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Artificial Intelligence Enabled Dual Diagnostic Based Algorithm For The Detection Of COVID-19 Patients

Swarnava Biswas[1], Debajit Sen[2], Moumita Mukherjee[3]

[1]The Neotia University, Kolkata, West Bengal, India
[2] Robert Bosch Engineering and Business Solutions, Bangalore, Karnataka, India
[3]Department of Physics, School of Science, Adamas University, Kolkata, West Bengal, India
Email: moumita.mukherjee@adamasuniversity.ac.in

Abstract

COVID-19, a global pandemic first surfaced in the city of Wuhan, China and has henceforth transcended differently across geographical borders, classes, and genders from different age groups, sometimes mutating its own DNA strands in the process as well. Hospitals and medical centres are getting overburdened by the sheer magnitude of the spread of the pandemic. While IoT in healthcare had already dominated the public discourse, the onset of COVID-19 has been a watershed development. The need of the hour is to deploy robots and IoT devices to keep a check on patient's body vitals, as well as monitor their other pathological data to further have a control on the spread. Needless to mention, there has never been a more urgent reason as today to mobilize digital innovations for providing healthcare services remotely through computing devices and patient-facing artificial intelligence (AI) powered medical aids. In this paper our group has developed an AI enabled Decision Support System for automating the entire process flow from estimation to detection of COVID-19 subjects as part of an Intelligent Value Chain algorithm for the first time. The proposed method is validated and computational complexity is estimated in different Single Board Computer (SBC) platform. The NVIDIA Xavier CUDA system provides very low training and predicted time when compared to raspberry pi-4 and Jetson Nano.

Keywords: Artificial Intelligence, Internet of Things, Deep Learning, Machine Learning, COVID-19 Detection, X-ray, Pathology Data, Stage Classification COVID-19, Raspberry Pi, Intel® Movidius™ Neural Compute Stick

INTRODUCTION

With data and analytics (Runkler, 2020) including direct and continuous connect with users, and natural language processing analysing vast amounts of people health data (Ebadi et al., 2021), the focus has clearly shifted to prevention ahead of cure. The predicted persistence of COVID (Fauci, Lane, & Redfield, 2020) in the future will necessitate diagnostic testing in remote location limited by point of care (Gubala, Harris, Ricco, Tan, & Williams, 2012) facilities. IoT in healthcare is challenged due to low levels of internet coverage, especially in countries like India (Sonune, Kalbande, Yeole, & Oak, 2017). As a holistic and preventive system, IoT in healthcare provides a shift from cost-based to value-based healthcare thereby strengthening existing medical centres limited by facilities (Yuehong, Zeng, Chen, & Fan, 2016). The reason the research group thought of proposing a solution for an IoT enabled healthcare to make preventative & control the spread as part of the modern health informatics system (Farahani, Firouzi, & Chakrabarty, 2020).

The motivation behind such a work can be explained in the way the world was found wanting during the peak stages of the viral spread in most countries (Chakraborty & Maity, 2020). The requirement for more tests to correctly identify and diagnose was the need of the hour which some countries failed to achieve. One of the main reasons could be the real time polymerase chain reaction (RT-PCR) test and the cost that the same demands both from facility and testing front. Hence the same could not be adopted by some of the local diagnostic centres for a mass testing. The other pitfall of such a process was the total turnaround time, more than 48 hours to be specific (Afzal, 2020). Our group has thus tried to propose a reliable estimation and efficient screening process to make the diagnostic centres ready for any future spike and proper identification with its available facilities.

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The authors have also proposed a two-step screening process for correct diagnosis of the disease. The total process time for screening is estimated to be around 15 minutes to 1 hour. The first step consists of the body sensor-based evaluation of the patient along with symptomatic analysis. The second step consists of high-resolution computed tomography (HRCT) evaluation along with the study of pathological data viz-a-viz from blood routine examination and body sensor vitals. Any radiography-based imaging technique has a higher sensitivity but lower specificity and can play a role in the diagnosis and treatment of this nature of disease. The novelty of this paper is thus best described by the above two-fold methodology.

