Design of an Efficient Approach for Performance Enhancement of COVID-19 Detection Using Auxiliary GoogLeNet by Using Chest CT Scan Images

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***Abstract*— In every country on this planet, COVID-19 disease s right now one of the most unsafe issues. The expedient and precise space of the Covid virus infection s major to see and take better treatment for the infected patients will increase the chance of saving their lives. The quick spread of the Covid virus has blended complete interest and caused greater than 10 lacks cases to date. To battle this spread, Chest CTs arise as a basic demonstrative contraption for the clinical association of COVID-19 related to a lung illness. A modified confirmation device is essential for assisting in the screening for COVID-19 pneumonia by making use of chest CT imaging. The COVID-19 illness detection utilizing supplementary GoogLeNet is shown in this study. Deep Convolutional Neural Networks were built by researchers at Google, and one of their innovations was the Inception Network. GoogLeNet is a 22-layer deep convolutional neural network that is a variation of the inception Network. GoogLeNet is utilized for a variety of additional computer vision applications nowadays, including face identification and recognition, adversarial training, and so on. The findings indicate that the GoogLeNet method is superior to the CNN Method in terms of its ability to detect COVID-19 sickness.**

Keywords*— *GoogLeNet, CNN, Deep Neural Network, COVID-19, ResNet50, VGG16

I. INTRODUCTION

From SARS-CoV-2, COVID-19, a virus that infects individuals worldwide, was derived. The virus was initially identified in December 2019 in Wuhan, China, and has since spread throughout the world [1]. The majority of COVID-19 cases are characterized by fever, dry cough, and exhaustion. Nonetheless, there have been incidences of COVID-19 that were not accompanied by any symptoms. As a result of their illness, numerous individuals report suffering pains, aches, throat problems, a continuously running nose, severe diarrhea, and some nasal congestion. [1, 2].

The fast spread of the pandemic was due to a number of reasons, including the capacity of the virus to survive on surfaces for lengthy periods of time and respiratory diseases that are spread from one individual to another. [3]. According to the statistics for the COVID-19 outbreak as of the June 20th, 2020, there have been a total of 8,804,268 people impacted all over the world, 463,510 people have died as a result of it, and 4,656,912 people have recovered from it. The number of patients requiring intensive care unit treatment has increased in response to the need for facilities to treat those with the most severe COVID-19 illness symptoms, despite the fact that many technologically advanced nations are unable to efficiently manage their healthcare system.

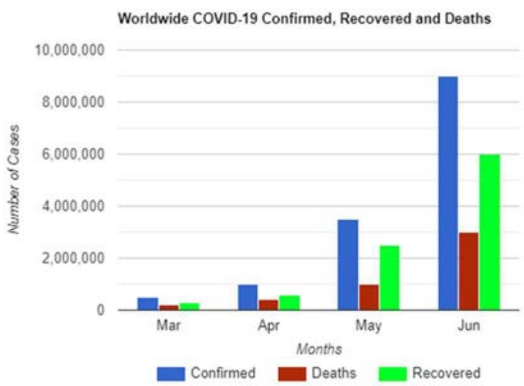

Figure 1. Status of the number of confirmed, recovered, and deaths cases of Covid-19 from Mar to June [4].

In Figure 1, we display the mortality and survival rates, as well as the spread of COVID-19 over the globe from January 22, 2020, to June 20, 2020. There were 205 people infected with COVID-19 and their samples were analyzed by W.Wang et al. [4]. The average age of the patients in the study was 44. The patients' symptoms included dry cough, fever, and weakness; severe syndromes affected 19% of the patients. The samples taken from the bronchoalveolar lavage had the greatest rate of positive findings (14 out of 15), followed by the samples taken from the sputum (72 out of that (5 out of 8) and (6 out of 13), and then the samples taken from the blood (44 out of 153). There was no positive result from a urine sample from any subject. The results of the study showed that a decrease in false-negative rates and an increase in sensitivity could result from evaluating specimens from multiple locations. Early on in the course of the illness, RT-PCR detection techniques have showed a low positive rate and a lower sensitivity value for COVID-19 samples [5]; COVID-19 symptoms are comparable to those of other kinds of viral

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pneumonia, but CT scans have shown distinctive characteristics that mark it apart. CT scans are one of the first diagnostic tools used by doctors, and this is why they've chosen them. In a case study with 1014 cases, chest CT images were found to be more helpful in the diagnosis of COVID-19 than initial RT-PCR tests [6].

