An Investigation of Machine Learning Algorithms on COVID-19 Dataset

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Abstract

This paper studies the different machine learning classification algorithms to predict the COVID-19 recovered and deceased cases. The k-fold cross-validation resampling technique is used to validate the prediction model. The prediction scores of each algorithm are evaluated with performance metrics such as prediction accuracy, precision, recall, mean square error, confusion matrix, and kappa score. For the given dataset, the k-nearest neighbour (KNN) classification algorithm produces 80.4 % of predication accuracy and 1.5 to 3.3 % of improved accuracy over other algorithms. The KNN algorithm predicts 92 % (true positive rate) of the deceased cases correctly with 0.077 % of misclassification. Further, the KNN algorithm produces the lowest error rate as 0.19 on the prediction of accurate COVID-19 cases than the other algorithm. Also, it produces the receiver operator characteristic curve with the output value of 82 %.

Keywords: COVID-19, Prediction, Classification, Machine learning algorithms, KNN

1. Introduction

Covid-19 [1-3] a disease which was caused due to a virus called coronavirus. It became a global epidemic disease according to World Health Organisation (WHO). It was started at Wuhan of China on end of 2019. The symptoms of this disease at the early stage are cough, fever, fatigue, and myalgias [1]. Later the patients suffer from heart damages, respiratory problems and secondary infection situations. Spreading of covid-19 happens very fast because it spreads through contact, contaminated surfaces and infected fluids. When the condition of the patient becomes worse with respiratory issues, the patient needs to be treated in intensive care unit with ventilation.

The mortality of this disease increases day by day and this disease becomes as a big threat to the human kind of entire world. Along with the clinical researches, the analysis of related data will help the mankind. Many researches have already been done on the Computed Tomography (CT) images of the patients [4-5], their symptom based analysis and on the influencing factors.

Researches on CT images were done for identifying the characteristics of the disease and also diagnosing the disease early. CT images of covid-19 cases have similarity in terms of inward and circular diffusion [4].

The classifications of Covid-19 are Influenza-A viral pneumonia, Covid-19 and healthy one [4]. The research is done based on CT images of 618 images with 224 images of Influenza patients, 219 images of covid-19 patients and 175 healthy humans and they achieved 87.6% accuracy. Another study [5] was done for segmenting and quantifying the infection of CT images. They used the CT images of chest and lung and they implemented it using deep learning technique. They used 249 images for training and 300 images for testing and achieved the accuracy of 91.6%. Pathological tests and analysis of CT images take some time. So researches are done based on the possibility of disease prediction based on the symptoms. This work uses some classification techniques for predicting the possibility of occurrence of covid-19 based on their characteristics.

The organization of this paper is as follows. Section 2 gives the related work of classification techniques, Section 3 discusses the different machine learning models, Section 4 analyses the performance metrics, experimental analyses, and results and Section 5 gives the concluding remarks with future work.

2. Related Work

Emergence of artificial Intelligence (AI) transformed the world in all the fields. Machine learning (ML), a subset of AI helps the human to find solutions for highly complex problems and also plays a vital role in making human life sophisticated. The application areas of ML include business applications, intelligent robots, autonomous vehicle (AV), healthcare, climate modeling, image processing, natural language processing (NLP) and gaming. The learning of in ML mimics the human intelligence and it is implemented based on trial and error method. The instructions to the algorithm were given mainly using control statements such as conditional if [6]. Many prediction based algorithms are available in ML [7]. The ML techniques are used for classification and prediction in various fields like disease prediction, stock market, weather forecasting and business.

