Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Enhancing Defect Image Through Generative Adversarial Network

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Abstract: - In recent years, technology has emerging with the modern era emerges. In today's contemporary world, technology influences in many aspects and the significance of the images has highest priority. This modern technology uses the image for different purposes, which includes the security, identity verification, entertainment, healthcare's mainly for hospitals, in professional works, and many more. Images can be captured in different devices and in different environments. The assurance that the image taken was very clear and without noise is not provided. And all devices will not work on all different environments. For example, the image taken in the mist or the image of the object in water, was not clear, it may blur or it may contain some noises. In this paper, will address the problem of impure images like low resolution or blur images to enhance the quality through GAN algorithm (Generative adversarial Network algorithm). GAN is important approach in deep learning models. GAN works on the principle of Generative models. The main principle of the GAN (Generative adversarial Network) model is to autonomously identify the similarity or pattern in the input data, and it will try to feasibly resemblance of the original dataset. Through this project, the low resolution or blur images where recovered to clear images.

***Keywords*:** GAN, Deep learning, Gaussian noise, Rayleigh Noise, Salt and Pepper noise.

1. Introduction

The main objective of this project is to deal with a significant problem in quality control and computer vision. Image recognition is critical to numerous industries, including manufacturing and healthcare, particularly for hospitals. Images with higher levels of noise, mistakes, blur, and other defects may do more harm in these sectors. The equipment used and the surroundings in which the photo was shot affect the image quality. The movement of the camera, subject motion, softness of the lens, shutter speed, insufficient depth of field, etc. might all be contributing factors to the blurry image. As compression rises, image quality will decline and data loss will begin.

Many models, such as CNN's cancer detection model, used images as input. In this case, the model requires a lot of datasets to determine if the user has cancer or not. There were occasions where the model obtained minimal input. In this particular case, the lack of sufficient input datasets may lead the model to incorrectly train. In this case, the Generative Adversarial Networks, or GANs, which will assist in producing a resemblance of the input data. This makes it possible for the generation of input images that sound like the input photos. Additionally, we may use such datasets to train other models.

The study makes use of deep learning techniques called Generative Adversarial Networks (GANs) to lessen this. The main objective is to provide data which is identical from actual data; low-quality images can be restored by modulating this ability. We can ensure that low-quality photos can be handled and regained by employing the GANs technique. When given noisy or low-quality image input, the GANs technique assists to process and produce a high-quality image.

The two primary functions of GAN are how the images were regenerated. Discriminator is one, and generator is the other. Based on the zero-sum game theory, the GAN operates. where the two players are the discriminator and the generator. One's gain is equivalent to the others loss, in the end the net improvement in benefit of the game will be in 0.

The study main focus is to give an image with a highly reliable in the field of manufacturing processes, hospitals, and other areas where the image plays an important role by increasing accuracy and reducing errors and noise in the picture.

2. Literature Review

In recent years, a number of methods for improving images using different deep learning models have been proposed. The generative model known as Generative Adversarial Network is favored by numerous writers among those models. The images produced by the generative model will resemble the original image after multiple iterations. These generative models will be useful in a variety of fields where images are essential. There are numerous varieties of generative models, including Vanilla GAN, CycleGAN, and GAN. This field was the focus of many researchers, and some references were

Reference	Publication Year	Algorithm	Summary	Future work
1	2021	GAN	In this study the author tries to propose a component enhancement network which is based on the GAN for recovering low quality image from low light	In the future, the author work will focus on the higher resolution research conducted on the low-light images.
2	2022	GAN. .	In this paper the author analyzed low-light image as a dataset for enhancement algorithm, and tries to improve the quality of images by analyzing some technical means and methods, and regain the original information of images	The limitation of this algorithm was it cannot restore the details of the overexposed areas well. In future it will be avoided and will work on solving the details of image enhancement.
3	2020	Image to image translation, GAN.	In this article, the author suggests a detailed rundown of GAN-based image-to-image translating methods and the variations between them.	To address the difficult problems with picture creation, quantum adversarial networks that generate images for image-to-image translation will be researched and utilised more in the future.
4	2022	GAN, denoising, robot, cyclegan	In this paper, the author used better Cycle GAN model is suggested that the model is based on three common noises, and finally, through a lot of experiments	In future, the author needs t work on wide range of datasets, improve and reduce the error more.

