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"COVID-19 DISEASE DETECTION AND CLASSIFICATION USING RESNET50 TECHNIQUE"

Anamika Singh [1], Dr. S. K. Pandey [2]

[1] *M Tech Scholar, Department Computer Science Engineering, VNS Faculty of Engineering, Bhopal, MP, India*

[2] *Professor, Department Computer Science Engineering, VNS Faculty of Engineering, Bhopal, MP, India*

ABSTRACT

The ongoing COVID-19 pandemic has caused significant global health concerns and has led to the development of various diagnostic techniques. In this study, we propose a deep learning-based approach for detecting COVID-19 using the ResNet50 architecture. The proposed method uses chest X-ray images to train a ResNet50 model for COVID-19 detection.

We evaluated the performance of our proposed method on a publicly available dataset of chest X-ray images. The results of our experiments demonstrate that the proposed method achieves high accuracy, sensitivity, and specificity in COVID-19 detection. Overall, our proposed method shows promising results in COVID-19 detection using chest X-ray images and can be useful in assisting healthcare professionals in diagnosing COVID-19.

Key Words: *ResNet50, COVID-19,segmentation, CT images, deep learning.*

I. INTRODUCTION

The coronavirus disease (COVID-19) is defined as a disease or infection evoked by a new breed of coronavirus called the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which was previously named 2019-nCoV [1]. It was first discovered in Wuhan Hubei City in China. The World Health Organization (WHO) reported the first COVID-19 case on 31 December 2019. The COVID-19 outbreak was declared as a global outbreak on 30 January 2020 (Sohrabi et al., 2020). Since 2009, the WHO considered H1N1 as an internationally pandemic disease; COVID-19 was the second pandemic disease declared [2].The disease spread mainly through close contact with infected individuals, although researchers are still investigating potential infection routes of the disease .The major signs of COVID-19 infection are fever, dry cough and breathing difficulty. Some patients may have muscle aches and experience fatigue and loss of taste or smell (anosmia), and up to 10% have GI-related symptoms, such as diarrhoea .As initially thought, one of the potential ways for the virus to spread between people is direct contact. Thus, social distancing can reduce the possibility of being infected. Disease transmission can occur at a distance of as far as 6 feet. As a result of that, the breathing drops generated from the infected person while talking or sneezing can be taken as one of the primary reasons to cause the disease to spread. Furthermore, the symptoms of COVID-19 in some cases are not noticeable.
In general, several approaches for diagnosing COVID-19 are available, such as nucleic acid-based methods using polymerase chain reaction (PCR) [4], next-generation sequencing computed tomography (CT) scan [3] .chest X-ray (CXR).These methods are used in monitoring changes in organs, and patients may need to undergo these pathological tests. The most popular of these pathological tests are CT scan and CXR.Regarding CT and X-ray chest techniques

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used for COVID-19 diagnosis, many advantages distinguished these technologies. For instance, the CT provides more details about the patient's status and relatively quick compared with the other technologies. Using the X-ray chest can get the results at a lower price and lower radiation. However, these technologies have some drawbacks that may affect their performance and usage, such as the CT scans of the brain can be affected by bone nearby, and the X-ray chest does not provide 3D information[6-10].

II. REALTED WORK

Jun Wang, Yiming Bao et.al. 2020[11] we propose a conceptually simple framework for fast COVID-19 screening in 3D chest CT images. The framework can efficiently predict whether or not a CT scan contains pneumonia while simultaneously identifying pneumonia types between COVID-19 and Interstitial Lung Disease (ILD) caused by other viruses. In the proposed method, two 3D-ResNets are coupled together into a single model for the two above-mentioned tasks via a novel prior attention strategy. We extend residual learning with the proposed prior-attention mechanism and design a new so-called prior-attention residual learning (PARL) block. The model can be easily built by stacking the PARL blocks and trained end-to-end using multi-task losses. More specifically, one 3D-ResNet branch is trained as a binary classifier using lung images with and without pneumonia so that it can highlight the lesion areas within the lungs. Simultaneously, inside the PARL blocks, prior-attention maps are generated from this branch and used to guide another branch to learn more discriminative representations for the pneumonia-type classification. Experimental results demonstrate that the proposed framework can significantly improve the performance of COVID-19 screening. Compared to other methods, it achieves a state-of-the-art result. Moreover, the proposed method can be easily extended to other similar clinical applications such as computer-aided detection and diagnosis of pulmonary nodules in CT images, glaucoma lesions in Retina fundus images, etc.