The sensitivity of chest CT in the detection of the disease has been demonstrated to be higher than that of RT-PCR testing. RT-PCR was able to identify positive results in 601 out of 1014 cases (or 59%), whereas chest CT images were able to identify positive results in 888 out of 1014 instances (or 88%) Huang et al. [7] conducted an analysis of the clinical symptoms exhibited by 41 individuals who had been infected with COVID-19. Along with typical start signs including severe fatigue, high fever, and continuous cough, all 39 instances were found to be infected with severe pneumonia, and the unseen abnormalities that were shown in their chest CT scan were demonstrated to be associated with pneumonia. In the CT scans that were taken, severe respiratory conditions, chronic heart damage, and various secondary contaminations were found. For the identification of COVID-19, a unique approach is necessary. Since RT-PCR test kits are hard to come by, the test takes a long time to conduct, the early stages of the test have poor positive rates, and substantial human expertise is needed. Because of the current state of the COVID-19 pandemic, there is a significant need for the development of more advanced methods of diagnosing, treating, and managing the disease.

Exploring techniques based on artificial intelligence appears to be a potential strategy for the efficient analysis of sickness. In such a never-before-seen circumstance, the alternative options studied should identify less expensive methods for diagnosing, controlling, and treating this global epidemic. In addition, the proposed strategy should aid researchers in gaining a comprehensive understanding of the disease's underlying causes and progression. Using engineering approaches such as medical image pre-processing and cutting-edge machine learning algorithms, An input sample can be categorized as either normal or disease-affected depending on the presence or absence of the disease. CT scans of the chest are used to diagnose pneumonia as one of the approaches. We have suggested using chest CT scans in conjunction with an advanced fully convolutional network architecture called U-Net, which was developed specifically for the purpose of biomedical image processing. Depending on whether or not any anomalies were found in the input sample, the sample might either be considered a normal case or a COVID-19-impacted case. Here's how the rest of the paper is put together. In section 2, the literature review, any problems that were found, and a Discussion is had over the most important contributions made by the proposed study. The datasets that were used, the approach that was presented, and the utilization of the U-NET architecture for the proposed study are all explained in Section 3. In section 4, the results of the experiments are shown, along with a comparison of those results with the performance of four other network architectures and with the best current methods. In the end, the important contributions of the paper and possible ways to do work in the future are talked about.

II. RELATED WORK

Convolutional neural networks (CNNs) have emerged as the most useful and widely used image-processing technique in the modern era of machine learning and artificial intelligence. We have reviewed the many different CNN algorithms and other methods that have been developed in recent years for analysing many diseases from medical pictures like chest X-rays and chest CT scans.

With the intention of making a diagnosis of COVID-19 disease, Xiaowei Xu and colleagues [8] came up with an innovative screening procedure. The technique evaluated its results with the use of CT scans and was carried out using 3D-CNN, which included extraction of features and segmentation. It was examined with the help of CT pictures. From the designated hospitals, a total of 605 samples were collected; out of these, 171 samples came from healthy persons, 225 samples were from patients who had pneumonia brought on by the influenza A virus, and 209 samples were impacted by COVID-19.

Overall, the authors claimed 86.7 percent precision. Baltruschat M et al. [9] examined many deep-learning strategies for analyzing X-ray pictures in order to diagnose sickness. This study covers the understanding of the potent architecture ResNet-50 and its enhanced versions. We classify X-ray images based not only on the diseases present (cardiomegaly, nodule, pneumonia, etc.), but also on some non-image factors like gender, age, and mode of acquisition. Using metrics like the Receiver Operating Characteristics Curve and rank correlation comparisons are made between the performance of the algorithms and that of a fivefold multi-label loss function and resampling. Area Under Curve (AUC) values were reported by the technique to be 0.795 for the ResNet-50 design, 0.785 for the ResNet-101 design, and 0.806 for the ResNet-38 design.

Nicolas Coudray and colleagues [10] pose that assistance in finding out about lung cancer could be helpful. Using Google's CNN - inception v3, the two types of lung cancer that are diagnosed most frequently are LUAD and LUSC. These subtypes of lung cancer may be differentiated from normal tissues in an easy and quick manner. In addition to demonstrating that the model is accurate for a selection of frozen tissues, the recommended approach was examined using pictures of whole slides, and the results indicated a sensitivity of 89%, specificity of 93%, and accuracy of 97%, respectively.