5	2021	GAN, BGAN, WGAN, LR-GAN	In this paper the author suggest the basic overview of GAN and its different types were introduced with its applications.	This work can be reached out by looking at later forms of GAN like BoundarySeeking GAN (BGAN), Wasserstein GAN (WGAN), Layered Recursive Generative Adversarial Networks (LR-GAN), etc.,.
6	2019	CNN,GAN	In this paper the author porposed a CNN to detect skin cancer with the input image which was generated by GAN.	In future, the author tries to increase the different types of cancers with more image classification and tries to improve accuracy.
7	2020	CNN, GAN, Image processing, Stochastic gradient descent	In this paper the author proposes the system for an self-parking system by the number plate recognition is discussed.	In future work the author try to enhance the accuracy of classification, for that author suggests to implement the hybrid approach known as CNN-SVM for vehicle number plate recognition.
8	2023	improved GAN	The author of this research recommends a better GAN-based highway traffic image augmentation approach.	In the future, the author hopes to broaden dataset's categories for various climates and further boost image improvement capabilities.

3. Methodology

The proposed work, Enhancing the images using the GANs is done through the training of the network to generate the high quality images which bear resemble to the input images but with improved or higher visual characteristics. GAN often try to create the image which was mostly like the input images and process it. Below is the basic methodology for enhancing the images through GAN.

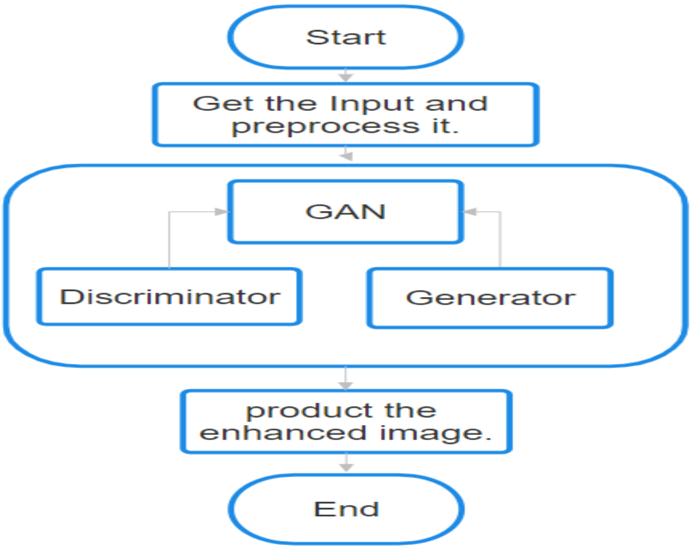

Figure 1: Workflow of the GAN model for enhancing image

3.1. Data collection and pre-processing

For this study the dataset pair used here is our own dataset. This dataset contains of low-quality or low-resolution and high-quality and high-resolution images for the input of GANs model. And be sure that the collected dataset is diverse and it represents all the scenario that the target required for GAN to handle. Pre-process the input, resize, normalize, and augmentation if needed.

Noise in an image is defined as the frequent changes in brightness or colour information in images. It can be produced by the image sensor and digital camera. There are some predefined noises that are identified in the past years. Those noises are the source for the study of removing noises and enhancing the images. The dataset used here is our own images and we are adding noises to the dataset. The noises like Gaussian noise, Rayleigh noise, Salt and Pepper noise, Uniform noise were added. And the model was trained with the noised image and for the target the image without the noise is used.

Gaussian Noise is a statistical noise which the model with a Gaussian distribution. It is used as additive noise to generate white Gaussian noise. As it stated in “GeeksForGeeks” sited as “https://www.geeksforgeeks.org/noise-models-in-digital-image-processing/”

$$p(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-m)^2}{2\sigma^2}}$$

Rayleigh Noise is a continuous probability distribution and it is used for positive valued random variables. This noise is recognized when a vector’s magnitude related to the elements with direction.

$$p(z) = \frac{2}{b}(z-a)e^{\frac{-(z-a)^2}{b}}$$

Salt and Pepper noise is also called as the impulse noise. This noise is often seen on digital images. The cause of the noise is by sharp and sudden interruption in the input image signal. By randomly changing the noise values like the pixels change to white, black or grey values. Those addition of noise is known as the salt and pepper noise.