Ashish Joshi (2022)[12] The advantages of the cloud environment for data processing and sharing are utilized by millions of people worldwide. A cloud system must inevitably provide data security and privacy. Users' widespread use and sharing of information creates security gaps. This study aims to discuss the cloud environment, its benefits, difficulties, and upcoming research trends pertaining to safe data processing and exchange. The widespread issue is caused by the increased adoption of cloud computing by several enterprises. As a result, utilizing any device to load and receive data from the cloud providers' facilities raises various security and privacy risks, such as data modification, data loss, and theft. Unauthorized access by insiders is one of the significant problems that might develop. Although there are various ways to prevent cloud administrators from gaining illegal access, such methods haven't been successful in keeping them from gaining access to client data in the cloud. The degree of protection a system may offer to the CIA triada paradigm that includes the information security qualities confidentiality, integrity, and availability is how information security is assessed. In this paper, we have analyzed such scenarios. This study analysis provided dangers to cloud data security, cloud assaults, and found vulnerabilities for several factors affecting cloud computing.

III. PROPOSED SYSTEM

The proposed approach involves training a ResNet50 deep neural network using chest X-ray images from COVID-19 positive and negative patients. The dataset should be balanced to avoid bias towards one class. The trained model can then be used for COVID-19 detection by inputting a chest X-ray image and obtaining a prediction on whether the patient has COVID-19 or not. The goal of this study is to find a way to find people infected with COVID-19 early on while reducing the number of false positive results. Figure 4.1 shows a summary of the steps that were taken to make the predictive system.
The website https://www.kaggle.com/tawsifurrahman/covid19-radiography-database was used to get a dataset that was used in this study. The dataset on this website came from many different places. Due to the limitations of the computers that were available, only 2000 of the images in the dataset were used in the experiment. The model put the images into one of two groups: COVID-19 Positive or (ii) COVID-19 Negative. There are pictures of both the good and bad results

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of the COVID-19 test. Predicting diseases caused by viral infections is a hard medical task that requires a lot of real data made up of many different variables. COVID-19 is known to be the deadliest disease on the planet, but no one has found a cure for it yet.

