

Prediction of COVID-19 By Applying Supervised Machine Learning Techniques

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Abstract: In the era of modern lifestyle, humans going to modernize everything with innovative brains finding the solution for the latest pandemic of this century which is COVID-19. The diagnosis of COVID-19 is a critical and slow process, to tackle this we decided to diagnose COVID-19 quickly by using machine learning (ML) due to its prediction for time-saving. Therefore, in this research, a patient admitted to the intensive care unit (ICU) has vital signs such as heart rate, oxygen saturation (SPO₂), blood pressure, and respiratory rate using wearable sensors which are the main vital signs of COVID-19. the predictive models using machine learning algorithms support vector machine (SVM), random forest (RF), and bagging tree (BG) for more accurate predictions. The proposed prediction model results used dataset, and models trained with Support Vector Machine in AUC= 0.9.1, ROC = 0.90 curve, Random Forest AUC = 0.920, and ROC = 0.91, and Bagging Tree AUC = 0.913, and ROC = 0.91 which shows the prediction accuracy. This research indicates machine learning's capability to predict COVID-19 quickly instead of conventional methods that have previously been adopted in pandemics such as influenza.

Keywords: Bagging Tree, Intensive Care Unit, Machine Learning, Support Vector Machine, Random Forest.

1- Introduction

The latest pandemic COVID-19, caused by the new SARS-Co-2 coronavirus is dangerous since many lives become morsels of death worldwide, thus with an emerging need to highlight the modern intelligent, and fast method to diagnose this disease. The machine learning techniques, using Support Vector Machines (SVM), Bagging Trees (BT), and Random Forest (RF), are being developed as supervisory tools for COVID-19.

The last century's influenza pandemic were all symptoms of Headaches, dry cough, acute malaise, runny nose, sore throat, etc. The most recent pandemic was COVID-19, with symptoms including weakness, weariness, reduced taste, fever, shortness of breath, cough, coughing up phlegm, muscle aches, and discomfort. The global mortality at the end of 2020 was 6,665,401, which damaged the global economy and severely harmed healthcare systems in Europe, Asia, North and South America, Africa, and Australia. COVID-19 prediction in the current day employs the most advanced biomedical tools, including tests such as Reverse Transcription



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Polymerase Chain Reaction (RT-PCR), CT scan, and Nucleic Acid testing of contaminated secretions [1].

The Severe Acute Respiratory Syndrome coronavirus 2 (SARSCOV 2), was discovered in China in 2020. As of May 20, 2020, the virus had infected 4,806,298 persons and killed 318,598. The World Health Organization (WHO) defines COVID-19 as a Coronavirus illness (COVID-19), a virus infection caused by the SARSCOV2 virus. Prediction of COVID-19 by blood test counts plasma biochemical profile, routine urinalysis, stool, coagulation function, blood gas analysis, ASO, CPR, RF, cyclic citrullinated peptide, PCT, ESR, PCT, blood type, cardiac enzymes, respiratory virus tests, and cytokines or by ultrasound of liver, pancreas, gallbladder, and spleen [2].

2- Literature Review

For the Recently conducted research, there has been a significant increase in the number of studies investigating the use of machine learning techniques for the prediction of COVID-19. The techniques SVM, Random Forest, and Bagging Trees have been used by researchers to handle various parts of the epidemic. S. Solayman et. al. worked on the prediction of COVID-19 automatically using machine learning techniques. The COVID-19 pandemic is the most disruptive global disaster of the twenty-first century, hurting millions socially, economically, and mentally. The goal of this study is to develop an intelligent web application for automatic COVID-19 detection using machine learning techniques. Preprocessing of the dataset included handling null values, feature engineering, and synthetic oversampling (SMOTE). Several classifiers and deep learning models were trained and evaluated, with the hybrid CNN-LSTM model incorporating SMOTE outperforming the others (96.34% accuracy and 0.98 F1 score). The model that resulted was deployed on a website enabling quick COVID-19 prognosis based on user symptoms, hence improving access to pandemic-related information [3].