Classification techniques are broadly categorized into semi-supervised [17, 18], supervised [19] and unsupervised [20-23]. Logistic Regression [24-25] is used for relationship analysis between various dependent variables. Artificial neural network (ANN) [26-31] is based on learning and classifies effectively. Support Vector Machine (SVM) [32-35] is another classification technique which separates the variables using hyperplane. In medical field also many ML algorithms are used for disease prediction [8] like coronary artery disease [9], predicting cardiovascular disease [10] and prediction of breast cancer [11]. Many researches are also done for covid-19 confirmed case live forecasting [12] and for predicting covid-19 outbreak [13]. These works will aid the higher authorities of the country for taking decisions to handle the situation by foreseeing [14]. At first the covid-19 was misinterpreted as pneumonia [15]. But the failure of multi-organs and high mortality rate [16] made it as a pandemic in whole world.

Many classification and prediction algorithms are applied to study about the possibility of spreading covid-19. A research was done on the occurrence of asymptomatic infection and they found it is higher (15.8%) in children under 10 years [36]. Some studies have done in identifying the symptoms and identified having lesser senses of taste and smell are the signs of Covid-19 [37]. Another work [38] also studied about the transmission process of this disease.

3. Methodology

In recent years, medical predictive analysis using machine learning techniques has tremendous growth with promising results. The machine learning algorithms are effectively applied in numerous types of applications in diverse fields. Many kinds of research have proved that the machine learning predictive algorithms had provided better assistance for clinical supports as well as for decision making based on the patient data [39]. In the healthcare field, the disease predictive analysis is one of the useful and supportive applications of the machine learning prediction algorithms. This research work applies the disease predictive analysis using machine learning prediction algorithms for the novel COVID-19 disease.

3.1 Data Preprocessing and Cleaning

The COVID-19 dataset from the Kaggle [40] is taken for the predictive analysis in this research work. The considered dataset was cleaned using the data preprocessing and data cleaning methodologies and resulted dataset have been considered for the several number of experiments over different classification algorithms. The COVID-19 dataset contains the patient’s details with recovered and deceased status. The vital patient’s information is used to diagnose and predict the COVID-19 disease among the infected population.

The considered COVID-19 dataset contains 100284 records. The dataset contains features of patients such as patient number, state patient number, date announced, estimated onset date, age bracket, gender, detected city, detected district, detected state, state code, current status, notes, contracted from which patient (suspected), nationality, type of transmission, status change date, source_1, source_2, source_3, backup notes, num cases, entry_id [40].

The data preprocessing and cleaning process removes the missing and outliers data values from the dataset. The resulted dataset after preprocessing is reduced to 730 records with three required relevant features of patient details. In the dataset, there are 730 patient details, out of which 156 cases are in the class of 'recovered from COVID-19 disease' and 574 cases are in the class of 'deceased by the COVID-19 disease' with 99554 records are missing required essential values. Two numerical features from the dataset are taken as the input attributes and one feature is considered as the output attribute. The COVID-19 patient's information is presented in Table.1.

Table.1 Sample record of cleaned dataset

Age	Gender	Outcome
13	Female	Recovered
96	Male	Recovered
89	Female	Recovered
85	Male	Recovered
27	Male	Recovered
69	Female	Deceased
26	Male	Recovered
65	Male	Deceased
76	Male	Deceased
45	Female	Recovered

The patient features such as age and gender is considered as input variables and outcome is taken as the output variable. The features such as 1. Age- denotes the patient at the time of infection by the COVID-19 virus; 2. Gender- classifies whether the patient is male or female; 3. Outcome-denotes whether the patient has been recovered from COVID-19 disease or deceased due to COVID-19 disease. Figure.1(a) illustrates the population infected by COVID-19 with respect to age. Figure.1(b) and Figure.1(c) depicts the count plot of gender and outcome of COVID-19 respectively.

