# Covid-19 Detection Based on Deep Learning Feature Extraction and AdaBoost Ensemble Classifier

Auwalu Saleh Mubarak[a,b*], Sertan Serte[a], Zubaida Sa'id Ameen[b], Chadi Altrjman[b], Fadi Al-Turjman[b]

[a]Department of Electrical and Electronics Engineering, Near East University Near East Boulevard, ZIP: 99138 Nicosia TRNC Mersin 10 – Turkey.

[b]Department of Artificial Intelligence Engineering, AI and Robotics Institute, Research Center for AI and IoT, Near East University, Nicosia, Mersin 10, Turkey

Email id: fadi.alturjman@neu.edu.tr

**Abstract:** In January 2020 the World Health Organization (WHO) declared the deadly disease Corona Virus 2 (SARS-CoV-2) or (COVID-19) as a global pandemic. The adopted benchmark test results for the detection of COVID-19 is Reverse Transcription Polymerase Chain Reaction (RT- PCR). The test is time consuming and expensive as well. With the nature of the virus, a rapid and efficient way of testing is needed. With the application of medical imaging in different fields of medicine and with the success of Artificial models in many fields of medicine, COVID-19 detection using Computed Tomography (CT) scan images can serve as an alternative to the RT-PCR test, as CT scan images are used in profiling COVID-19 patients in hospitals. In this study, two types of training were performed on three different pre-trained deep learning models namely ResNet-50, ResNet101, and VGG16 by employing the Transfer learning method, in the first training feature extraction and classification were carried out by the pre-trained models, while in the second training, features were extracted utilizing the pre-trained models feature extraction part and AdaBoost ensemble classifier for classification. ResNet-50 with the AdaBoost ensemble classifier outperformed the state of the art models employed on the same dataset.

*Keywords:* Artificial Intelligence; CT Scan; COVID-19; AdaBoost Ensemble.

## 1. Introduction

In December 2019, a deadly respiratory disease Corona Virus 2 (SARS-CoV-2)/(COVID-19) which was different from SARS-CoV and MERS-CoV was reported in Wuhan, Hubei Province, China [1] the disease spread was suspected to have started from wild animals which are illegally sold in a seafood market in Wuhan, in few days the deadly disease spread to many cities in China and other countries [2]. On 30th January 2020, World Health Organization declared SARS-CoV-2 as a global pandemic [3], By 16th of march 2020, the number of active and death cases reported in the world was 168,826 and 6,503[4], and by the 27th of August 2020 the confirmed cases reaches 24,514,320 and total death of 832,660, the rate of infection is increasing exponentially, the common symptoms of the disease include fever, dry cough, fatigue, lymphopenia and acute respiratory distress with severe pneumonia[5]. A very rapid and efficient method of detecting COVID-19 is needed to curve the spread of the virus as it affects the whole world.

Due to the widespread COVID-19 in the world, fast and early detection of COVID-19 and the low-cost test is very important, many people have been isolated because they show mild symptoms and the virus has an incubation period of 14 days [6]. The benchmark test result for COVID-19 today is RT- PCR test for the detection of the nucleic acid forms stem from the COVID-19 [7]. The test is performed by collecting respiratory specimens such as oropharyngeal swabs, in the receiving place of specimen human error can occur[8]. The PCR test is time-consuming and costly, patients awaiting results must be isolated which will increase cost either to the government or patient, also the chances of getting the correct result are 30% -50% [9]. An alternate to PCR is medical imaging whereby Computed Tomography (CT) scan images can be applied most especially in the case of pregnant and small children [10], [11]. Though CT is associated with high dosage and is also costly [12] but was used for COVID-19 evaluation and profiling in [12][10]. [10][13]recommended Xray than a CT scan but did not consider pregnant women and children.

### 1.1. Related works

The deadly disease of COVID-19 still has an impact on the world by crippling activities [14]. Several approaches have been taken into account in tackling the spread of deadly disease [15]. Mathematical models have been analyzed to predict the spread of disease by considering the number of infected, susceptible and recovered patients [16], and this modelling is a classic approach [17]. To achieve real-time prediction, AI models coupled with IoT have been used to help medical practitioners diagnose and monitor COVID-19 by looking at parameters such as temperature, blood pressure, and heart rate, given the high number of cases, the privacy of data transmission and the energy efficiency of the low-power device used to collect information is very important, as proposed by [18], to have an efficient system for patients data privacy, power consumption efficiency, and transmission. To reduce the effect of the economic impact caused by COVID-19. In [19], they proposed an AI model that is data-driven to predict lock-down and non-lock-down area boundaries to reduce the economic impact of the COVID-19 pandemic, the adopted method of lock-down by many countries was a total lock-down, this method is not good for the economy, with the proposed model [19], A near-real-time prediction of areas with high active cases has been predicted and can serve as an avenue for smart cities. [20] IoT based system was proposed to identify COVID-19 by gathering information from patients such as X-ray images, temperature, breathing ventilation, sweat transition, and heart signals. The system classifies X-ray images and predicts the state of patients using three deep learning models, namely ResNet50, InceptionV3 and InceptionResNetV2. This study will help health workers manage and detect COVID-19 patients.

