www.ijecs.in
International Journal Of Engineering And Computer Science
Volume 13 Issue 10 October 2024, Page No. 26551-26559
ISSN: 2319-7242 DOI: 10.18535/ijecs/v13i10.4915

An Efficient Automatic Covid-19 Detection from Medical Images Using Hybrid Cnn-Rnn And Gan Network

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Abstract

Coronavirus, commonly known as COVID-19, is a viral illness caused by the SARS-CoV-2 virus, which stands for severe acute respiratory syndrome coronavirus 2. The global spread of COVID-19 has had a deleterious effect on both the public health and economy. One major step in the battle versus COVID-19 is detecting the virus in patients through positive chest X-rays. Early studies have identified abnormalities in the chest X-rays of infected patients that are indicative of the disease. Research has shown high accuracy in identifying COVID-19 patients using chest X-rays, which has spurred the development of various deep learning algorithms. Convolutional neural networks (CNNs), a type of deep learning model, require large amounts of training data. However, due to the recent emergence of the pandemic, gathering a substantial dataset of radiographic images in a short time has been difficult. To address this, our study introduces a model called CovidGAN, which employs a Generative Adversarial Network (GAN) to generate synthetic chest X-ray (CXR) images. Additionally, we propose a hybrid CNN-RNN network for identifying COVID-19 in X-ray images, achieving a classification accuracy of 98.75%.

Keywords: Automatic Covi-19 Detection, GAN Network, Medical Images.

1. Introduction

COVID-19 disorder is a respiratory condition induced by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The ongoing COVID-19 pandemic, which originated in Wuhan, China, in December 2019, has since circulated globally. By May 12, 2020, over 4.18 million persons and 286 thousand deaths had been reported across more than 200 countries and regions. With no vaccines or specific treatments available at that time, the most effective way to curb the spread of COVID-19 was to conduct widespread testing and promptly isolate infected individuals.

Chest X-rays and specific health indicators can be used to diagnose this illness. Radiologists may rely on chest X-rays as a visual marker for coronavirus infection. This has led to the growth of various machine learning techniques, with experiments showing a high probability of accurately identifying COVID-19 infections through X-ray images. CNN networks, when provided with enough data, have achieved advanced performance in medical imaging [1]–[4]. This success is due to training with labeled data and fine-tuning millions of parameters. The generalization performance of CNNs is heavily dependent on the quantity of labeled data, as they tend to overfit on small datasets due to their massive number of parameters. The biggest challenge in medical imaging is the limited size and diversity of available datasets [5]– [7]. Gathering medical images is a costly and time-consuming procedure which needs the expertise of radiologists and researchers [6]. Moreover, because the COVID-19 pandemic is so recent, it is difficult to collect sufficient chest X-ray (CXR) data. To address these limitations, we propose using artificial data augmentation to mitigate the shortcomings of small datasets. Data augmentation techniques are used to artificially expand training datasets. These techniques typically involve simple transformations such as scaling, rotating, flipping, blurring, sharpening, adjusting contrast or brightness, and modifying white balance [8]. This traditional approach is fast, reliable, and easy to implement, but the changes made to the data are minimal since it only produces slightly altered versions of existing samples. Thus, it doesn't generate entirely new data.

To overcome these limitations, synthetic data augmentation has emerged as a more advanced method. One example is the Generative Adversarial Network (GAN), a model that creates entirely new, synthetic images. GANs work by pitting two networks against each other: a generator (G(z)) that creates fake images, and a discriminator (D(x)) that tries to distinguish between real and fake images. The generator aims to deceive the discriminator, while the discriminator works to maximize the cost function V (D, G), with the generator striving to minimize it [9]. X-rays are one of the primary tools for diagnosing COVID-19 because they are affordable and pose minimal radiation risk [10], [11]. However, identifying COVID-19 from X-rays is a complex task. Radiologists must carefully analyze the images for white areas filled with fluid and pus, which takes time and expertise. Furthermore, diseases such as pulmonary tuberculosis can be mistaken for COVID-19 by radiologists or specialized physicians [12].

