International Journal of Computer Applications (0975 – 8887)
Volume 184– No.36, November 2022

Framework for Analysis and Prediction of Risk Factors of Covid-19

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ABSTRACT
In March 2020 Covid-19 was declared a global pandemic. There was a shortage of hospital beds all across the country. Because of this, an efficient resource allocation system is essential. This can be achieved through severity prediction of patients on hospital admission and allotting proper resources to the most severe cases first. In this study, a severity prediction model has been described which is made using Deep Neural Networks. It predicts how severe a patient will possibly get, using 26 clinical factors like Hemoglobin, HCT, RBC, etc. The model showed an accuracy of around 85%. RT-PCR is currently used as the primary test to detect Covid-19, but studies have shown it is not very reliable as it can give false negatives during the early stages of the disease. To tackle this problem, a CNN model has been applied to a dataset of chest x-ray images of patients who were tested for Covid-19. The model showed 98.33% accuracy for Covid-19 detection. Statistical analysis and data visualization modules for Covid-19 are included in the framework for researchers, the general public, and the healthcare system to keep track of the global pandemic.

Keywords
COVID-19, Severity Prediction, Clinical Factors, Covid Detection, RT-PCR, Chest X-Ray, Statistical Analysis, Data Visualization, CNN, Deep Neural Networks

1. INTRODUCTION
COVID-19 is caused by the novel severe acute respiratory syndrome coronavirus 2, which emerged in China in the city of Wuhan [1]. In the midst of March 2020, WHO declared the novel coronavirus (COVID-19) outbreak a global pandemic [2]. The pandemic troubled the healthcare systems all over the world, which placed a huge burden of cases with COVID-19 on medical facilities, highlighting the important role of effective patient prioritizing is to allow adequate clinical care for those more severely deteriorating to critical COVID-19. As soon as the coronavirus outbreak started, it took awfully little time to swamp the hospitals.

And as soon as the medical facilities got swamped, the death rate peaked. The most likely symptoms of the virus are fever, sore throat, dry cough, headache, muscle pain, loss of taste or smell, diarrhea, and shortness of breath. What makes the Covid-19 virus so deadly is that since it is highly infectious, it easily spreads among the entire human community, and is transmitted through usual everyday contact with your peers who might be infected either by touch, talking, or sneezing, or coughing [3].

The COVID-19 upsurge was first revealed to have been detected at the end of December 2019 and over 240 million people have been affected by this global pandemic since and more than 4.9 million all over the world have died as of October 2021 in keeping with the information collected from World Health Organization [1] which is additionally shown in Figure 1. This huge number of patients overwhelms the hospitals hence, there is a dire need for giving priority to more severe cases to save lives. An extensive amount of raw data related to COVID-19 is available on various government and health organization websites, to make this data useful, there is a need to statistically analyze and visualize this data to extract valuable information from it.

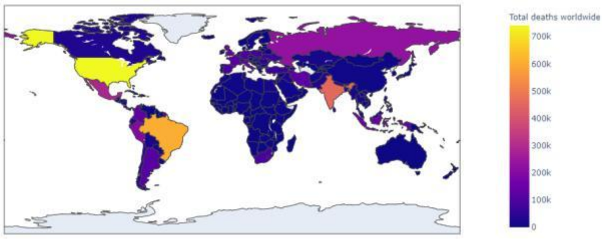


Fig 1: Total deaths worldwide

Figure 2. shows total COVID-19 cases worldwide

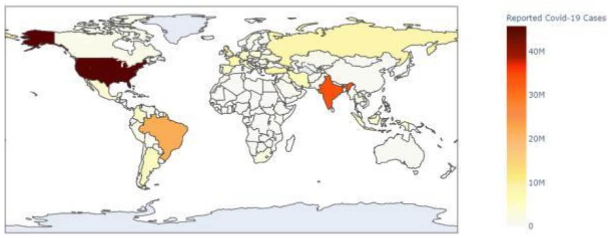


Fig 2: Count of Cases around the world

The main symptoms during the COVID-19 outbreak are not severe and the majority of patients fully recuperate, a major fraction of cases now experience long-term health repercussions. People use social media quite excessively these days and this huge data can be used to determine the post covid symptoms and other difficulties people experience after recovering from covid.

Figure 3. shows the country-wise Mortality rate of COVID.