LITERATURE REVIEW

Lassau et al. have presented a deep learning CT scan based model in combination with biological and clinical variable to predict severity of the COVID-19 patient. This is a multi-hypothesis based approach where the authors have collated 58 clinical and biological data along with CT scan to address the objective (Lassau et al., 2021). Salehi et al. has presented a review on radiography image findings of different patients. This paper is basically a clinical study of the affected area in the radiography slices contributing towards the severity of the disease (Salehi, Abedi, Balakrishnan, & Gholamrezanezhad, 2020). Ahuja et al. have presented a deep learning automated detection of COVID –19 from lungs CT scan slices. The methodology is divided into three phases, i.e., data augmentation of the slices, COVID-19 detection performed on those data augmented slices and abnormality localization on the CT scan slices (Ahuja, Panigrahi, Dey, Rajinikanth, & Gandhi, 2021). Zhu et al. have presented the article which is a joint prediction and time estimation of COVID-19 based on CT scan for developing severity symptoms. The authors have used a classification and regression based technique to jointly predict the disease progression and the conversion time. Hence ultimately contributing towards saving lives who may develop severe symptoms of COVID-19 (Zhu et al., 2021). Down the line, Lee et al. have formulated an article on chest CT scan based COVID Detection. Over here they tried to address three main objectives such as, a simple to use classification model validated across 13 diverse sites across the world, investigated on the generalizability in these 13 places and discussed the contribution of the participants outside of China on model performance and tracked the disease scores of COVID positive patients by using the DCD features over time (Lee et al., 2021). In view of the current COVID-19 second wave and understanding the new variant of the same which is believed to be evading antibodies and also not being detected in RT-PCR, the authors have proposed a complimentary testing procedure to correctly identify the COVID-19 subjects. The authors have used the combination of different medical vitals along with a CT scan image as our dataset. The authors have used a transfer learning on a pre-trained convolutional neural network (CNN) as their first hypothesis, the second hypothesis is based on a conventional machine learning based methodology which takes the other medical vitals as its input feed. The two results are fused using a probabilistic metric to accurately predict the presence of the disease. In this paper, as of the best of author's knowledge, they have reported for the first time the deployment of the entire architecture on SBC platform which have been prototyped for validation and testing to be used in medical facility.

METHODS

Pathological data-based machine learning model development

The pivot around which our proposed mathematical model revolves to give a predictive response for detailed Detection and Diagnosis of COVID-19 is based on radiography image viz-a-viz Computed Tomography (CT) scan. It would thus offer valuable information in the screening process quickly. The technique would also act as an aid to the conventional PCR

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based method to isolate the contracted individuals quickly and an efficiently. The proposed methodology involves a deep learning (DL) model in combination with a classical machine learning (ML) Model in some processes to detect COVID-19, based on chest radiography, other medical and pathological vitals like temperature, saturation percentage of oxygen (SpO_2) and leukocyte and lymphocyte counts.
The first evaluation starts with the collection of different medical vitals from body sensors like temperature, saturation percentage of oxygen (SpO_2) and using a classical machine learning technique to predict an outcome. Our Deep Network Architecture (DNA) then acts on the CT scan based analysis for a firmer classification.
The new normal trend in any commercial, housing complex, or even in hospital premises is to screen the visitors by a thermal gun and making the person answer a list of questionnaires. The process can help to identify some suspicious cases at the entry point. Our objective is to remove the human factor out of the equation to reduce the manual error. We have used an AI-based classification tool that we have trained on a huge data set from to classify the COVID from the normal based on temperature and oxygen saturation percentage.
The data set contained age, gender, temperature and SpO_2 as parameters for correct classification of COVID individuals were trained using the Classification Learner App in MATLAB® and the Model with the highest accuracy was automatically returned. The details of the training model along with the different performance evaluation visualizations are given below in Table 1. The ensemble method was tested separately for Bag, Ada Boost & RUS Boost. The Number of Learners was tested from **10 to 500**, the Learning Rate was varied as **0.001 to 1**, the Number of Splits was tested from **1 to 560,** and the Number of Predictors was tested from 1 to 4. The Cost Matrix for Misclassification was fixed as Default and PCA was disabled. The Final Model obtained is returned as given above.

Table 1. Pathological data-based machine learning model development parameters

MODEL: OPTIMIZABLE ENSEMBLE		**OPTIMIZED HYPERPARAMETERS**		**OPTIMIZER OPTIONS**	
Learner Type	Decision Tree	Ensemble Method	Bag	Bayesian Optimization	
Accuracy	82%	Maximum No of Splits	556	Training Time	300 S
Total Misclassification Cost	104	No of Learners	58	Iterations	30
Prediction Speed	~790 observations/sec	No of Predictor Samples	4	Training Time	TRUE
Training Time	312.59 sec				

Body vitals data based machine learning model development

The second step starts with another secondary hypothesis using another machine learning tool to study the complete blood count (CBC) Data from routine examination of blood. The data set contained age, gender, Leukocyte, Lymphocyte & Neutrophil count as parameters for correct classification of COVID individuals, was trained using the Classification Learner App® in

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MATLAB® and the model with the highest accuracy was automatically returned. The details of the training model along with the different performance evaluation visualizations are provided in the following Table 2. The Optimizable Tree method was tested separately for Gini's Diversity Index, Twoing Rule and maximum deviance reduction to get the best split criterion method. The number of splits was tested from **1 to 560.** The Cost matrix for misclassification was kept as default and PCA was disabled. The Final Model obtained was returned as given above.

