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Classification and Prediction of Covid-19 Using Naive Bayes and Random Forest Algorithm

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Abstract: Classification is a supervised learning algorithm in machine learning that involves assigning predefined categories or labels to input data based on their features. The primary objective of classification is to create a model that can precisely predict the appropriate label or class for new, unseen data. Covid-19, an infectious and severe disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), spread from bats to humans through an unknown intermediary in Wuhan, China, in late December 2019. This disease can cause organ damage, affecting vital organs such as the liver, heart,and kidneys, as well asthe blood and the immune system. The focus of this study is to classify and predict Covid-19 using two algorithms: Naïve Bayes (NB) and Random Forest (RF). The research utilizes the COVID_Data.CSV dataset, which comprises a total of 316,800 data points. 70% of the data is used as a training data set, while the rest 30% is allocated for testing. The Naïve Bayes classifier achieves an accuracy of 87.39%, while the Random Forest classifier achieves a slightly higher accuracy of 87.47%. Comparative analysis indicates that the Random Forest classifier outperforms Naïve Bayes and is the superior model and classifier for the classification and prediction of Covid-19 using Machine Learning (ML) technique.

Keywords: Classification, Prediction, Naive Bayes, Random Forest, Data Pre-processing, Machine Learning, Covid-19, Dataset, Coronavirus.

1. Introduction

Classification involves categorizing objects, data, or information into distinct classes or categories based on shared characteristics or attributes. It is a method of organizing data or objects into meaningful groups according to their similarities and differences. In the context of machine learning, classification is a supervised learning task where a model is trained to assign input data to predefined classes. The goal is to learn a decision boundary that can separate different classes based on the features of the input.

After training the model, it gains the ability topredict the class of new, unseen data. Classification algorithms are a type of supervised learning technique used to categorize new observations. To train a classification model, the algorithm requires a labeled dataset

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consisting of examples of input data and their corresponding labels. The algorithm then learns to identify patterns associated with each label, enabling accurate predictions for new, unseen data.

Prediction involves using data and statistical or machine learning techniques to estimate or forecast future events or outcomes based on observed patterns and trends in historical data. Accurate predictions rely on high-quality, relevant data that pertains to the event or outcome being predicted. This data is used to build predictive models, which represent the observed patterns and relationships in a mathematical or statistical form. The aim of prediction is to make informed forecasts about future occurrences based on past events and trends.

In data mining, the data is typically prepared by cleaning and pre-processing to ensure its quality, consistency, and relevance. The data is then explored and analyzed using techniques such as clustering, association rules, and regression analysis to identify patterns and relationships. These patterns and relationships serve as the basis for building predictive models that support informed decision-making.

COVID-19 is a highly dangerous viral illness that has created a significant impact in the 21st century. The virus SARS-CoV-2brings forth this disease. It primarily affects the respiratory system and can lead to fatal outcomes. The real-time Reverse-Transcription Polymerase Chain Reaction (RT-PCR) test is usually employed to find the presence of Covid-19 in individuals (Zu et al., 2020).

The main aim of the current study is to classify and predict Covid-19 using the Naive Bayes and Random Forest algorithms. Machine Learning, as stated by Arthur Samuel in 1959, is a field that empowers computers to learn without explicit programming. It is revolutionizing various domains. In Machine Learning, the model we create from data and labels is referred to as a model. As of January 17, 2023, there have been 671,545,004 reported Covid-19 cases and 6,731,897 deaths worldwide (source: https://www.worldometers.info/coronavirus/). The current study aims at developing a machine learning model which could classify and find whether a patient is affected by Covid-19 based on symptom attributes. Figure 1.1 illustrates the schematic representation of the Machine Learning model.