Using a CNN that was specified by Anthimopoulos et al. [11], a classification system was developed for each of the six distinct interstitial lung disorders. In the proposed CNN, there are a total of five convolutional layers, and the activation function is a Leaky Rectified Linear Unit (RELU), with max-pooling and a soft-max classification function coming next. From 120 CT pictures received from two local hospitals, 14,696 patches of mages were created. Cross-entropy minimization of the loss function yielded an 85.61% overall accuracy, according to the author. Bone dislocations, fractures, lung infections, malignancies, and pneumonia can all be diagnosed with the help of X-ray technology that is used to scan critical body regions. CT scanning, a subset of advanced X-ray technology, examines the extremely malleable structure of the dynamic body part and generates more comprehensive photos of the internal soft tissues and organs [12]. Researchers explored the potential of analysing chest X-rays for automatic image processing and identification of COVID-19 [13]. Three distinct convolutional neural networks are utilized in the evaluation of the performance of automatic detection (Inception ResNetV2, ResNet50, InceptionV3).

The researcher utilized 110 chest CT X-ray images, 55 from Kaggle and 55 from GitHub. Due to the scarcity of available image examples, a deep transfer knowledge-build training strategy was utilized. According to the Times of India [14], scientists from India have proposed an AI-based technique for distinguishing COVID-19 and other lung-related disorders in Kyoto, Japan. Zhao et al. [15] proposed a convolutional neural network (CNN) hybrid built on AlexNet and LeNet for the purpose of identifying malignant lung nodules. For the purpose of evaluating the proposed agile CNN, a total of 743 CT images were employed. Altering the learning rate, kernel size, and several other factors allowed for the performance of the recommended CNN to be assessed and reviewed. According to the author's assertions, the accuracy was 0.822%, and the AUC i.e. area under the curve was 0.877. Transferred learning, or transferring generated data to a classifier such as a Support Vector Machine, was suggested as a method for achieving further improvement (SVM).

Zheng et al. [16] suggested a 3D weakly superimposed deep CNN for detecting COVID-19 in chest CT images. In order to segment CT scans, we used a pre-trained U-Net between the dates of December 13, 2019, and February 6, 2020, 630 CT images were obtained from hospitals for use as samples. Of those pictures, 499 were used for training with no lesion labelling, and 135 were employed in order to test the proposed CNN architecture. Samples were classified as either being influenced by COVID-19 or being unaffected by the virus based on the use of a probability threshold of 0.50. The suggested method was evaluated and found to have an accuracy of 0.901, a positive predictive value (PPV) of 0.840, and a negative predictive value (NPV) of 0.982.

For the purpose of identifying COVID-19, Gozes et al. [17] suggested using a two-dimensional Deep CNN that was constructed using the ResNet-50 architecture. The segmentation of CT images was accomplished by the utilization of the U-Net architecture. The CT pictures of 56 patients who were verified to have COVID-19 disease were used in this study. The sensitivity of the algorithm was found to be 0.982, while its specificity was reported to be 0.922, and its AUC was 0.996.

Barstugan et al. [18] investigated the COVID-19 detection algorithm by using a number of feature extraction approaches, such as the Discrete wavelet transform, Grey level co-occurrence matrix, the Grey-level size zone matrix, and so on. The collected characteristics were then entered into a support vector machine (SVM) classifier, which was used to determine whether or not the input sample was afflicted by COVID-19. This allowed the researchers to determine whether or not the input sample was impacted by COVID-19. In order to create a variety of data samples, the technique retrieved CT image patches in a variety of sizes, including 16 by 16, 32 by 32, and so on. Using 2-fold, 5-fold, and 10-fold cross-validations, the algorithm's performance on 150 CT abdominal images was assessed across a variety of metrics, including sensitivity, specificity, F-score, and accuracy.

Author [22] et al approach includes a proposal for an evaluation of the driver's weariness levels based on the key facial highlights. Facial key points characterize the facial locales of identification. VGG16 s utilized as the CNN engineering. Subsequently, our Android application is a continuous framework as it has a high activity speed. It is ready to identify the sluggishness example of any person who's utilizing it and in like manner gets a representation chart. Affirmation through the alert, at whatever point location, is done, and functions admirably. [15] The model has been prepared and tweaked utilizing the laziness discovery dataset from Kaggle. A near investigation of three pre-prepared models specifically, VGG-16, inception, and ResNet-50, utilizing move learning was performed and VGG16 was accounted for to accomplish the greatest preparing just as approval correctness's and least preparing just as approval misfortune. Hence, a similar model has been utilized in the preparation.

