Enhancing the medical diagnosis of COVID-19 with learning-based decision support systems

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ABSTRACT

Since late December 2019, the COVID-19 pandemic has had substantial impact and long-lasting impact on numerous lives. The surge in patients has overwhelmed hospitals and exhausted essential resources such as masks and gloves. However, in response to this crisis, we have developed a robust solution that can ease the burden on emergency services and manage the influx of patients. Our proposed framework comprises deep learning and machine learning models that can predict and manage patient demand with high accuracy. The first model, is specifically designed to classify computed tomography (CT) scan images for COVID or non-COVID cases. We trained multiple convolutional neural network (CNN) models on a large dataset of CT scan images and evaluated their performance on a separate test set. Our evaluation showed that the ResNet50 model was the most effective, achieving an accuracy of 93.28%. The second model uses patient measurements dataset to predict the likelihood of intensive care unit (ICU) admission for COVID-19 patients. We experimented with the XGBoost machine learning algorithm and found that the accuracy score achieved 88.40%.

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1. INTRODUCTION

The world health organization (WHO) has officially designated the coronavirus outbreak as a worldwide pandemic [1]. The coronavirus or COVID-19 is a novel that was first identified in 2019. It is similar to other coronaviruses, such as the severe acute respiratory syndrome coronavirus (SARS-CoV) virus was responsible for the SARS pandemic that occurred between 2002 and 2004 [2]. COVID-19 primarily spreads via respiratory droplets, for instance, when an infected individual coughs or sneezes. Additionally, transmission can occur through contact with contaminated surfaces, such as doorknobs or countertops. As of March 2020 the virus has now reached more than 100 countries, with over 100,000 confirmed cases and a tragic toll of 3,000 lives lost. The researcher of all domains tries to develop all possible solutions to help decrease the impact of this pandemic. In this context, artificial intelligence and subfields like deep learning and machine learning can revolutionize the field of medicine [3], [4]. Deep learning is providing new insights into disease and opening up new possibilities for diagnosis and treatment with its ability to learn from vast amounts of data. For example, it can be used to identify patterns in x-rays and computed tomography (CT) scans that are indicative of certain diseases [5]. Deep learning is also being used to automatically segment images [6], which is valuable for identifying tumors or other abnormalities. Additionally, deep learning is being used to develop new methods for analyzing and interpreting medical data (see Figure 1). As more data is collected, like using imaging of the lungs through either a chest radiograph or a CT scan, it is crucial for accurately diagnosing an infection. The algorithm of deep learning will become even better at finding patterns and making predictions [7]. This will allow doctors to make even more accurate diagnoses and develop more effective treatments. Deep learning will also help us to better understand the complex biological systems that underlie disease. Ultimately, this knowledge could lead to the development of completely new and innovative treatments.

In this paper, we present a framework that integrates a deep learning and machine learning models that are highly accurate in predicting COVID patient and admissibility in intensive care unit (ICU). The first model is a specialized model designed to classify CT scan images as COVID or non-COVID cases. This model is crucial for the identification and diagnosis of COVID-19 patients as CT scans can provide a more accurate diagnosis than traditional COVID-19 tests. To train this model, we use multiple convolutional neural network (CNN) models on a large dataset of CT scan images. The CNN models underwent training on a wide-ranging dataset of CT scans to ensure that they could accurately identify COVID-19 in different cases. We evaluated the performance of the models on a separate test set to ensure that they were accurate and reliable in detecting COVID-19 cases. The second model in the proposed framework uses patient measurements dataset to predict the likelihood of ICU admission for COVID-19 patients. This model uses machine learning algorithms to analyse patient data, including vital signs, blood test results, and other relevant information to predict the likelihood of ICU admission for COVID-19 patients. The accuracy of this model is critical in managing patient demand and allocating resources effectively, as it can help healthcare providers identify patients who require intensive care and prioritize their treatment. The models' accuracy is continually being monitored and refined to ensure that they provide the best possible predictions for healthcare providers, ultimately helping to improve patient outcomes and manage patient demand more efficiently. The organization of this paper is as follows: the second section furnishes an extensive overview of relevant literature and prior research efforts. Our research method is outlined in the third section. The fourth section presents a discussion of our results. The implementation of our models is explained in the fifth section. Finally, the paper concludes with a summary in the last section.

