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License Plate Image Super Resolution Using Generative Adversarial Network(GAN)

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***Abstract*—Super resolution of images in the field of Computer Vision is a widely used for the conversion of images into high resolution without the loss of pixel data into the images. Due to fast movement of vehicles and low quality of camera the image cannot be verified easily so, the techniques of Generative Adversarial network have been applied for the Super resolution of license plate Images which works to recover the loss data of license plate images without loss of pixel data. Earlier, mean square error (MSE) and peak signal to noise ratio (PSNR) was used as content loss to minimize the error but at optimal minimization the images get over smoothen and pixel data were lost. This paper has proposed and applied VGG-19 as pretrained neural network along with MSE and PSNR to minimize the content loss which overall optimizes the perpetual loss, and over smoothness of the images gets controlled which saves pixel data. Later, the pre-trained neural network is integrated with Generative Adversarial Network [GAN] of discriminator and generator to produce high resolution images. Taking the PSNR as an evaluation metrices for the images, it increases from 26.184 to 28.696 and accuracy from 58% to 84%.**

Keywords—Super Resolution, Generator, Discriminator, Peak signal to noise ratio, VGG-19

I. INTRODUCTION

The field of Image processing and computer Vision has taken a core place in the field of engineering and technology. Super resolution of images has been developed very much is very short period. The Computational work and Complexity of the work as compared to past years has been developed a lot with a great efficiency. Algorithms are being developed day by day with some greater value and efficiency on a particular time series [4]. The application observed in the era and as expected to grow in the coming years things are going to change more drastically. Super Resolution a very well-known domain of computer vision where we try to retrieve fine texture details to make high resolution images from given low resolution images. Super Resolution of an image can be done using various methods, including bicubic interpolation, convolution neural networks. The interpolation technique uses pre-known pixel values to estimate values for generated pixels. The CNN techniques include SRGAN and Super Resolution using Residual Network which gives better ratio of peak signal with respect to noise which we call as PSNR metrics. Better result is obtained by PSNR as compared to interpolation techniques [19]. An SRGAN comprises of two parts or models, the generator which has the generating image's function and discriminator which has discriminating image's function. Generator model is used to create Super Resolution images while the discriminator model classifies the image as a real High-Resolution image or generated Super Resolution image. The two models compete to get better in their respective works [6]. The Super resolution over a license plate image is like SRGAN as they have a similar Generative model. In the GAN model of License plate images, loss function has two components, adversarial loss and perceptual loss [20]. The perceptual loss pushes our model to produce Super Resolution images which are more feature wise inclined to High-Resolution images. Super resolution of images with GAN network is useful in research field for the field of computer vision that has been considered for gaining the unknown and useful information in the field of medical imaging, space technology, industry world, surveillance and security and is applicable for building different new technology in the field of image analysis. This learning gives great inspiration, different applications based on Image super-resolution has been studied through researchers and scientist across the world, The traditional method was inappropriate and thus, the sequential progress and technologies used in the super-resolution of images inspires more, earlier we used deep networks i.e., CNN, Resnet and then we proceed to GAN with Concepts of Residual blocks and Skip Connections. The idea and sentiments used by researchers and scientists for the formation of architectures and then results obtained on the sample images have a proper frequency match that inspires to learn and implement these techniques with novelty fill of interest and enthusiasm. In this project, we plan to dive deep into the approaches and the various technologies that tackle Super-Resolution using GAN to learn more about the key areas that affect it. The major problem with Super Resolution is the missing fine texture details in the output image [5]. Also, the unavailability of a uniform metric to gauge the performance of the super-resolved image poses a challenge. Many approaches discussed in the report have created their own version of models and loss function for the same and we aim to compare their advantages and disadvantages, to ultimately get a measure of the key methodologies used in the domain of super-resolution images [18].

II. LITERATURE SURVEY

In this section the survey of the past works over the super resolution of images is developed. Researchers tried to overcome the problem of missing texture details in SR photos in license plate when done at a large upscale factor [29]. As the main target of other algorithms remained to minimize MSE loss to increase Peak signal to noise ratio (PSNR), that makes the overall super-resolution photos smooth but lacks fine texture details. But it was shown that it's not necessary that an image with high PSNR will give high texture details. Researchers aims to enhance the existing SRGAN by carefully analyzing all components of network architecture, including generative model, discriminative model, and loss function. In brief, the author introduces the Residual in Residual block (RRDB) in the generator, Relativistic Discriminator [31]. The existing method used per pixel loss to train the optimized SR methods researcher observed it by using for pretraining model to conclude high-level feature to calculate loss between two images. Earlier, authors have combined per pixel loss and perpetual loss to train feedforward neural networks [32]. Along with optimization in the loss function, there are some optimizations in feedforward networks for image generation [30]. Through this survey we have carefully compared the various approaches that have been undertaken, solving the given problem of super resolution of single image. “GAN” is a broad topic that encompasses different methodologies and definitions which are used to detect the texture qualities of the output super-resolution photo [33]. The resolution of image is enhanced based on Residual network, Residual-in-Residual network, Adversarial Multi-Path Residual Network and Generative Adversarial using Multiple Cycle to Cycle Networks. In depth analysis of each of these methods throws light on the areas for improvement of the problem statement “Super resolution Images” [2].

