Detection of COVID-19 and its severity using chest X-rays and electronic health records

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Abstract

COVID-19 first emerged in December 2019 in Wuhan, China, and has since spread throughout the world. More than one year has passed, and the virus continues to mutate and infect individuals at an increasingly alarming rate. Providing proper treatment to patients during the initial stages of the infection is highly vital for their survival. There is also a need for quicker testing.

Such a situation demands an automated, easy-to-use COVID detection toolkit. Recent research using computer vision techniques suggests that chest X-rays contain essential features about the effects of the virus in the chest region. Advanced deep learning techniques and clinical imaging can be utilized to create a tool to detect COVID-19 and its severity. The proposed tool considers chest X-rays as well as a patient's symptoms to predict whether the patient has COVID or not and predict the severity for positive cases.

Keywords—Coronavirus (COVID-19), Deep Learning, Electronic Health Records, X-Rays, Transfer Learning, Convolution Neural Networks (CNN), Machine Learning

I. Introduction

Coronavirus or COVID-19 was announced as a pandemic by the World Health Organization more than a year ago, on 11th March 2020 [1]. As a result, countries worldwide have been in a state of lockdown for months together, with people restricting themselves to their homes and staying out of public places as much as possible. As of 1 June 2021, over 171 million cases have been identified globally [2].

The incubation period of this virus is between 3 to 10 days, and it is transmitted through saliva or discharge from the nose or mouth. The symptoms of an infected person range include cold, breathing problems such as shortness of breath, and chest pain. Coronaviruses typically present with respiratory symptoms that can be between mild and moderate. However, in severe cases, it can also lead to death. Older adults and individuals with comorbidities are typically more prone to the severe effects of the disease and might require hospitalization [3]. Patients with a severe case of the disease also develop COVID-induced pneumonia [4].

Currently, there are two primary methods for detecting the virus: the antibody test and the RT-PCR. The reverse transcription-polymerase chain reaction test works by detecting nucleic acid in the upper and lower respiratory specimens, and it typically takes 3 – 4 hours for the test results [5]. The other method is the antibody test which looks for antibodies in the blood. However, this test is not very reliable and cannot detect COVID-19 cases in its initial phases [6]. Hence, there is a need for a quicker way to detect COVID-19. Having such a tool can prevent the spread of the virus and also allow patients to recover quickly.

A critical domain in this area is clinical imaging. Clinical imaging refers to techniques that analyze images of parts of the human body and attempts to diagnose health conditions from it. The images include X-rays and CT scans. Deep learning methods can be employed to extract features from these images and classify them. However, a notable limitation of models that use machine learning algorithms to detect diseases is the lack of a clinical context—the diagnosis is provided by just using images [7]. As a result, health parameters or symptoms (like fever, cough, loss of smell) are not considered while diagnosing a condition, leading to possible errors. Therefore, it is critical to consider the patient's symptoms along with the chest X-rays to increase the reliability of such a system.

COVID-19 directly affects the lungs, and its symptoms can be observed in chest X-rays right from the early stages of the infection [8, 9]. Recent findings report the presence of lung opacities a common finding in CT scans of lungs, which is an indicator of lung injury [10]. In severe cases, typical findings of acute respiratory distress syndrome (ARDS) are noticed in CXR [11].

Considering this, we propose a system for detecting COVID-19 and its severity using chest X-rays and electronic health records. We aim to construct a system that takes chest X-rays (Posterior Anterior view) and a patient's health records as input. A deep learning model will then process these inputs to predict whether the patient has COVID or not, and in the case that the patient tests positive, the model also predicts the severity of the case by looking for adverse effects of the virus on the lungs in the form of lung opacity. The proposed model considers the problems with other diagnostic tools such as time and cost and tries to overcome them.

Fig. 1 illustrates the conceptual design of the proposed system. An image of the X-ray of the lungs is first passed through a deep learning model for the diagnosis of COVID-19. If the model produces a result of COVID positive, then further analysis is performed to determine the severity of the case. This is done by analysing the health records (symptoms) of the patient as well as the same X-ray (for the presence of lung opacity). The final severity is realized by combining the results of the individual severities, which are then returned to the patient.