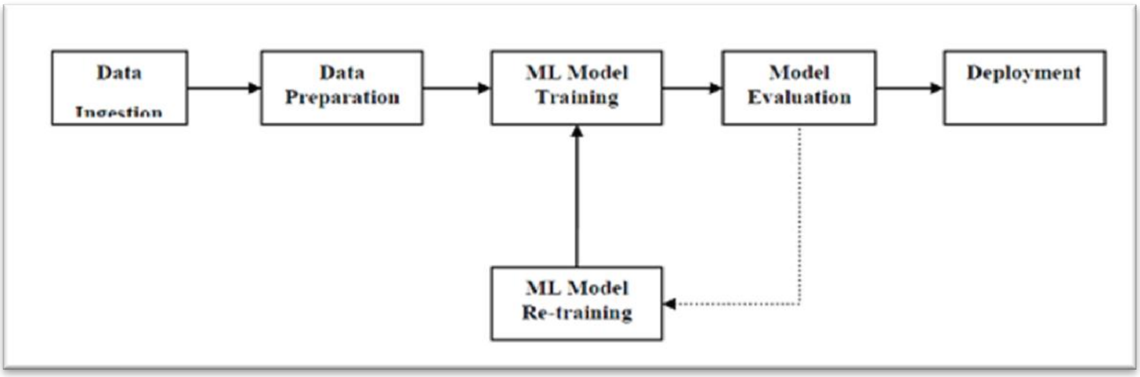

Figure 1.1: The schematic representation of the Machine Learning Model

1.1 Covid-19 Statistics

According to the statistics from the Worldometers.info website, the US has reported the maximum number of coronavirus cases. Table 1.1 presents the Covid-19 statistics for various countries.

Table 1.1: Covid-19 Statistics from Worldometers (as of January 17, 2023)

Sl. No.	Country	Total Cases	TotalDeaths	Total Recovered	Active Cases	Serious Cases
1	USA	103,583,738	1,125,558	100,422,095	2,036,085	4,491
2	India	44,681,884	530,726	44,148,309	2,849	698
3	France	39,453,006	163,463	39,056,473	233,070	869
4	Germany	37,605,135	163,775	37,063,800	377,560	1,281
5	Brazil	36,661,526	695,461	35,580,516	385,549	8,318
6	Japan	31,471,011	62,963	21,370,395	10,037,653	687
7	South Korea	29,821,035	32,984	28,898,191	889,860	510
8	Italy	25,363,742	185,993	24,824,106	353,643	310
9	UK	24,243,393	202,157	23,926,710	114,526	146
10	Russia	21,860,902	394,438	21,278,106	188,358	2,300
11	China	503,302	5,272	379,053	118,977	7,557

Source: https://www.worldometers.info/coronavirus/#countries

The World Health Organization (WHO) has identified five major symptoms of Covid-19.These symptoms are considered the main indicators of Covid-19, and they are shown in Table 1.2.

Table 1.2: Symptoms of COVID-19 suggested by the World Health Organization (WHO)

Sl.No.	Symptoms
1	Fever
2	Tiredness
3	Difficulty in Breathing
4	Dry Cough
5	Sore Throat

This research study utilizes the attributes listed in Table 1.2 for the diagnosis of patients. By observing the symptoms mentioned in Table 1.3, it becomes possible to classify and predict whether the person is affected by Covid-19 or not.

Table 1.3: factors for the Determination of COVID-19

Sl.	Symptoms	COVID-

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No.	Fever	Tiredness	Dry Cough	None Experiencing	Sore Throat	Diarrhea	Runny Nose	Difficulty in Breathing	Nasal Congestion	19 or Not (YES / NO)
1	y	y	y	y	y	y	y	y	y	y
2	y	y	y	y	y	y	y	y	n	y
3	y	y	y	y	y	y	y	n	n	y
4	y	y	y	y	y	y	n	n	n	y
5	y	y	y	y	y	n	n	n	n	y
6	n	n	n	n	n	n	n	n	n	n
7	n	n	n	n	n	n	n	n	y	n
8	n	n	n	n	n	n	n	y	y	n
9	n	n	n	n	n	n	y	y	y	n

2. Literature Review

This partoffers a summary of prior research done in the field of COVID-19 classification using Naive Bayes and Random Forest machine learning algorithms.

