CREATION OF SYNTHETIC DATA OF CHEST X-RAYS FOR DETECTION OF COVID-19 USING UNETGAN

[1]Dr. T. Srinivasulu, [2]Dr. Ranga Swamy Sirisati, [3]C. Sunil, [4]Dr. K. Srinivasa Rao

[1]Department of Mathematics, Vignan's Institute of Management and Technology for Women, Kondapur, Ghatkesar, Hyderabad, Telangana

[2,3]Department of Computer Science & Engineering, Vignan's Institute of Management and Technology for Women, Kondapur, Ghatkesar, Hyderabad, Telangana

[4]Department of Computer Science and Technology, Yogi Vemana University, Kadapa, india

ABSTRACT: People began exploring using available chest x-ray images of lungs in 2019, when COVID-19 began spreading as a viral infection over the world. However, the research paper discovered that the available photos are limited, and the majority of the symptoms are comparable to pneumonia sickness. So, before completing the multiclassification procedure, this study aims to increase the dataset size by merging the UNET with cyclic GAN's. The majority of real-world data is in an unbalanced state, which has an impact on the design's overall architecture and performance. Many researchers have used manipulation techniques such as translation, rotation, and others to increase dataset size, but these fundamental and easy procedures have little effect on the model due to the high dimensionality of medical pictures. By executing segmentation utilising the UNET operation, the improved cyclic GAN's mechanism aids the research article in creating a balanced dataset with a greater number of augmented or reconstructed CXR images.

Keywords: Cyclic GAN, Semantic Segmentation, UNET's, Up-Down sampling, Cycle Consistency, Contraction and Expansion Path

INTRODUCTION:

For the past few years, CNN has been the most often used word by most researchers, industry professionals, and other significant AI figures. CNN is a deep learning method for distinguishing between different input items based on the weights applied to them in a prioritized order. The fundamental benefit of artificial neural networks is their ability to recognize relationships between spatial and temporal variables using various types of filters. Any network's main goal is to interpret the input images with the fewest amount of trainable parameters possible. In a real-time scenario, we can see images of various colour systems such as RGB, CMYK, and others, necessitating the creation of a network that can efficiently convert the image into an easy-to-process format while maintaining all of the image's important features in order to obtain accurate prediction results. The following are the major components of networks:

i. Kernel: Also known as a "filter," this component is used to read the image's pixel values one by one. The size of the kernel determines how many pixels it must process. If K is 4*4*1, then reading the entire image will need 16 shift operations (reading four values horizontally and vertically).The convolution layers' main goal is to create a convoluted matrix that holds information about high-level characteristics. We can get low-level properties like colour, gradients, and others by increasing the number of layers.

ii. Padding: This is an attribute that controls the size of the output. If the padding property is valid, it returns an output matrix with smaller dimensions. If the padding attribute is set to the same value as the input, the output matrix will have the same number of dimensions as the input matrix.

iii. Pooling Layer: As the number of features in the image grows, the system's time complexity grows. This pooling layer is used by the CNN to preserve all of the key features while processing at high speeds. It also reduces the system's computing power. To extract the features from the image, the suggested method uses the max pooling layer.

iv. Fully Connected Layer: Prior to transferring the input to this layer, the system must flatten the matrix and resize it to the required dimensions. This layer's job is to detect the attributes that have non-linear relationships after obtaining the flattened values. To classify a person's age, the suggested system uses both feed forward and reverse propagation techniques, as well as the softmax activation function.

LITERATURE SURVEY:

Efficient GANs were created by Saleh Albahli, Swamy, S. et al [1], [2] utilising CXR images to balance the dataset. Because the dataset contains several classes ranging from no disease to invasion, the photos are scored on a scale of 0 to 5 to construct augmented images using a combination of auto encoders and GANs. If any image exceeds the threshold value, it is discarded, and in the end, this model has generated 5000 photos for each class label and balanced them in order to produce a correct detection system. The deep learning model has one pooling layer, one flatten layer, and two fully connected layers that are used to construct fake images using simple image alterations and a pre-trained model called "Inception." Residual units are also used in the model to improve the model's work flow by simplifying the linkages.