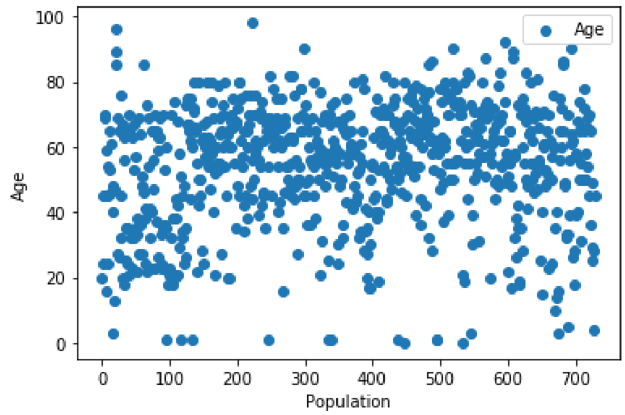
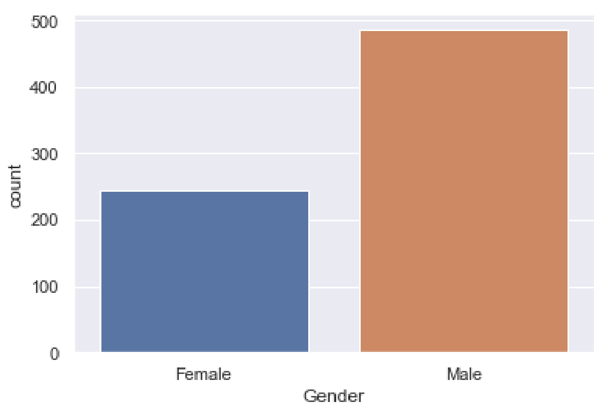


Fig.1 (a) Population vs Age



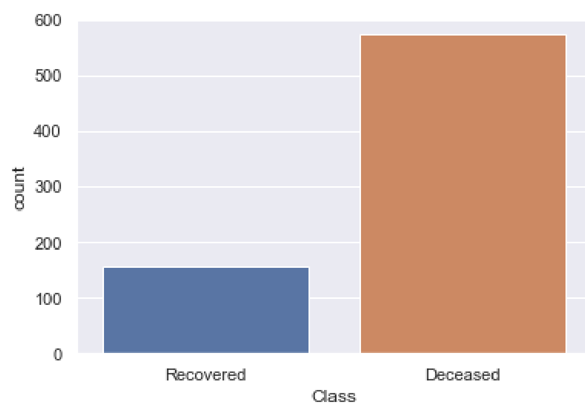


Fig.1 (b) Gender **Fig.1 (c) Outcome**

This research work analysis the prediction of recovered and deceased patients infected by COVID-19. Different classification models are applied on the COVID-19 dataset and its performance in term of accuracy, error rates, etc are evaluated. The classifiers evaluated in this research work are Logistic Regression (LR), K-Neighbors Classifier (KNN), Decision Tree (DT), Support Vector Machines (SVM), and Multi-Layer Perceptron (MLP).

3.2 Logistic Regression (LR)

One of the simple and powerful prediction algorithms is logistic regression. The logistic regression uses the sigmoid function for predictive modelling of the given problem. It models the dataset maps them into a value between 0 and 1. The logistic regression performs the predictive analysis based on the relationship between the binary dependent variable and other one or more independent variables from the given dataset. In order to predict the output value (Y), the input values (X1, X2,…Xn) are linearly combined using the coefficient values [41]. Let us consider, 'Y' as the output prediction variable and X1 and X2 are input variables, then the logistic regression equation is given as (1),

$$Y = \frac{1}{2}\left[\frac{e^{(m*X1+c)}}{1+e^{(m*X1+c)}} + \frac{e^{(m*X2+c)}}{1+e^{(m*X2+c)}}\right] \tag{1}$$

Where 'c' represents the intercept, 'm' is the coefficient of input value X1 and X2 (in our case, X1, X2 are age, gender). The coefficient value 'm' can learn from the training dataset for each input value (X1, X2) [41]. This work to classify the deceased and recovered cases of the COVID-19 disease using the equation (1).