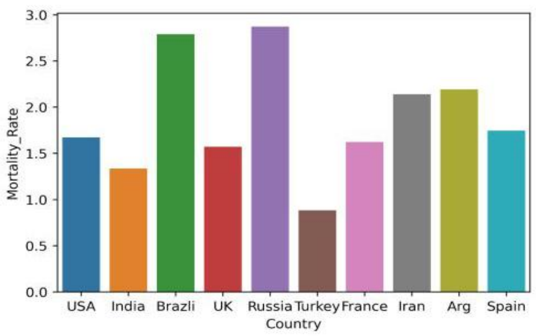


Fig 3: Global Situation regarding the pandemic

Figure 4 shows the country-wise active cases of COVID-19.

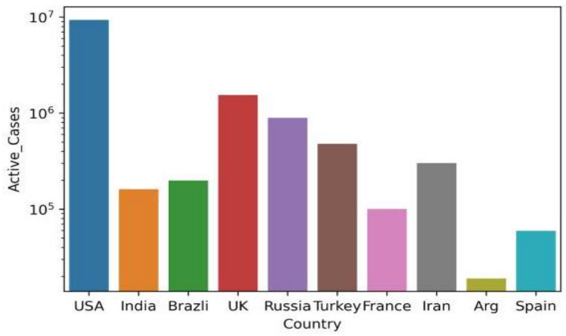


Fig 4: Country-wise active cases of COVID-19

The choropleths were made using the python module Plotly. While the bar plots were created using the Seaborn. The data for all the plots were taken till 27th October 2021.

The most staggering fact about COVID-19 in the world is that even though being the second-most populous country in the world, the death rate of India is one of the lowest with less than 4.7 lakh deaths in total cases of more than 3.46 crore, which makes its mortality rate 1.36 (as of November 2021) [5].

The rest of the paper is organized as follows: Section 2 describes the literature review, Section 3 describes the proposed framework, Section 4 describes the models used, Section 5 gives the results and Section 6 gives the Conclusion.

2. LITERATURE REVIEW

Many researchers and analysts started studying the COVID-19 after the upsurge in China in the city of Wuhan in late December of 2019 and developed different studies for the prediction of its contamination rate and the number of deaths due to this pandemic. Some research is in accordance with the creation of dashboards, statistical analytics, data visualization, severity, and mortality predictions along with a covid detection for this global pandemic. Few of these recent studies are discussed here.

To predict the severity of cases of COVID-19 based on the condition at admission to the hospital using ML algorithms, a model has been introduced by Dan Assaf, Ya'ara Gutman, and Amit Tirosh. The proposed Solution given for the particular objective comprises the three different ML models, ANN, RF Classifier, and CRT (Classification and Regression Tree) used to predict patient severity. Results showed that Machine-learning models reached an accuracy of 92% in predicting severe COVID-19 [6].

A study of 1,182 hospitalized patients was conducted with seven different statistical analyses and machine learning techniques to try and predict COVID-19 survival and discharge time probability. The seven methods are namely, IPC-Ridge, Cox-PH, Cox-net, Stagewise GB, Component wise Gradient Boosting, Fast Support Vector Machine, and Fast Kernel Support Vector Machine. They compared these ML models used in the prediction of patients surviving and assessed the effects of age and gender as two important severity variables [7].

Mohammad Pourhomayoun and Mahdi Shakibi have proposed an algorithm based on Artificial Intelligence and a different Machine Learning algorithm that predicts the risk of mortality among the patients with COVID-19 and also gives details about the health risk of the patient. The Neural Network algorithm also helps different healthcare, hospitals, and other medical organizations to choose which patients should be prioritized. The authors have chosen 2,670,000 lab-approved COVID-19 patients from 146 different countries all over the globe. After the feature selection process, only 57 features were chosen. After this, they used various algorithms and compared the calculated overall accuracy of all the algorithms. It was found that the neural network algorithm showed a better accuracy compared to allthe other algorithms used. The AUROC of a neural network is 0.93 and the accuracy of mortality prediction of a neural network is 89.98% [8].