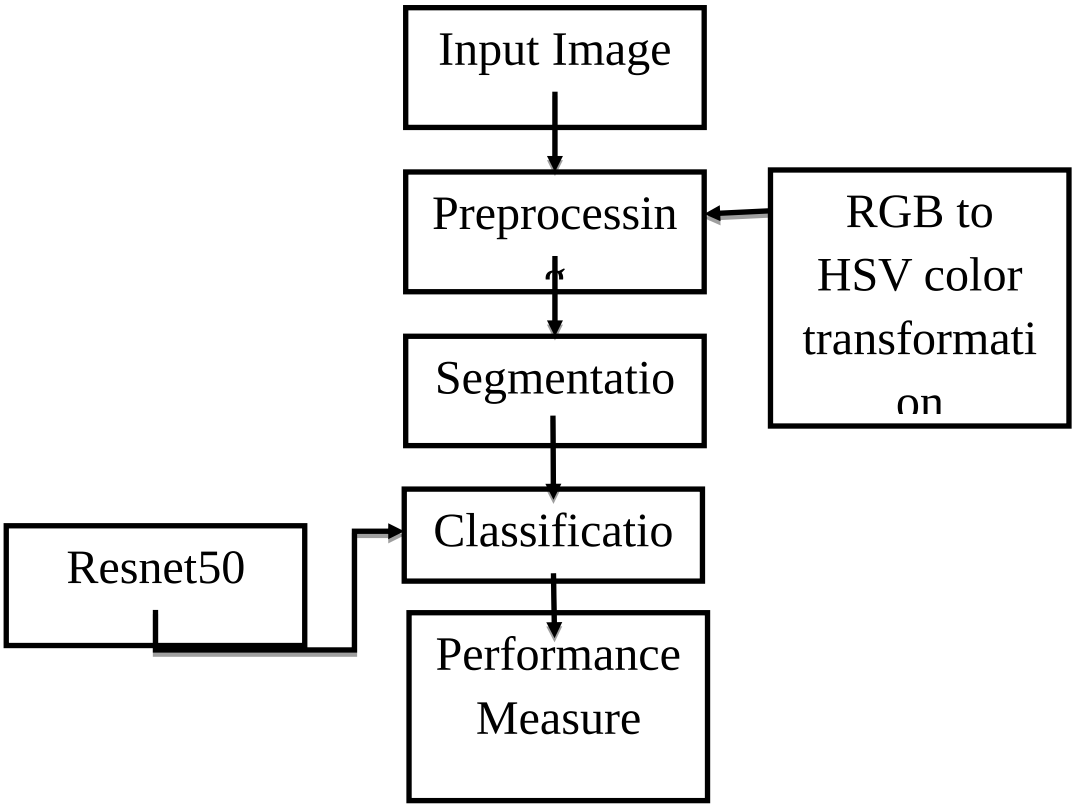

Fig.1 Proposed Flow Diagram

To stop the spread of this virus, it is important to find a logical way to show how it spreads by using data from a large number of people who have been infected. An algorithm was made that uses the ResNet50 functions of three different artificial neural networks to predict COVID-19. We put DL algorithms to work on the extracted dataset of COVID-19 patients to find out how bad the symptoms were. It was checked to see how well this model worked. used the programming language MATLAB to put DL techniques into use.