3.3 K-Nearest Neighbors (KNN) Classifier

K-Nearest Neighbors algorithm is the non-parametric algorithm. The learning and prediction analysis is performed based on the given problem or dataset. The KNN classification model, the prediction is purely based on neighbour data values without any assumption on the dataset. In KNN, the 'K' represents the number of nearest neighbour data values. Based on 'K', i.e. the number of nearest neighbour, the decision is made by the KNN algorithm on classifying the given dataset [42].

The KNN model directly classifies the training dataset. It means the prediction of a new instance is made by searching the similar 'K' neighbour instances in the entire training set and classifying based on the class of highest instances. The similar instance is determined using the Euclidean distance formula. Euclidean distance is the square root of the sum of squared differences between the new instance (x_i) and the existing instance (y_j) [42].

$$Euclidean_{i,j} = \sqrt{\sum_{k=1}^{n}(x_{ik} - y_{jk})^2} \tag{2}$$

3.4 Decision Tree (DT)

The decision tree algorithms are the powerful prediction model used for both classification and regression problems. The decision tree models are represented in the form of a binary tree. It means the given problem/dataset is solved by splitting or classifying them as a binary tree. In the decision tree, the prediction is made by taking the root node of the binary tree with a single input variable (x), splitting dataset based on the variable, and its leaf nodes of the binary tree have resulted as the output variable (y). That is, from the root node, the tree is traversed through each branch with their divisions and prediction is made based on the leaf nodes. It uses the greedy method for splitting the dataset in a binary manner [43].

In this research work, the COVID-19 dataset with two inputs (x) is taken as age, gender, and output is whether the patient is recovered or deceased. The decision tree classification algorithm uses the Gini index function to determine the impurity level of the leaf nodes for the predictions. The Gini index function (G) is given in equation (3).

$$G = \sum_{i=1}^{n} xk * (1 - xk) \qquad (3)$$

Where x is the proportion of training instances in the input class k. Binary tree representation of the dataset makes the prediction as straightforward [43].

3.5 Support Vector Machines (SVM)

The support vector machine can handle categorical and continuous variables. Also, the SVM model works well on classification and regression problems. The support vector machine is a classification algorithm that creates the hyperplanes for each class labels in the multidimensional space by employing the margin values. The SVM intends to maximize the margins among different classes by optimally separating hyperplanes [44]. The hyperplane is a data instance of the given dataset used by the support vectors. The margin is the maximum distance among the support vector and the hyperplane [44]. If the given dataset is linear bounded, then linear SVM can be adopted and the dataset is nonlinear bounded, then Non-linear SVM can be adopted for the classification tasks [45].

Let us consider, a dataset (A_1, B_1,….A_n, B_n); where ($A_{1,\ldots}$ A_n) is the set of the input variable, (B_1,…,B_n) is output variable, and C is the intercept, then the SVM classifier [44] is given as like equation (4).

$$SVM = \sum_{i=1}^{n} \beta_i - \frac{1}{2} \sum_{i,j=1}^{n} b_i b_j C\left(a_i, a_j\right) \beta_i \beta_j \qquad (4)$$

In the equation (4), i=1,2,,3….n; and C=$b_i\beta_i + b_j\beta_j$. The SVM equation (4), is used in this research work to classify the deceased and recovered cases of the COVID-19 disease.

3.6 Multilayer Perceptron (MLP)

The Multilayer Perceptron algorithm is suitable for classification problems and predictive analysis. The MLP is the classical neural network with one or more layers of hidden neurons. It comprises the input layer (where the data variables are fed), hidden layer (with function to operate on the data), and output layer (contains the predicted values). MLP uses the back-propagation to learn from the given input and output dataset. The activation function $A_j(X, W)$ of the MLP is the summation of the inputs (X_i) multiplied with respective weights (W_{ij}) as represented in equation (5). The output function (O_j) with sigmoid activation function of the MLP back-propagation [46] algorithm is given in equation (6).

$$A_j(X, W) = \sum_{i=0}^{n} (X_i\,, W_{ij}) \qquad (5)$$

$$O_j(X, W) = \frac{1}{1 + e^{-A_j(X,W)}} \qquad (6)$$

4. Results and Discussions

This section summarizes the prediction results of the logistic regression, k-neighbours classifier, decision tree, support vector machines, and multilayer perceptron algorithms.