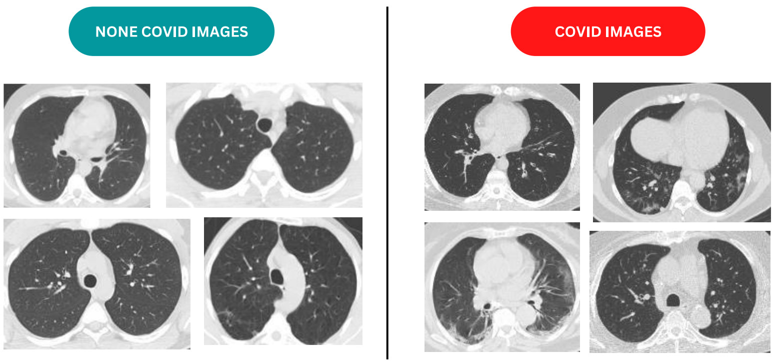


Figure 1. Samples from dataset of COVID-19 from lung CT-scan slice images

2. RELATED WORK

CT scans are a vital tool used in the diagnosis and identification of the virus responsible for the current COVID-19 pandemic. Due to a shortage of trained radiologists, possibly infected individuals may not receive a timely diagnosis during the epidemic. As result, automated methods of diagnostics are in high demand. Several effective methods for identifying and categorizing COVID-19 from CT scans have been developed. We regroup and show in Table 1, the latest related work which achieves a high prediction rate using different techniques and expose the limitation of every method.

Deep learning techniques have been increasingly used in medical image analysis, including COVID-19 detection from CT scans. However, there are limitations associated with these techniques, which are highlighted in the table. One common limitation is the small dataset size used for training. Several studies e.g., [8]–[12] were trained on a smaller dataset, which could lead to overfitting and poor generalization performance on new data. Additionally, performance may degrade rapidly due to the scarcity of data [13].

Therefore, it is important to have large and diverse datasets for deep learning models to learn robust and generalizable features. Another limitation is the lack of sensitivity analysis, as noted in several studies [8], [9], [13]. Sensitivity analysis helps understand how a model’s performance changes with variations in the input data or model parameters. It is crucial for determining the robustness of a model and its applicability in real-world scenarios. The need for parameter optimization is also highlighted in one study [14]. Deep learning models have several hyperparameters that need to be optimized to improve prediction ability. Poor parameter selection could lead to suboptimal model performance. Finally, some studies e.g., [13], [15] used techniques like bidirectional encoder representations dari transformers (BERT) and generative adversarial network (GAN) that are not designed explicitly for image analysis. These methods have been adapted for image analysis and achieved good results, but the lack of clarity in how they are used in image analysis could limit the interpretability of the models. Overall, while deep learning techniques have shown promise in COVID-19 detection from CT scans, careful consideration should be given to their limitations to ensure their effective use in clinical settings.

Table 1. Summary of related works

Reference/year	Title	Technique	Results (%)
[15]/2021	A 3D CNN network with BERT for automatic COVID-19 diagnosis from CT-scan images	CNN and BERT classifier	Accuracy: 92.78 Precision: 92.78 F1 score: 92.61
[8]/2023	Classification of COVID-19 from CT chest images using convolutional wavelet neural network	Convolutional wavelet neural network	Accuracy: 99.97
[9]/2023	Deep learning models-based CT-scan image classification for automated screening of COVID-19	MobileNetV2 and DarkNet19 classifier	Accuracy: 98.91
[13]/2022	Generative adversarial network based data augmentation for CNN based detection of COVID-19	GAN and CNN classifier	Accuracy: 99.2
[14]/2022	A deep ensemble learning-based automated detection of COVID-19 using lung CT images and vision transformer and ConvNeXt	Vision Transformer and ConvNeXt	Accuracy: 96.96 Precision: 96.68 F1score: 96.31
[10]/2022	Deep learning algorithms to improve COVID-19 classification based on CT images	CNN ResNet	Accuracy: 98.1 Sensitivity: 98.6
[11]/2021	Detection of COVID-19 from CT lung scans using transfer learning	VGG-19 and CLAHE	Accuracy: 95.75 Recall: 97.13 F1-score: 95.75
[12]/2020	Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy	CNN	Sensitivity: 90 AUC: 96