Xie Y and colleagues [19] introduced a deep learning architecture called Multi-View knowledge-based collaborative for the differentiation of cancerous nodules from benign nodules by the use of CT scans. This architecture is designed to prioritize malignant nodules. In order to investigate the overall look, the heterogeneity in shape, and the voxels of the nodules, three pre-trained ResNet-50 topologies were utilized. For the purpose of classification, an adaptive weighting system that was kept current using backpropagation and contained 9 KBC sub-modules was used. [3] A conventional cross-entropy function is supplemented with a penalty loss function in order to achieve the desired reduction in the rate of false-negative results. The aforementioned module was tested using 1945 pictures taken from the LIDC-DRI dataset, which included a total of 1201 benign and 543 malignant nodules. The results showed that it had an overall accuracy of 92.60% and an Area under the ROC Curve of 95.70%.

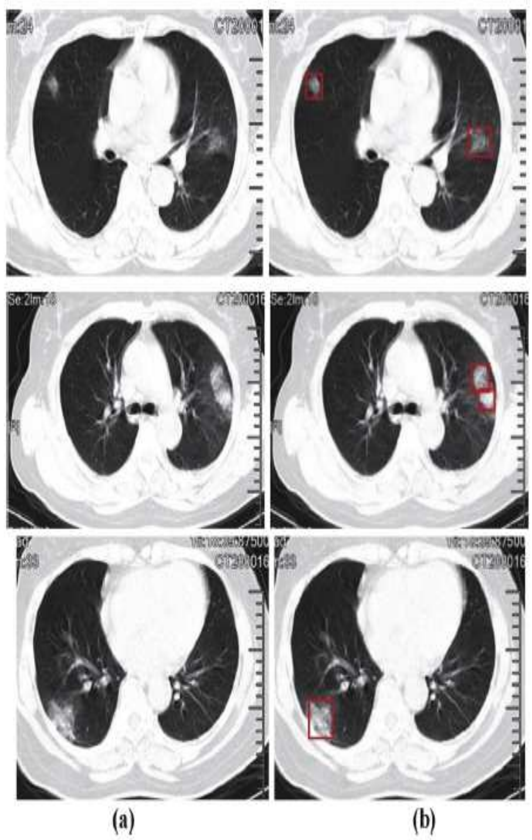

Figure 2. a) Input CT images to GoogLeNet and CNN b) Infection of COVID-19 disease detected by GoogLeNet

III. METHODOLOGY

As can be seen in Figure 3, the focus of the work that was presented was on applying GoogleNet to the detection of covid-19 utilizing chest CT scan pictures.

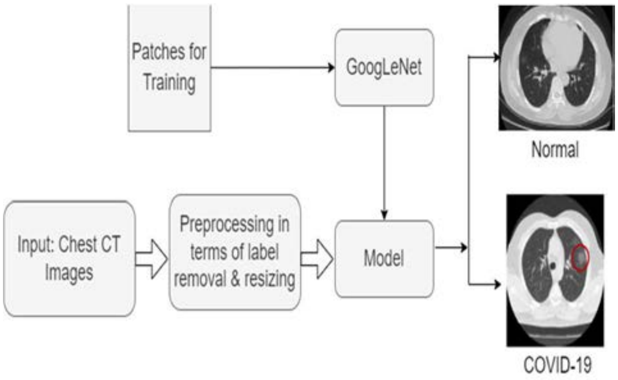

Figure 3. The architecture of Proposed Methodology

It was completed in the following three stages: 1) Obtaining the chest CT images and performing any necessary pre-processing to remove any labels or other identifying information. 2) Train the fully convolutional GoogLeNet Architecture so that it suffers the least amount of loss. 3) Testing the input image that was applied using a trained version of Google Neural Networks to identify COVID-19-affected cases.

A. *Pre-processing*

The obtained chest mages were pre-processed so that any labels that may have contained the patient's information could be removed. It was necessary to resize the photographs because they came from a variety of sources so that we could use them. Every one of the input pictures, including the CT scans that were utilized for training and testing, was shrunk down to a resolution of 512 by 512 pixels.

B. *GoogLeNet Processing*

Inception Network, which was created by Google, is a Deep Convolutional Neural Network. GoogLeNet is a form of inception Network that has 22 layers and is known as a Deep Convolutional Neural Network. Computer vision tasks such as picture classification and object recognition were successfully completed by the GoogLeNet architecture that was presented at the imageNet Large-Scale Visual Recognition Challenge 2014 (LSVRC14). Today, a wide range of computer vision applications, such as face detection and identification, adversarial training, and many more, make use of GoogleNet.

