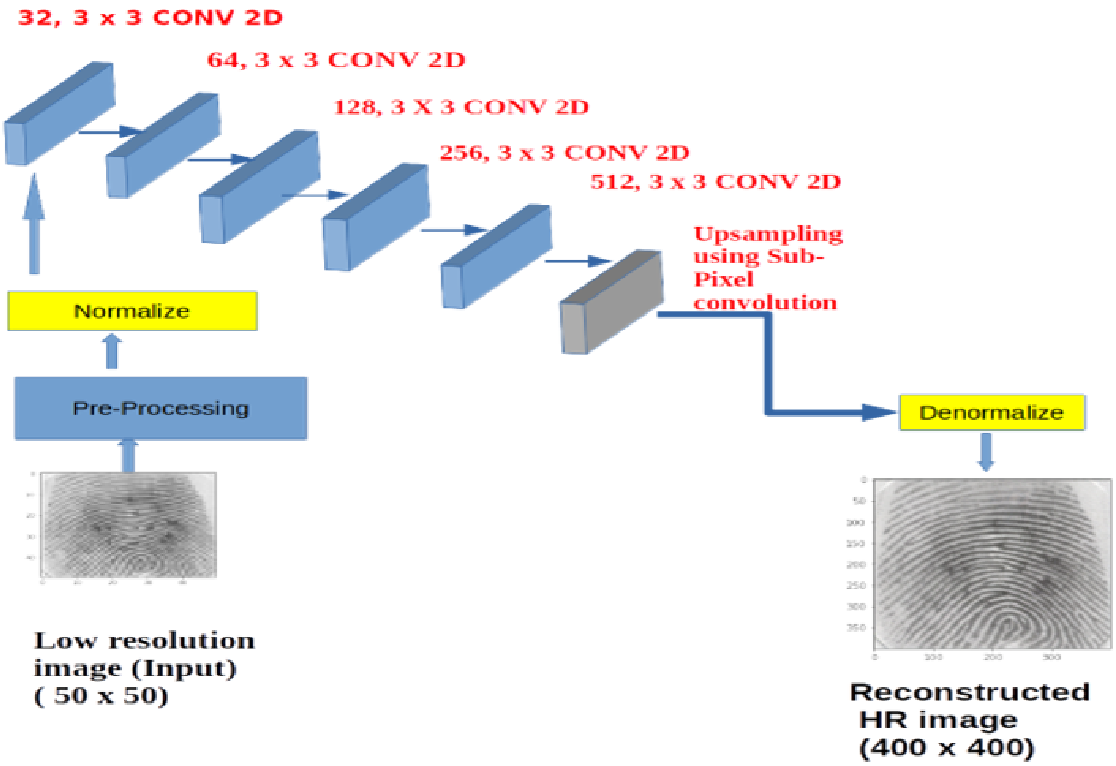

Fig. 1. Proposed Model Architecture.

TABLE II. MODEL BEHAVIOUR AND PERFORMANCE IN TERMS OF NUMBER OF TRAINABLE PARAMETERS, MODEL SIZE, PSNR, SSIM AND MSE VALUES, BY VARYING NUMBER OF FILTER CHANNELS & NUMBER OF CONVOLUTIONAL LAYERS