3. METHOD

3.1. Datasets

In our study, we employ two distinct datasets. The dataset utilized for constructing the machine learning model was gathered from hospitals in São Paulo, Brasilia, and Sírio-Libanês [16], adhering to global best practices and guidelines for annotation and anonymity. This dataset comprises a comprehensive array of measurements from COVID-19 patients, offering a wide spectrum of information, comprising 54 features divided into three categories: demographic information (3 features), past diseases (9 features), laboratory tests (180 features), and vital signs (36 features). Additionally, the dataset is enhanced by additional computed variables for each time window, including vital signs and laboratory test averages, medians, as well as the maximum and minimum values (max-min) of these parameters. The second dataset is SARS-COV-2 CT-scan [17], containing 1252 CT scans that are positive for SARS-CoV-2 infection (COVID-19) and 1230 CT scans for patients non-infected by SARS-CoV-2, 2482 CT scans in total.

3.2. Proposed method

Our goal is to develop a hospital platform specifically designed for viral illnesses, with three primary aims. Firstly, we intend to create a decision support tool for medical professionals. Secondly, we aim to ease the burden on emergency services and assist healthcare staff in making informed decisions that avoid any unjust outcomes. Finally, we plan to create a medical record tool that can be used for statistical analysis, as illustrated in Figure 2. To achieve these objectives, we propose a pipeline that predicts the likelihood of ICU admission in COVID-19 patients, and a deep learning model that classifies CT scan images as either COVID or non-COVID cases, thus validating the false positives of polymerase chain reaction (PCR) tests. To predict ICU admission likelihood, we categorize patients’ symptoms into three groups, and a machine learning model can act as a decision-support tool to identify which patients should be referred to the ICU. Deep learning can be employed to examine chest CT scan images more precisely than traditional approaches, detecting even subtle changes. Machine learning can take into account other factors like the patient's medical history and symptoms, providing a more precise estimate of ICU admission likelihood. While the proposed method of combining machine learning and deep learning shows promise, potential drawbacks include the complexity of machine learning algorithms for predicting ICU admission likelihood and the computational expense of deep learning algorithms. The accuracy of the results will also depend on the quality of the data used and the accuracy of the algorithms. Despite these limitations, the method of combining deep learning and machine learning has several advantages. Deep learning can detect subtle changes in chest CT scans that are not visible to the human eye, while machine learning can factor in the patient's medical history and symptoms to provide a more accurate ICU admission prediction. Overall, the effectiveness of this approach will depend on the accuracy of the algorithms used and the quality of the data collected.