Figure 2. Raw input dataset

3.2. Define Generator and Discriminator Networks

GAN algorithm is working on the basis of the two networks known as Generator and Discriminator. GAN is made up of Generator and Discriminator where both are trained under the earning methods [5]. Both will work together to enhance the image. The Generator's work is to create an image that is closely resembling the image and produce it as output. Those images were then passes as the input for the Discriminator. GAN is a unsupervised learning which [9] gives high quality images by analysing with the GAN. The Discriminator's is simply a classifier that says similar or not. It will keep on trying to identify the distinguish between the real image and the image which is generated by Generators.

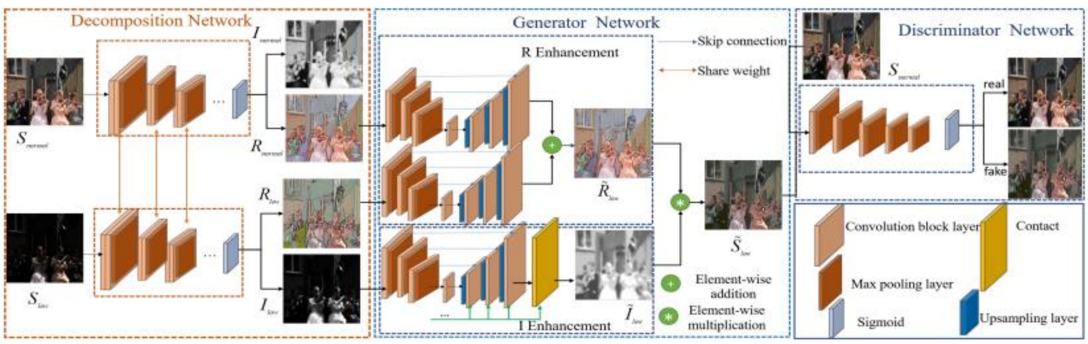

Figure 3: - Referred from "Ning Rao, Tao Lu" from the paper title "Seeing in the Dark by Component-GAN" published in 2021.

3.2.1. Generator

The main work of the Generators is to create a fake data that are nearly resembling the real image. It will act upon the feedback which comes from the discriminator. Classical generative models are unable to precisely imitate complicated distributions [12] and instead employ various versions of the probability density function. The Generators keeps on learning till the discriminator fails to identify the image as fake. It will work till the Discriminator classify the generated image as a real image. GAN takes the random noise as the input and it will try to match the real image and it sends to Discriminator. The Generator learns from the Discriminator's comments since it has no direct access to learning; the real dataset [5]. The training of the generators includes,

- It will take the random noise as input.
- The generator network will transform the random input into a data with information.
- The discriminator network identifies the difference between the generated data.
- The discriminator output will be passed to loss functions.
- The generator loss which works on the output of the discriminator will punishes the generator model for not succeeding to fool the discriminator.

In general, neural network model working, the model will predict the model with some initialized weights and biases to predict the output and it was updated in backtracking to reduce the error and loss of its output. Like those neural network this GANs algorithm learns from the output, however this is not directly connected to the loss functions that we are trying to affect. The generators were connected to the Discriminator and the discriminator connected to two loss functions.

The residue or error of network is handled by backpropagation. It will adjust each weight in the right to left means the weight of the generator will have adjusted after the discriminator. The changes will be done only while the Generator network was running.