Chobdar H et. al. have developed three ML models using the SVM framework and collated them to find out which model gives the best accuracy and performance in the

mortality prediction. The 1st model is an invasive model for which the input features were taken from the laboratory results, 2nd is a non-invasive model where the input features are the patient's clinical and demographic data, 3rd is a combination of both models. The authors afterward used records of 492 patients hospitalized at Masih Daneshvari Hospital as a dataset. It was found that having favorable features where the information content is more effective and increases the possibility of mortality prediction. So after comparing it was found the non-invasive model has a better prediction performance than the invasive model because some non-invasive feature majorly contributes to the mortality prediction and also has remarkably high information content for mortality outcome prediction. The Non-invasive model has an accuracy of 0.77± 0.04 which is better than the invasive model which has 0.75 ± 0.4 [9].

Aziz Alotaibi, Mohammad Shiblee, and Adel Alshahrani initially try to identify the main factors that can be responsible for the severity of COVID-19. They use relief algorithms that can select the topmost features to identify the severity. Most of the features selected were from the patient's medical and biological history and the current clinical measures. Originally a dataset containing 52 features was selected, since such a huge amount of features would not necessarily impact, they used feature selection algorithms to look at what features their data necessarily depends on. 32 features having a positive effect on criticalness were selected, while the ones having negative effects were discarded. Next, machine learning models were applied. Various different types of machine learning algorithms were applied like Random Forest (RF) Classifiers, SVM, and Linear Regression. High accuracy and precision were seen, and Random Forest outperformed most of the algorithms [10].

In [11] severity affecting inputs and a model for analysis of severity were selected. For feature selection, LASSO was used along with regression. 21 markers were decided to be used. Clinical features were reviewed by physicians, and laboratory markers like CRP were measured. Continuous values were given as median while categorical variables were given as output in the form of numbers. R software was used to conduct most of the procedures. The Area under the curve was used as a performance measure. The ridge regression model gave the best output compared to other models. The model was validated in an independent dataset using the external dataset for testing and obtained a noteworthy AUROC of 0.827. Some limitations were identified and it seemed like none of the critical cases seemed to appear in the training set while mild cases were observed to be in the validation set.

Mohammad M. Banoei, Roshan Dinparast Saleh, Ali Vaeli Zadeh, and Mehdi Mirsaeidi applied predictions to various markers like those of blood, and other factors like comorbidities and clinical features. This two-component algorithm based on SIMPLS had moderate accuracy. This model was checked in larger populations to be better analyzed. They proved that clinical and chemical factors show limited prediction contrary to studies that prove otherwise [12].

In [13], some machine learning methods were implemented and tested to make predictions on the COVID-19 outbreak. Support Vector Machine algorithm has been applied to make predictions on the dataset with 303 patients. The Model was implemented in Python language using the latest portable version of the Jupyter notebook. Because of the minimized death rate of COVID-19 cases, the dataset faces the issues of data imbalance. The results that were obtained seemed to prove that random forest worked the best among other models. A bunch of factors was used in the experiments such as all the top ten features, and twenty features, respectively. In the study, they used various modern algorithms. Data imbalance is a critical issue faced in data analytics and usually leads to overfitting in the results. In this paper, SMOTE was used to avoid data imbalance and have more balanced data.

Asket Kaur and Maryam Sedghi have built an interactive dashboard that processes and presents raw data in the form of various visualizations, graphs, and text data. This interactive data-driven dashboard allows users to see current trends, as well as displays important analytics and predictions for next week. They used various python modules for visualizations, managing data, and analytics. Their dashboard was divided into four tabs. This proposed solution was evaluated against three other publicly available visualization frameworks. The performance evaluation showed that the proposed dashboards perform better than other solutions. Hence, the proposed dashboard presents various visualizations and analytics while giving better performance. Another advantage of the dashboard is interactiveness. In today's times, interactive dashboards allow users to visualize information easily and understand it [14].

In [15], the authors have developed a dashboard to help researchers and enthusiasts to analyze and visualize different aspects, trends, and patterns of COVID-19. Their dashboard was divided into five different tabs namely Data Summary, World Data, Visualization, Information, and News. They used data from Johns Hopkins University's Github repository which is open source and well trusted. When covid was declared a pandemic, lots of dashboards were created but all of them lacked in one way or another so the authors created a single dashboard divided into multiple sections, which gives user knowledge of the data. Since the dashboard was divided into 5 sections where each page contained different summary and visualizations to get different levels of knowledge, this divided styled layout helped users to directly look at the level of details they were looking for. From abstract level to detailed visualizations of countries.