Case#	No of convolutional layers	Number of filter channels in each layer	Filter kernel size	Activation function applied	Optimizing function used	Mean PSNR, SSIM, MSE values	Number of trainable parameters and model size
1	5	Layer1 :8, Layer 2: 16 Layer 3: 32, Layer 4:64 Layer 5:128	3 x3	ReLu	Adam	PSNR: 8.4521 SSIM: 0.2475 MSE: 84.884	542,995 2.1 MB
2	5	Layer1 :16, Layer 2: 32 Layer 3: 64, Layer 4:128 Layer 5:256	3 x3	ReLu	Adam	PSNR: 19.45 SSIM: 0.687 MSE: 37.457	11,32,131 4.4 MB
3	5	Layer1: 32, Layer 2: 64 Layer 3: 128, Layer 4:256 Layer 5:512	3 x3	ReLu	Adam	PSNR :34.875 SSIM 0.9458 MSE: 22.04	2,897,923 11.13 MB
4	5	Layer1: 64, Layer: 128 Layer 3: 256, Layer 4:512 Layer 5:1024	3 x3	ReLu	Adam	PSNR: 35.788 SSIM : 0.9521 MSE: 18.967	87,795,87 33.5 MB
5	5	Layer1: 128, Layer 2: 256 Layer 3: 512 Layer 4:1024 Layer 5:2048	3 x3	ReLu	Adam	PSNR: 34.116 SSIM: 0.9501 MSE: 17.64	29,943,235 114.3 MB

Structural similarity index: SSIM measure similarity with greater accuracy and consistency than MSE and PSNR. It measures similarity between two images. It compares two images in terms of luminous, contrast and structure. The SSIM measure between two images x and y of size $N \times N$ is given as

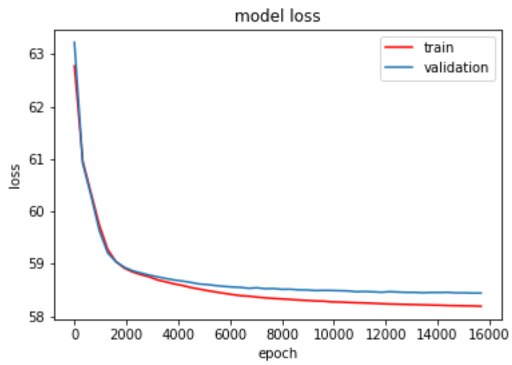

Fig. 2. Training and Validation Loss Curves.

TABLE III. PSNR VALUES OBTAINED DURING MODEL TESTING USING TEST SAMPLE IMAGES AND ITS COMPARISON WITH STATE OF ART METHODS EMPLOYED ON SAME DATA-SET

Image #	EDSR	WDSR	GAN Based model	Proposed Model
1	30.1	31.43	30.1	34.87
2	30.22	31.53	30.45	34.98
3	30.6	31.56	30.75	34.65
4	30.22	31.7	29.98	34.95

TABLE IV. MSE VALUES OBTAINED DURING MODEL TESTING USING TEST SAMPLE IMAGES AND ITS COMPARISON WITH STATE OF ART METHODS EMPLOYED ON SAME DATA-SET

Image #	EDSR	WDSR	GAN Based model	Proposed Model
1	25.36	27.73	29.87	22.05
2	25.55	27.43	29.1	22.1
3	25.22	27.1	29.43	21.98
4	25.62	26.98	29.1	22.01

$$SSIM(x_{(i,j)}, y_{(i,j)}) = \frac{(2\mu_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (4)$$

Where C1, C2 are constants, μ_x and μ_y represents average of x and average of y. σ_x, σ_y represents standard deviation between ground-truth and regenerated images. SSIM values ranges between (-1,1).

In order to analyse the performance of the proposed model quantitatively we measured SSIM, PSNR and MSE values using reconstructed image with reference to the ground-truth image.

C. Training Strategies

The proposed model is trained and evaluated on a Nvidia Quadro T1000 4GB GPU based PC with 64-bits Windows Intel Xeon CPU at 2.60 GHz. Programs were written in Python language with Keras technology having TensorFlow as backend.

Input size is fixed as 50×50. Total there are 720 finger print images. We split the full dataset into train set and test data in the ratio of 9:1. So, 648 train data and 72 test data. Model is trained for 16000 epochs. During each epochs better model with lesser validation loss than previous is saved to hard disk using callback function of keras technology. So, after perfectly trained, best model with least validation loss is saved to hard disk for further testing and evaluations.