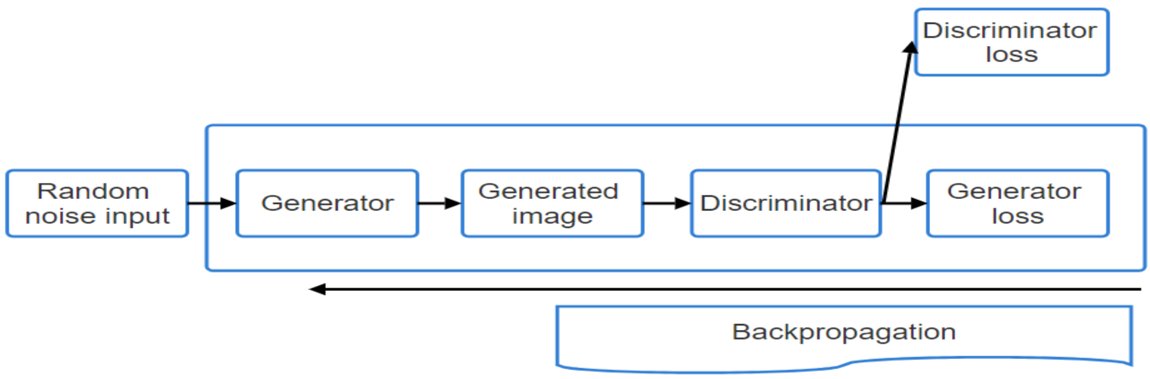

Figure 4: - The above figure explains the workflow of the generator of GAN.

The architecture of generator is divided into two parts down-sampling, up-sampling. In up-sampling, transpose convolutional layer is used. The main difference between the transpose and normal convolutional layers is that decreases input elements through the kernel, the transposed convolution present in the model suggests input elements in the kernel, thereby generating an output which is higher than the input. This will be responsible for the reconstruction of features that are extracted from the down-sampling. And the normalization and ReLU is connected in the up-sampling.