G. Raman et. al. conducted a study on the prediction for COVID-19 severity at hospitals using machine learning techniques. This study created machine learning models to estimate outcomes using data from the University of Texas Southwestern Medical Centre from May 2020 to March 2022 using tenfold cross-validation and identified the best predictive models by assessing 25 relevant variables such as laboratory data and starting respiratory status. The Random Forest classifier for 30-day mortality had 0.72 sensitivity, 0.78 specificity, and 0.82 AUC in a cohort of 1795 patients, whereas the model for predicting mechanical ventilation got 0.75 sensitivity, 0.75 specificity, and 0.81 AUC. This objective risk score aids in the early assessment of COVID-19 severity within six hours of admission [4].

G. Wang et. al. research on the diagnosis of COVID-19 was based on multimodal optimized SVM and D-S evidence fusion. To improve self-diagnosis, a multi-modal strategy was used to solve the issue of correct classification of COVID-19. An optimized support vector machine was used in conjunction with the modified whale method to extract various features from CT signals and experimental data using weighted D-S evidence theory, probability distribution functions, and similarity measures to construct a multi-domain feature fusion prediction model. This

method, which incorporates several signs such as CT, laboratory data, and serum markers, increases the precision and accuracy of autonomous COVID-19 diagnosis [5].

M. Singh et. al. worked on the automatic detection of COVID-19 based on SVM using lung computerized tomography scan data, an unprecedented pandemic caused by SARS-CoV-2, requires early discovery in order to be contained. In this research, four classifiers (DCNN, ELM, online sequential ELM, and bagging ensemble with SVM) are tested using truncated VGG16 architecture for feature extraction from CT scan images and Principal Component Analysis (PCA) for feature selection. The bagging ensemble with SVM was the most effective, achieving 95.7% accuracy, 95.8% precision, an AUC of 0.958, and an F1 score of 95.3% [6].

Gnana Sheela K. and Anu Rose V. developed a Machine Learning Based Health Monitoring System using Raspberry Pi instead of traditional methods of identifying COVID-19 for the patients admitted to the ICU. Machine Learning is a supervised learning area of Artificial Intelligence (AI) by using support vector machines and random forests that can help forecast COVID-19. With only five vital signs (ECG, oxygen saturation (SpO₂), body temperature, pulse rate, blood pressure) and achieving high accuracy prediction made by COVID-19's five vital signs are shown on the webpage consisting of doctor and patient login [7].

M. Nour et. al. worked on medical infection detection of COVID-19 diagnosis based on deep features and Bayesian Optimization in Wuhan, China. This study introduced an intelligent computer-aided model for COVID-19 positive prediction and proposed the application of support clinical delay. The model proposed for prediction using convolutional neural networks (CNN) consisted of five layers, applied to X-ray images, k-nearest neighbor, support vector machine, and decision tree for experiments were conducted on the radiology database. The range of results were recorded for SVM accuracy of 98.97%, a sensitivity of 89.9%, a specificity of 99.75%, and an F-score of 96.72% [8].

S. Singh et. al. proposed the study of ARIMA and least square SVM model for COVID-19 prediction. Rapid worldwide transmission statistics necessitates highly accurate forecasting models. In this study, we use ARIMA and LS-SVM models to analyze daily SARS-CoV-2 cases in the five most affected countries. Researchers forecast verified instances for one month and check forecasts against test data. LSSVM outperforms ARIMA, indicating a global case surge. The LSSVM model results are better accuracy than the ARIMA model [9].

L. Sun et. al. worked on the prediction of clinical indicators for severe symptoms of being infected by COVID-19. The study examined 336 COVID-19 cases in Shanghai, training and test dataset and collecting 220 clinical and laboratory findings. This research discovered 36 clinical signs, mostly involving thyroxine and immune-related factors, that were linked to severe symptoms. The Results of SVM model optimized an AUROC of 0.99 in training and 0.97 in testing, with age, GSH, and CD3 ratio. High recall rates were obtained (93.33% and 100%.) The regression of Cox-multivariate and survival analysis validated the model's discrimination capacity as well as the importance of the clinical indicators used [10].

P. Kumar et. al. proposed this research on COVID-19 detection based on SVM deep features. SVM, chosen for processes deep features fully connected layer of a CNN model with its

suitability for small dataset. The approach divides X-ray pictures into COVID-19, pneumonia, and normal categories. SVM model attains the best performance with Resnet 50 plus, attaining 95.33% accuracy, sensitivity, 2.33% FPR, and 95.34% F1 score by utilizing deep features from 13 different CNN models. This research uses publicly available X-ray image repositories to demonstrate SVM's robustness in smaller dataset when compared to transfer learning SVM achieved 93.4% accuracy [11].