Table 2. Body vitals data based machine learning model parameters

<table>
<tr><th colspan="2">MODEL: OPTIMIZABLE TREE</th><th colspan="2">OPTIMIZED HYPERPARAMETERS</th><th colspan="2">OPTIMIZER OPTIONS</th></tr>
<tr><td>Surrogate decision splits</td><td>OFF</td><td>Maximum No of Splits</td><td>73</td><td colspan="2">Bayesian Optimization</td></tr>
<tr><td>Accuracy</td><td>82%</td><td rowspan="4">Split</td><td rowspan="4">Max deviance reduction</td><td>Training Time</td><td>300 S</td></tr>
<tr><td>Total Misclassification Cost</td><td>101</td><td>Iterations</td><td>30</td></tr>
<tr><td>Prediction Speed</td><td>~17000 observations/sec</td><td rowspan="2">Training Time</td><td rowspan="2">TRUE</td></tr>
<tr><td>Training Time</td><td>58.164 sec</td></tr>
</table>

HRCT scan based detection

The CT Scan based detection technique by virtue of a more informative imaging technique would enable the AI based model to draw more indicative inferences. The technique is a highly popular one when a detailed information for a region is required for a more corrective diagnosis. In a remarkably similar manner our screening phase-III would be a confirmatory diagnostic approach for a COVID-19 detected individual. Following the same philosophy for radiography assisted technique we have deployed pre-trained Convolutional Neural Network (CNN) to perform a transfer learning to correctly recognise the affected individuals.

For the CT scan assisted diagnostic process as well, we have employed an AI enabled method which is hence powered by a powerful Multi-Layer Convolutional Neural Network, also known as Deep Neural Network in short. There are many pre-trained networks that are available, but we have chosen the one which has been successfully used in the field of Medical Imaging and related works (Hassan, Ali, Alquhayz, & Safdar, 2020). The Deep Network used by us is RESNET-50 (Rezende, Ruppert, Carvalho, Ramos, & De Geus, 2017). we have restricted our classification problem to a Binary Class Problem only, i.e. COVID & NORMAL. The other important aspect of this paper emphasizes the power of a combined hypothesis, based on the pathological study as explained above, and AI-enabled radiography assisted technique for COVID detection. The objective of this part is to distinguish between "COVID", and "NORMAL" subjects based on radiography images using this model. Furthermore, the authors have tried to classify the different stages of "COVID" based on the CT scan images. The RESNET-50 is a multi-layer Direct Acyclic Graph (DAG) Network, pre-trained to perform 1000 Image Classifications, and has been previously trained on millions of images. The concept of Transfer Learning helps to re-use a pre-trained network as per our requirements by replacing the final few layers. The next important step is to tune the network to achieve the optimum most performance. The above steps are performed to obtain the most optimum model, to be

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used for classification. The Basic Steps that we have employed to see the Pre-trained Model & perform Transfer Learning on the same to achieve our objectives is given in Figure 1.

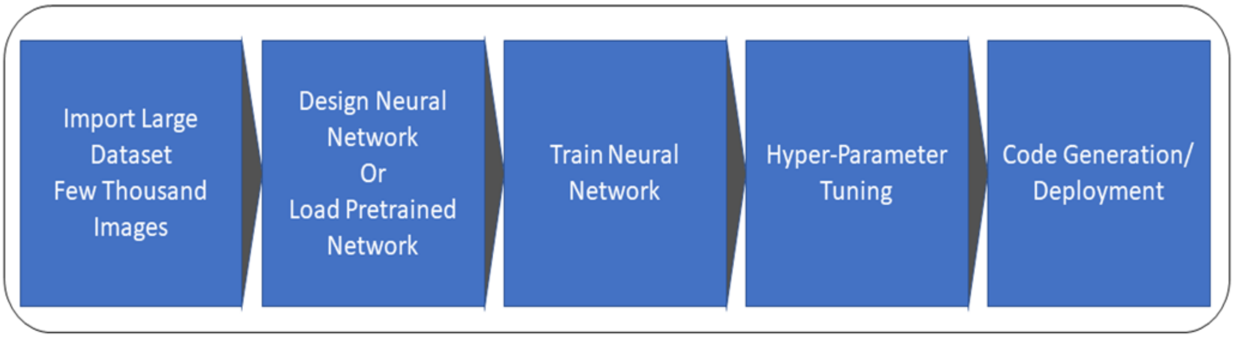

Figure 1. Basic Workflow Diagram for Convolutional Neural Network (CNN) Based Deep Learning Model for Radiographic Image for COVID-19 Identification