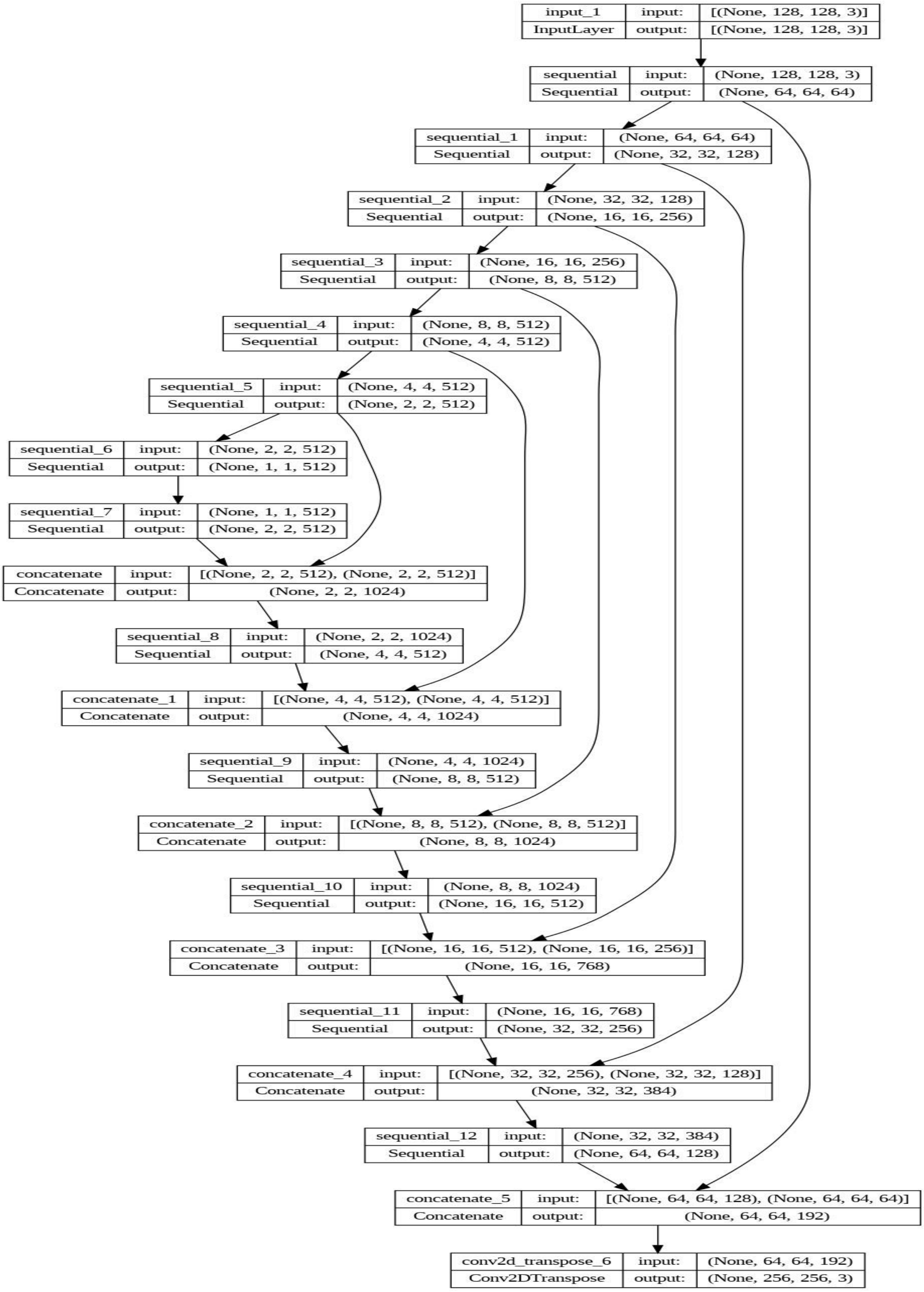

Figure 5: - The above diagram shows the model architecture of the generator model.

3.2.2. Discriminator

The main work of the Discriminator is to find the distinguish between the real image and Generator network generated fake image. The discriminator is simply a Classifier. The Discriminator is a Deep convolutional network. The discriminator will extract the features of the images in different layers like as Convolutional Neural Network. It will work to reject the generator generated image. The Discriminator training data's where classified into two,

- Real data: - This is nothing but the original picture that are passed to enhance. Discriminator uses the real data as true values during training.
- Fake data: - This instances were built by the generator. Discriminator will treat this data as a negative example during the training.

Discriminator architecture connected with two loss functions. They were Discriminator loss and Generator loss. Discriminator only deals with the discriminator loss in discriminator training. The generator loss will be deal when the Generator training is going on. The discriminator loss will penalize the discriminator each time when the discriminator fails to classify the fake image, misclassify the image as real image as fake or fake image as real. The discriminator will receive the penalty and it will train accordingly.

Working of Discriminator

- The discriminator will receive the real image and fake image as a input.
- It will try to distinguish between the both images, and try to classify it.
- The discriminator loss will penalize the discriminator for misclassifying.
- The weights of the will be adjusted through the backpropagation from the discriminator loss.

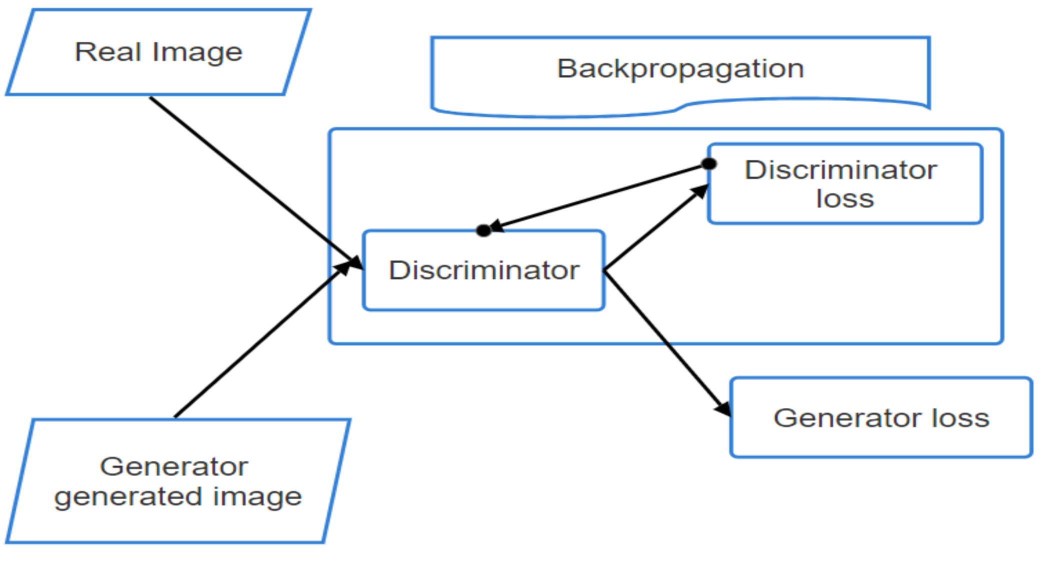

Figure 6: - The above flowchart explains the workflow of Discriminator.

Two image pairings made up of I and G(I) are the discriminator D's input. D is trained to discriminate between these two image pairs, and its output is a scalar in the range [11, 12].