L. N. Mahdy et.al. proposed the study of implementing SVM classification on multilevel for automatic lung X-ray images for COVID-19 detection. The diagnosis of SARS-CoV-2, which is a critical cause of COVID-19. The SVM effectively differentiates COVID-19-affected lung X-rays using deep features with 95.76% sensitivity, 99.7% specificity, and 97.48% accuracy, the suggested system including multi-level thresholding with SVM obtained high accuracy [12].

C. Iwendi et. al. carried out a study on the prediction of COVID-19 affected patients' health using Boosted-Random Forest. The integration of artificial intelligence (AI) into wireless infrastructure and real-time data processing is becoming increasingly popular. AI shows great promise for detecting and forecasting large-scale pandemics like COVID-19, which has stressed healthcare systems around the world. This research uses COVID-19 patient data to predict case severity and outcomes using a carefully calibrated Random Forest model with AdaBoost. The model shows a positive link between gender and mortality which has a 94% accuracy and an F1 Score of 0.86, shows, as well as a patient age range of 20 to 70 years [13].

F. Rustam, et. al. described machine learning (ML) techniques are increasingly vital in predicting perioperative outcomes and prioritizing threats across various domains. This study focuses on forecasting COVID-19 impacts using four common models: linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), and exponential smoothing (ES). These models predict new cases, deaths, and recoveries over the next 10 days. ES emerges as the most effective, followed by LR and LASSO, in accurately forecasting infection rates, death tolls, and recovery rates. However, SVM underperforms in all scenarios based on available data. These findings underscore the potential of ML in addressing COVID-19 challenges [14]. This literature review missing the SVM, BT, and RF and combine these model's predictions to fill this gap.

3- Proposed Method

The vital signs for median, mean, min, max, relative diff, and diff. the data obtained from and grouped in the patient's encounter and combined by windows in chronological order. In addition, the test dataset has features of gender aged 65 years or above. On these data's features, it can develop a model for COVID-19 prediction using binary features for test results. The input or features are vital signs mentioned in Table 1 below and the labeled or output is the ICU. The proposed method used in this study is shown in the block diagram Fig. 1.

Table 1. Shows the input features and out-labeled data in the dataset

Inputs	
(A) Basic Information (Features)	
(1)	Age (maximum 65)

(2)	Gender (male or female patients)
(3)	Age Above 65
(B)Vital Signs (Features)	
(4)	Blood Pressure Systolic
(5)	Blood Pressure Diastolic
(6)	Heart Rate
(7)	Respiratory Rate
(8)	Body Temperature
(9)	Oxygen Saturation
Output	
(C) Labeled Data	
(10)	ICU {If predicted then (1) of Not then (0)}

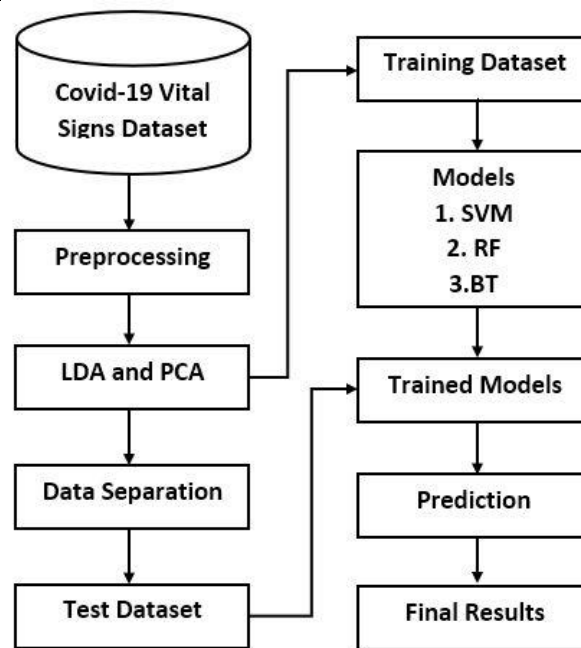


Figure 1. Proposed work flow for COVID-19 prediction

3.1 Prediction Model

The prediction was generated by using a Support vector Machine model, Random forest, and Bagging tree. These algorithms are widely used for tabular data in the field of machine learning. Now the SVM, RF and BT for prediction of COVID-19 are used. We used the following libraries ‘pandas’, ‘NumPy’, ‘sklearn’, and ‘scikit learn’ classifiers for RF, GT, SVM. the data frame was split into ‘X’ being input feature and ‘Y’ as targeted variable (ICU), then read each CSV file into a pandas Data frame, using the loop the list of filenames. The data frame is split into features ‘X’ and target variable ‘Y’. The approach ‘train_test_split’ split the data into testing and training with a test size of 20 % from ‘scikit learn’ and a random state for reproducibility. Initialize machine learning models of RF, SVM, and BT, and use the machine learning model to train the training data. To obtain the positive class (ICU = 1) for predicted