Artificial intelligence once an efficient technique has been applied in many medical fields as a fast predictive and efficient way of profiling many medical conditions related to brain surgery, pulmonary diseases, and cardiology[21]–[26]. Different AI models were employed to classify COVID-19 and non-COVID-19 x-ray and CT scan in which (81.5% – 95.2%) and (95.4% – 100%) were achieved in CT scan and x-ray scan respectively[27]. CovXNet was employed to classify x-ray images of normal, COVID, viral, and bacterial types of pneumonia, the classification on the four classes achieved the highest accuracy of 90%[28]. [29] employ transfer learning through the Resnet50 pre-trained model, in retraining 41 epoch was adopted and an accuracy of 96.3% was achieved on all classes. RT PCR results were compared with CT scan images in COVID-19 detection, the earlier RT PCR shows negative results while the CT scan results show positive, this shows the efficiency of adopting medical imaging in profiling COVID-19 as it can detect the virus at early stage[30]. Grey Level Size Zone Matrix (GLSZM) coupled with SVM was employed to to classify CT scan images of COVID-19 and non COVID-19 images, base on tuning hyperparemeter validation fold 2, 5,10, the 10 fold achieve the highest accuracy of 99.68 [31].classification of pneumonia, covid 19 and non relevant to pneumonia or covid 19 was performed on CT scan images, the motivation of their work is to find an alternattive to RT PCR, and the highest ccuracy score was 86.7 %[32]. [33] compare two deep learning models, ResNet50 and Generative Adversarial Network(GAN), the training was performed on [34] dataset, the performance on the model was compared based on training set with augmentation and without augmentation, the best performing model was ResNet50 with accuracy=92.9, specificty =0.871 and sensitivity=0.778.

### 1.2. Contributions

The motivation in this study is to find a way to reduce the spread of the deadly COVID-19 and to detect COVID-19 at an early stage, the presently adopted benchmark COVID-19 testing method by WHO is the RT PCR, the RT PCR is costly as not all people in the world can easily have access to the test as most countries in the world economies are not good, most especially the third world countries. Proposing an accessible method of detecting COVID-19 is very important, that is why we looked at the most options used in screening COVID-19 positive patients, CT scans images can serve as a fast and efficient method compared to RT PCR and with few radiologist numbers in the world, the best alternative is to employ efficient Artificial Intelligence models. Our contributions in this work are:

(i) Three pre-trained deep learning models ResNet-50, ResNet-101, and VGG16 were proposed to classify COVID-19 and non-COVID-19 CT scan images.
(ii) AdaBoost Ensemble Classifier was introduced as a classifier to the pre-trained models which Serves as feature extractors.
(iii) The performance of the models based on the two classifiers Softmax and AdaBoost Ensemble Classifier was compared.
(iv) The best performing model outperformed the state of the art models employed on the same dataset.

## 2. COVID-19 Detection.

This section explains the features of the dataset used and the proposed pre-trained deep learning models for the identification of COVID-19.

### 2.1. Dataset

In this study, the dataset from [34] contains 349 COVID-19 positive images, and 397 non-COVID-19 images were used for the training of different deep learning networks, 80% of the data was used for training, and 20% of the data was used for testing. Samples of COVID-19 and Non-COVID-19 CT scan images are presented in fig.1. and fig.2. respectively.

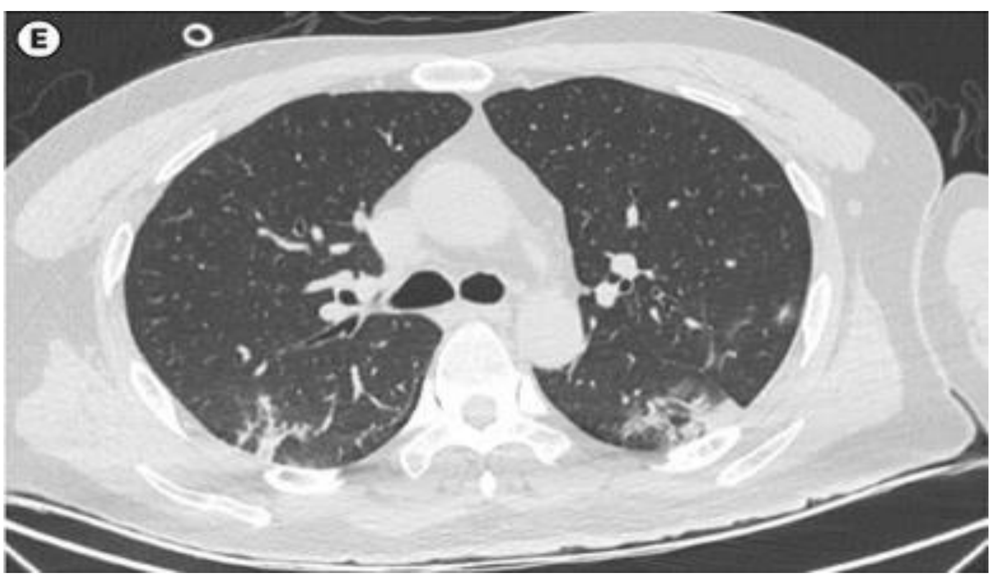



Fig 1. COVID-19 CT image.