In respect to the above symptoms, we can explain the lung condition in the mentioned manner. The metric used to determine the correct stage are Ground Glass Opacity (GGO) & Lung Consolidation. GGO is a hazy increased opacity in lung parenchyma without the obscuration of the underlying vessels. At the initial stage, the virus invades the alveolar epithelium, and replicates in the epithelial cells, causing the alveolar cavity to leak, and the alveolar wall or the alveolar space to become inflamed or thickened (W. Yang et al., 2020; Yoon et al., 2020). The consolidation is the increased lung opacification with the obscuration of the underlying vessels. As inflammation progresses, the body reacts and a strong inflammatory reaction that results in large exudation in the alveoli (Guan et al., 2020). The airspace opacities like ground-glass opacities and consolidations are the most frequent findings in COVID, often bilateral peripheral distribution particularly at the lower zone (Ludvigsson, 2020; Rodrigues et al., 2020). The central parenchymal abnormalities, pleural involvement is rare (3%) (Holshue et al., 2020). The severity score is based on the involvement of bilateral bronchopulmonary segments (R. Yang et al., 2020). The 18 segments of both lungs were divided into 20 regions. Each of the segment involvement carries scores of 0, 1, and 2 if parenchymal opacification involved 0%, less than 50%, or equal or more than 50% of each region. The optimal score of 19.5 is identified as severe COVID-19 with 83.3% sensitivity and 94% specificity.

Decision Fusion Algorithm

Any decision fusion algorithm plays a crucial role in the multi-hypotheses situation and hence can be seamlessly used in clinical diagnostic procedures as well. The concept of multi-hypotheses will act as a valuable second opinion to doctors and hence will be an enabler for any diagnostic-based approach.

To elaborate the first of the two sub diagnostic measures in our screening processes is based on pathological data of subjects

In the second screening step, we have proposed the idea of combining the conventional radiography-based classification to help the doctors to identify any presence of strain more correctly with an annotated stage.

Since we have created a dual pool hypothesis scenario from two different algorithms hence, we are proposing an algorithm "Whoever Scores Most" in terms of a probabilistic metric to correctly recognize the affected subject concerned in decision conflict scenarios. Our algorithm finally scans through the sets of inferences and finally returns the output of the class which has a higher probability score. The equation of our methodology is described below:

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C_1 represents the output class predicted by the machine learning algorithm for pathological data.
S_1 represents the probability score for class C_1
C_2 represents the output class predicted by the deep learning model for radiographic images
S_2 represents the probability score for output class C_2
Let say X represents the single output given, two different output from different algorithms.
$X = \arg\max(S_1, S_2)$; for all output classes.

IoT enabled Deploybility

To make this composite system available to the diagnostic facilities, the authors have used the concept of the internet of things (IoT), a technology extremely popular in telemediation. Internet of Things (IoT) has been a trusted friend of various medical facilities ever since its inception. The concept of telemedicine or remote patient monitoring system has evolved in many ways with the use of IoT based devices. The authors have used the concept of IoT to complement our AI-based patient diagnostic system to increase reliability and performance. The Intel® Movidius™ Neural Compute Stick (NCS) is a new piece of hardware used for enhancing the inference process of computer vision models on low-powered edge devices. The Intel Movidius™ product is a USB appliance that can be plugged into any device such as laptops, Raspberry Pi, or even tablets. We have deployed our trained models into the Intel Movidius™ Neural Compute Stick for a classification of COVID affected subjects. The power of the device lies in running parallel ML models, hence useful in the multi-hypothesis scenario. The device is chosen by the authors for its popularity in different medical imaging activities by other peer groups.
Our models were initially designed and trained on a capable host machine (a development computer in our case). Then one of the supported Application Programming Interface (API) was used to profile, tune, and compile to convert the model to the format supported by the VPU hardware. With the newly formatted model, the model was validated, and the working prototype was generated on the same host machine. The hardware is physically connected to the machine and was accessed using available methods in the API. The development process using NCS is explained in Figure 2

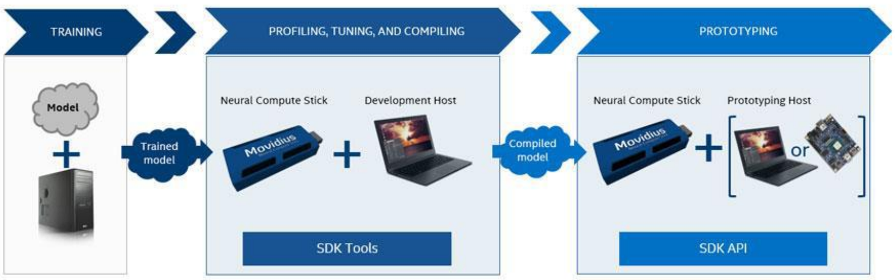

Figure 2. The development process of the NCS is presented in the workflow diagram
The philosophy of the software architecture to be used for deployment is described in Figure 3.