In [16], the authors have developed a model to predict COVID-19 severity using Computed Tomography scans and clinical factors. Data was collected from 981 patients. They extracted radiomics features from chest CT of patients. This was combined with clinical variables. This model which uses both CT and clinical factors for prediction achieved the highest AUC as compared to only CT radiomics features or only clinical factors or the combination of visual CT severity scores and clinical factors.

In [17], the authors worked on a dataset containing 1,521 patients with pneumonia that included CT images, 130 clinical features, and a lab certified COVID-19 status. They've trained a model using a deep learning algorithm for predicting COVID-19 morality and morbidity outcome. During validation, the algorithm was able to discriminate between negative, mild, and severe cases with AUC of 0.944, 0.860, and 0.884, respectively.

In [18], CNN is trained with the Visual Geometry Group (VGG) model which is a transfer learning model, using the dataset of x-ray images of Covid-19 patients. The dataset consisted of 4300 x-ray images with 5 classes. An accuracy of about 99% was obtained. This paper proposed that using IoT along with this application can result in real-time detection of covid-19 suspected patients. GoogleNet is a CNN that has 22 layers of depth to it. It was applied on a dataset of chest x-ray images of Covid-19 patients. The GoogleNet model is very different from other networks like ZF-Net or even AlexNet. It proved to be a better choice for this application as it gives an accuracy of about 98.5% trained along with the CNN model [19].

The existing models like the one proposed in [14], [15] that focus on visualizations in a single dashboard lack the elements like severity prediction like the one proposed in [11], [12]. The aim is to merge these features under a single interface.

3. PROPOSED FRAMEWORK

As we've seen from the literature review, the previous dashboards and algorithms have some limitations. Such as in [15] no functionality involving prediction was added. If the prediction part was added, the dashboard can be useful to various healthcare systems, government organizations, etc. The same was for [14], a prediction module was present but some important predictions such as mortality rate, and covid detection were not included.

The main aim of our framework is to make a one-stop solution that will be helpful to normal users, researchers, and enthusiasts as well as healthcare systems in predicting various factors such as mortality rate, and covid detection. The framework has the following modules:

1. Data Collection
2. Data Summary
3. Visualizations & Analytics
4. Predictions

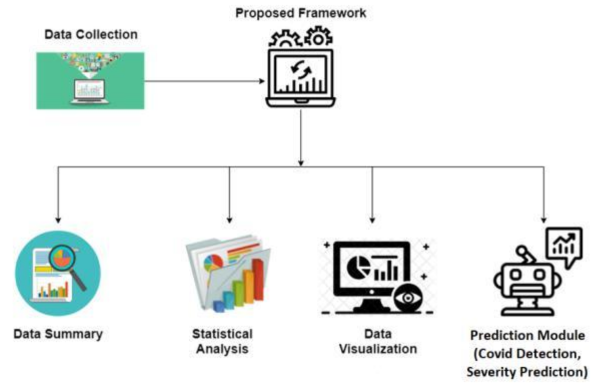


Fig 5: Proposed Framework

As can be seen above, the framework has multiple modules namely, Data Collection, Data Summary, Visualizations & Analytics, and Predictions. These modules serve various functions.

In the framework, data is collected from one of the well-trusted sources Johns Hopkins University's Github repository[4] in the Data Collection module. This repository is being used as it is readily available, contains all necessary factors required to propose the framework, and it is well maintained, well trusted and open source.

In the Data Summary module, a data summary containing basic information such as active cases count, the total number of deaths, and the most affected countries/states, countrywide cases, total discharged patients, etc.

Fig 6: Visualisation section of our proposed framework

Various statistical operations are performed on the collected data and obtained results is shown in the form of plots and visualizations in the Visualizations & Analytics module. Various plots are available showing correlation between various factors using which researchers and enthusiasts will be able to analyze aspects and patterns of COVID-19. Users are able to choose a country from a dropdown list of available countries.

The Predictions module contains the prediction part in which important factors like Mortality Rate as well as covid detection are included. These predictions are done using user input.

4. PROPOSED MODEL

4.1 Dataset

The data for Covid 19 severity prediction was taken from iCTCF[20] which maintains a repository of Chest Tomography and Clinical Factors for patients affected with Covid 19. The dataset contained over 1521 patients whose clinical factors had been noted down. This dataset was extracted from the website using Selenium and Python web scraping framework, BeautifulSoup. The page for each patient was fetched using Selenium, from which the required information was extracted using BeautifulSoup.