III. METHODOLOGY

This section deals with the tools and concepts of the stacks and technology used for the Super resolution of images of License plate images.

A. Datasets

The datasets used for the research work was obtained from the Chinese datasets which contains numerous sets of license plate images for carrying out the training of model and applying the relevant technical stacks of Computer vision for image super resolution out of which it contains total of 2362 training images, 5000 testing images and 1890 validation images [14-17].

B. Data Preprocessing

This section discusses the preprocessing of the datasets which includes the filtering of the images and obtaining the new cycle images from the datasets required for the model generation. The task of preprocessing is carried out with the extraction of image coordinates from the file path implementing a particular constant of image mean and image deviation. The images are then cropped to obtain a particular image reliable for model preparation. The large image plates are discarded and finally the images which are suitable for training is fixed as a particular dataset [26-27].

C. Generative Adverserial Network (GAN)

A generative adversarial network is a machine learning algorithm that uses input data in an unsupervised modelling challenge to uncover and learn patterns in data [25]. It does it in such a way that the model may be utilized to create new plausible cases from the original data [13].

$$minG\ maxD\ V\ (D,\ G) = Ex{\sim}Pdata(x)\ [logD(x)] + Ez{\sim}Pz(z)\ [log\ (1 - D(G(z)))]\ \ldots\ldots\ldots\ldots\ (1)$$

E[x] is expectation value overall P data set
D(X) represents output of discriminator
G(X) represents output of Generator

A GAN comprises two parts or models, named the discriminator after the generator. This generator is to create enhanced output while the classification model classifies the newly created output. The two models are trained such that they are adversarial and until the discriminator model is accepted almost in half the instances, as it implies that the output given by the generator model creates correct examples [1].

1) Generator

The generator part of GAN generates the data which helps the discriminator part to learn and classify its output data as real data. The figure 1 shows the architecture of generator of the GAN. One convolutional layer extracts high frequency information, followed by eight residual blocks in the generator network [28]. Each residual block is made up of two convolutional layers with a kernel size of 33 and 64 feature maps, with the activation function being ParametricReLU. In the system the generator coefficient i.e., learning rate of generator is taken as 1e-4.

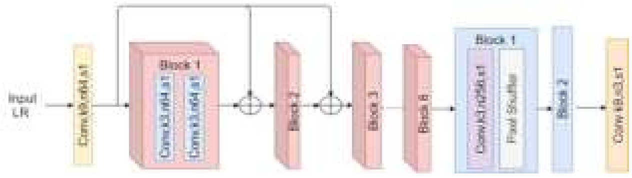

Fig.1` Generator Architecture, where s is the stride k is the kernel size, and n is the output feature maps

2) Discriminator

The main task of Discriminator is classifying the real data from the data created by generator. The Discriminator Part of GAN is tightly integrated to the generator part as to perform the min-max operation and discriminates well between the real obtained images and ground truth images. The discriminator network begins with a single convolutional layer of kernel size 3X3 and a leakyReLU activation function of factor 0.2, followed by seven blocks. Figure.2 shows the discriminator network [3].

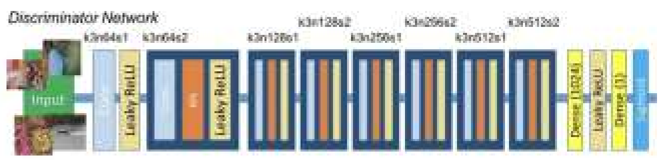

Fig.2 Discriminator network

D. Loss Function

Loss function consider a texture gradient loss L_{teg}, a content loss L_{co}, and loss named adversarial network gradient L_{adg}

$$L_{all} = L_{co} + \alpha L_{teg} + \beta L_{adg}\ \ldots\ldots\ldots\ldots\ldots\ldots\ (2)$$

1) Content loss

Content Loss on output Image Lco: Its goal is to increase the mathematical quality of SR photos by lowering the L1 factor in the error in between produced SR photos and genuine HR images, that may be expressed as

$$Lco = 1\ N \sum N\ i = 1\ |li - l\hat{}i| \ldots\ldots\ldots\ldots \quad (3)$$

For the license plate super resolution, the content loss is the sum of alpha times perceptual loss and mean absolute error (MAE) where alpha is 0.1.