4.1 Cross-Validation

To evaluate and validate the performance of the machine learning model resampling methods are adopted. This method estimates the prediction ability on the machine learning algorithm on new unseen input data. The k-fold cross-validation is one of resampling procedure used in this work to validate the machine learning models on the limited data sample. The 'k' represents the number of times the data model is to split. Each split of the data sample is called as a subsample or sampling group. These subsamples are used to validate the training dataset. In this work, the 'k' value is chosen as 10, therefore, it can be called as a 10-fold cross-validation resampling method. The 10-fold cross-validation method intends to reduce the bias of the prediction model [47].

4.2 Performance Metrics

Typically, the performance of the machine learning prediction algorithms measured by using some metrics based on the classification algorithm. In this work, the prediction results are evaluated by using the metrics such as accuracy, mean square error (MSE), root mean square error (RMSE), Kappa score, confusion matrix, the area under curve (ROC_AUC), classification performance indices, sensitivity, specificity, and f1 score values.

Mean Square Error (MSE): It is the average of the squared difference between predicted results (P_i) and actual results (A_i). It is calculated by using the equation given in (7), where n is the number of samples [48].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(T_i - A_i)^2 \qquad (7)$$

Root Mean Squared Error (RMSE): The RMSE is the square root of the average of squared differences between predicted and actual results likewise given in (8). It depicts the inconsistencies among the observed and predicted values [49].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T_i - P_i)^2} \qquad (8)$$

Accuracy: accuracy of the prediction algorithm is the ratio of the total number of correct predictions of class to the actual class of dataset. The equation (9) calculates the accuracy of the model. Typically, any prediction model produces four different results such as true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) [42].

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \qquad (9)$$

Precision: precision of the prediction algorithm is the number of correctly predicted recovered COVID-19 cases that is belonging to the actual recovered COVID-19 cases [42, 47].

$$Precision = \frac{TP}{TP + FP} = \frac{True\ Positive}{Total\ predicted\ positive}$$

Recall: recall of the prediction algorithm is the number of correctly predicted recovered COVID-19 cases made out of all recovered COVID-19 cases in the dataset. It is true positive rate [42, 47].

$$Recall = \frac{TP}{TP + FN} = \frac{True\ Positive}{Total\ predicted\ positive}$$

F1 Score: it is the measure of the balanced score (harmonic mean) of both precision and recall [42].

$$F1\ Score = \frac{Precision * Recall}{Precision + Recall}$$

Cohen's kappa Score: Cohen's kappa score estimates the consistency of the prediction model. It compares the result of the predicted model with actual results. It is a statistic value between 0 and 1. The value near to 1 might have the great consistency [47].

$$K = \frac{[TP + TN/N] - [(TP + FN) * (TP + FP) * (TN + FN)/N^2]}{1 - [(TP + FN) * (TP + FP) * (TN + FN)]/N^2]}$$

Confusion matrix: The confusion matrix provides a complete insight into the performance of a prediction model. It produces prediction results in the matrix form with the information of the number of correctly predicted cases, incorrectly predicted cases, errors of incorrect, and correct prediction cases [47].

Receiver Operating Characteristic (ROC)-Area Under Curve (ROC_AUC): The ROC_AUC curve is a graphical illustration of the performance of the prediction model [47]. The ROC curve is the relationship between the recall and precision over varying threshold values. The threshold is the positive predictions of the model. The ROC_AUC curve plotted by keeping x-axis a false positive rate and y=axis as true positive rate. Its value ranges from 0 to 1 [47].