For Covid 19 detection, chest X-ray images of Covid 19 positive cases were collected from [20], for the negative ones, images were collected from [21]. The two datasets were merged together and was then used for covid detection.

4.2 Dataset Preparation

4.2.1 Missing Values

The dataset, now present in an excel sheet, contained a lot of missing values, which needed proper techniques for preparation for an accurate dataset, to train our model. The following plot in Fig.5, of the missing values in every column has been prepared using Matplotlib.

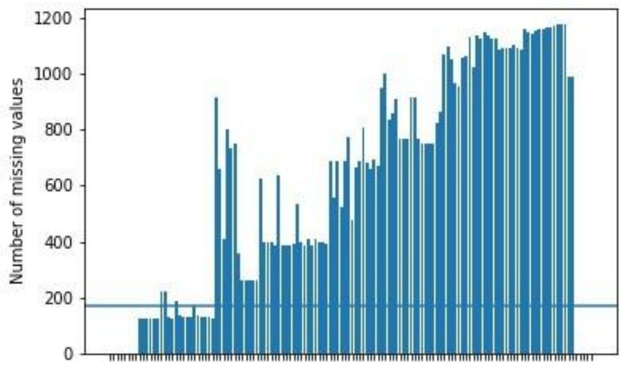


Fig 7: Missing values for each column of dataset

I. Removal of columns with a high number of missing values: Initially the features having more than 172 missing values were removed. 172 was calculated to be the minimum number required to retain maximum patient information.

II. Simple Imputation of features with mean values: The remaining missing values were imputed with the mean of the corresponding columns with the help of sklearn library SimpleImputer.

4.2.2 Label Encoding and One Hot Encoding of features

Some of the features were present in Categorical form which had to be converted to numerical form as our model needs numerical inputs to apply mathematical functions. Thus those input features namely, the presence of SARS Cov 2 nucleic acids, the results of Computed Tomography, and the output feature of Morbidity Outcome were One Hot Encoded, as the data points were categorical.

4.2.3 Standardization

As the input features belonged to widely different numerical ranges with some like One Hot encoded columns belonging to a binary range, while some of the features like Hemoglobin having range 130-175 g/L, MCHC having range 316-354 g/L, etc. to make the data standard, having a mean of 0 and variance of 1, to make the model not have varying ranges, since this would lead to some features being dominant due to their values, thus making our model weaker.

For an element x, belonging to a column y,

x_{new}= (x-mean(y))/ (y),

mean(y) is arithmetic mean of column y,

while (y) is standard deviation of column y.

4.3 Models

4.3.1 Severity Model

The final dataset contained patients with 26 features. The output consisted of four classes; Mild Cases, Regular severity cases, In control cases, and cases that needed Hospitalization. This was one hot encoded to produce a matrix of dimensions (995,4).

Due to the low number of patients, a Deep Neural Network with a narrow layer was used [23].

To ensure a proper split into the train and test data, functions were used that would ensure a random split according to the desired ratio. The dataset was split in the ratio of 85:15.

With the help of PyTorch, a Python machine learning framework, a deep neural net model was formed. After some trials, a single hidden layer neural network with 128 neurons was used. A single hidden layer was used for faster convergence[24]

A relu activation function was used in the input, while a softmax was used to produce the output probabilities, to solve the multi-class classification.

The dataset contained over 400 samples of the mild cases class while just over 150 samples of the hospitalised classes. Since our model was critical in identifying hospitalized cases, oversampling was used to balance the dataset.

One of the major oversampling techniques used called SMOTE [13], which uses kNN to synthesise new data points from the minority class, was used. With the use of Imbalanced Library, an instance of SMOTE function was used, where the minority class points were increased to 270 data points.

An instance of the model was created and the next step consisted of deciding the hyperparameters. To avoid overfitting an optimal value of epochs, that is 25, was used. With a few iterations, an optimal value for the learning rate equal to 0.007, where the loss followed a continuous decreasing curve, was used. A momentum of 0.9 [25] was used for the model to converge quickly to the solution.

Cross entropy loss was used in order to calculate against the softmax probability outputs generated by the model.