In recent years, the use of artificial intelligence in medical diagnosis has gained traction. AI has been used to detect brain tumors in MRI scans [13–14], diagnose brain disorders using EEG [15–16], identify breast cancer in mammograms [17–18], and detect lung diseases, including COVID-19, using X-rays [19] and CT scans [20]. Deep learning, a subset of ML, has revolutionized beliefs in many AI usages, particularly in medical image analysis, where it has achieved human-level accuracy [21], [22]. Over the past decade, DL has significantly impacted data processing across a wide range of tasks, including medical diagnosis [22]. Several recent studies have focused on developing deep learning classifiers for detecting COVID-19 using medical images [23–26]. Researchers often design multi-class classifiers to differentiate between normal X-rays, viral pneumonia, bacterial pneumonia, and COVID-19, leveraging the available datasets. However, COVID-19 X-ray datasets typically contain only a few hundred images, limiting the amount of training data. To address this, many studies have explored the use of Generative Adversarial Networks (GANs) for data augmentation to enhance the available dataset [27–28]. In this study, we propose an efficient CNN-RNN model for detecting COVID-19 from X-ray images. This hybrid neural network is designed to detect and classify patient images more accurately. In the first stage, the model extracts image features using a deep convolutional neural network (CNN). These extracted features are then passed to the RNN layers for final classification. By combining convolutional neural networks with recurrent neural networks (RNNs), the proposed model improves detection accuracy.

This study makes the following contributions:

1. Introduction of a Conditional Generative Adversarial Network (CGAN) for generating synthetic chest X-ray (CXR) images to augment the training dataset.
2. Proposal of a hybrid CNN-RNN model for detecting COVID-19 in X-ray images.

The structure of this paper is organized as follows: Section 2 explains the dataset and the CNN-RNN architecture used for COVID-19 detection. The results are discussed in Section 3, and the conclusions are presented in Section 4.

2. Material and method

This part details the attributes of the dataset used, the generation of synthetic images through the GAN network, and the application of CNN and RNN neural networks. The flowchart of the proposed method is presented in Fig. 1, which is further detailed in the next subsections.