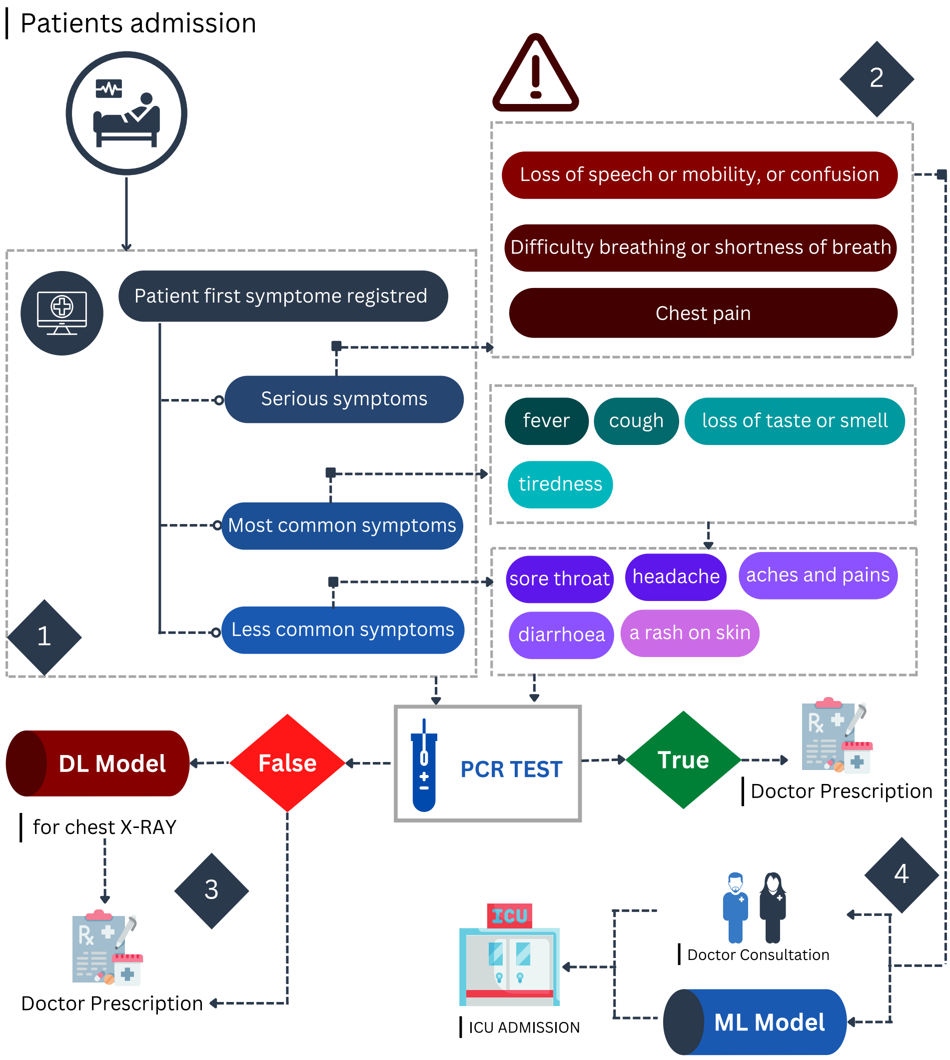


Figure 2. Pipeline that can be used in viral illness case of study (COVID-19)

3.3. Transfer learning

Transfer learning is a technique that allows knowledge gained from one task to be applied to another [18], [19]. In recent years, the popularity of this approach has surged because it can swiftly and effortlessly customize existing models for novel tasks, saving time and money in the process. Transfer learning is particularly useful in cases where there is a lack of data available for training [20], [21]. By leveraging the knowledge gained from a different, yet related, task, the model can learn from a smaller set of data [22]. This makes it possible to create models even when data is scarce. Utilizing transfer learning can further enhance model accuracy, as it enables the model to harness the knowledge acquired from a closely related task.

In addition, transfer learning can also be used to speed up the training process. By transferring knowledge from a related task, the model can quickly and easily adapt to the new task. In our work, we are going to use six best-exiting novels CNN-based to choose the most adequate model for our framework that allows us to improve the accuracy of detecting COVID-19 in CT scans.

3.4. Evaluation metrics

For the study of deep learning models, four quantitative measures were used to evaluate the performance and efficacy of every model defined with the following functions: accuracy (1), precision (2), recall (3), and F1 score (4). These metrics are calculated using the following definition:
– True positive (TP): COVID images that have been classified (predicted) correctly as COVID.
– False negative (FN): COVID images that have been classified incorrectly as non-COVID.
– True negative (TN): non-COVID images that have been classified correctly as non-COVID.
– False positive (FP): non-COVID images that have been classified incorrectly as COVID.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{4}$$

4. RESULTS AND DICSUSSION

4.1. Machine learning for ICU admission

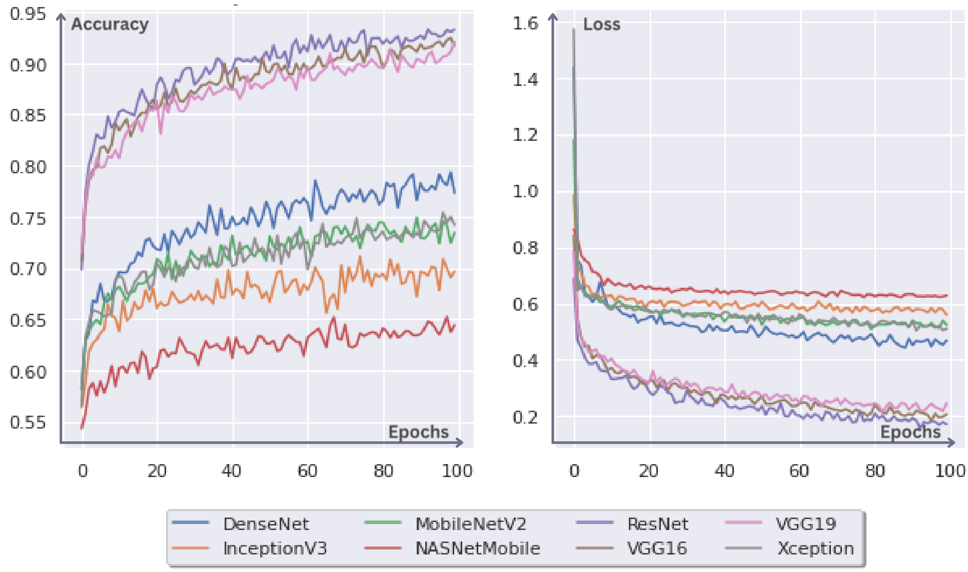
In this experiment, we tested three different machine learning algorithms: LightGBM, XGBoost, and CatBoost. We evaluated the performance of each algorithm based on accuracy and receiver operating characteristic-area under the curve (ROC-AUC), which is a metric used to measure the capability of a model in distinguishing between two classes (binary classification). The results of this experiment showed that XGBoost had the highest accuracy score of 88.40%, while CatBoost had the highest ROC-AUC score of 92.38%. LightGBM had the lowest accuracy score of 87.19%, but still had a relatively high ROC-AUC score of 90.68%. The results of this experiment demonstrate the effectiveness of ensemble machine learning algorithms. In particular, XGBoost and CatBoost both achieved very good accuracy and ROC-AUC scores in predicting ICU admissions. LightGBM performed relatively well, but not as well as the other two algorithms. However, LightGBM still achieved a ROC-AUC score of 90.68%, which is still very good. Overall, these results suggest that ensemble machine learning algorithms can be highly effective for predicting the admissibility of COVID patients in the ICU.