When it was first conceived, the architecture of GoogleNet was intended to be a formidable machine that would significantly improve the computational efficiency of the network in comparison to some of its forerunners or other networks developed about the same time. One of the ways that GoogleNet is able to achieve its goal of efficiency is by decreasing the size of the input image while preserving essential spatial information. Even if the height and width of the input picture are decreased by a factor of four at the second convolution layer and by a factor of eight before it reaches the first inception module, more feature maps are still produced.

As a result of dimensionality reduction, the second conv layer has a depth of two and makes use of the 1x1 conv block. Dimensionality reduction using the 1x1 conv block reduces computational effort by decreasing the number of layer operations.

The architecture of GoogleNet is made up of nine different conception modules. Notably, certain inception modules are sandwiched between two max-pooling layers. The input will be downsampled as it travels through the network as a result of the work performed by these max-pooling layers. We are able to achieve this result by relaxing the limitations placed on the width and height of the input data. One more efficient strategy for reducing the computational burden of the network is to cut down on the size of the inputs between the inception module. The most recent inception module generates feature maps, and the average pooling layer calculates a mean value for each of them. It then changes the input's height and width to be 1 by 1 in order to use the average value. A dropout layer that is forty percent thick is used right before the linear layer. In order to avoid the overfitting of the network during the training process, a regularisation strategy known as the dropout layer is utilized.

C. *Image classification*

GoogleNet is utilized in this scenario for the purpose of object detection. Abnormalities are considered to be items of interest. Furthermore, If the count of items that have been found in the picture is more than zero, then it is decided that the image is a Covid-19 impacted instance. This is because the design of GoogleNet is able to recognize anomalies as objects.

D. *Evaluation platform and parameters*

Python and MATLAB were used throughout the process of putting the suggested techniques into practice. For the purpose of simulating the aforementioned algorithms, a laptop outfitted with an Intel-7 2.4 G CPU, 16 G DDR3 RAM, Windows 10, and MATLAB R2019a was utilized. After the training of the network had been completed, testing of wizards was carried out on a single kit utilizing Raspberry Pi.

Parameters metrics such as Specificity, Accuracy Sensitivity, and Precision are used to evaluate the CNN and GoogLeNet models' efficacy. The sensitivity measures how well one can identify positive cases, whereas the specificity measures how well one can identify normal samples. Accuracy demonstrates how accurate a forecast is, whereas precision demonstrates how stable that accuracy is over time. Those equations specify these parameters. (1–4). A few definitions are in order: Positive COVID-19 cases (TP), negative COVID-19 samples (TN), the number of COVID-19-affected cases (FN), and positive COVID-19 chest CT pictures (FP) are all abbreviations representing the results of the proposed FCN.

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \qquad \text{Equation. 1}$$

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN}+\text{FP})} \qquad \text{Equation. 2}$$

$$\text{Accuracy} = \frac{(\text{TN}+\text{TP})}{(\text{TN}+\text{TP}+\text{FN}+\text{FP})} \qquad \text{Equation. 3}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \qquad \text{Equation. 4}$$

E. Training

It was determined, on the basis of what was read in the AI literature [20] that training and testing the hyperparameters should be done using data that wasn't initially utilized the model. This was done so that the model might be more accurate. As a result, the input samples were first divided into a training set consisting of 900 photographs and a validation set consisting of 100 pictures using a 90/10 split. The 900/100 division has preserved more samples for training from the full dataset of 1000 photos. In addition, the test set size of 100 photos was somewhat tiny, presenting a significant challenge when assessing performance. To lessen the impact of sample partitioning on performance evaluation, we used 10-fold validation on a total of 1000 samples. Using a total of 900 photos as training data, we were able to train a model to estimate the test error rate using data from the validation set. The U-Net model was trained using a batch size of 100 pictures taken from a total of 900 CT scan data, as well as lesion masks with defined positions. The lesions masks were created by extracting the abnormality patches from the Covid-19 training pictures.

The input for the training phase included not just of the pictures themselves, but also of references to the specific locations on the brain that were provided by the lesion masks. Patches were put to the patient's skin that had ground-glass opacities (GGO) of different halo sign patches, parenchymal density, the component of consolidation patches with the opacities of ground-glass, and crazy-paving patterns. These patches were used for intense training. In order to understand the model, it was important to make use of patches of multifocal modular with freshly identified foci of ground-glass opacities and consolidation, in addition to ground-glass opacities found in the surrounding area. In addition to that, training included the use of curvilinear subpleural lines.