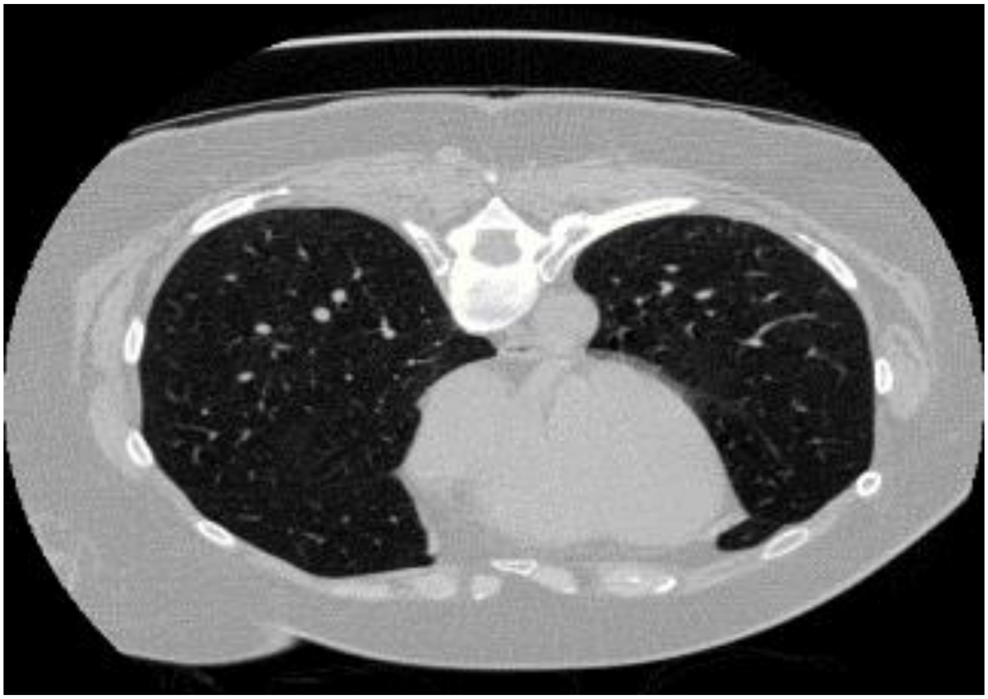


Fig 2. Non-COVID-19 CT image.

2.2. Transfer Learning

Transfer learning is a research problem in machine learning that centres to preserve the knowledge learned while solving a problem and applying it to another, but a related problem. Transfer learning can be achieved by retraining the fully connected layers of pre-trained models and freezing the extraction features such as filters and other parameters. [22], [28], [35]–[37].

2.3. ResNet

ResNet is a deep learning algorithm used in classifying images. The key concept behind ResNet is to deal with disappearing gradients that degrade network output induced by piling up a convolution layer over a pooling layer in deep network architecture, shortcuts that include identity is a residual block, the idea of inserting skip connections effectively removes a high training error, other deep networks do not contain an identity connection. That is why ResNet is different, ResNet-50 contains 50 layers and ResNet-101 contains 101 layers.

2.4. VGG16

VGG16 is a deep learning model that contains 16 layers, out of the 16 layers 5 are convolutional layers, 3 trainable layers, and the remaining layers are max-pooling layers. This architecture was the 1st runner up of the Visual Recognition Challenge of 2014 i.e. ***ILSVRC-2014***

2.5. AdaBoost Ensemble Classifier

AdaBoost is an ensemble strategy that trains and sequentially adopts trees. AdaBoost implements boosting where a group of weak classifiers is associated in sequence such that each weak classifier can increase the classification of samples misclassified by the previous weak classifier. In this way, the fusion of weak classifiers would be improved in sequence to create a strong classifier. Decision trees used in boosting approaches are referred to as "stump" since each decision tree appears to be shallow constructs that are not over-fitting but may be biased. The real tree is taught to pay particular attention to the absence of the previous decision tree. The weight of the sample misclassified by the preceding tree will be raised so that the next tree will work on the correct classification of the previously misclassified specimen. Classification precision improves with the inclusion of weaker classifiers to the model in sequence, although this can lead to unnecessary over-fitting and a decrease in generalization capabilities. AdaBoost is suited for imbalanced datasets but does not perform well in the presence of noise. The AdaBoost hyperparameter optimization is much more complex than the RF classifier.

## 3. Preprocessing and Training

### 3.1. Preprocessing

Data preprocessing in deep learning is the process of perfecting data in such a way that it can fit the input of a network and increase the number of datasets for robust and better training. There are several types of data preprocessing such as resizing, augmentation, and smoothing in training medical images. In this study, to improve the robustness of the deep-learning network training and increase the number of training data, data augmentation was performed on the training set data, these augmentation methods are random reflection, random translation along the x-axis, random translation along the y-axis, random rotation and flip[25], [33].

### 3.2. Training

In this study, three pre-trained deep learning models were employed namely ResNet-50, ResNet-101[38], and VGG16[39]. Two types of training were performed to determine the models with the best performance.

(i) Employing transfer learning using the pre-trained networks for feature extraction and classification
(ii) Employing transfer learning using the pre-trained networks for feature extraction and AdaBoost Ensemble Classifier for classification.

In the first set of training two CT scan images of COVID-19 and Non-COVID-19 classes were classified by fine-tuning the pre-trained networks hyperparameters Epoch=20, validation fold=3, Mini batch size =20, and learning rate = 0.0001. the whole network structure was used. The batch size determines the stability of training, to reduce error generalization small batch sizes are adopted in most training though they are noisy, they offer regularization and also make it easier to fit one batch size on GPU [40]. while in the second training features were extracted using the pre-trained models' layers from the input layer up to the last pooling layer, the fully connected layers and the softmax classifier are replaced by the AdaBoost Ensemble classifier. The process of the training is presented in fig.3.