V. RESULTS AND DISCUSSIONS

Model trained for 16000 epochs, and got converged at 15680th epoch with validation loss of 58.4445. Fig. 2 shows the training and validation curves of model training stage.

Fig. 3 shows generated high resolution image of size 400×400 from low resolution input image of size 50×50. The generated HR image is visually compared with original ground truth image of size 400×400. In Fig. 3, generated images are visualized in a zoomed-in form just to visible the finger print patterns clearly. From the result figure, visually there is no any difference between the original ground truth image and generated HR image.

A. Research on Model Architecture

In order to build a suitable model for enhancement of fingerprint images, we developed and tested five different behaviours of this architecture from scratch by changing number of filter channels as shown in Table II. In each case we measured performance metrics quantitatively in terms of PSNR (Peak signal to noise ratio), SSIM (Structural similarity index), MSE (Mean squared error), Validation loss, Number of trainable parameters and Model size.

In first case, employed five convolutional layers and number of filter channel applied are 8, 32, 64, 128 and 256 accordingly. In this case, we obtained resultant image of poor quality in terms of different performance metrics mentioned above. In second case we adopted filter channels in each of the five convolutional layers are 16, 32, 64, 128 and 256 and obtained a result better than first case. In third case we employed convolutional layers with filter channels as 32, 64, 128, 256 and 512. In this case we obtained good quality image with significantly better value for performance metric like PSNR, SSIM, MSE, pixel-loss, number of trainable parameters and model size. In fourth case, we applied number of filter channels in each convolution layer as 64, 128, 256, 512, 1024. In this case, results obtained is slightly better than previous three cases except model size, which is a higher value. In last case, we adopted number of convolutional channels are 5 and number of filter channels employed are 128, 256, 512,1024, 2048. This case also we got better value in all performance metrics except model size and number of trainable parameters, which is a higher value than all other cases. From this comparison of five cases, we fixed third case as our proposed