PirMasoom Shah, Sirisati R [3], [4] used Deep Convolution GAN to create synthetic images. The model in this study uses three sorts of class labels: healthy, pneumonia, and covid. The main benefit of this study is that it verifies the generality of the validation data using K-Means clustering on the three class labels before doing the classification. It used an Attenuation map to verify the confidence value of each image in the decision-making process to determine the relevance between the features of the image. After that, the system generates synthetic data and uses EfficientNETB4 to train it for classification. The activation maps are used in this model to provide more information about the internal relationships concealed in the image.

Nour Eldeen M. Khalifa [5] created a GAN-based transfer learning model that was fine-tuned. The combination of three pre-trained models with GANs, namely ALEX, GOOGLE, and RESNET-18, was compared in this model, and it was discovered that RESNET-18 outperforms the other two models. The generator model in this study caused noise using the Gaussian mechanism, and to classify the model, the researchers created a fine-tuned model by combining the Squeeze, ALEX, and GOOGLE, with 12 layers of augmentation to mislead the discriminator as much as feasible.

To analyse the best strategy to forecast Covid-19, Soumya Ranjan Nayak[6] conducted a comparative research on multiple deep learning techniques using pre-trained models. The author of this article examined eight pre-trained models to determine if a person has Covid-19 or not based on a chest X-ray. The ImageNet dataset is used in the comparison study. The research proposed the best pre-trained model based on well-fine-tuned hyper parameters. Based on accuracy, the author demonstrated that ResNet-50 and ResNet-34 are the best models.

Sirisati, R.S., Kumar, C.S [7] suggested a light-weight approach for binary and multi-category categorization. The binary classification model does not use transferred learning. The model uses a pre-trained ResNet8 model with Adam and cross-entropy optimization functions, and the training is done with Conditional GANS, which are commonly used to create new synthetic images. The loss function, which analyses the difference between real and predicted labels, is used to evaluate neural network models . The optimizer's job is to find the loss function that gives the most accuracy with the least amount of loss. Stefanos Karakanis [8] suggested model uses the Adam optimizer, which determines the average of momentum exponentially among the optimizers available. When the process becomes slow, Adam's main benefit is that it uses bias correction. Swamy, S.R. [9] suggested conditional GANs create new images[10-14] dependent on the received information's conditions.

PROPOSED METHODOLOGY:

In the proposed research, the model worked on the dataset collected and published by the NLM, USA. The dataset contains 326 healthy images, 330 pneumonia and 400 COVID patient details. A few sample of CXR images are illustrated in figure 1.

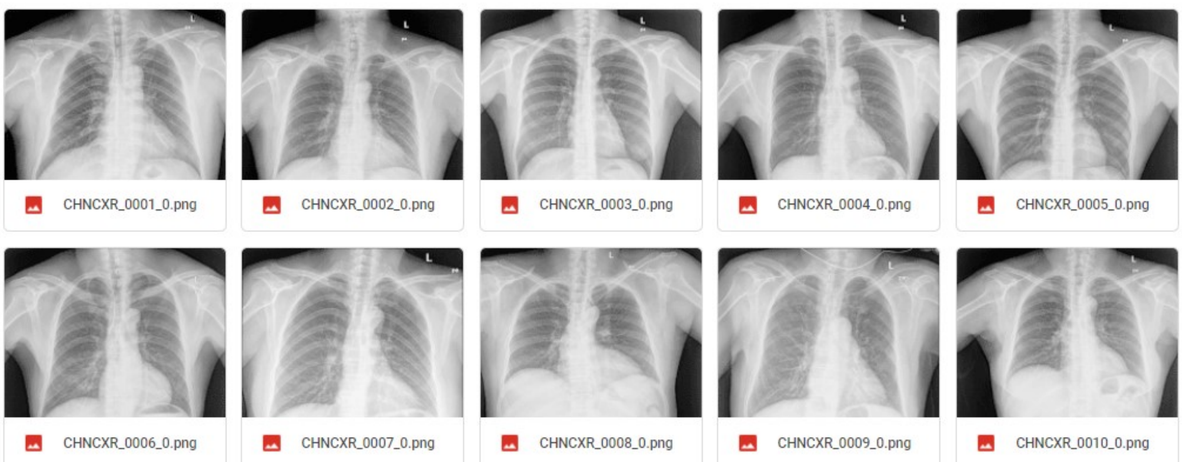

Figure 1: Sample Images of CXR collected by NLM, in association with various hospitals

These modest amounts of samples are insufficient for designing an efficient deep learning neural network, resulting in either significant bias or large variance. To address this problem, the model proposes that synthetic data be generated using UNET integrated GANs, in which augmented images for masked images are constructed by translating and reconstructing the complete image. The following parts depict the full procedure:

Data Visualization: It is simple to grasp the data relationship between features in machine learning, but in deep learning, the relationship between complex features cannot be displayed using linear elements. However, learning the features from training data is critical in learning applications. As a result, the suggested research used a typical way to analyse the data, plotting photographs as shown in figure 2.