Discriminator's architecture in this study is built on with the initializer, input layers, resizing the input, concatenation, Down-sampling blocks, Zero padding, convolutional layers, Model definitions. The architecture is initialized with the mean 0 and with the standard deviation of 0.02. The weights in the model was initialized on the basis of the mean and the standard deviation. In this study, there are two input layers were created, one input was defined for the input image and the other input was defined for the generator's output image. The input images are in shapes for the [128,128,3] and [256,256,3] respectively. Down-sampling of the image were done for the compression. The first block of the down-sampling will reduce the spatial dimension of the image from (256,256) to (128,128). The second down-sampling will reduce the image by (64,64) and it followed and reduced to (32,32). Before applying the convolutional layer, the image was zero padded, so that every nook and corner of the image were analysed. The convolutional layer is applied in the architecture. The 512 filters with the kernel size of 4X4 was applied. The last convolutional layer is applied with the 1 filter with the kernel size of 4X4. Batch normalization is introduced between the network of convolutional layers. Through this architecture the discriminator was defined.

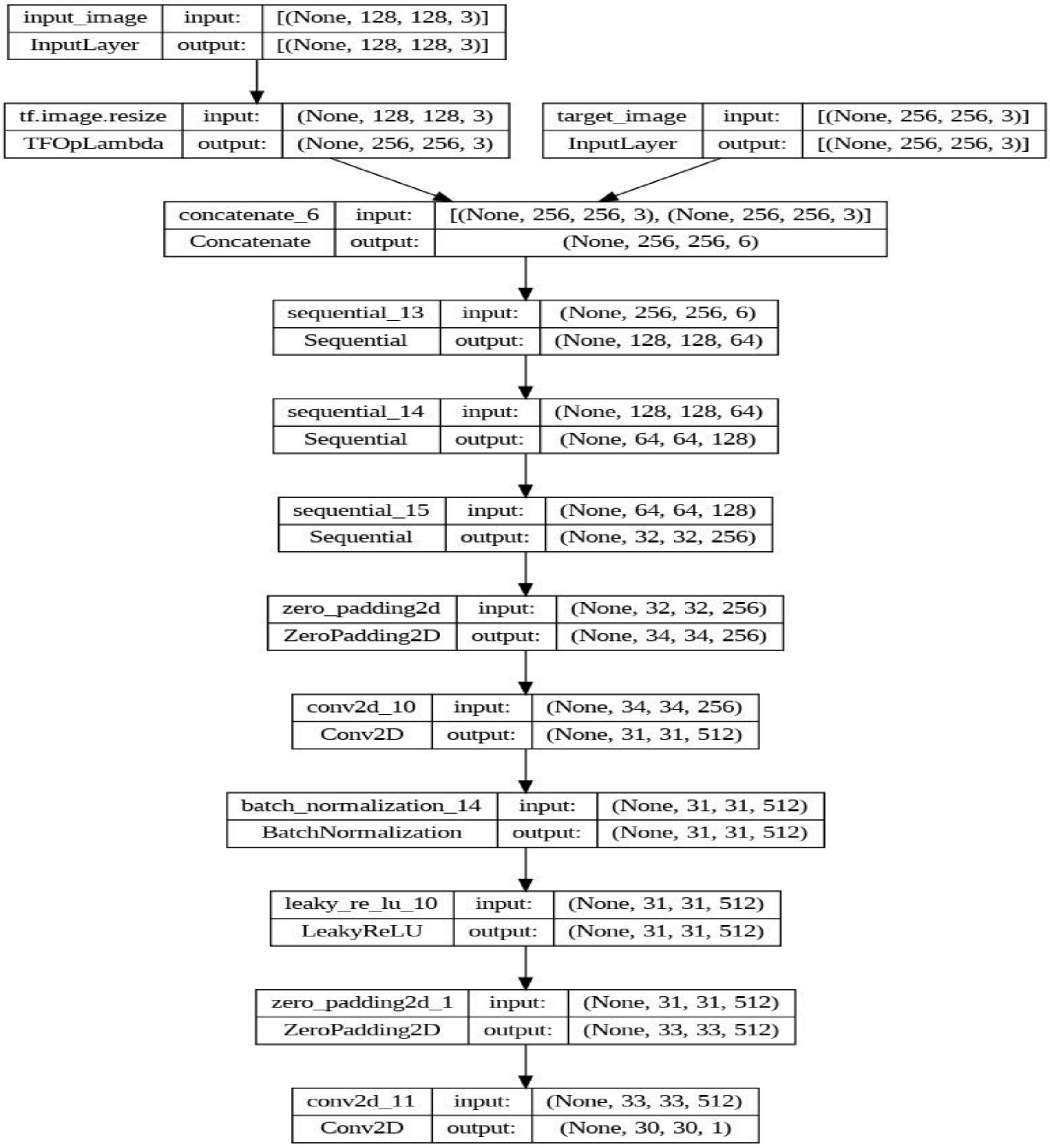

Figure 6: - Architecture of the discriminator in GAN.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

3.3. Loss functions

GAN model uses two loss function. Generator loss and Discriminator loss. The overall loss function of the network model is [2]

$$Loss = \lambda_1 L_S^G + \lambda_2 L_S^L + \lambda_3 L_G^G + \lambda_4 L_G^L$$