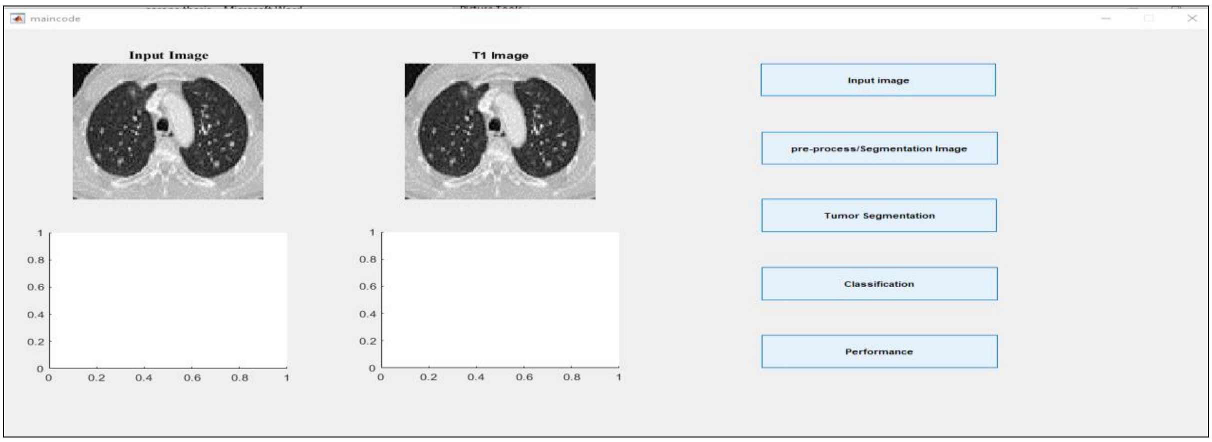

Fig.2 pre-process and Segmentation Image

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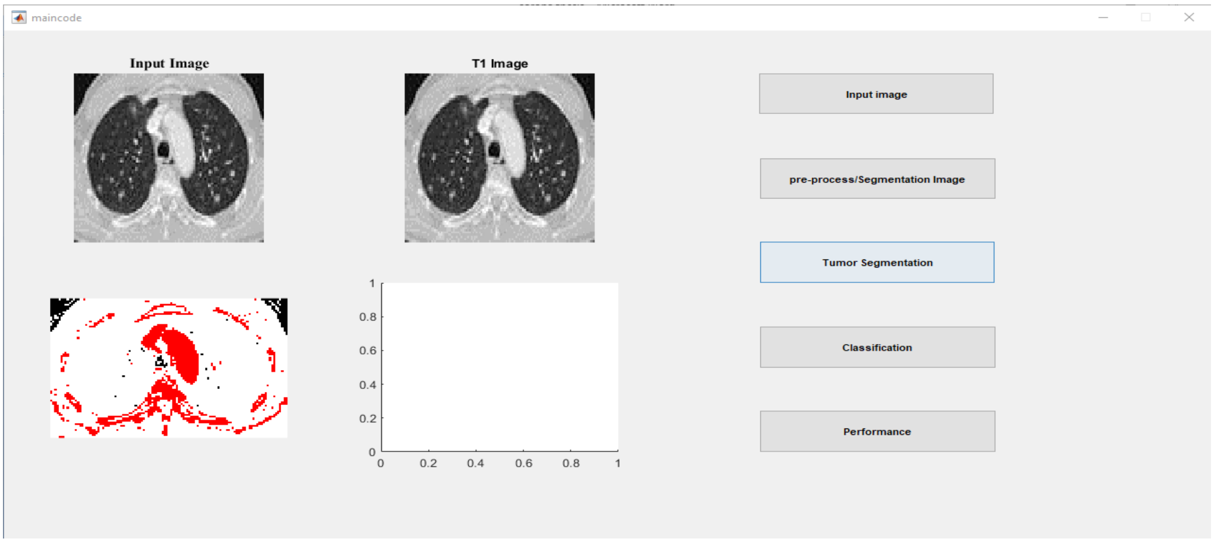