2) Texture Gradient Loss Lteg

It concentrates on gradients of the photos to learn the optimized SR photos with higher objective and perceptual quality. It reduces the gradient error between the produced SR picture and the real Higher resolution Photos, which is be written as

$$Lteg = 1\ N \sum N\ i = 1\ |Sobel(li) - Sobel\ (l\hat{}i)| \ldots\ldots\ldots \quad (4)$$

3) Perceptual Loss

Perceptual loss is closer to human visual perception. Perceptual loss rather than focusing on pixel-wise loss calculates the loss of feature in SR photos from HR photos. Perceptual loss with reference to the paper is the distance Euclidean in space or MS distance between the output of the map of features of the i_{th} layer of VGG network Φi[23-24].

E. Residual in Residual Dense block (RRDB) Architecture

This Architecture is introduced without the use of batch normalization which helps the discriminator to find the relative realness of the image instead of absolute value. This architecture provides the improved accuracy with increase in the performance of the computational complexity in different evaluation metrices like PSNR [9-10].

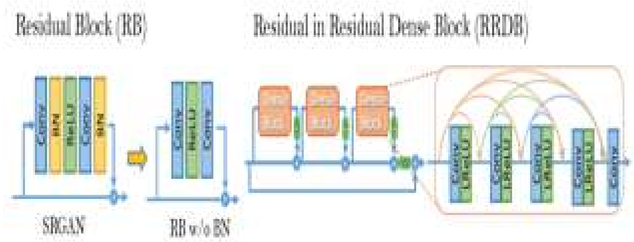

Fig.3 RRDB architecture

We preserve Super resolution using GAN's high-level architecture design and utilize a new basic block called RRDB, as shown in the figure.3. The proposed RRDB uses a deeper and more complicated structure than the original residual block in SRGAN, based on the notion that extra layers and connections may always improve performance. The primary channel uses dense blocks, which allows the network capacity to grow because of the dense connections [22].

F. Model Training

The training of the model with the basic algorithmic and neural network implementations has been carried out using TensorFlow [8].

IV. RESULT ANALYSIS

This section discusses the result obtained for the license plate image super resolution using GAN. The super resolution of license plate has different parts on which the work has been carried out starting from data preprocessing to building the neural network and Architecture of GAN, implementing residual in residual dense block, optimizing the loss function by adding the VGG-19 Pretrained network, model training and then obtaining a high-resolution images of license plate with optimized and efficient evaluation metrices called PSNR. The result has been calculated and measured over 2 different factors, initially the results were carried out over bicubic interpolation and then adding VGG-19 loss function to the MSE loss to create a whole optimized perceptual loss [11-12]. The images obtained through bicubic interpolation was enlarge and sharp which has sometimes higher and sometimes lower PSNR values which was not able to identify the pixel data and the data were lost. While Applying GAN without VGG-19 Network it was seen that the result obtained through the sum of MSE loss and perceptual loss as a content loss, the value of PSNR was very high as a result due to high PSNR value and low MSE the obtained images were over smoothened and due to over smoothness of the images, the pixel data was lost which was not very much efficient. After applying VGG-19 loss to content loss, the PSNR value was optimized, and pixel data were not lost. The adding of VGG-19 to Content loss with MSE was seen to be the best optimized result in all the cases on which the experiment was performed [21].

Fig.4 High resolution images obtained with VGG-19 loss

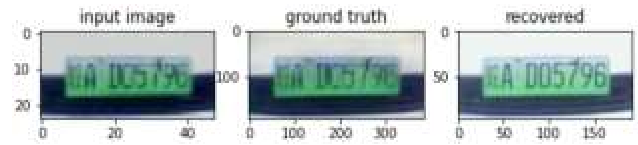

Fig.5 HR images obtained with VGG-19 Loss

Fig.6 HR images obtained with VGG-19 Loss better than ground truth image

Now, taking the values of the evaluation metrices i.e., PSNR and SSIM with bicubic interpolation, vgg-19 network and tabulating them in Table.1

	Bicubic interpolation	Without VGG-19 approach	With VGG-19 approach
PSNR	22.187	26.184	28.696
SSIM	0.914	0.958	0.984

Table.1 Evaluation metrices

V. CONCLUSION AND FUTURE WORK

In this paper, we discussed the License plate super resolution system (LPR). The application developed has a significant contribution to modern world and technology. License plate super resolution results over the algorithms implemented in this paper gives accurate results and is satisfactory but it can be more optimized as per time complexity series using Cycle to cycle GAN architecture for Super resolution of images and even Hyper parameter can be used to stable the learning rate of generator and discriminator of the GAN's Network which will yield efficient and optimized values in evaluation Metrices. This algorithm of cycle-to-cycle implementation is slight complex to implement, and researchers are working on to develop the efficient and reliable algorithms to get access to more advanced field of super resolution of images in the field of computer vision [7].

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