II. Related Work

There have been prior studies carried out for the detection of COVID-19 using chest X-rays; however, these studies do not analyse the severity of the patient while providing the diagnosis. Furthermore, none of the studies consider the medical context of patients along with the CXR. Providing information regarding severity can be quite vital in determining the kind of medical aid that a patient requires, especially in countries where the healthcare infrastructure is not equipped to handle a large number of cases. Deciding which patients require home isolation and which ones require hospitalization can prove to be helpful in such situations.

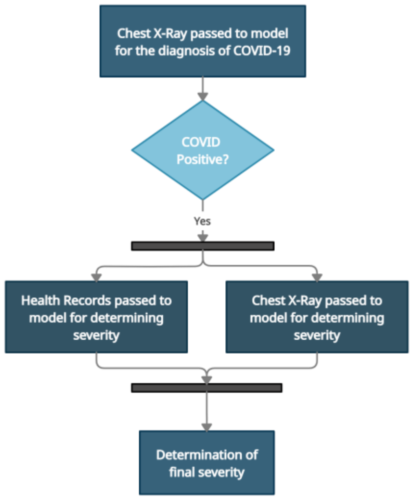

Fig. 1. Overall workflow of the proposed tool

The studies conducted in [12] - [16] used CNN based models for the prediction of COVID, achieving high accuracies; however, they do not make any predictions on the severity of the case. Elaziz et al. [17] developed a machine learning method for the image-based diagnosis of COVID, which extracts features from CXR using FrMEMs and modified Manta-Ray Foraging Optimization. Luz et al. [18] proposed a memory and processing time efficient method for screening chest X-rays for COVID based on the EfficientNet family of deep artificial neural networks and achieved an accuracy of 93.9%.

Ozturk et al. [19] proposed a deep neural network for the detection of COVID using X-rays for binary classification (COVID vs. No-Findings) and multi-class classification (COVID vs. No-Findings vs. Pneumonia). The authors of [20] developed a GAN for the detection of COVID-19, Bacterial Pneumonia, and Normal cases from chest X-rays. Their binary model obtained an accuracy of 98.7% accuracy, and the three-class model achieved 98.3%. The authors of [21] developed models for the classification of COVID-19, non-COVID-19 viral pneumonia, bacterial pneumonia, and normal CXR scans.

Cohen et al. [22] developed a deep learning model for predicting COVID-19 pneumonia severity from CXR by predicting each lung's geographic extent score and lung opacity score. The dataset used in this study was labelled by radiologists, and the authors achieved a mean absolute error (MAE) of 1.14 for geographic extent score and 0.78 MAE for lung opacity score.

Studies [23], [24], [25] utilized CT images for the diagnosis of COVID. While CT scans provide greater detail than X-rays, they are expensive and are not available in all hospitals.

Iwendi et al. [26] used an EHR dataset to provide COVID-19 severity prediction with an accuracy of 94%. The same dataset has been utilized in this study as well.

This paper is organized as follows: Section III focuses on the overall design and provides a brief description of the modules used in the system. Section IV provides implementation details of the modules, while Section V outlines the results obtained and possible shortcomings of the system. Finally, the conclusion and future work is specified in Section VI.

III. Design and Methodology

A. *Detailed Design*

The proposed design comprises three primary modules:

1. Module 1: Detection of COVID-19 using chest X-rays
2. Module 2: Prediction of recovery using electronic health records
3. Module 3: Prediction of lung opacity using chest X-rays

Fig. 2 summarizes the sequence of execution of the modules.

- The X-rays are first processed by Module 1 to determine if the patient is COVID positive or not.
- If the patient is negative, no further processing takes place.
- If the patient is COVID positive, Modules 2 and 3 are processed in parallel. Module 2 uses the patient's symptoms to predict if the patient might recover without hospitalization or not, while Module 3 examines the CXR for traces of lung opacity. These two steps are performed to gauge the severity of the patient.
- The results of these two modules are aggregated to obtain the final severity result, which is divided into three severity buckets, namely Mild, Moderate, and Severe.