Fig. 3 Segmentation Image

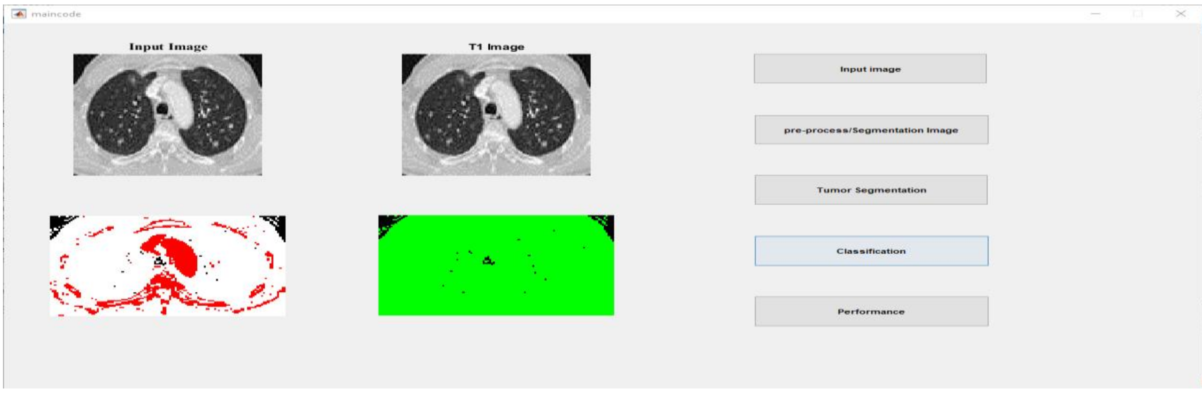

Fig 4.Classification image

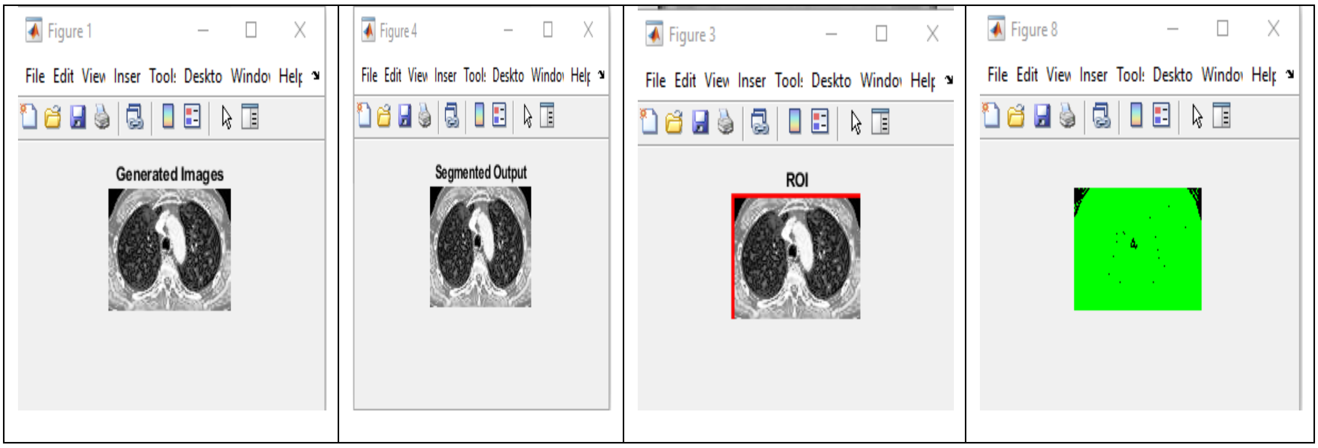

Fig.5 Generated Image, Segmentation, ROI,

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Fig.6 Classification image

IV. Result Discussion

The confusion matrix is important because it shows how many predictions based on known true values are right and how many are wrong. This data is used to figure out how well the classifier works. True Positive (TP): When both the actual value and the model's prediction of that value are right; True Negative (TN): When both the actual and expected numbers are off by the same amount; False Positive (FP): When the actual value is false, but the model thought it would be true. False Negative (FN): When the actual value is true, but the model expected it to be false. The letters FP and FN stand for "False Positive" and "False Negative," respectively**. Intersection over Union** (IOU): The IOU, which is sometimes called the Jaccard Index, is a good way to measure how much two bounding boxes or masks in a segmented image overlap. IoU is the area where the ground truth segmentation and the predicted segmentation overlap, divided by the area where the ground truth segmentation and the predicted segmentation meet. This metric goes from 0 to 1, which is the same as 0% to 100%. When the value is 0, there is no overlap, and when the value is 1, there is perfect segmentation overlap. Our goal is to get an IOU value of 97% or higher while following a guideline of 0.5. **[13-15]**

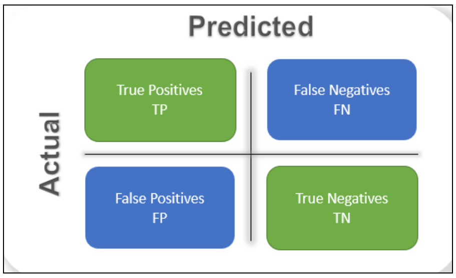

Figure 7 Model evaluation parameters

Green region: Our model estimates 1 (lesion mask) and the ground truth is 1. (True Positive, TP)
Blue region: Our model estimates 1 (lesion mask) but the ground truth is 0. (False Positive, FP)
Our model estimates 0 (absence of lesion) but the ground truth is 1. (False Negative, FN) Our model estimates 0 (absence of lesion) and the ground truth is 0. (True Negative, TN)