4.3 Performance Evaluation

In most of the research works, the accuracy of the prediction model has been taken as one of the common performance metrics while working on prediction algorithm [42]. In this work, the prediction accuracy (that is whether the COVID-19 infected patient is recovered or deceased) of

Table.2 Accuracy score of classifiers

S. No	Classifier	Accuracy
1.	Logistic Regression (LR)	78.5388
2.	K Neighbors Classifier (KNN)	80.3653
3.	Decision Tree (DT)	75.3425
4.	Support Vector Machines (SVM)	78.9954
5.	Multi-Layer Perceptron (MLP)	77.1689

different machine algorithms (logistic regression, k- nearest neighbour, decision tree, support vector machines, and multilayer perceptron) are determined. Each classification model has a different prediction accuracy based on its hyperparameters and certain level of improvement over other prediction models. This work considers 70 % dataset for training and 30 % of the data samples for testing in classification algorithms. In this work, each model's accuracy is compared and its prediction results are summarized in Table.2.

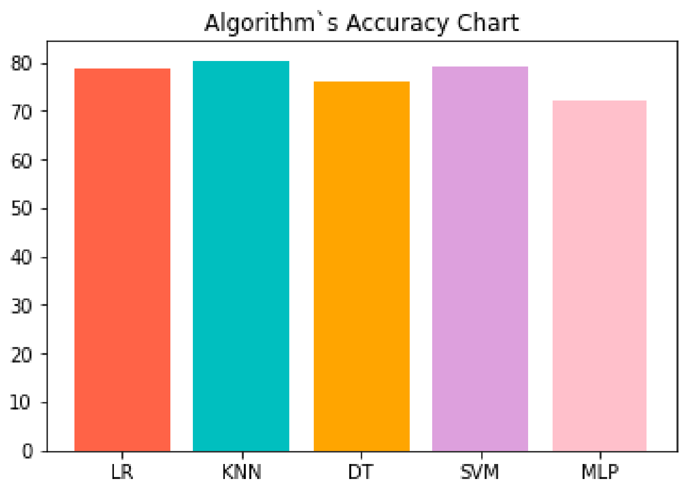


Fig.2 Covid-19 Dataset

In Table.2, the classification algorithms such as logistic regression, k-nearest neighbour, decision tree, support vector machines, and multilayer perceptron have the prediction accuracy of 78.5388, 80.3653, 75.3425, 78.9954, and 77.1689 respectively. Whereas, the k-nearest neighbour algorithm predicts the outcome of the COVID-19 cases (based on age and gender) more accurately than the other algorithms. Figure.2 depicts the accuracy scores of different classification algorithms. From Figure.2, we can clearly see that the k-nearest neighbour algorithm has the highest accuracy of 80.4. The KNN algorithm has 1.5 to 3.3 % of improved accuracy as compared to LR, DT, SVM, and MLP algorithms.

Table.3 presents the performance error metrics of the various machine learning algorithms. The error metrics mean square error, root mean square error, and Cohen's kappa score values for each algorithm is evaluated. The logistic regression, k-nearest neighbour, decision tree, support vector machines, and multilayer perceptron have the MSE error rate as 0.2146, 0.1963, 0.2466, 0.21, and 0.2283 respectively. As per Figure.3(a), the KNN classification algorithm produces the lowest error rate as 0.19 on the prediction of accurate COVID-19 cases than the other algorithm.

Table.3 Error metrics of classifiers

S. No	Classifier	MSE	RMSE	Kappa
1.	Logistic Regression (LR)	0.2146	0.4633	0.4109
2.	K Neighbors Classifier (KNN)	0.1963	0.4431	0.469
3.	Decision Tree (DT)	0.2466	0.4966	0.3043
4.	Support Vector Machines (SVM)	0.21	0.4583	0.4266
5.	Multi-Layer Perceptron (MLP)	0.2283	0.4778	0.3411

Similarly, the KNN's RMSE error rate also very low (0.44) as compared to the error rates of LR (0.46), DT (0.50), SVM (0.45), and MLP algorithms. Cohen's kappa score estimates the consistency of the classification algorithm based on its predictions. As depicted in Figure.3(b), the KNN classification algorithm produces the highest consistency among the evaluated algorithms as 0.47. The SVM algorithm offers the next highest consistency (0.42) on correctly predicting the COVID-19 cases. Moreover, the prediction of the decision tree algorithm has the lowest consistency value as 0.30. The LR and MLP have the consistency values of 0.41 and 0.34 respectively.