probabilities against each model. After the preprocessing step, the dataset is divided into six sub-datasets. Here used the one dataset for trading the models. These models have been trained and confirmed positive cases.

3.2 Machine Learning Models

3.2.1 Support Vector Machine

SVM is performing the binary classifier here to best separate the two classes to find the hyperplane which margin keeps to maximize. In the context given dataset 'X' features binary label 'Y' (1 for positive and 0 for negative) COVID-19 prediction. The maximum margin is $\frac{2}{\|w\|}$ where 'w' is the weight vector of the hyperplane and $\|w\|$ represents the magnitude of the norm of weight vector. The maximize $\frac{2}{\|w\|}$ divided by the weight vector's magnitude. 'w'. The maximize margin reflects improved split between the two classes, we strive to maximize this term, which corresponds to the hyperplane's margin. The equation shall be for all data points 'i'

$$Y_i(wX_i - b) \geq 1 \quad (1)$$

Where Y_i is the label of the binary data point 'i' which data point belongs to ICU = 1, and X_i is feature vectors of 'I' data points.

3.2.2 Random Forest

The RF predicts the 'Final Prediction' that is the class label. Number equations consecutively with equation numbers in parentheses flush with the right margin, as in (1). The outcomes of various decision trees are combined using majority voting in a Random Forest for classification. The final prediction is the class that gains the most votes from the various trees. The final prediction is equal to argmax:

$$\text{argmax} (\sum \delta(C, T_i)) \quad (2)$$

Where $\delta(C, T_i)$ is a function that can return 1 if 'c' class is predicted by individual T_i tree otherwise 0. ' \sum ' are individual overall trees T_i in RF. 'argmax' returns the labeled class with individual trees the sum of highest of votes.

3.2.3 Bagging Tree

The BT classification final prediction can mathematical expressed as:

$$\text{Prediction} = \text{mode}(T_1, T_2, T_3, \dots, T_n) \quad (3)$$

'Prediction' is the class label predicted (1 for positive, 0 for negative) COVID-19, 'mode' is a function which arrives from often occurring class between predictions from individual $l(T_1, T_2, T_3, \dots, mT_n)$ decision trees. The prediction is the class (1 or 0) that emerges mostly between these individual decision tree predictions. The equation for predicting COVID-19 ICU admissions means that you combine the predictions from each decision tree within the ensemble Bagging Tree.

4. Results And Discussion

4.1 Dataset Collection

The dataset source is Hospital Sírío Libanes, São Paulo, Brazil [15] which recorded data based on vital signs regarding the Intensive Care Unit (ICU) [16-17]. The data available in the dataset is the patient's demographic information, previously grouped diseases [18-19], vital signs of COVID-19, and blood results. The dataset consists of 54 independent variables that are expanded in columns when patient to median, mean, min, max, relative diff, and diff. where:

1. Diff. = Max. – Min
2. Relative Diff. = Diff./Median

4.2 Preprocessing

As efforts by defined studies, the missing values are handled by the process of preprocessing. Linear discriminant analysis (LDA) and Principal component analysis (PCA) are both techniques used for feature reduction for this purpose “Python” language for PCA uses libraries “pandas” and “scikitlearn” to load and drop the ‘null value’, separate the target values from the feature, standardize the data as PCA is sensitive to scale and at last apply PCA to reduce dimensionality specify the number of components. Same as using LDA continuing the preprocessing method to load the data file removing all null values, creates a dictionary from the list of documents, create a document term matrix, build LDA model to extract the features from the created documents [20-21].