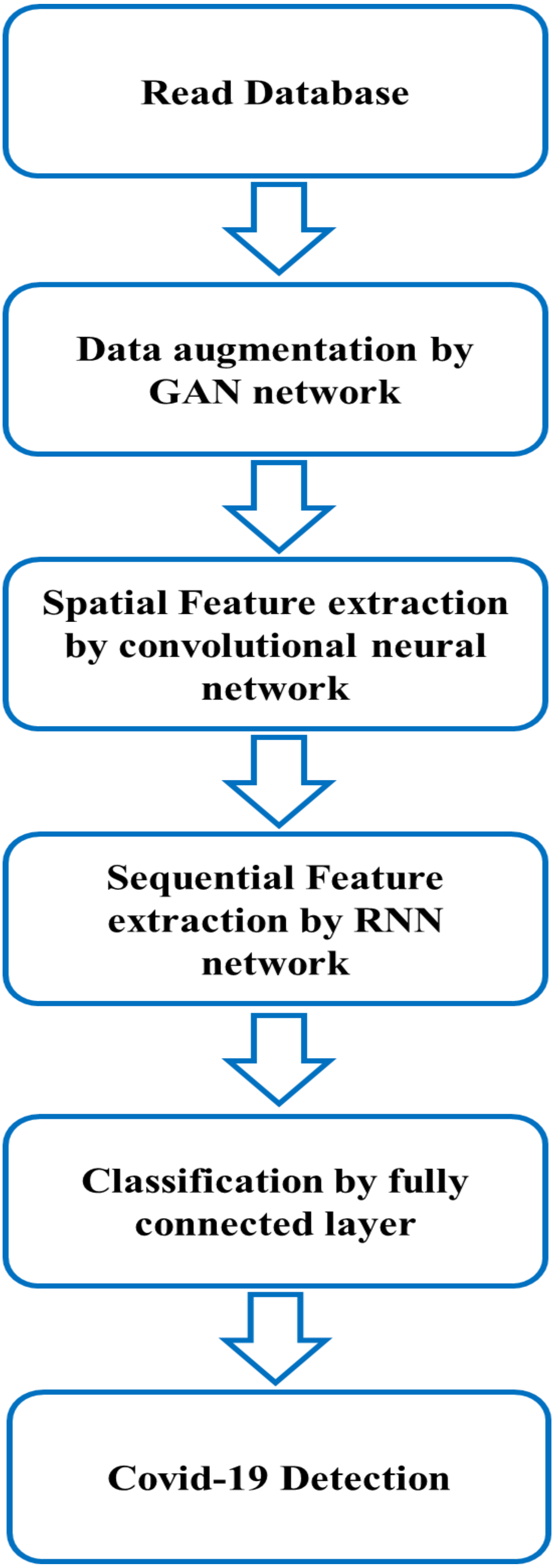

Figure 1- block diagram of presented model

2-1-Dataset description

In this study, we utilized the IEEE Covid Chest X-ray dataset (IEEE Covid Chest X-Ray Dataset. Accessed: Mar. 7, 2020. [Online]. Available: https://github.com/ieee8023/covid-chestxray-dataset) to obtain X-ray images for diagnosing COVID-19. This open-source database is freely accessible to both the public and the scientific community. To ensure data integrity, duplicate images were deleted from the database using the image hashing technique, which generates a unique hash value based on the content of each image, allowing for the accurate identification and elimination of duplicates.

2-2- generating synthetic images with GAN Network

Generative Adversarial Networks (GANs) generate new virtual samples of data that can be presented as real data by using two competing neural networks: the generator and the discriminator. These two networks work against each other to improve the quality of the generated data. The structure of the GAN network is illustrated in Figure 2. The following sections provide a detailed description of each component of the GAN model, along with corresponding diagrams.

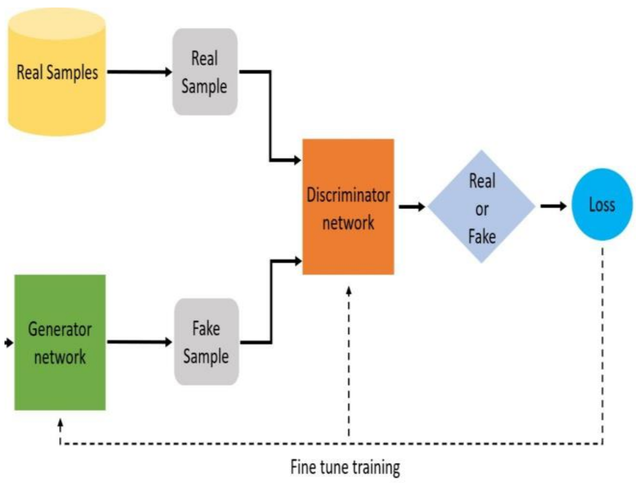

Figure 2. Architecture of GAN Network

2-2-1- Generative system

The generative model in a GAN creates samples within the problem domain from a random input vector of fixed length. This vector is randomly obtained of a Gaussian distribution and used during the generation process. After training, a compact representation of the data distribution is formed, where instances in this multidimensional vector space correspond to instances in the problem domain. This vector space is mentioned as the "latent space" or "a vector space with hidden variables". Latent variables represent essential aspects of a problem but are not directly visible.

Latent variables and latent space are often considered a compact delineation or abstraction of the data distribution. In simpler terms, a latent space produces a compressed or high-level understanding of the original data, same as the distribution of the input data. In GANs, the generative model works with points in a chosen latent space, enabling the generation of new samples by presenting fresh points from the latent space as input. After training, the generative system is maintained and used to produce new data examples.