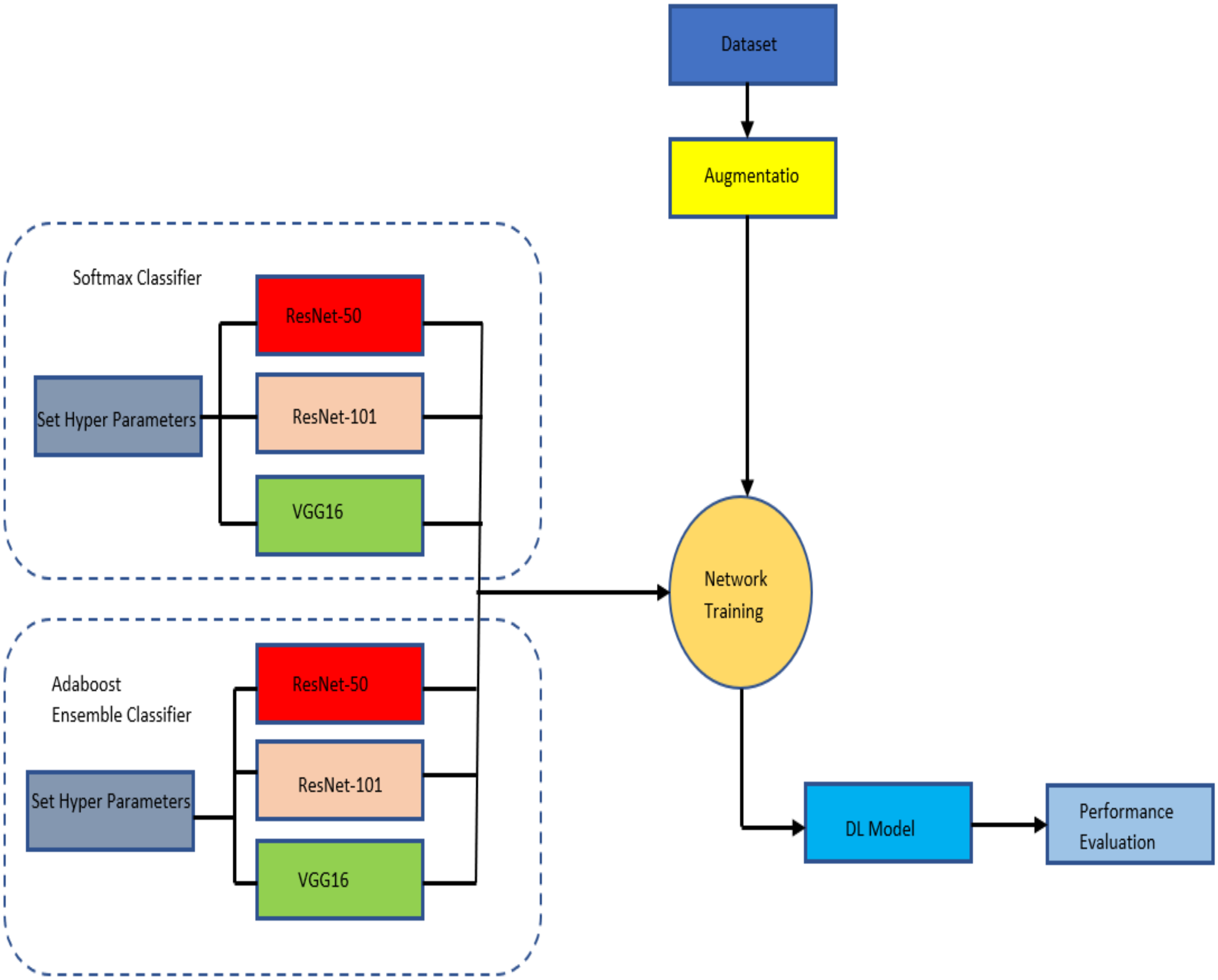



Fig.3. Training process

**Results and Discussion**

In this study, we improved the state of the art models employed on the dataset [34] by employing transfer learning, data augmentation and changing the architecture of the pre-trained models by applying AdaBoost Ensemble Classifier, the three different pre-trained network ResNet50, ResNet101, and VGG16 models were trained and compared with the state of the art model.

In table 1, base on the three models ResNet50, ResNet101 and VGG16. ResNet50 achieved validation accuracy=87.5%, sensitivity=0.83, specificity=0.82, precision=0.99, F1-score=0.95, Yonden Index=0.78 and AUC=0.92. ResNet101 achieve a validation accuracy=85.71, sensitivity=0.83, specificity=0.87. F1-score=0.91, precision=0.99, Yonden index=0.91and AUC=0.81. for the VGG16 accuracy=74.9, sensitivity=0.89, specificity=0.63. F1-score=0.94, precision=0.88 , Yonden index=0.52 and AUC=0.76. ResNet-50 with AdaBoost Ensesemble classifier achieves an accuracy of 97.33, sensitivity of 0.92, specificity of 0.95, F1 score of 0.94, Precision of 0.935, Yonden Index of 0.94 and AUC of 0.989. the ResNet-101 with AdaBoost Ensesemble classifier achieves an accuracy of 85.3, sensitivity of 0.857, specificity of 0.850, F1 score of 0.845, Precision of 0.833, Yonden Index of 0.707 and AUC of 0.854, while the third models VGG16 with AdaBoost Ensesemble classifier achieves an accuracy of 78.7, sensitivity of 0.80, specificity of 0.775, F1 score of 0.778, Precision of 0.757, Yonden Index of 0.575 and AUC of 0.788.