The research suggests by applying machine learning models to the prediction of COVID-19 cases. These predictions branch from a model crafted through machine learning techniques. Four classification algorithms Random Forest, Support Vector Machine, and Bagging Tree are assessed using hospital records. The goal is to identify the most effective algorithm for COVID-19 prediction. Each algorithm is trained on dataset containing 481 or 482 records, and its performance is evaluated through various metrics. The accuracy score and ROC curves according to dataset, when evaluating classification models on dataset, accuracy score and receiver operating characteristic (ROC) curve are vital metrics [22]. Accuracy score offers a comprehensive measure of model correctness, showcased in Figure 2. Furthermore, ROC curve aids in distinguishing between classes, facilitating model effectiveness assessment. Results reveal random forest model achieved 92% accuracy, followed by bagging tree model with 91.3%, and support vector machine with 90.1%, as depicted in the Fig. 3.

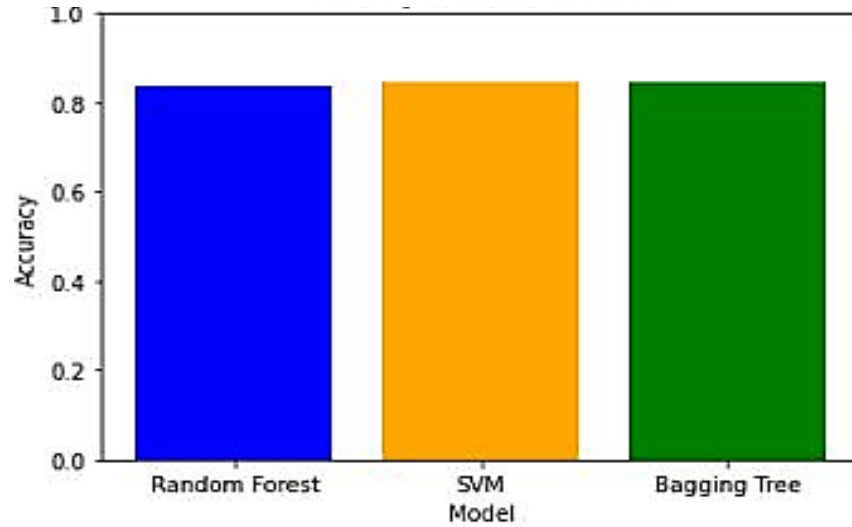


Figure 2: Accuracy score of prediction models for dataset

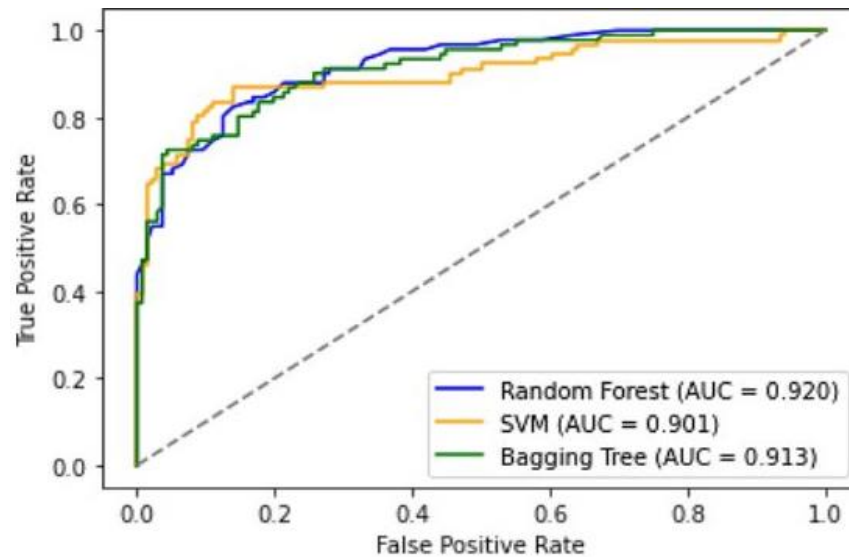


Figure 3: ROC curve of support vector machine, random forest, and bagging tree dataset

4.3 Training Results with Method

First of all, for each accuracy score of datasets initialize an empty list of AUC scores, true positive rates (TPRs) false positive rates (FPRs). To calculate the AUC score and ROC curve for each model and store them then TPR and FPR are compared for each model for ROC curves. At last, calculate the accuracy scores for each model. The performance metric called AUC-ROC is used to evaluate a binary classification model's discriminatory capability. An AUC value that is greater (closer to 1) indicates better overall performance in terms of true positive and false positive rates. This measure reflects the model's capacity to distinguish between the two groups.