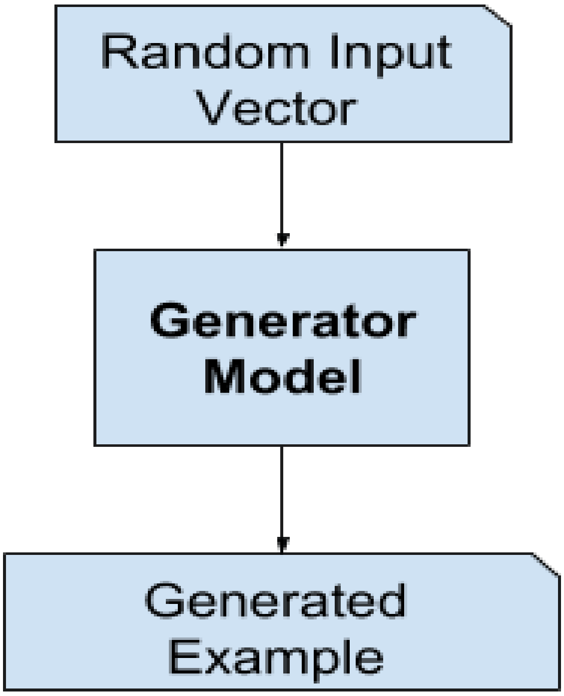

Figure 3: An example of a generative system in a GAN network

2-2-2- Discriminator system

The discriminator system classifies input samples of the domain as either real or generated (false). During training, the dataset includes real-world examples, while the generative model produces synthetic samples. The discriminator, a well-known classification model, is effective at distinguishing between genuine and generated samples. As the generator becomes proficient at extracting features from the problem domain, it can be repurposed for new applications. Transfer learning programs can leverage any or all of the feature extraction layers when using similar input data.

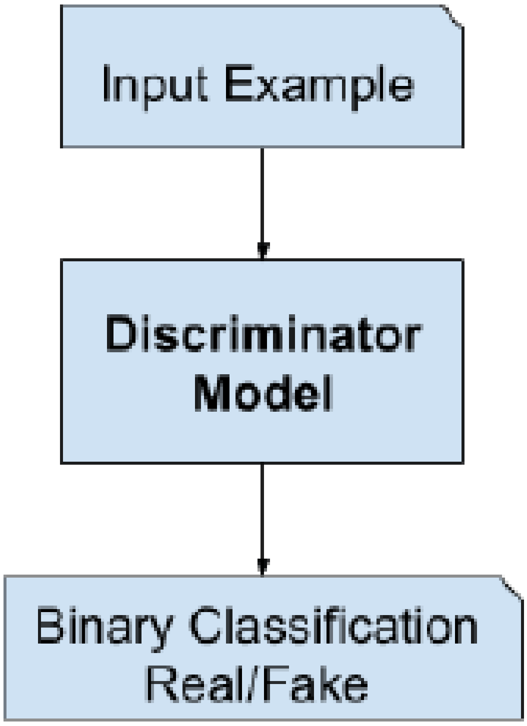

Figure 4: An example of a GAN network discriminator system

In this study, we utilized a GAN network consisting of two systems: a generator and a discriminator, both designed based on CNN architecture. Using this GAN network, we generated synthetic CT scan images of the lung.

2-3- Feature extraction using pre-trained and RNN neural network

Once the synthetic images are generated and the dataset for coronavirus classification and diagnosis is assembled, the next step is to extract effective features from these images to achieve optimal performance. Convolutional neural networks (CNNs) are particularly effective for feature extraction from images. In this study, we will use a pre-trained ResNet deep network for feature extraction, followed by an RNN deep network for classification.