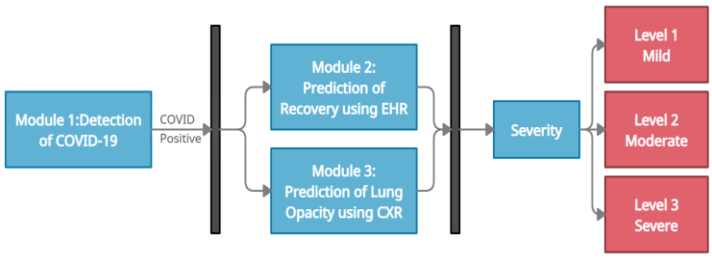

Fig. 2. The proposed design

B. *Dataset*

The dataset of images utilized in this study was obtained from Kaggle [27, 28, 29] and consists of images of healthy lung X-rays, COVID positive X-rays, and pneumonia-affected X-rays (that have developed lung opacities). For health records of patients, the dataset was obtained from [30] and contained data about the age, gender, symptoms, country, etc of COVID affected individuals.

C. Module 1: Detection of COVID-19 using chest X-rays

This module uses Chest X-Rays (CXR). The dataset used consists of COVID affected and healthy lung X-rays. The input image provided by the patient is first pre-processed and then sent to a deep learning model, which provides a prediction of 1 if the CXR indicates that the patient is COVID positive, and 0 for negative.

Fig. 3 is a snapshot of images from the dataset, with healthy lung X-rays in the top row and COVID positive X-rays in the bottom row.

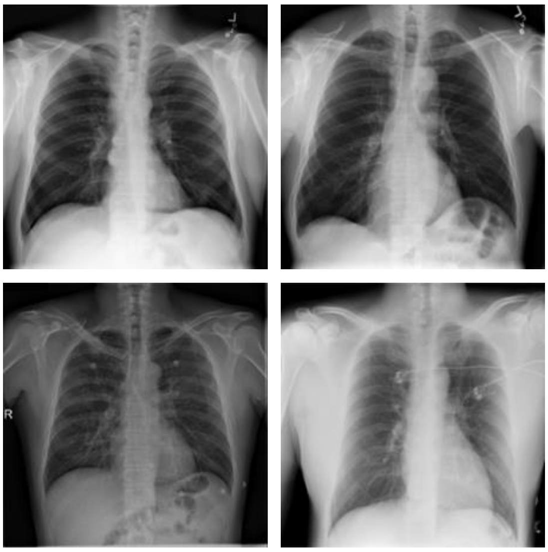

Fig. 3. Images from the dataset – healthy CXR (top row) and COVID positive CXR (bottom row)

D. Module 2: Prediction of Recovery using electronic health records

This module makes use of the Electronic Health Records (EHR) provided by the patient and utilizes the following data: Gender, Age, Symptoms. The symptoms considered are Fever, Cough, Difficulty in breathing, Pain, Fatigue, Diarrhea, Cold, Pneumonia, Vomiting, and Malaise. This data is passed to a supervised machine learning model, which predicts 0 if the patient is likely to recover, and 1 if the patient is unlikely to recover without medical aid or hospitalization.

E. Module 3: Prediction of Lung Opacity using chest X-rays

This module uses CXR to predict the presence of lung opacity in the lungs of the patient, which is an indicator of the severity of the case [10].

The input images are first pre-processed and then passed to a deep learning model. The result is classified into 1 (lung opacity present) or 0 (lung opacity absent).

F. Final Result

Patients who wish to test for COVID-19 first upload their chest X-ray image along with their symptoms, age, and gender. Once the data is submitted, the image goes through Module 1, which predicts if the patient tested positive or negative.

If the patient tests negative, no further step is needed, and the result is returned to the user.

If the patient tests positive, then the patient's data is passed onto Modules 2 and 3. Module 2 provides a result of 1 (cannot recover) or 0 (can recover), while Module 3 predicts 1 (opacity present) or 0 (opacity absent). The result of the modules is merged to give the final result of severity by classifying the severity into Mild (Level 1), Moderate (Level 2), and Severe (Level 3)

Table I depicts the criteria for classification into different severity levels.

TABLE I. CRITERIA FOR CLASSIFICATION OF SEVERITY

Module 2 Output	*Module 3 Output*	*Final Severity*
0	0	Level 1 - Mild
0	1	Level 2 - Moderate
1	0	Level 2 – Moderate
1	1	Level 3 - Severe

Once the severity level has been calculated, the result is made available to the user.