4.4 Models Performance and Comparative Analysis

4.4.1 Proposed Models Performance Evaluation

The outcomes of the SVM, random forest and bagging tree are explained through various metrics to ensure thorough examination. Figures 4, 6, and 8 displays the confusion matrix, providing complex insights into true negatives (TN), true positives (TP), false negatives (FN),

and false positives (FP). In comparative analysis section Tab. 2 additions this by presenting precision, F1 score, specificity, and sensitivity calculations. Additionally, visual aids such as the sensitivity-tradeoff, precision-recall pairs, and ROC curves are depicted in Fig. 5, 7, and 8 to enhance understanding.

Table 2: Confusion matrix-based models evaluation performance

Matrix	Bagging Tree	Support Vector Machine	Random Forest
Precision	0.8214	0.7662	0.8023
F1 Score	0.7885	0.7023	0.7796
Sensitivity	0.7582	0.6483	0.7582
Specificity	0.8897	0.8676	0.875

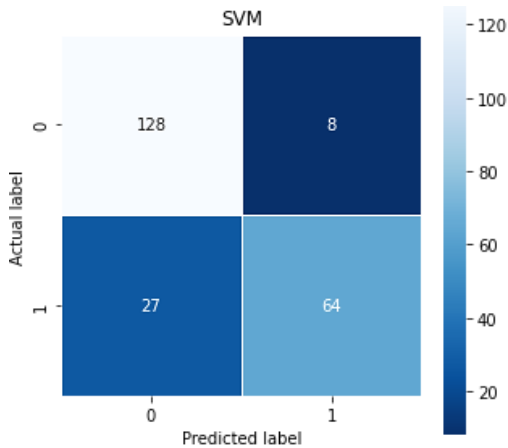


Figure 4: Confusion matrix of support-vector-machine

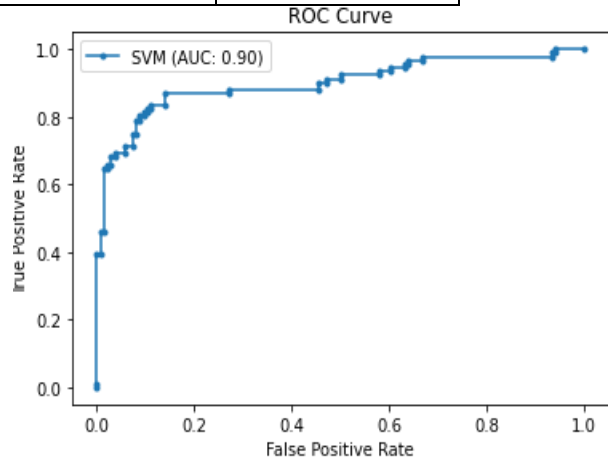


Figure 5: ROC (Receiver-operator-curve) of support-vector-machine

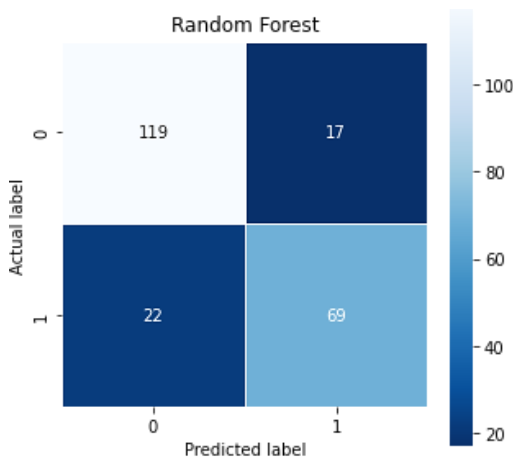


Figure 6: Confusion matrix of random forest

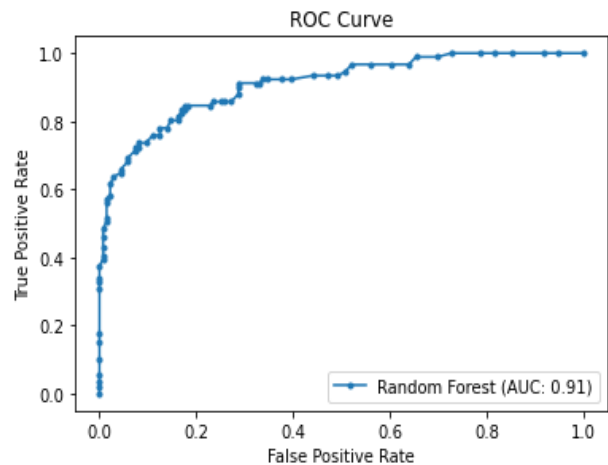


Figure 7: ROC (Receiver-operator-curve) of random forest

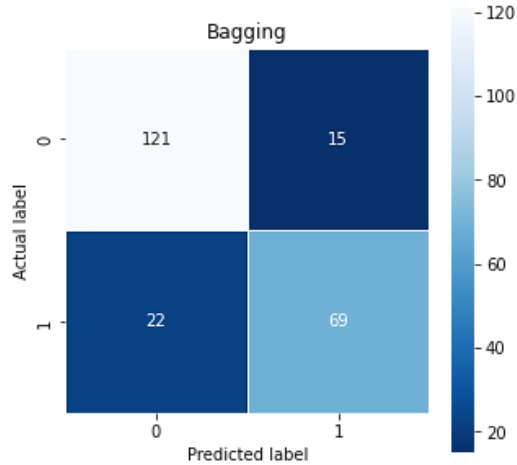


Figure 8: Confusion matrix of bagging tree

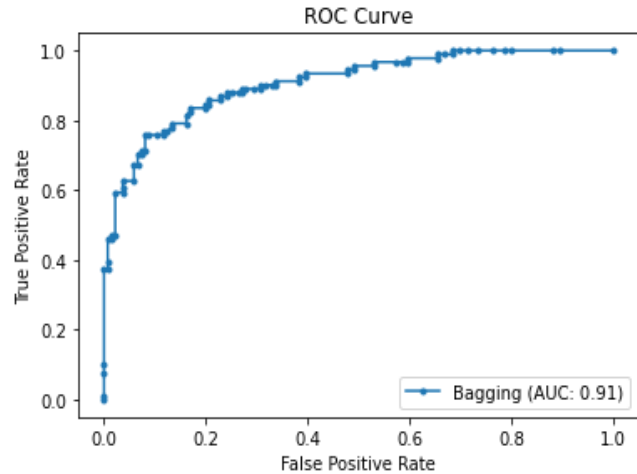


Figure 9: ROC (Receiver-operator-curve) of bagging tree

4.4.2 Limitations

The dataset acquired from the online repository so the results are limited based on the given dataset in the dataset which research works on the vital signs of COVID-19. The COVID-19 prediction is based on binary classification using support vector classifications in SVM and tree-based classification in bagging tree and random forest. This proposed study is limited to COVID-19 vital sign-based prediction it does not work on blood tests.

5. Conclusion and Future Work