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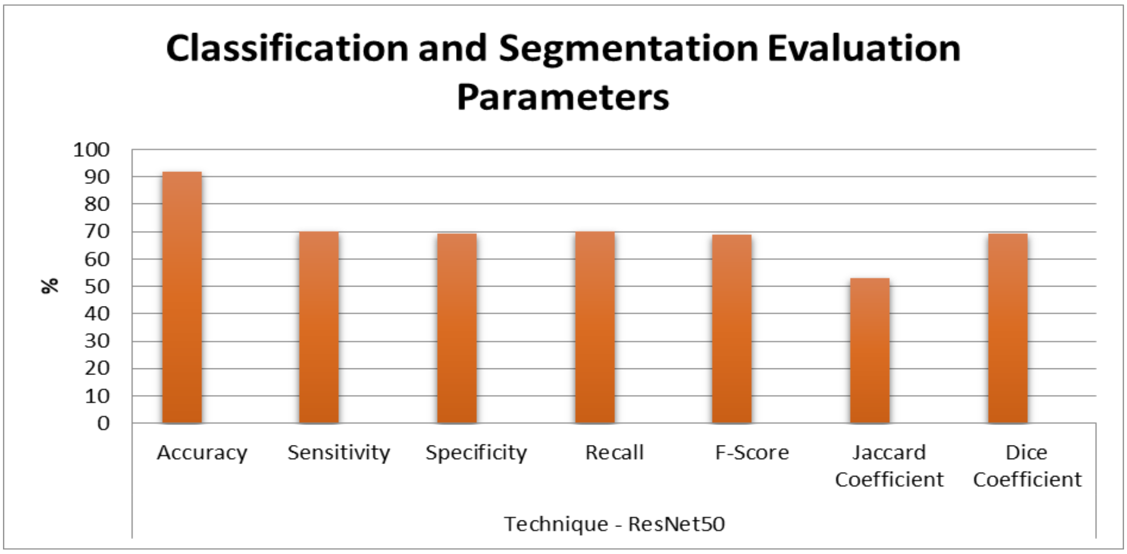

Fig.8 Classification and Segmentation Evaluation Parameters

Positive Predictive Value (PPV) and Negative Predictive Value (NPV) - It is the number of patients who had positive test results divided by the number of patients who had a positive diagnosis (including healthy subjects who were incorrectly diagnosed as patient). If the test works, you can figure out how patient a person is likely to be in real life based on whether they have this trait or not. Both the positive predictive value (PPV) and the negative predictive value (NPV) are directly related to how common a disease is and tell you how likely it is that a patient has a certain condition.

Positive Predictive Value (PPV) = 100xTP/(TP+FP)

Negative Predictive Value (NPV) = 100xTN/(FN+TN)

Table 1 Predicted value Results

Technique	PPV	NPV
ResNet50	68.6503	70.7625

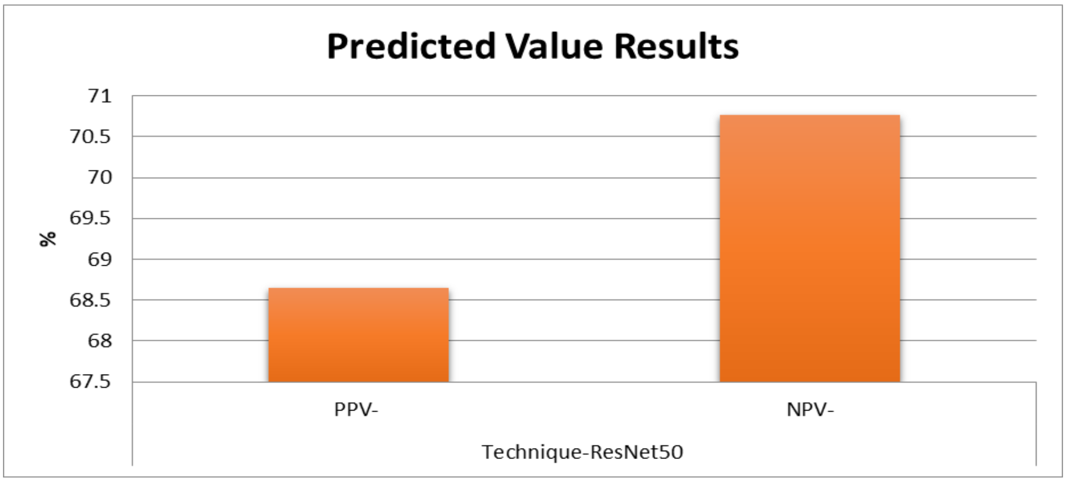

Fig.9 Predicted value Results

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Table 2 comparison result with existing work