2-3-1- CNN Network Architecture

The convolutional ResNet50 architecture achieved first place in the 2015 ILSVRC competition. Before its introduction, deep neural networks with many layers faced significant challenges, particularly the vanishing gradient problem. ResNet50 addressed this issue effectively, allowing for networks with up to 152 layers.

Traditional deep learning networks, such as AlexNet and VGGNet, use convolutional layers followed by fully connected layers for classification, without skip connections. As the depth of such networks increases, they often encounter problems like vanishing or exploding gradients, making it difficult to train deeper networks by simply adding more layers.

ResNet50 tackled these challenges by introducing skip connections, also known as residual connections. These connections bypass one or more layers, effectively allowing the network to take shortcuts between layers and thus mitigating gradient-related issues. The architecture of the convolutional ResNet50 network used in this paper is illustrated in Fig.5.

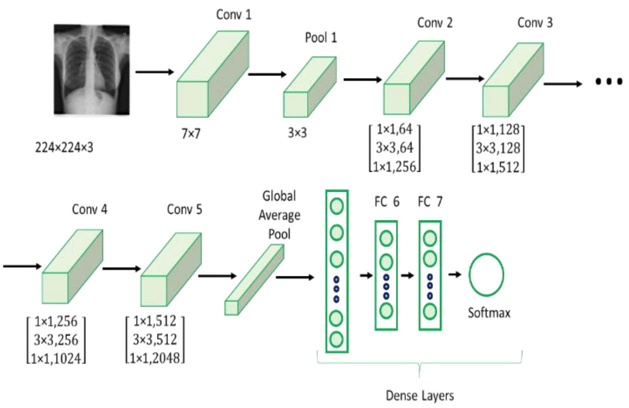

Figure 5. ResNet50 Architecture

2-3-2- RNN Network

This article uses a Recurrent Neural Network (RNN) to diagnose COVID-19. The RNN architecture is specifically designed for modeling sequential data, leveraging its sequential memory capabilities to enhance performance. The RNN comprises three layers: the input layer, the hidden layer, and the output layer. The structure of the RNN is illustrated in the diagram below.

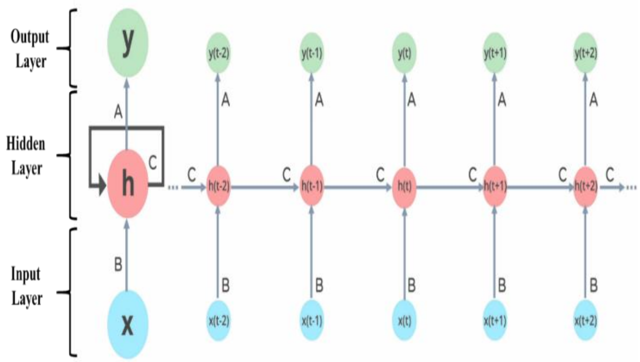

Figure 6: Architecture of RNN Neural Network

As illustrated in the figure, the network processes the initial input x(t−i), which is extracted by the CNN from the input sequence, and generates the output h(t−i). This output is then combined with x(t−i+1) for the next step in the network. Similarly, h(t−i+1) and x(t−i+2) are processed together in the subsequent step, and this process continues in the same manner until the final output is reached. The final output represents the classified data produced by the RNN neural network.

3- Experiment and results

This section presents the numerical results obtained from simulating the proposed method for diagnosing coronavirus disease. All simulations were conducted using MATLAB software, version 2024. The simulations involved lung X-ray images, which are detailed in the description of the database provided below. Additionally, this chapter will describe the measurement criteria, RNN network parameters, and the numerical results of the proposed method.

3-1- Evaluation metrics

Using the data augmentation approach, we evaluate the efficiency of the CNN network based on recall (sensitivity), precision, F1-score, and Accuracy. Precision measures the classifier's ability to avoid misclassifying negative samples as positive, while recall indicates the classifier's ability to correctly identify all individuals with the condition (true positive rate). The F1-score is the weighted average of precision and recall. Also to overall accuracy, we also computed the macro-average and weighted average. The following formulas outline these metrics:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Sensitivty = Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (3)$$

$$Total\ Accuracy = \frac{\sum TP}{Total\ Covid19\ Sampels} \quad (5)$$

In the formulas above, TP stands for true positive, FP denotes false positive, and FN represents false negative.