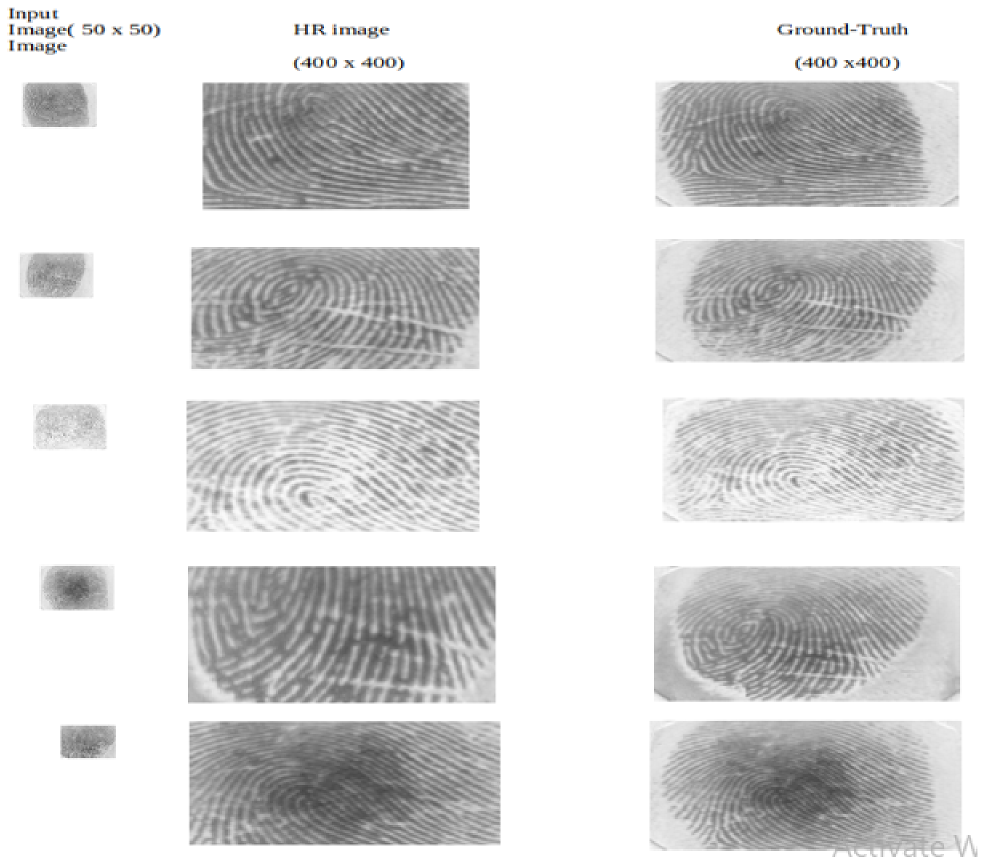

Fig. 3. Visualization of Some Input Images, Corresponding Generated Output Images and its Ground Truth Images.

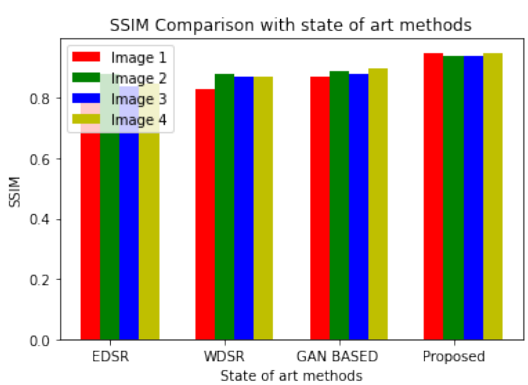

Fig. 4. SSIM Comparison with State-of-the-Art Methods.

model in which performance metrics like number of trainable parameters, model size and pixel loss are considerably less compared to other cases and PSNR, SSIM and MSE values are much better.

B. Comparison with State-of-the-Art Models

In order to analyse the performance of the proposed model quantitatively we measured SSIM, PSNR and MSE values using reconstructed image with reference to the ground-truth image.

Fig. 4 shows the comparison of SSIM index of proposed system with the state-of-the-art SR image generation techniques. For this comparison, we took four images and calculated SSIM values from the output values of other techniques like EDSR, WDSR, and GAN-Based technique. From this chart figure it is understood that proposed technique has got best performance than other technique in the perspective of SSIM index. Table III shows the comparison of proposed technique's PSNR with other techniques. Similarly Table IV shows the MSE values obtained during model testing using test sample images and its comparison with state of art methods employed on same data-set. From these two tables, it is understood that, proposed technique's performance is superior to other state-of-the-art methods.

VI. Conclusion

Fingerprints are used in many different applications like security control, law enforcement, smart phones, and criminal investigations. Over a lengthy period of time, the forensic community has used fingerprints as their most common biometric characteristic. Using a convolutional neural network, a light weight neural network for feature extraction and image reconstruction, followed by sub pixel convolution for upsampling, has been proposed as a novel architecture in this paper for resolution enhancement of low-resolution fingerprint images to high-resolution images. In this study, we looked at five different behaviours of this model, analysed model performance by altering the number of filter channels in each of the five convolutional layers, and then fixed the model, which exhibits a notable improvement in performance metrics like PSNR, SSIM, MSE, model size, validation toss, and the number of trainable parameters when compared to other state of art methods. With no loss of the promising feature in the LR image, the proposed model enhanced the LR image eight times. Big data applications that analyse or compare fingerprint images for personal identification and verification confront significant challenges in meeting the necessary hardware and software requirements. In this case, the suggested model significantly contributes to improving the resolution of fingerprint images by taking a 50×50 input image and enhancing it eight times without losing any promising aspects, making it appropriate for real-time applications as well. Future work will build on this work by altering the model architecture through the use of a GAN-based network with perceptual loss while maintaining the computational viability of the model, making it appropriate for real-time applications as well.

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