	Accuracy (%)	Sensitivity (%)	Specificity (%)
RESNET[1]	93.3	87.6	95.5
RESNET50	96	92.1316	90.2987

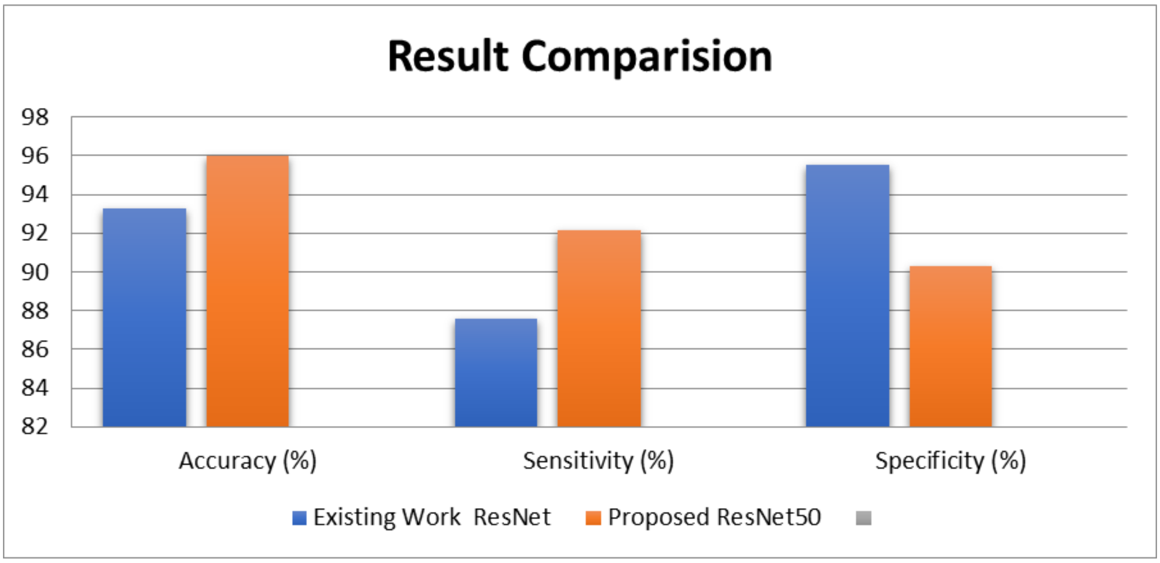

Fig .10 comparison result with existing work

provided some results for the accuracy, sensitivity, and specificity of two models, RESNET and RESNET50, in detecting COVID-19.For RESNET, the accuracy is 93.3%, with a sensitivity of 87.6% and a specificity of 95.5%. For RESNET50, the accuracy is 96%, with a sensitivity of 92.1316% and a specificity of 90.2987%.overall, these results suggest that deep learning models, such as RESNET and RESNET50, have the potential to accurately detect COVID-19 from medical images.

V. Conclusion

This work is a state of the art that gives an overview of some of the most important digital solutions that have been used around the world for COVID-19 disease screening and diagnosis, contact tracing, drug and vaccine development, prognosis and forecasting, and contact tracing. There is also separate information about each scientific contribution, such as the nature of the application, the used machine learning techniques and the findings from a data science perspective. It will be demonstrated that the rapid development of automated diagnostic systems based on machine learning not only protects healthcare personnel by reducing the number of times they interact with COVID-19 patients, but also saves money, expedites the process, and improves the accuracy of diagnoses. All of these benefits will be discussed.

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