4.2. Deep learning for COVID-19 image classification

In our training set, we obtain different results using transfer learning as shown in Table 2. This study compares the performance of eight different deep learning algorithms on the SARS-COV-2 Ct-Scan dataset. The performance metrics considered were accuracy, loss, precision, recall, and F1-score. The table shows the results of training various CNN models on CT scan images to detect COVID-19. The results indicate that ResNet50 had the highest accuracy (93.28%), followed by VGG16 (91.17%), and VGG19 (89.65%). On the other hand, DenseNet, and MobileNetV2 had lower accuracy scores (77.31% and 73.43%, respectively), indicating that they were not as effective in detecting COVID-19 from CT scan images. The F1 score is a measure of a model’s accuracy that considers both precision and recall. The F1-score for the top-performing ResNet50 model was 92.06%, indicating that it had high precision and recall. The precision and recall for the ResNet50 model were also high, with values of 91.96% and 92.17%, respectively. This indicates that the ResNet50 model is effective in correctly identifying COVID-19 cases while minimizing false positives and false negatives. It is important to note that the number of parameters in the model is not always a good indicator of performance, as seen with the NASNetMobile model which had the lowest accuracy score (64.40%) despite having a relatively high number of parameters (4,811,413). Additionally, it is important to evaluate models on large and diverse datasets to ensure that they are robust and generalizable. The training process is shown in Figure 3. Illustrates the training process of transfer learning models, providing a comprehensive view of model performance over time. Figure 3(a) showcases the accuracy evolution of the trained models throughout the training epochs. The plot demonstrates how the models progressively improve in their ability to correctly classify data, offering insights into the learning dynamics. In parallel, Figure 3(b) presents the corresponding loss values during the training process. A decreasing trend in the loss signifies the models' optimization, highlighting the refinement of their predictive capabilities. This visual representation offers a valuable overview of the training dynamics, aiding in the assessment and understanding of the transfer learning models' performance.

Table 2. Attained results for the CNN models

Deep learning algorithm	Number of parameters	Accuracy (%)	Loss (%)	Precision (%)	Recall (%)	F1-score (%)
ResNet50	24,637,313	93.28	17.16	91.96	92.17	92.06
VGG16	14,977,857	91.17	20.63	89.56	90.44	90.00
VGG19	20,28,553	89.65	24.57	87.57	88.40	87.98
DenseNet	7,562,817	77.31	46.82	73.60	75.28	74.43
MobileNetV2	2,914,369	73.43	52.42	69.97	69.78	69.87
Xception	21,911,081	74.18	51.00	70.34	70.65	70.49
NASNetMobile	4,811,413	64.40	62.76	62.89	51.47	56.61
InceptionV3	22,852,385	69.65	55.91	65.97	63.28	64.60



(a) (b)

Figure 3. Training process of transfer learning models; (a) the accuracy of trained models and (b) the loss of trained models