Figure.4(a) illustrates the normalized confusion matrix of the k-nearest neighbour classification algorithm. In all classification algorithm, 30 % of the data samples are taken for testing with the 70 % training dataset. In this figure, the x-axis represents the percentage of predicted values and y-axis represents the percentage of true values. It can be seen that the KNN algorithm predicts 92 % (true positive) of the deceased cases correctly with 0.077 % (false positive) of misclassification.

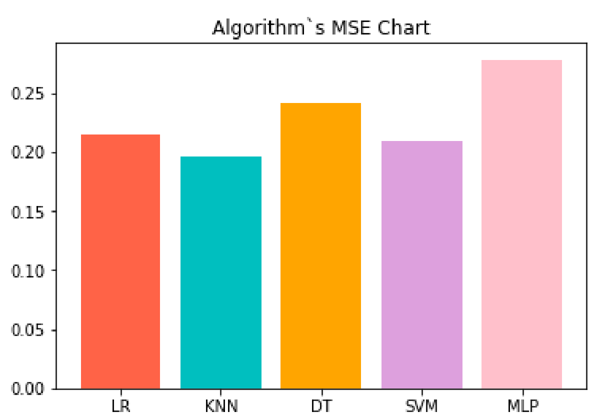


Fig.3(a) MSE rates

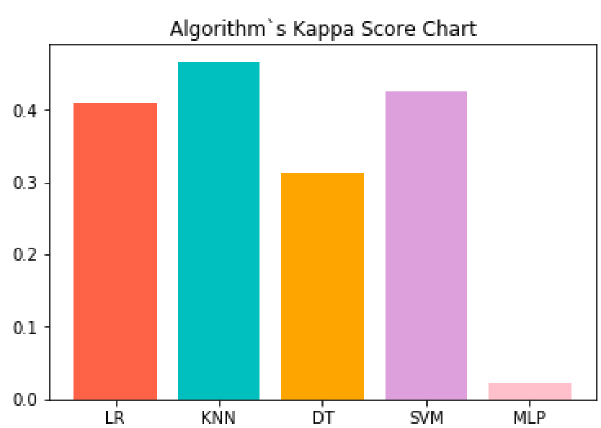
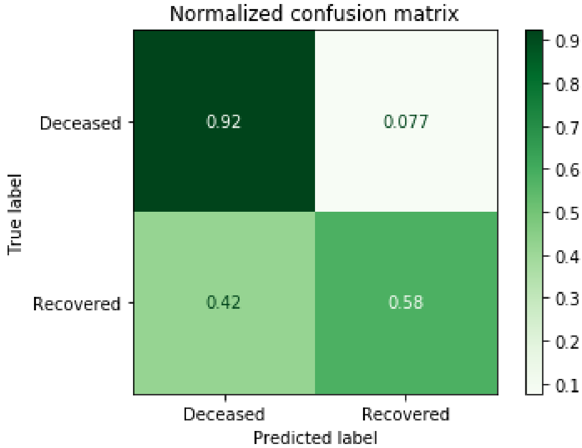


Fig.3(b) Cohen's kappa scores

Similarly, in Figure.4(b) the confusion matrix without normalization is depicted, where 160 cases are correctly predicted as deceased cases and 13 cases are misclassified. Further, 31 cases are correctly predicted as deceased cases and 31 cases are misclassified. Also, it correctly predicts 29 patients (true negative) as the recovered cases and 21 cases are misclassified (false negative).