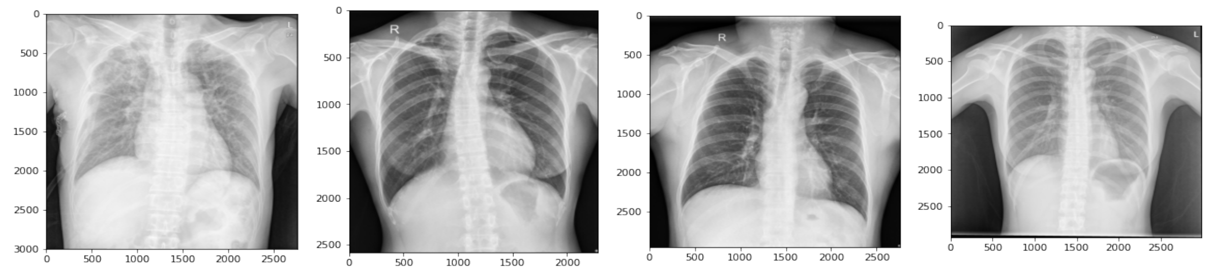

Figure 2: Analysis on the Original Chest X-ray Images

Cyclic GAN: The major goal of using cycle GAN in this study is to translate one image to another by executing pixel-by-pixel operations. A simple image is represented as a map vector in the CGAN process, and the encoder conducts embedded operations on it, producing "Translated Styles" as the generator's output. The Discriminator takes two inputs: "Translated Styles" and "Targeted Styles," and builds a vector map that labels false as "0" and real as "1." The vector operations are carried out in the latent space. The loss sustained owing to consistency as a result of the cycle formation, i.e., translating one image to another and re-constructing the original image from the created image, is given more attention in this study. Equation 1 shows how to calculate the consistency loss.

G(G New (Image))=Loss(Image)– (1)

UNET Segmentation: The primary goal of merging UNET and CGANs is to produce semantic pictures, and UNETS are widely used for semantic segmentation. This semantic segmentation method adds a class label to each image pixel and searches deep for the predicted class labels. The UNET model is made up of an encoder that uses covenant layers in conjunction with pooling layers to extract the factors that affect each component of the layer, and a decoder that uses a transposed CNN to identify the localised parameters, all of which are connected in fully connected mode.

RESULTS AND DISCUSSION:

The various outputs produced during the training and GAN designing phases are discussed in this section. The Generator and Discriminator are shown in Figure 3 during the contraction phase of UNET Segmentation. The sizes of the translation and reconstruction architectures are clearly indicated.