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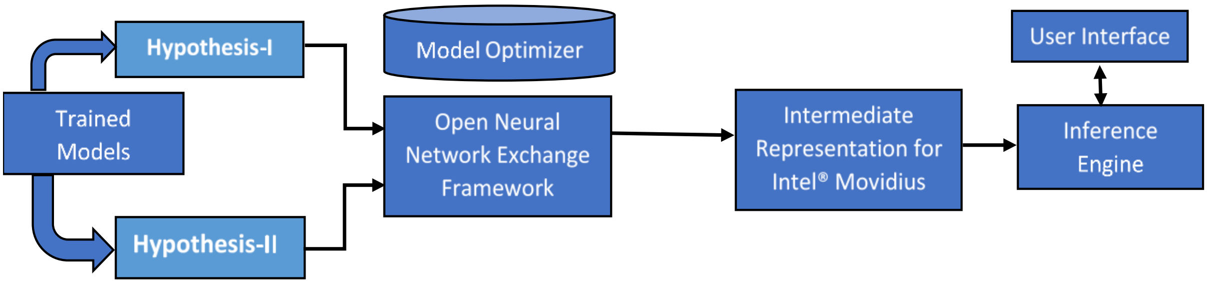

Figure 3. The philosophy of the AI Software Architecture to be used for deployment

The steps followed for inference on the edge are explained in Figure 4.

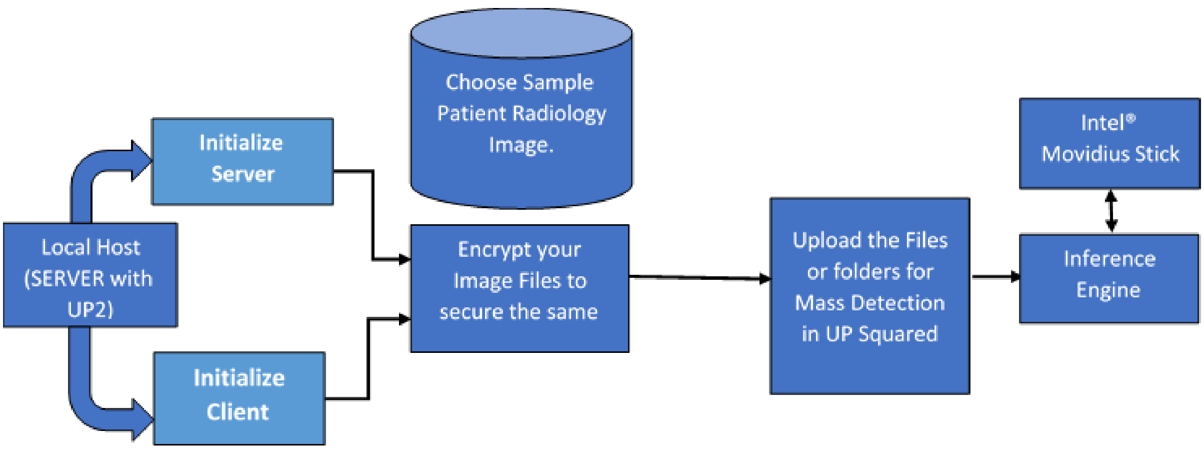

Figure 4. The setting up the server to test a COVID-19 Positive or Normal sample

The basic steps for drawing inference from the deployed models are as follows-

- The server needs to be set to start up on the localhost. In our case, it is the 'UP Squared Device'.'UP Squared Device' is a piece of hardware from intel with which the NCS is connected.
- A set of encryptions was performed on the same to secure the files or folders from access to the outside world
- The set of collected radiography images from the different subject or single individual was uploaded to the UP Squared for using it for the server.
- The models running on the Intel® Movidius™ stick can be used for drawing inference on the set of Radiography Images.
- It was observed that using the Intel® Movidius™ product on a 'UP Squared device', there is no difference in classification accuracy to the development machine; which in my case was a Windows 10 Home with Intel Core™ i3 6006U with only a slight difference in the time the classification process took to complete. The platform was marginally faster than my computer.

The authors have proposed a network architecture for making the medical facility an IoT enabled unit. The same is being proposed for faster detection and isolation of COVID-19 subjects. The network architecture is prototyped by an IoT enabled alarm system using a NVIDIA Xavier CUDA, Raspberry Pi device and NVIDIA Jetson Nano. The NVIDIA Xavier CUDA, Raspberry Pi device and NVIDIA Jetson Nano is virtually connected with the server so that for any COVID-19 positive subject, the server can trigger specific actions on the IoT

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network for communicating with the device. The performance and computation time of different devices are observed. The results that are captured from the classification of images in the server are sent to the Raspberry Pi device where the actions like turning on a red LED and a buzzer when COVID-19 is detected and turn on a blue LED when the classification results when “Normal” being detected have been programmed and activated. This is an amazingly simple Proof of Concept (POC) which shows a possibility of its powerful applications that can save time for medical staff and could help save lives through early and accurate detection.