Table 1. Comparison of models performance with state of the art models.

| **Ref.** | **Models** | **ACC(%)** | **SN** | **SP** | **F1-Score** | **PR** | **YI** | **AUC** |
|---|---|---|---|---|---|---|---|---|
| | ResNet-50 | 76.3 | 0.659 | 0.763 | | | | |
| | ResNet-50+augmentation | 82.1 | 0.776 | 0.876 | | | | |
| | GAN | 73.3 | 0.8 | 0.943 | | | | |
| [33] | GAN+augmentation | 81.4 | 0.617 | 0.819 | | | | |
| | VGG16 | 76 | | | 0.76 | | | 0.82 |
| | ResNet18 | 74 | | | 0.73 | | | 0.82 |
| | ResNet-50 | 80 | | | 0.81 | | | 0.88 |
| | DensNet121 | 79 | | | 0.79 | | | 0.88 |
| | DensNet169 | 83 | | | 0.81 | | | 0.87 |
| | EfficientNet-b0 | 77 | | | 0.78 | | | 0.89 |
| [41] | EfficientNet-b1 | 70 | | | 0.79 | | | 0.84 |
| | ResNet50 | 87.5 | 0.83 | 0.82 | 0.99 | 0.95 | 0.78 | 0.92 |
| | ResNet101 | 85.71 | 0.83 | 0.87 | 0.99 | 0.91 | 0.91 | 0.81 |
| | VGG16 | 74.9 | 0.89 | 0.63 | 0.88 | 0.94 | 0.52 | 0.76 |
| | ResNet50+AdaBoost | 97.33 | 0.928 | 0.950 | 0.94 | 0.935 | 0.94 | 0.989 |
| | ResNet101+AdaBoost | 85.3 | 0.857 | 0.850 | 0.845 | 0.833 | 0.707 | 0.854 |
| **Ours** | VGG16+ AdaBoost | 78.7 | 0.800 | 0.775 | 0.778 | 0.757 | 0.575 | 0.788 |

While comparing the performance of the proposed models, it was observed in fig.4 and fig.5 that the model which achieves the highest accuracy and specificity was ResNet-50 with AdaBoost ensemble classifier, as presented in fig.6 and fig.7, this shows that the combination of pre-trained deep leap learning model as feature extractor and AdaBoost ensemble classifier can improve the detection of COVID-19, this combination also outperformed the sate of the art models used in classifying COVID-19 and non-COVID-19 CT scan images of the same dataset used in this study. Finding a very efficient and cost-effective way of detecting COVID-19 is very important, an alternative to RT PCR is looking towards medical imagine most especially for pregnant women and children who are not supposed to be exposed to radiation[10], [11]. The study [12][10] shows the capability of medical imaging, in this work, we compare the performance of trained models on CT images and achieve very efficient models that can detect COVID-19, as the deadly COVID-19 is declared as world pandemic, low cost and accessible method of detecting the virus at an early stage is very important considering countries with poor health facility and poor economy, though CT scan is a little bit expensive, the performance on the model shows a promising solution.