3.3.1. Generator Loss

The generator loss will be activated after the discriminator network. The generator loss is defining to minimize the difference between real image and generated image. One common loss function used is binary cross-entropy loss. The generator minimizes this loss by fooling the discriminator into classify the generated image as real. The loss function used for this study is min-max loss function and cross-entropy loss function. The min-max loss function is like a two player game one tries to minimize and other to do it opposite. Here the generator tries to minimize the function while the discriminator tries to maximize the function.

E_x [$\log_x$(Dis(x))] + E_s [$\log_s$(1 – Dis (Gen(s)))]

The cross-entropy loss function is a function that is used to the entropy of a random variable is the average uncertainty, or information of the possible outcomes.

$-\sum f_s(x) \log f_s(x)$

3.3.2. Discriminator Loss

In GAN, Discriminator Loss is function used to train the discriminator model to know the difference between real data and fake data accurately. The Discriminator loss function used is binary cross-entropy loss, it measures the contrast in the predicted probability distribution in discriminator and in the actual labels. For discriminator the loss function that were added are min-max loss function and the cross-entropy function as mentioned above.

$$L_S^G(x, G(x)) = 1 - \frac{1}{N} \sum_{p=1}^{N} (S(p))$$

The above mentioned is the difference in local structure similarity between the generated image's matching local small blocks and the randomly cropped local blocks from the underwater image [2].

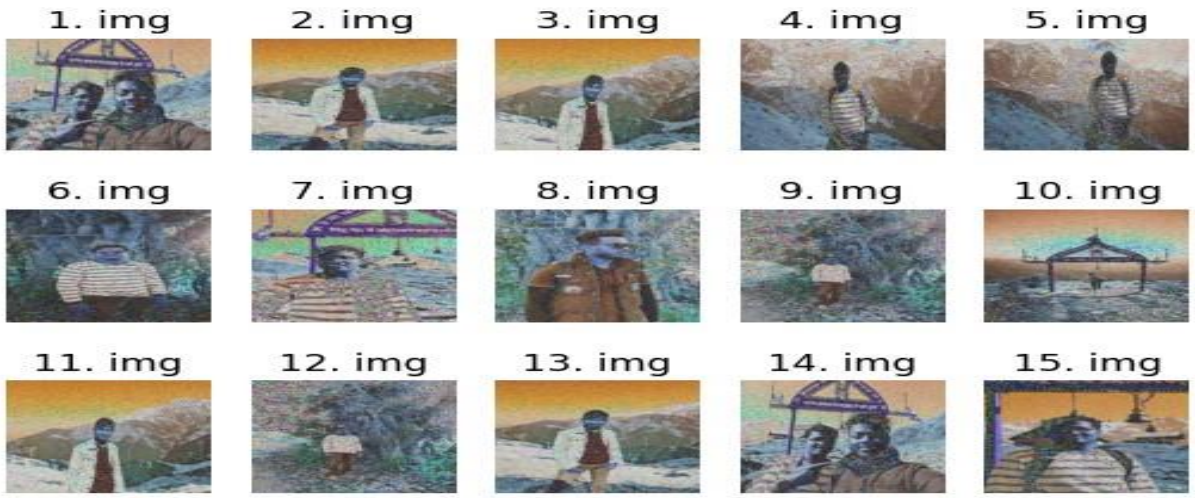

Figure 7: - Input images that are passed to the architecture.