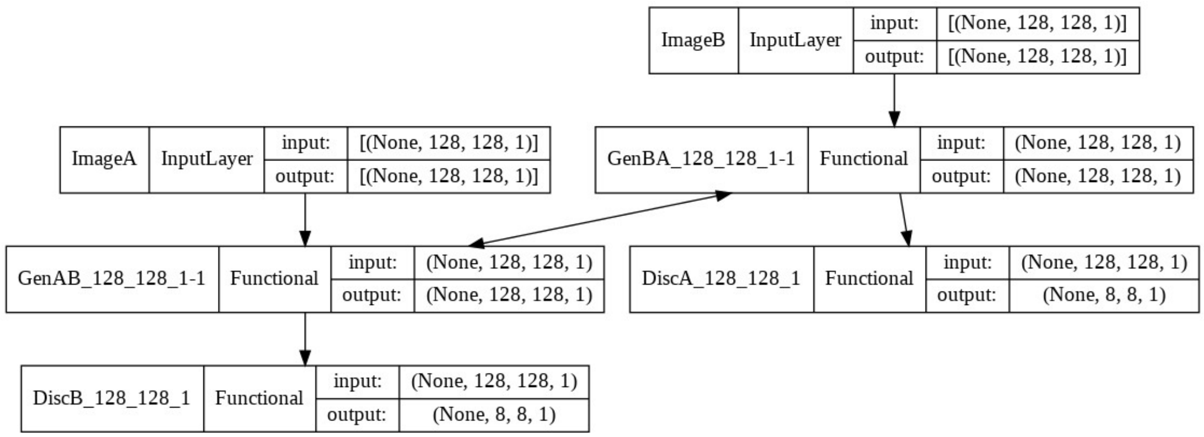

Figure 3: Generator and Discriminator Functional Creators for both Images

The final output produced by the HCU GAN is represented in figure 4. These images are passed as input for the discriminator to classify the images as real and fake.

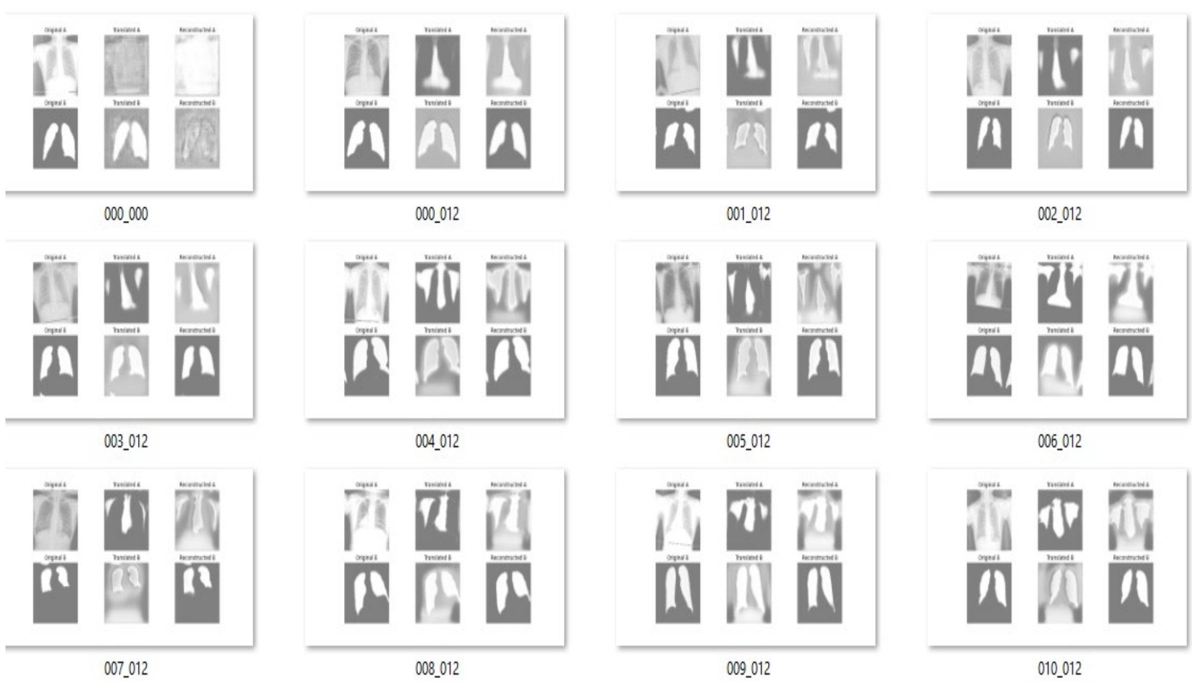

Figure 4: Augmented Images creation of Chest X-rays using GAN's

CONCLUSION:

In a real-time setting, the conditions are uncontrolled, and the system may confront challenges such as sickness dataset labelling, addressing the data imbalance problem, and overfitting issues due to the smaller amount of diagnostic clues. Because selecting and applying all of the possible geometric changes involves a significant number of computations, the system suffers from overfitting. The auto augmentation procedure can effectively improve accuracy by using pre-trained models and building a sound policy schema, such as Hybrid Cyclic UNET GAN. The system is able to tackle the problem of overfitting that occurs as a result of simple photo processing since the Hybrid Cyclic UNET GAN modules generate additional training data. Instead of using trained models, the suggested model used a semantic segmentation component known as "UNET" and achieved a best accuracy of 97.19, which is around 1.5 percent better than the base model.

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