3-2- The Proposed Networks Architecture

To implement the proposed method, we first used the GAN network to augment the database images. Starting with 100 original images, we generated 60 synthetic images using the GAN network, resulting in a total of 160 images in our dataset. We then allocated 70% of these images for training the proposed network and the remaining 30% for testing and evaluation. The deep network parameters are detailed in Table 1.

Table 1- deep network parameters

Parameter	**Amount**
Num Hidden Units	40
Ma xEpochs	20
minibatch Size	15
Dropout probability	0.2
Learning Algorithm	stochastic gradient descent with momentum (SGDM)

3-3- Evaluation of Simulation Results

This subsection presents the performance of the proposed approach. Figure 7 displays the confusion matrix for the network on the test data. The classification task involves two categories: individuals with Coronavirus and healthy individuals. The confusion matrix shows that all cases of Coronavirus in the first category were correctly identified by the proposed method. However, in the healthy category, two individuals were incorrectly classified as having Coronavirus. Overall, the proposed method achieved an accuracy of 98.8% in detecting Coronavirus.

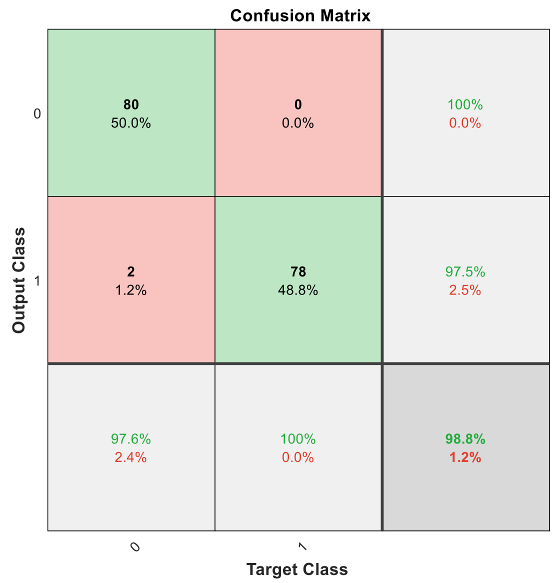

Figure 7: Confusion matrix for Covid-19 identification

In machine learning, the performance of a binary classifier across different cutoff points can be represented using a Receiver operating characteristic ROC curve, that is relying on True and False positive rates (TPR and FPR). The TPR, also known as sensitivity or recall, represents the ratio of true positives to all actual positive cases. The FPR, on the other hand, denotes the rate of negative samples that are incorrectly categorized as positive, and is determined as follows:

$$FPR = \frac{FP}{TN + FP} \quad (6)$$

The interchange between the True Positive Rate (TPR) and False Positive Rate (FPR) of a classifier can be visualized by drawing the True Positive Rate versus the False Positive Rate for all possible thresholds. A high-performing classifier will be positioned towards the top-left angle from the Receiver operating characteristic curve, indicating a high True Positive Rate and a low False Positive Rate. Conversely, a poorly performing classifier will be found towards the bottom-right angle of the Receiver operating characteristic curve, reflecting a low True Positive Rate and a high False Positive Rate. A random classifier would appear along the diagonal of the Receiver operating characteristic curve, where TPR and FPR are equal [29].

Figure 8 shows the Receiver operating characteristic curve for presented method. As depicted, the curve is close to the top-left angle, indicating that our model achieves a high TPR and a low FPR. This demonstrates which our model effectively classifies COVID-19 with high accuracy.