5. IMPLEMENTATION

To implement our proposed method and models, we developed a web application that incorporates our DL and ML models. Our application uses spring boot [23] as the back-end and angular [24] as the front-end to provide a user-friendly interface for medical professionals to use. We deployed our models using TensorFlow for JavaScript [25], which allows for efficient and easy deployment of machine learning models in web applications. The web application is divided into four sections to provide a seamless user experience. The first section is the home page, where we present the global result of our models. In the top section, we show the final decision gathered from a vector decision, which is a combination of all the results from the deep learning and machine learning models. The second section of the application is the symptoms Registration section, where medical professionals can enter the patient's information, including symptoms and vital signs. This section is critical as it provides the necessary data for our models to make accurate predictions. The third section of the application is the AI detection section, where medical professionals can upload the patient's CT scans. Our deep learning and machine learning models then analyze the CT scans to provide predictions for COVID-19 diagnosis and the likelihood of ICU admission. This section is essential as it allows medical professionals to make informed decisions based on the patient's diagnosis and the likelihood of ICU admission. Finally, the fourth section of the application is the doctor prescription section. Here, medical professionals can visualize the patient's information, as provided by our predictive models, and provide prescriptions and instructions to the patient based on their diagnosis and likelihood of ICU admission. Overall, our web application provides a comprehensive platform that integrates our proposed method and models to assist medical professionals in making informed decisions for COVID-19 patients (see Figure 4).

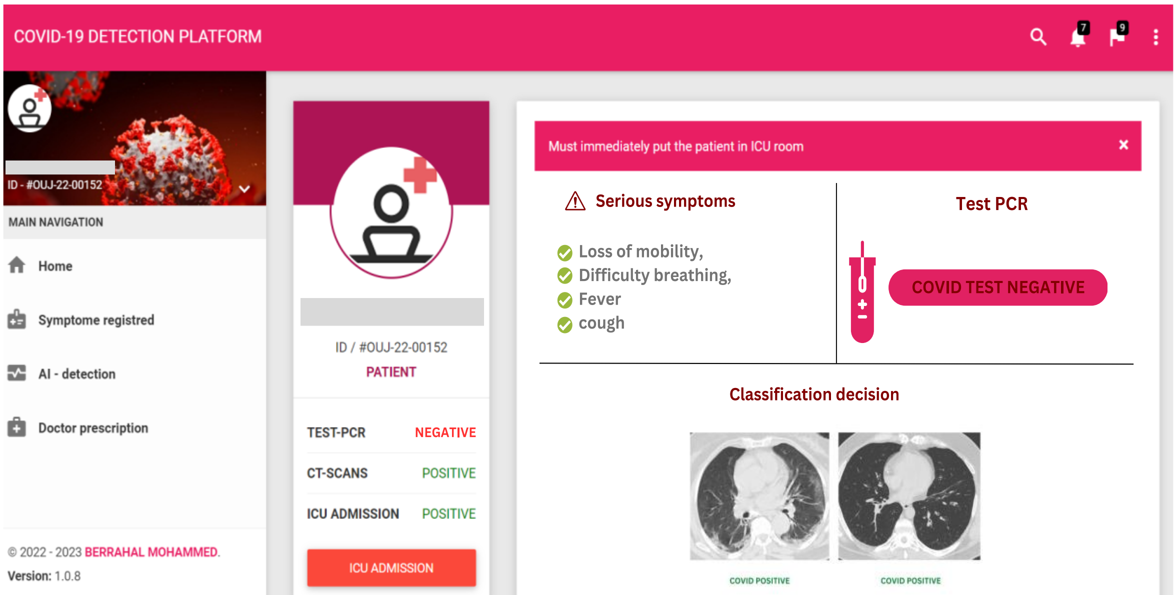


Figure 4. Implementation of our trained model on web application

6. CONCLUSION

The COVID-19 pandemic has had a profound and lasting impact, overwhelming hospitals, and depleting essential resources. To address this, we developed a robust solution using deep learning and machine learning models to predict and manage patient demand effectively. Our first model, designed to classify CT scan images, achieved an outstanding 93.28% accuracy in detecting COVID-19 cases. The ResNet50 model proved most effective in this regard. Furthermore, our second model, utilizing patient measurements, accurately predicted ICU admission likelihood for COVID-19 patients with an impressive 88.40% accuracy score, employing the XGBoost algorithm. Implementing these models in a functional web application for hospitals optimizes resource allocation and aids early detection, mitigating the pandemic's damages. With this framework, we contribute to saving lives and conserving valuable resources, providing a significant step forward in combatting the global health crisis.

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