Sugandh Bhatia et al. (2021) proposed the application of the Naive Bayes classifier as a machine learning technique to predict the novel coronavirus. Their study explores various data mining techniques aimed at predicting positive COVID-19 cases, with the primary objective of designing a mechanism for disease prediction.

Nehal A. Mansour et al. (2022) discussed a precise detection approach for COVID-19 victimswhich is based on the Feature Correlated Naive Bayes (FCNB) classification technique. Thisnovel diagnosis strategyconsiders feature correlations. The researchers also emphasized the significance of chest radiological imaging, including techniques like Computed Tomography (CT) scans and X-rays, in the early identification and treatment of COVID-19 victims.

L. J. Muhammad et al. (2021) suggested supervised machine learning models for finding COVID-19 infections using an epidemiology dataset. In their research, 80% of the data was utilized as a training dataset, while the remaining 20% was allocated for testingpurposes. The Naive Bayes model achieved the maximum specificity of 94.30%.

H. Zakiyyah et al. (2021) presented a prediction model for COVID-19 infectionsusing machine learning techniques in Indonesia. Their study investigated three prediction models: Decision Tree (DT), Gaussian Naive Bayes (GNB), and Support Vector Machine (SVM).By evaluating ten provinces in Indonesia using the CITSAD, they discovered that the DT model achieved a maximum accuracy of 70% while maintaining a processing time of 60 seconds.

3. Framework Of The Proposed System

This part gives an elaborate description of the framework for the proposed COVID-19 classification model. Figure 3.1 illustrates the schematic representation of the developed model for COVID-19 classification.

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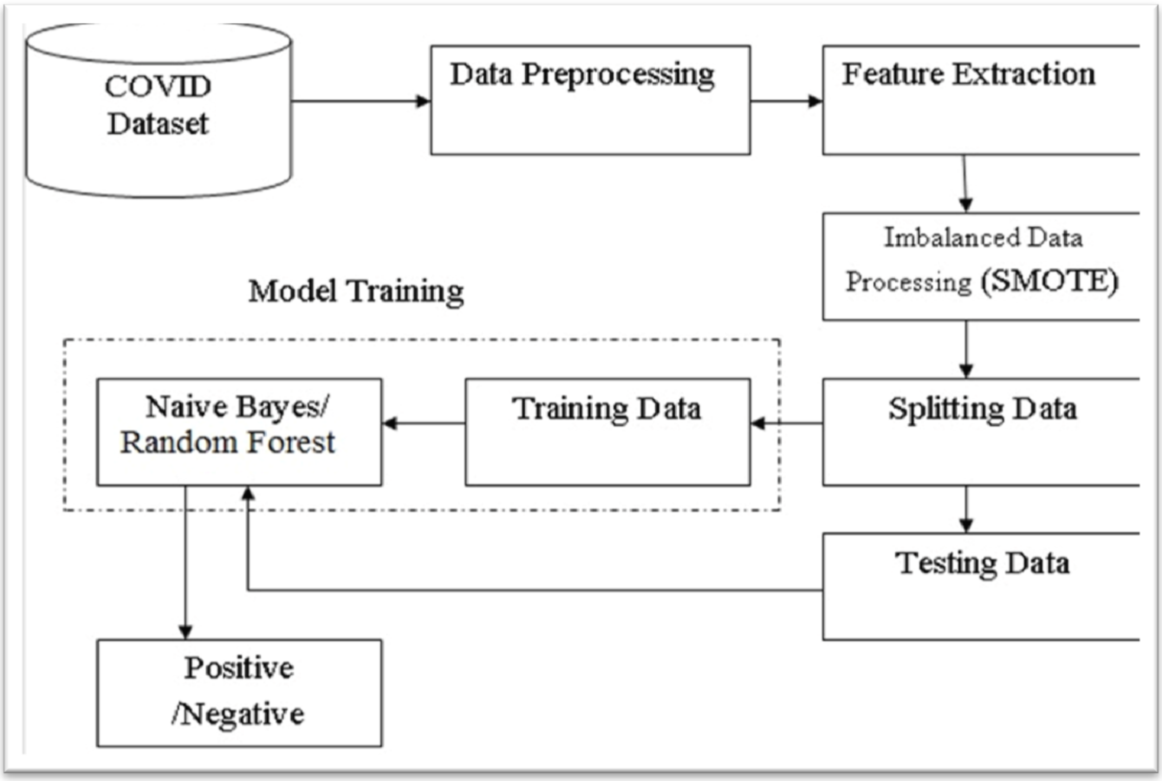