In the dominion of healthcare, effectively predicting and treating diseases with high resistance, such as Coronavirus, holds immense importance for public health. To expedite and enhance the accuracy of diagnosis, automated detection frameworks are anticipated to play a pivotal role. In this article, we present an AI-driven framework tailored for detecting Coronavirus through vital sign dataset. Given the current limitations in accessing comprehensive Coronavirus data, our framework operates on dataset with limited information and imbalanced class distributions. These datasets serve as the foundation for extracting features used to train Support Vector Machines (SVM), Random Forest (RF), and Bagging Tree for COVID-19 prediction. We leverage various openly available dataset to evaluate our proposed method and demonstrate its superiority over alternative machine-learning approaches. Our study offers valuable insights for researchers aiming to facilitate early detection of COVID-19 cases, particularly in dataset-based research domains. Looking ahead, we recognize the necessity of employing well-balanced dataset to further refine our detection capabilities. Additionally, we plan to explore Supervised Learning-based models to achieve even higher performance levels with such dataset. These advancements hold promise for significantly improving the accuracy and efficiency of COVID-19 diagnosis in the future.

The knowledge collected from this study can help researchers, politicians, and medical professionals make wise decisions and comprehend the course of the virus as we fight the COVID-19 pandemic. The requirement is that these models must be improved and adjusted in

order to remain accurate and relevant in addressing the changing nature of the pandemic. More recent data integration and modeling technique improvements may result in predictions that are even more accurate and provide greater support for decision-making processes during public health emergencies.

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