3.4. Working

The input images were passed to the GAN model. Firstly, the Generator in GAN takes the random image with noise content and process it and produce the output. Then it will pass on to the Discriminator model. The Discriminator will take two input. One is the real image and the Generator generated image. Discriminator will try to distinguish the difference between the actual image and generated image. The role of Generator is make the image that Discriminator can't distinguish between the real and fake and pass the output as real image for fake image. The discriminator output will evaluate by the two loss function. Generator loss function will penalize the generator not to do the job correctly. And Discriminator loss function will penalize if fails to classify. If the discriminator identifies the fake image, then the weights for both the discriminator a d generator one by one through backtracking. It will change the generator weight when the generator network is running and discriminator weights also updated when the discriminator was running to avoid confusion. Then this steps will be repeated till the Discriminator identifies the generated image as real image.

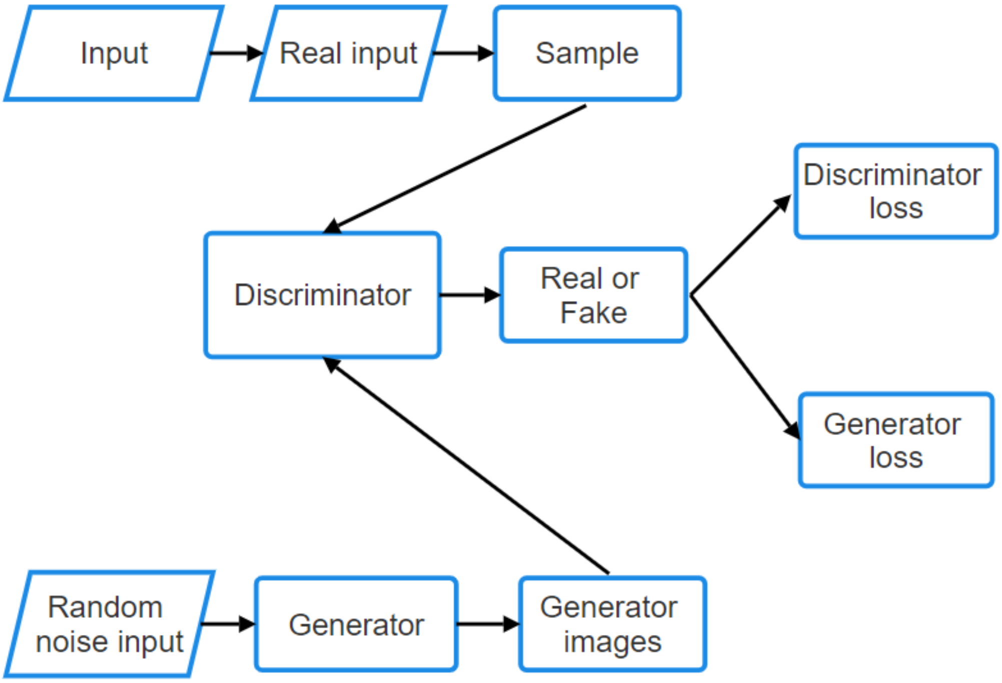

Figure 8: - Explains the workflow of the GAN

3.5. Convergence

GAN convergence is one problem to keep in mind. Convergence occur when the weights are not updated or it was updated by very low value. Then the discriminator will not train and it will classify wrongly. So that the generator also thinks that the very low or no update requires. The training of the generator also stops, and it will give the same output. This will pass on to the next iterations too. Then the model will not train anything. So in this research the convergence was monitored and tried without any convergence.

4. Conclusion

This study has employed the enhancing the image by using the Generative Adversarial image. Firstly, a generator was constructed. Through the generator the model produced the more similar image to the input image. The discriminator network was constructed and it was running after the generator. The discriminator was successfully classifying the generator generated image as true. As a result, the GAN produces the image that were similar to the real image and generator generated image. The proposed model is able to identify the noises in the images and also trained to eliminate the noise while training. The noised images that are stored for the testing was tested. The model is able to recognize the noise and it eliminates the noises and it produces the images that are merely close to the original image. In future this model is further developed so that the images with any noise is removed and the it may produce more quality images.

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