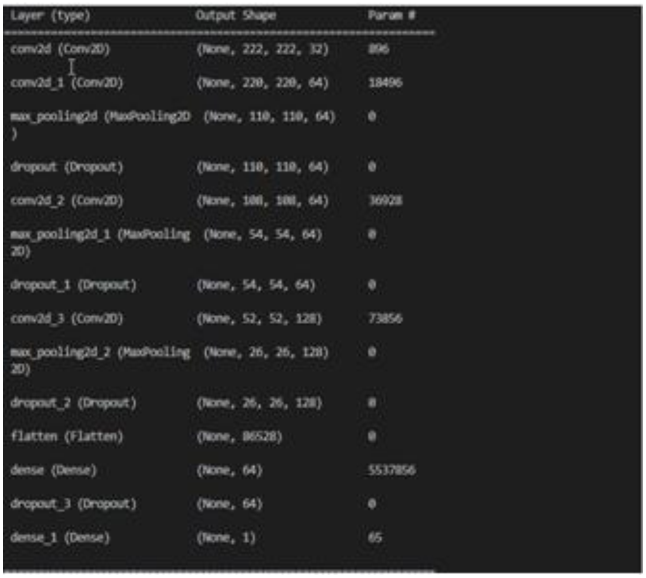
A framework was made, with necessary computational parameters calculated at each epoch like accuracy, loss, etc.

4.3.2 Covid 19 Detection Model

A Xray based model was used with the help of consecutive Convolutional layers accompanied by max pooling layers. The model was derived from previous architectures[26].

To generate more images from the input dataset, the ImageGenerator function was used.

It consists of 4 Convolutional layers, followed by subsequent max-pooling layers, as given in the below figure.



Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
conv2d_1 (Conv2D)	(None, 220, 220, 64)	18496
max_pooling2d (MaxPooling2D)	(None, 110, 110, 64)	0
dropout (Dropout)	(None, 110, 110, 64)	0
conv2d_2 (Conv2D)	(None, 108, 108, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
dropout_1 (Dropout)	(None, 54, 54, 64)	0
conv2d_3 (Conv2D)	(None, 52, 52, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
dropout_2 (Dropout)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 64)	5537856
dropout_3 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Fig 8: Layers in our model

Dropout regularization is added to reduce overfitting[27]. The final dense layer is used to evaluate the output for the detection model.

Since the detection model is a binary classification model, sigmoid was used as an activation function while mean squared error was used as a loss function.

5. RESULTS

5.1 Results for severity predictor

With the application of SMOTE, the recall calculated for cases where hospitalization was necessary reached as high as 80±3%, the recall for the subsequent classes was found to be, 100% for patients under control, 100% for patients with regular symptoms, and around 75% for mild cases. The Fig.6 shows a double bar graph of the correctly predicted labels for each class. The model performed with a test accuracy of around 85±2%.

$Recall_{(class)}$ = (Correctly predicted class labels)/(Actual count of class)

Table 1: Performance metric of the model.

Accuracy	85 ± 2%
$Recall_{mild}$	75%
$Recall_{regular}$	100%
$Recall_{controll}$	100%
$Recall_{severe}$	80 ± 3%

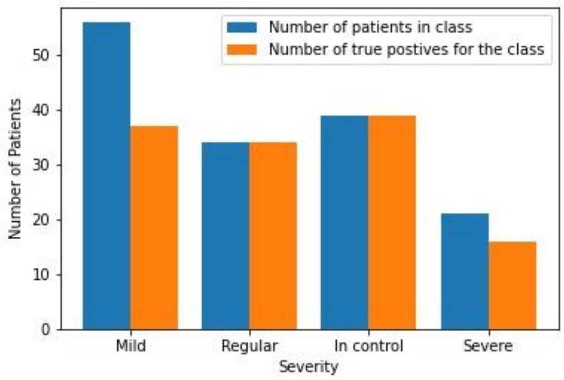


Figure 9: Plot to visualize recall for each class

5.2 Results for Covid 19 Detection

The accuracy for Covid 19 Detection using X-ray images reached a value of around 98%.

6. CONCLUSION

In this paper, we've proposed a framework that is an all-in-one web application that will allow us to help researchers, healthcare systems as well as enthusiasts. The Framework has 4 modules namely: Data Summary, Visualization, Analytics, and Predictions. This divided layout will help users in navigating through the web app easily. It will allow normal users to gain some important information regarding COVID-19 at a glance as well as help researchers and enthusiasts in their studies by providing valuable analysis. The framework also includes an accurate severity prediction model for COVID-19 as well as a covid detection model which will aid in clinical decision making and proper resource allocation. It will also be useful to government authorities for decision making and resource allocation which will aid in handling the pandemic.

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