IV. IMPLEMENTATION

A. Module 1: Detection of COVID-19 using chest X-rays

1) Dataset

The dataset of chest X-rays was obtained from Kaggle, which is maintained by a group of researchers [27, 28]. The dataset contains 3616 images of COVID-affected chest X-rays and an even larger number of X-rays of healthy lungs. We utilized all the COVID-affected X-rays and an equal number of randomly chosen healthy X-rays to ensure that the dataset is balanced. The total number of images used is 7232.

2) Preprocessing

The images in the dataset were pre-processed by applying the following operations: Image Resizing to 224 x 224 pixels. RGB reordering, and one-hot encoding the target labels

3) Deep Learning Model

After applying the pre-processing techniques, the final output images are fed to a transfer learning model with VGG-16 as the base. On top of the base model, we applied additional layers to obtain a total of 21 layers. The loss of the model was also monitored, with mechanisms to stop training when the model starts overfitting. The model ran for 27 epochs. The accuracy obtained on the test dataset is 97.84%, with an F1 score of 0.978.

B. Module 2: Prediction of Recovery using electronic health records

1) Dataset

For this module, a dataset [30] containing health records of patients diagnosed with COVID was used. The dataset had 1085 rows and 21 columns. The columns included country, reporting date of the case, summary, gender, age, symptoms, hospitalization date, etc. The final column was 'death', indicating whether the patient recovered from COVID-19 or not.

2) Preprocessing

Pre-processing involved dropping unnecessary columns (such as country name, id, summary, source, link, etc.), removing rows that did not contain any symptoms, and converting data types to the appropriate formats.

The symptoms provided in the dataset contained unstructured data, where the symptoms were written in text format, separated by commas. Further analysis of the dataset showed that there were ten recurring symptoms in most patients. Based on this observation, separate columns were created for each of the following symptoms: Fever, Cough (including sore throat), Difficulty in breathing, Pain (including headache), Fatigue, Diarrhea, Cold (including a runny nose), Pneumonia, Vomiting, and Malaise. The patients' symptoms were assigned to these columns with a value of either 0 (for symptom absent), or 1 (for symptom present).

We also noticed an imbalance in the amount of data present for the final classification of recovery or death. To balance this, we performed oversampling of the minority class to balance the dataset. The final dataset contained 522 rows and 13 columns.

3) Machine Learning Model

The next step was training the models on the pre-processed data. The dataset was first divided into training and testing data, with an 80:20 split. The following models were then applied to the data: Multiple Linear Regression, Logistic Regression, Decision Tree, Pruned decision tree with a depth of 3, Support Vector Machine, Random Forest, and a Neural Network.

4) Performance Comparison

Table II summarizes the models that were applied to the data and the accuracies obtained for each.

Graphs of the performance of the various models were also plotted based on Accuracy, Precision, Recall, and F1-Score. Fig. 4 depicts the same. It can be observed from these that Random Forest was the best performer for all the specified metrics with an accuracy of 97.14 % and an F1 score of 97.08

TABLE II. ACCURACIES OF THE MODELS USED ON EHR DATA

Model	*Accuracy*
Multiple Linear Regression	37.2 %
Logistic Regression	81.9 %
Decision Tree	93.3 %
Pruned decision tree with a depth of 3	79.04 %
SVM	77.14 %
Random Forest	**97.1 %**
Neural Network	79 %

Fig. 4. Comparison of the models' performances

C. Module 3: Prediction of Lung Opacity using chest X-rays

1) Dataset

The dataset of chest X-rays used was obtained from Kaggle [29]. The dataset consisted of around 1500 images of healthy chest X-rays and more than 4000 X-rays of lungs that have developed lung opacity caused by pneumonia. We utilized all the healthy X-rays and an equal number of randomly chosen pneumonia-affected X-rays to ensure that the dataset is balanced. The total number of images used is 3166.

2) Preprocessing

As a part of pre-processing, the following operations were performed on the images in the dataset: Image Resizing to 224 x 224 pixels, RGB reordering, and one-hot encoding the target labels.

3) Deep Learning Model

A CNN model was constructed with 14 layers along with a mechanism to monitor the loss of the model, to stop training in case the model starts overfitting. This was done by defining a patience value of 4, i.e., if the loss increases in four iterations, then training will be stopped after that epoch. A similar process was used for reducing the learning rate as well. The model ran for 25 epochs. The accuracy obtained on the test dataset is 98.5 % and an F1 score of 0.98.