Figure 3.1: Schematic representation of the developed Model for COVID-19 Classification

3.1 Pre-processing of Data

In the process of classifying COVID-19, data pre-processing plays a major role. In the real world, almost data are incomplete, meaningless, and noisy. The primary objective of data pre-processing is to eliminate unnecessary noisy data that lacks meaningful information.

3.2 Extraction of Features

Feature extraction aids in reducing redundant data within a dataset. It involves selecting appropriate variables from the dataset, which significantly contributes to enhancing the performance and accuracy of prediction techniques. By reducing dimensionality, feature selection enables the acquisition of essential information from large datasets, resulting in improved processing time and performance.

3.3 Synthetic Minority Over-sampling Technique (SMOTE)

Synthetic Minority Over-sampling Technique (SMOTE) is a statistical method mainly used for balancing imbalanced datasets by increasing the number of cases in a controlled manner. Imbalanced datasets are commonly encountered in real-world applications, where the instances of one class are significantly fewer than others. Such an imbalance can lead to biased models that favor predicting the majority class, resulting in poor performance in detecting instances of the minority class. SMOTE is a powerful tool employed to address this issue and is widely utilized in various machine-learning applications.

The objective of SMOTE is to generate synthetic samples for the minority class that resemble the existing minority samples. This process aims to balance the class distribution and enhance classification performance.

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The SMOTE algorithm operates as follows:

- Split the original data into two sets: the minority class samples and the majority class samples.
- Calculate the ratio of imbalance between the minority and majority classes, which is determined by dividing the number of majority-class samplesby the number of minority-class samples.
- Set the desired imbalance ratio, which represents the ratio of the number of majority class samples to the number of minority class samples you want to achieve in the balanced dataset. Calculate the number of minority class samples that need to be generated to achieve this balance. This is done by subtracting the number of minority class samples in the original dataset from the number of minority class samples in the desired balanced dataset.
- For each minority class sample, select k (typically set to 5) nearest neighbors from the minority class samples.
- For each of the k neighbours, generate a synthetic sample by randomly selecting a point on the line connecting the minority sample and the neighbour. Add a random fraction of the difference between the two points to the minority sample. The synthetic sample becomes a new point in the feature space.
- Merge the original minority class samples along with the synthetic minority class samples to create a fresh balanced dataset. This balanced dataset can then be used to train a classifier or any other machine-learning model.

By creating synthetic minority class samples that resemble the existing minority class samples, the SMOTE algorithm helps reduce the bias towards the majority class and improves classification performance.

4. Dataset

The role of data is of utmost importance in unleashing the potential of machine learning, just as machine learning is essential for uncovering insights hidden within the data. Machine learning technology assists in detecting COVID-19-positive cases based on the data and its features.

4.1 Data Collection

For data collection, the researchers utilized a dataset available on Kaggle titled "COVID_Data." This dataset comprises 27 features and contains 316,800 records. The details of the dataset are presented in Figure 4.1.