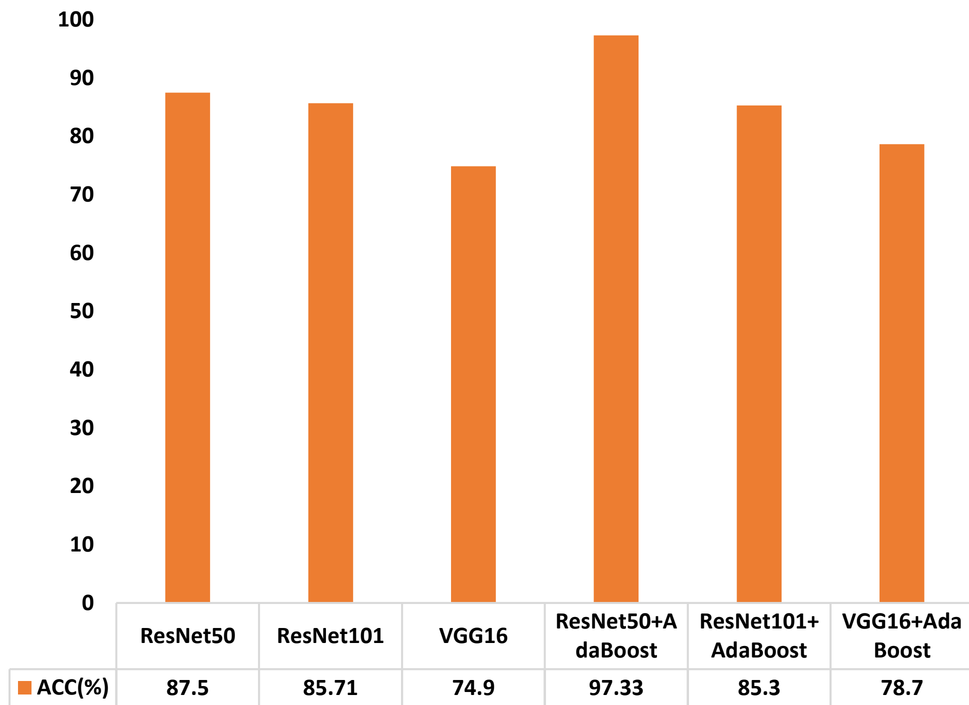
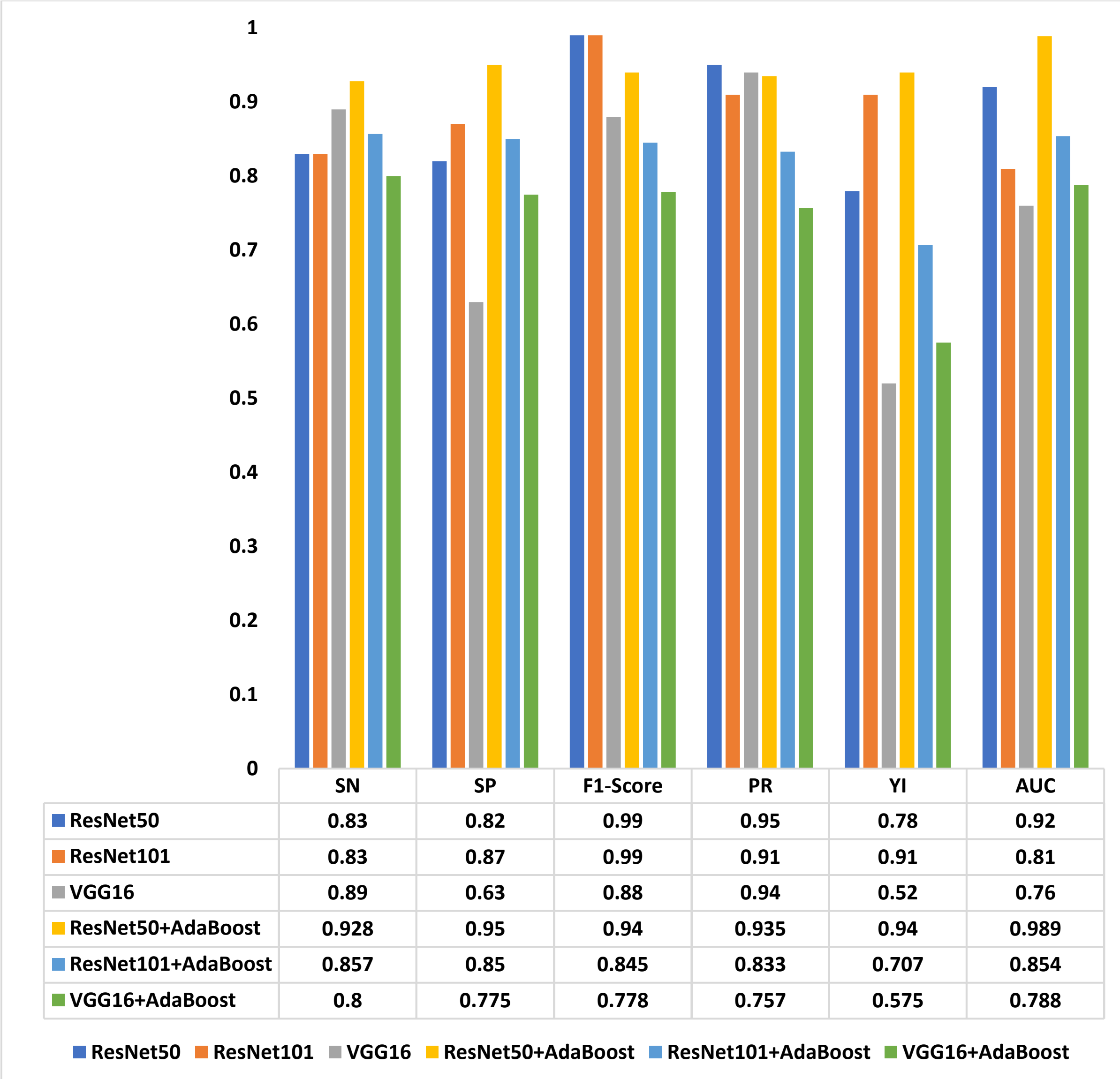



**Fig.4.** Proposed models accuracy comparison.




| | SN | SP | F1-Score | PR | YI | AUC |
|---|---|---|---|---|---|---|
| ResNet50 | 0.83 | 0.82 | 0.99 | 0.95 | 0.78 | 0.92 |
| ResNet101 | 0.83 | 0.87 | 0.99 | 0.91 | 0.91 | 0.81 |
| VGG16 | 0.89 | 0.63 | 0.88 | 0.94 | 0.52 | 0.76 |
| ResNet50+AdaBoost | 0.928 | 0.95 | 0.94 | 0.935 | 0.94 | 0.989 |
| ResNet101+AdaBoost | 0.857 | 0.85 | 0.845 | 0.833 | 0.707 | 0.854 |
| VGG16+AdaBoost | 0.8 | 0.775 | 0.778 | 0.757 | 0.575 | 0.788 |