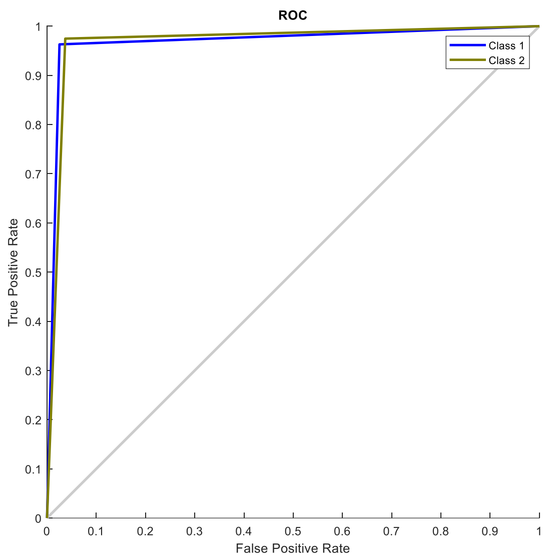

Figure 8: ROC curve for Covid-19 identification

A comparison between the method proposed in this work and those from other studies, based on evaluation criteria, is presented in Table 2 and Figure 9. The proposed method achieves an accuracy of 98.75%. The next highest accuracy is obtained by the DenseNet-VGG-16-InceptionV3 method, which reaches 98.0%.

Table 2: Comparison of the suggested method's outcomes with those from previous works

Author	Method	F-Score	Recall	Precision	Accuracy
Constantinou et al. [30]	InceptionV3	95.00	95.00	95.00	95.00
Constantinou et al. [30]	ResNet50	95.00	95.00	95.00	95.00
Constantinou et al. [30]	ResNet101	96.00	96.00	96.00	96.00
Hussain et al. [31]	VGG-16-DenseNet-201-Ensemble-Learning	97.00	95.00	96.00	97.00
Ukwuoma et al. [32]	DenseNet-VGG-16-InceptionV3	96.00	96.00	96.00	98.00
Nahiduzzaman et al. [33]	lightweight CNN (ChestX-Ray6)	98.59	98.28	98.43	97.94
presented	GAN-ResNet-RNN	98.7	97.5	1	98.75

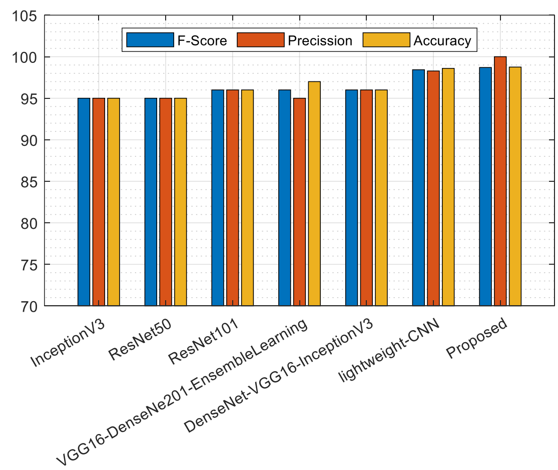

Figure 9: Comparison of the suggested method's outcomes with those from previous works

4- Conclusion

A key challenge in medical research is the scarcity of data. In this work, we address this issue by proposing the use of a GAN neural network to augment data related to coronavirus disease, in conjunction with pre-trained deep networks and an RNN for diagnosis. We employed lung X-ray images for this purpose, starting with 100 initial images and generating an additional 60 synthetic images using the GAN network. Of these images, half are related to coronavirus and the other half are from healthy individuals. We used the pre-trained ResNet deep network to extract features from the lung X-ray images. The extracted feature vectors were then input into the RNN for binary classification (coronavirus or healthy). The advantage of combining ResNet with RNN is that ResNet, with its convolutional layers, excels at extracting spatial features from images, while RNN is effective at capturing temporal relationships in the data. This synergy significantly enhances the accuracy of coronavirus disease detection. Our proposed method achieved an accuracy of 98.75%, demonstrating very high performance.

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