V. RESULTS AND DISCUSSION

This study presents three modules to determine if a person is affected by COVID-19 and predicts the extent of the progression of the virus. The presence of the virus is detected using CXR, while severity is measured using both EHR and CXR. The health records contain information regarding the symptoms shown by the patient.

Module 1 uses transfer learning with VGG16 as the base model and predicts with an accuracy of 97.8% and an F1 score of 0.978. Module 2 uses the Random Forest algorithm with an accuracy of 97.14% and an F1 score of 97.08. Finally, Module 3, a Convolution Neural Network has an accuracy of 98.5 % with an F1 score of 0.98.

Real-time data from patients affected by COVID-19 was collected and tested on the models. Five such samples were obtained, and, in each case, the model produced accurate results. Fig. 5 portrays one such case for a 50-year-old male COVID-positive patient who had symptoms of fever, cough, difficulty in breathing, and body pain. The result of Module 1 was 1, i.e., COVID positive. The result of Module 2 was 0, i.e., the patient can recover without hospitalization, and the output of Module 3 was 1, i.e., lung opacity present. Hence, the final severity of the patient was classified as Moderate. The result obtained is consistent with the condition of the patient as diagnosed by the physician.

Fig. 5. Chest X-ray of a 50-year-old COVID-positive patient

Similarly, Fig. 6 shows another case for an 87-year-old male COVID-positive patient who had symptoms of fever, difficulty in breathing, fatigue, and body pain. The result of Module 1 was 1, i.e., COVID positive. The result of Module 2 was 1, i.e., the patient requires hospitalization, and the output of Module 3 was 1, i.e., lung opacity present. Hence, the final severity of the patient was classified as Severe. Again, the result obtained was consistent with the condition of the patient as diagnosed by the physician.

Shortcomings of the proposed model include the fact that physicians and radiologists have not validated the results produced. It is extremely vital to do this before deploying such a system in real-time, which could be a replacement for the current methods of testing.

Lack of availability of quality data is also a concern, especially for health records/symptoms of patients. The dataset used for Module 2 was outdated, with plenty of vital information that was missing. There are not many datasets available that contain information regarding patients' symptoms. Availability of such data would make the models more reliable.

Another shortcoming of the deep learning models developed is that lung X-rays that contain opacity caused due to other viruses might be wrongly classified and thereby produce inaccurate results. Further work needs to be performed to prevent this misclassification.

Fig. 6. Chest X-ray of a 87-year-old COVID-positive patient

VI. FUTURE WORK

It has been more than one year since COVID-19 struck the world. Multiple vaccines have been developed to provide immunity from the virus, but it could take years to inoculate everyone in the world. Meanwhile, the virus continues to mutate into variants that are becoming increasingly lethal and can spread quickly from one individual to another.

There is a need for a tool that can swiftly detect the virus in a non-invasive and quick way. This study aims to provide such a tool by using CXR and EHR to predict whether a patient has COVID or not, and in the case that the patient tests positive, the tool also aims to predict the severity of the progression of the virus.

There is a shortage of hospital rooms or ICUs all over as the world tries to combat the virus, and analysis of severity could help indicate whether the patient might require hospitalization or not. Moreover, this tool could also help reduce the load of healthcare workers and frontline workers since patients could get tested for COVID from the comfort of their homes.

Future work on this study involves consulting radiologists, who could cross-check the results generated by the model and ensure that it can be used in real-time.

A shortcoming of the models developed is that it fails to produce accurate results if the patient is affected by other lung infections. Further analysis and development can be performed on this facet to ensure accurate predictions.

Lastly, the data generated by the model can be analyzed on a day-to-day basis to keep a tally of the total active cases, new cases per day, recoveries per day, etc. Present methods to keep track of these metrics are quite inaccurate, and a centralized system could act as a fool-proof way to measure these values. The data produced can also be used to identify containment zones or areas with a large number of cases. Data regarding the severity of patients can be leveraged to identify the number of ICUs required daily.

There are various use cases for the data generated by the tool, and using it could be highly advantageous to the healthcare industry by taking off some of the pressure from doctors, nurses, and frontline workers who have been working round the clock for more than a year now.

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