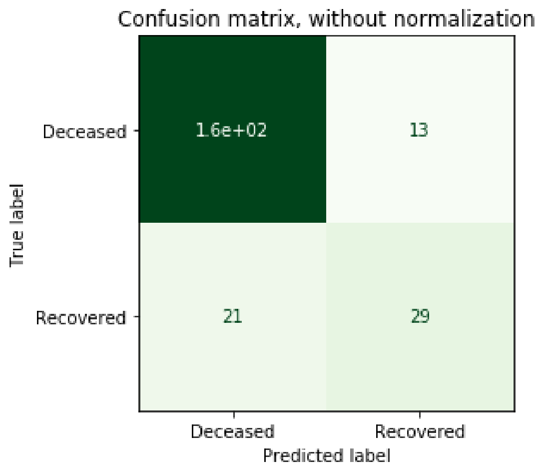


Fig.4 (a) Normalized Confusion matrix **Fig.4 (b) Confusion matrix (no normalization)**

Figure.5 is the pictorial representation between the false positive rate and true positive rate in the form ROC area under the curve. The k-nearest neighbour classification algorithm produces the highest value of 0.82 as compared with LR, DT, SVM, and MLP algorithms.

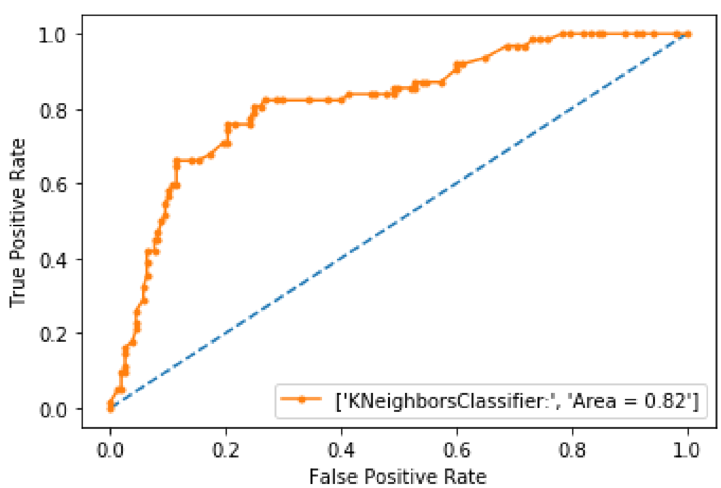


Fig.5 ROC_AUC Curve

Figure.6 summarizes the performance metrics such as precision, recall, and confusion matrix of the k-nearest neighbour classification algorithm. The KNN algorithm produces the precision (true positive rate) value of 0.82 for the recovered cases and 0.72 for the deceased cases. The recall values for the recovered and deceased cases are 0.92 and 0.50 respectively. Further, the F1 score for recovered and deceased cases are 0.87 and 0.59 respectively.

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KNeighborsClassifier:
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MSE: 0.1963470319634703
RMSE: 0.4431106317427628
Kappa_score: 0.46685161071165715
Accuracy: 80.36529680365297

Classification Report:

              precision    recall  f1-score   support

   Recovered       0.82      0.92      0.87       157
    Deceased       0.72      0.50      0.59        62

    accuracy                           0.80       219
   macro avg       0.77      0.71      0.73       219
weighted avg       0.79      0.80      0.79       219
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Fig.6 Summary of Performance metrics scores of KNN algorithm

5. Conclusion and Future Enhancements

The disease predictive analysis is the major application area. This work has implemented logistic regression, k-nearest neighbour, decision tree, support vector machines, and multilayer perceptron to classify the COVID-19 dataset. The KNN classification algorithm has the 1.5 to 3.3 % of improved accuracy over other machine learning algorithms reported in the work. Moreover, KNN classification algorithm produces the lowest error rate as 0.19 on the prediction of accurate COVID-19 cases than the other algorithm. In order to improve the accuracy of predictions, the future work will concentrate on predicting the COVID-19 cases using classification and optimization algorithm.

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