RESULTS AND DISCUSSIONS

The different performance evaluation criteria were used to validate our mathematical model based on pathological data and body vitals is given in Figure 5. The evaluation parameters have been given in Table 3

Table 3: Confusion matrix table for different machine learning models

Pathological data-based machine learning model		**Body vitals data-based machine learning model**	
Evaluation Parameter	Score	Evaluation Parameter	Score
Sensitivity	90.71%	Sensitivity	91.19%
Specificity	58.87%	Specificity	62.097%
The area under the curve (AUC) of ROC	0.82	The area under the curve (AUC) of ROC	0.77
Misclassification Error	0.165	Misclassification Error	0.18

From Table 3, the authors have deduced that the two main factors that play a pivotal role in selecting the correct model are sensitivity & specificity. In simple terms and as an explanation for the above observations the authors find that “COVID” (target class) detected as “COVID” (output class) defines the sensitivity. It is observed that the sensitivity test for “COVID” has a higher accuracy return. Moreover, since the overall accuracy of an AI-based system is built around the true positives & false negatives count hence, the authors may observe that the entire model was made to cater to the same. The basic step that the authors have employed for the implementation of the AI-based radiography assisted technique is the concept of transfer learning. The concept is useful when the output classes do not match the classes in the pre-trained model. It also helps in the reduction of training time and does not require the model to be developed from scratch.

The authors have used the K-fold cross validation concept (Fushiki, 2011), to reduce our misclassification error (Kuha, Skinner, & Palmgren, 2014) and increase the model accuracy in return. The K-fold validation shuffles the training set randomly & iteratively and deploys K different algorithms to automatically return 5 models which can individually be evaluated on some performance criteria to obtain the best out of the lot. We have chosen the value of K as ‘5’ in our case. The best validated model on the training data was returned whose confusion matrix and receiver operating characteristics (ROC) (Streiner & Cairney, 2007) curve further justified its selection for the purpose of HRCT scan assisted diagnostic approach.

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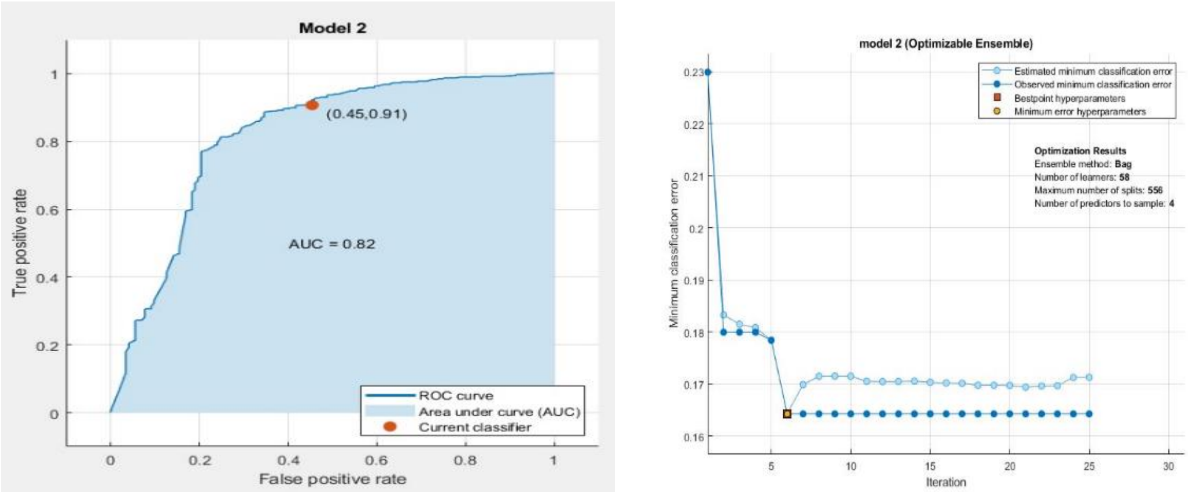

Figure 5. (a) Receiver Operating Characteristics Plot of Machine Learning Model on Pathological Data (b) Misclassification Error Plot of Machine Learning Model on Pathological Data

Hence in our case we find that deep network model for K-fold validation exhibits higher accuracy in terms of detecting COVID for the test set in particular. The other two important factors which help us to know the right model are false negatives & false positives. The area under the curve (AUC) is the best (**0.9623**) for the 5^{th} k-fold model as was returned by our algorithm. Since accuracy is proportional to AUC hence the 5^{th} K-fold model wins the race. RESNET-5 deep network has outperformed the other models in terms of overall accuracy (**87.4%).** The sensitivity rate **(96%**) is also higher in case of RESNET-5. The false negative rate **(4%**) is also within acceptable limits. The only drawback of the model lies in the number of false positives & hence the specificity as well. A little compromise on this point is still acceptable since the true objective of the model is met. In line with this the precision rate is hence considered to be under reasonable limits around **80.7%.** The confusion matrix and AUC are given Figure 6.