IV. Result and Discussion

Figure 2 shows the results of the input chest CT images and the anomalies discovered by FCN (a & b). Most pulmonary CT images showed patchy ground-glass opacities that extended both per-bronchially and peripherally/ subpleural. Within some of the ground glass sections, reticular opacities were also discovered in some of the cases (crazy-paving pattern). Figure 2 (a) shows the chest CT scans provided to CNN and GoogLeNet together with different illnesses, and Figure 2 (b) shows the chest CT scans produced by GoogLeNet after it discovered multiple abnormalities associated with COVID-19 sickness.

A. Using CNN: We get the following values for various parameters.

i.e. TP = 0.93, FP=0.07, FN= 0.11, TN=0.89

B. Using GoogLeNet*:* We get the following values for various parameters.

i.e. TP = 0.97, FP=0.03, FN= 0.00, TN=1.00

Figure 4. Confusion matrix for GoogLeNet Method

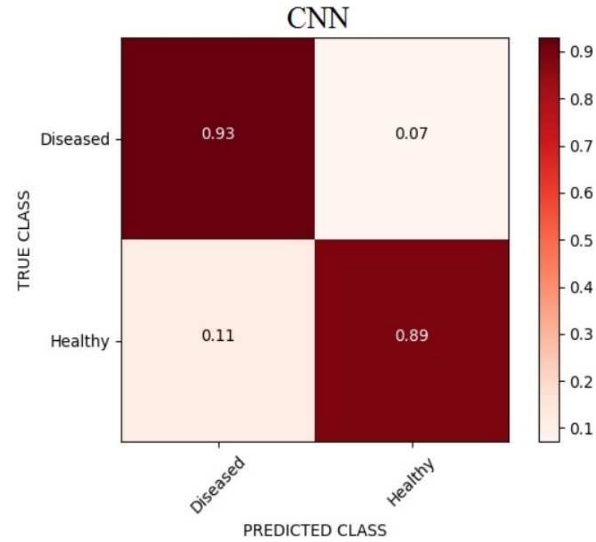

Figure 5. Confusion matrix for CNN Method

TABLE I. Comparative Results

Parameters	CNN	GoogLeNet
1. Sensitivity	0.894	1.00
2. Specificity	0.924	0.971
3. Accuracy	0.91	0.985
4. Precision	0.93	0.97

The results of the experiments are listed in Table 1. The CNN model shows a sensitivity (0.894), specificity (0.924), accuracy (0.91), and precision (0.93) and the GoogLeNet model shows a sensitivity (1.00) which is more as compared to the CNN base model, specificity (0.971) which more as compare to CNN based model, accuracy (0.985) which more than CNN based model, precision (0.93) which is best as compare to CNN based model.

Figure 6 shows the comparison between the CNN and GoogLeNet methods considering the sensitivity, specificity, accuracy, and precision factors. The red line represents the GoogLeNet and the blue line represents the CNN method.

By referring to the results of the comparison test we can conclude the GoogLeNet-based method is best as compared to CNN based model for the detection of COVID-19 disease.

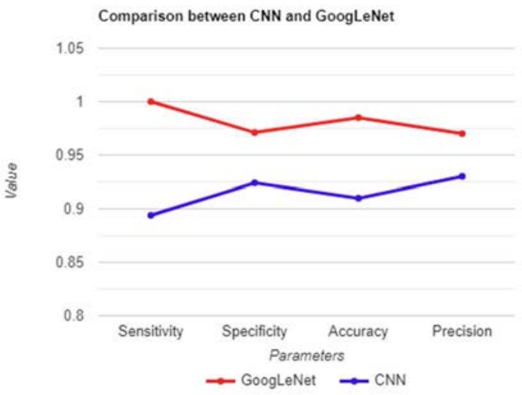

Figure 6. Comparison between CNN and GoogLeNet

V. Conclusion

As a means of responding to the pressing need that has come up in the course of the fight against the spreading pandemic, we have developed a method based on AI that is capable of the automated identification of COVID-19 sickness. This was done in an attempt to address the urgent demand that has developed in an ongoing fight against the epidemic that is now taking place. The fact that the algorithm was able to enhance specificity, accuracy, and Sensitivity with input samples coming from a wide range of sources is proof that it is reliable and dependable. In light of the facts, we are able to reach the conclusion that the approach based on GoogleNet is more successful than the model created based on CNN when it comes to identifying occurrences of COVID-19. This is the conclusion that we can make from the findings.

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