**Fig.5.** proposed models performance comparison.

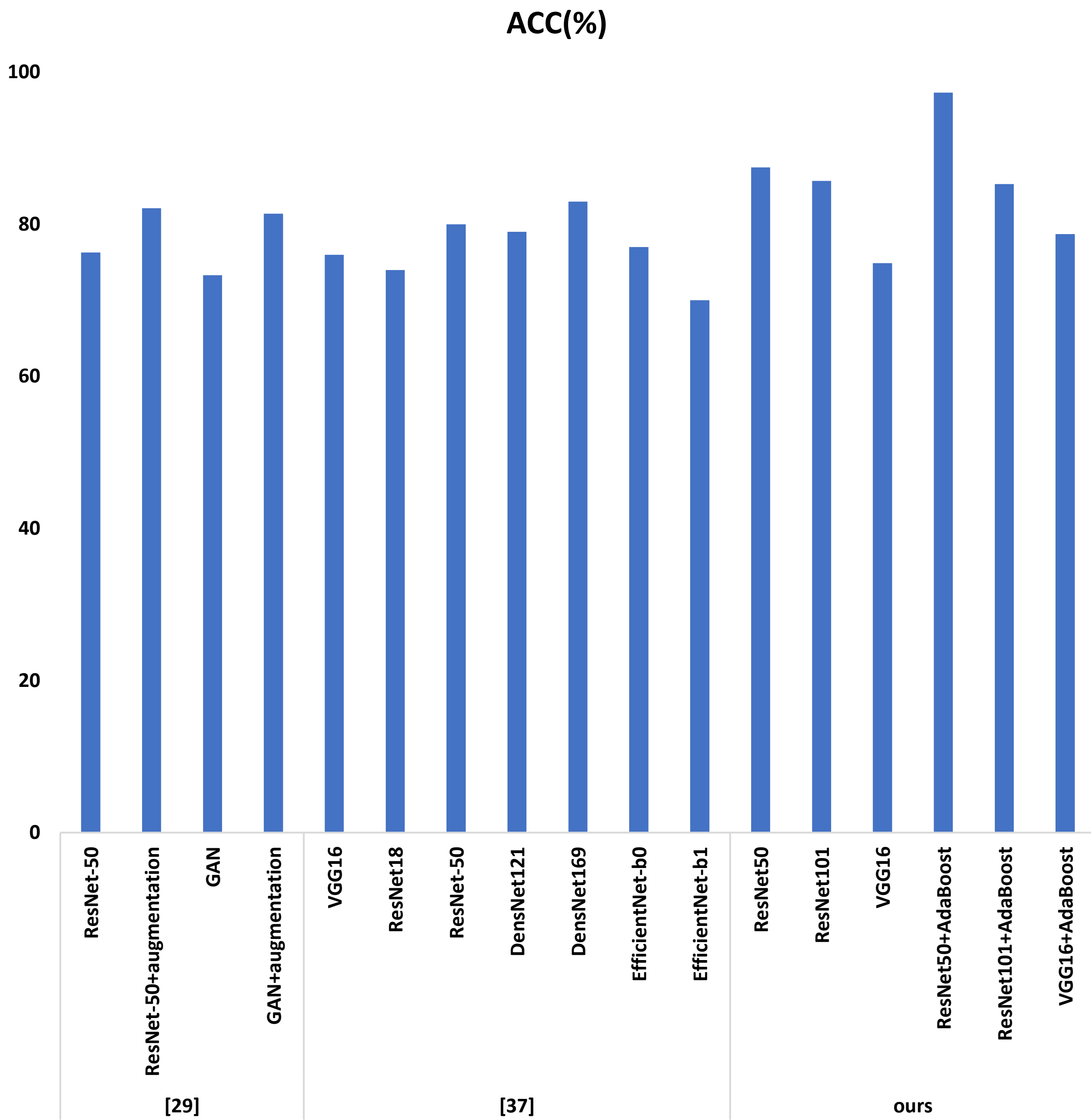



**Fig.6.** Proposed models accuracy compared with the state of the art models accuracy

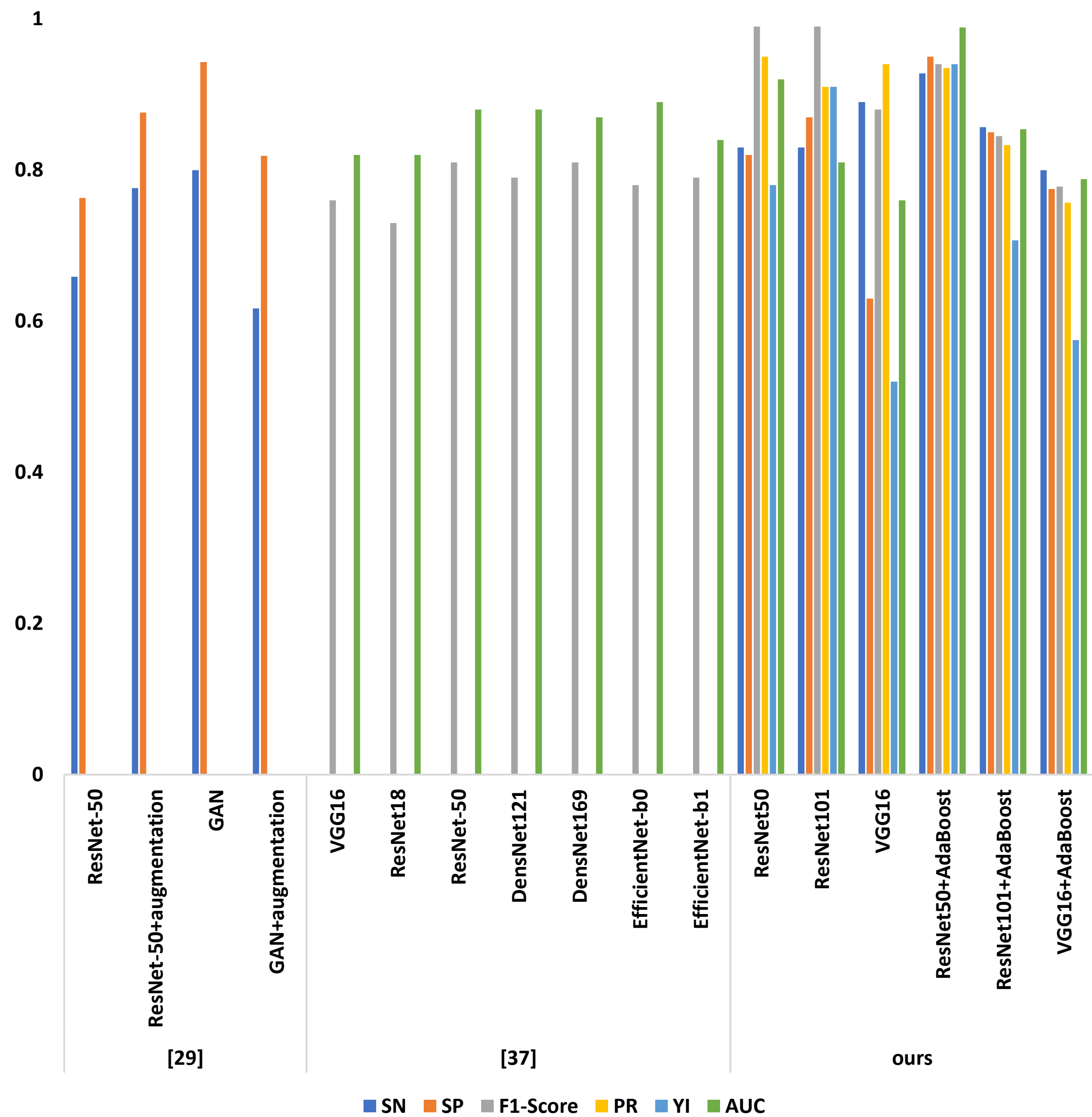



**Fig.7.** Proposed models performance compared with the state of the art models performance

## Performance Criteria

### Accuracy

Accuracy is a measure that gives insight into how well the model learned and is producing a reliable result. It is the fraction of predictions that were provided correctly by the model. The accuracy of a model is the ratio of correctly predicted samples to the number of input samples. The number of correctly predicted samples is the sum of the number of true positives and false negatives

$$Accuracy = (TP+TN)/(TP+FP+FN+TN) \qquad (1)$$

**Sensitivity or Recall**

Is the ability of a model to test correctly and identify patients with a disease as Presented in equation (2).

$$Recall/sensitivity = TP/(TP+FN) \qquad (2)$$

**Specificity**

Specificity is a measure of how many negatives the trained model managed to capture out of the entire set of correctly predicted negative values by labelling the samples as negative. The relation for calculating specificity is presented in Equation 3.

$$Specificity = TN/(TN+FP) \qquad (3)$$

**F1-Score**

F1-score is a measure of the balance between the precision and recall of a model. It is used to perform a statistical analysis of the test accuracy. The F1-score of a model lies between 0 and 1. It is said to be very good if its value lies near one and very bad if it is near zero. It is calculated as given in equation 4

$$F1\ Score = 2*(Recall * Precision) / (Recall + Precision) \qquad (4)$$

**Yonden Index**

Is the cut-point that optimizes the biomarker’s distinguishing ability when equal weight is given to sensitivity and specificity, it also gives the summary of the receiver operating characteristic (ROC) curve. presented in equation 5.

$$Yonden\ Index=(sensitivity+specificity)-1 \qquad (5)$$