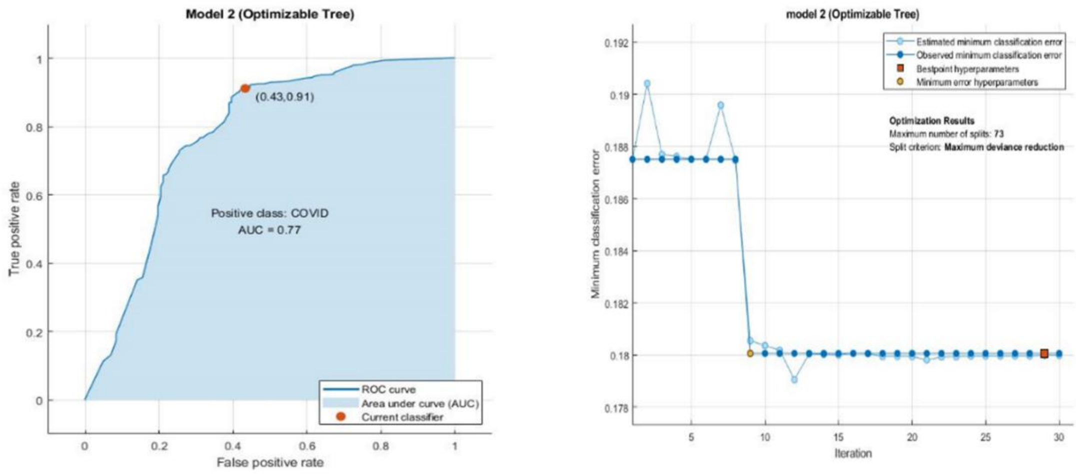

Figure 6. (a) Receiver Operating Characteristics Plot of Machine Learning Model on Body Vitals (b) Misclassification Error Plot of Machine Learning Model on Body Vitals

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Similarly, the immediate next objective was to choose the correct K-fold Validation model (Fushiki, 2011) from the 5 Models as returned by our proposed methodology. The comparison table for the selection of the right model based on a performance evaluation metric is given below in Table 4.

Table 4: Comparison between 5 different k folds of RESNET 50

Different K Fold RESNET 50 Models	Evaluation Parameter	Scores in %
K = 1 type	Sensitivity	62.7
	Specificity	81.8
	Precision	88.9
	Accuracy	68.5
K = 2 type	Sensitivity	74.5
	Specificity	77.3
	Precision	88.4
	Accuracy	75.3
K = 3 type	Sensitivity	70.6
	Specificity	63.6
	Precision	81.8
	Accuracy	68.5
K = 4 type	Sensitivity	68.6
	Specificity	63.6
	Precision	81.4
	Accuracy	67.1
K = 5 type	Sensitivity	74.5
	Specificity	81.8
	Precision	90.5
	Accuracy	76.7

RESNET-5 deep network has outperformed the other models in terms of overall accuracy (**76.7%).** The sensitivity rate **(74.5%**) is also higher in case of RESNET-5. The false negative rate **(20.5%**) is also within acceptable limits. The only drawback of the model lies in the number of false positives & hence the specificity as well. A little compromise on this point is still acceptable since the true objective of the model is met. In line with this the precision rate is hence considered to be under reasonable limits around **90.5%.**The performance of the Model is Further validated by another indicative visualization known as the Class Activation Mapping (CAM) (Selvaraju et al., 2017). This method can help us to understand the reason behind a classification in terms of a gradient map or score. In our case the red coloured zones enabled the model to classify the image under any class. Some Sample observations on Images along with the CAM zones is given in the following Figure 7.

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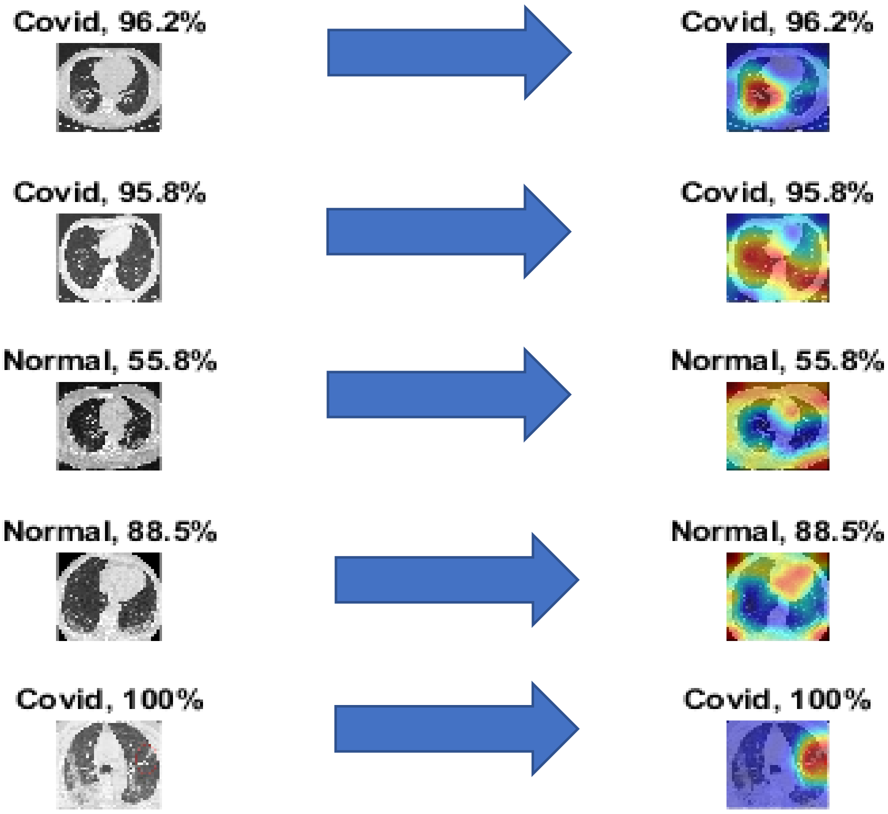

Figure 7. Classification Activation Mapping (CAM): Annotated Results to Show Affected Lung Area

The Figure 8 elucidates the learning time complexity in different SBC platforms. The NVIDIA Xavier CUDA platform provides reduced computational and time complexity when compared with the Raspberry pi 4-8GB module and NVIDIA Jetson Nano.

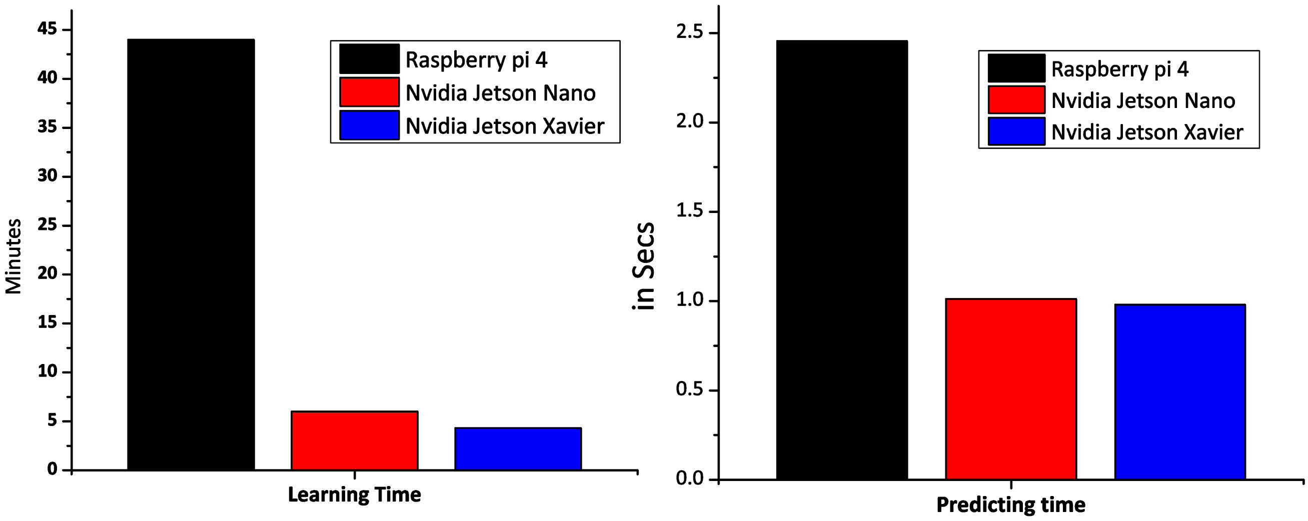

Figure 8. The learning time complexity in different SBC platforms Area

CONCLUSION

The solution pipeline as discussed is a more composite and robust one since it includes a three-step screening process. Our algorithm would be developed into a software as part of our future work and would hence act as an aid to the health practitioners & other medical staff and provide a valuable second opinion in the existing diagnostic process. Our algorithm is not intended to replace the more acceptable PCR Process but act like an aid to the same. In addition to being an aid, it is also a highly cost-effective Solution for the prediction of COVID-19 cases. The false negatives as explained is expected to be reduced by using a series of secondary hypotheses using other machine learning algorithms. The PCR-test is specific, but has a lower sensitivity, which means that the test can be negative even when the patient is infected. Another problem is, that you have to wait for the test results, which can take more than 24 hours, while CT results are available right away. Common laboratory findings in COVID-19 are a decreased lymphocyte count and an increased CRP and high-sensitivity C-reactive protein level. Our proposed methodology may help to accelerate the testing process and hence increase the number of testing cases conducted per day with efficient Identification and Isolation process. It may also help in centres not having the PCR facilities as well. The model was trained and validated on data available from different sites. The same is tested and validated in different SBC like Raspberry Pi 4, NVIDIA Jetson Nano and Xavier boards and their performances are compared. Hence the authors provided a IoT enabled solution for testing of COVID-19 affected patients in a deployable format.

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