**Precision**

Precision is a measure of how precise or accurate the model is in terms of positive classifications. In other words, it measures the number of true positives out of all the predicted positives. The relation for precision is presented in Equation 6

$$Precision = TP/(TP+FP) \qquad (6)$$

**Conclusion**

In this study, we have achieved the classification of CT scan images by employing transfer learning with different classifiers using ResNet50, ResNet101, and VGG16 pre-trained networks, the performance achieved base on the performance criteria validation accuracy, sensitivity, and specificity, precision, F1-Score, AUC, and Yonden Index show how great the deep learning models can perform in COVID-19 detection using CT scan images. Base on the results on the best performing model ResNet50 with AdaBoost Ensemble Classifier, it shows that we achieved higher accuracy, sensitivity, specificity, precision, F1 score, Yonden Index, and AUC Compared to the state of the art models employed on the dataset. By adopting deep learning for COVID-19 detection using CT scan images, the method will help in profiling the patient’s status very fast and efficiently. To reduce the spread of the virus as the virus incubation period is 14 days, though most of the patients show mild symptoms, before confirming their status they need to be isolated, which will come with cost penalty on the patient or the government, with early detection the patients can be put on medication at an early stage and recover on time and for pregnant and children the CT scan will be the best alternative.

**Acknowledgement**

This research focuses on those affected by the COVID-19 pandemic and those who are helping to fight this war in whatever way they can. We would also like to thank the doctors, nurses, and all healthcare providers who are putting their lives at risk in the fight against the coronavirus outbreak.

**Competing interests: None**

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