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```
Data columns (total 27 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Fever                     316800 non-null  int64
 1   Tiredness                 316800 non-null  int64
 2   Dry-Cough                 316800 non-null  int64
 3   Difficulty-in-Breathing   316800 non-null  int64
 4   Sore-Throat               316800 non-null  int64
 5   None_Sympton              316800 non-null  int64
 6   Pains                     316800 non-null  int64
 7   Nasal-Congestion          316800 non-null  int64
 8   Runny-Nose                316800 non-null  int64
 9   Diarrhea                  316800 non-null  int64
 10  None_Experiencing         316800 non-null  int64
 11  Age_0-9                   316800 non-null  int64
 12  Age_10-19                 316800 non-null  int64
 13  Age_20-24                 316800 non-null  int64
 14  Age_25-59                 316800 non-null  int64
 15  Age_60+                   316800 non-null  int64
 16  Gender_Female             316800 non-null  int64
 17  Gender_Male               316800 non-null  int64
 18  Gender_Transgender        316800 non-null  int64
 19  Severity_Mild             316800 non-null  int64
 20  Severity_Moderate         316800 non-null  int64
 21  Severity_None             316800 non-null  int64
 22  Severity_Severe           316800 non-null  int64
 23  Contact_Dont-Know         316800 non-null  int64
 24  Contact_No                316800 non-null  int64
 25  Contact_Yes               316800 non-null  int64
 26  Country                   316800 non-null  object
dtypes: int64(26), object(1)
```

Figure 4.1 Detailed Descriptions of the Dataset Used in the Study

Figure 4.2 displays the sample dataset pertaining to COVID-19. The data related to COVID-19 is stored in the .CSV format.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Fever	Tiredness	Dry-Cougl	Difficulty-	Sore-Thro	None_Syn	Pains	Nasal-Con	Runny-No	Diarrhea	None_Exp	Age_0-9	Age_10-1	Age_20-2
2	1	1	1	1	1	0	1	1	1	1	0	1	0	0
3	1	1	1	1	1	0	1	1	1	1	0	1	0	0
4	1	1	1	1	1	0	1	1	1	1	0	1	0	0
5	1	1	1	1	1	0	1	1	1	1	0	1	0	0
6	1	1	1	1	1	0	1	1	1	1	0	1	0	0
7	1	1	1	1	1	0	1	1	1	1	0	1	0	0
8	1	1	1	1	1	0	1	1	1	1	0	1	0	0
9	1	1	1	1	1	0	1	1	1	1	0	1	0	0
10	1	1	1	1	1	0	1	1	1	1	0	1	0	0
11	1	1	1	1	1	0	1	1	1	1	0	1	0	0
12	1	1	1	1	1	0	1	1	1	1	0	1	0	0
13	1	1	1	1	1	0	1	1	1	1	0	1	0	0
14	1	1	1	1	1	0	1	1	1	0	0	1	0	0
15	1	1	1	1	1	0	1	1	1	0	0	1	0	0
16	1	1	1	1	1	0	1	1	1	0	0	1	0	0
17	1	1	1	1	1	0	1	1	1	0	0	1	0	0
18	1	1	1	1	1	0	1	1	1	0	0	1	0	0

Figure 4.2: Illustrates Sample Dataset

5. Utilizing the Naïve Bayes Classifier for COVID-19 Classification

The Naïve Bayes Classifier is a supervised probabilistic Machine Learning Algorithm that relies on the principles of the Bayes theorem. This algorithm is primarily employed for

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classification tasks. Based on the Bayes theorem, which involves events A and B, and assuming P(B) is non-zero, the conditional probability can be computed using the mathematical equation 1 provided.

$$P(A|B) = \frac{P(B|A)*P(A)}{P(B)} \quad \text{...................................} \text{ Equation (1)}$$

The Bayes theorem is employed for determining conditional probability, which represents the likelihood of an event transpiring given information about past events. Equation 1, presented above, encapsulates this concept.

P(A│B) represents the conditional probability of event A occurring given event B (Posterior Probability).

P(A) refers to the probability of event A occurring (Prior Probability).

P(B) represents the probability of event B occurring (Marginal Probability).

P(B|A) denotes the conditional probability of event B occurring given event A (Likelihood Probability).

To calculate the Posterior Probability (P(A│B)), the first step involves creating a frequency table.

5.1 Operation of the Naïve Bayes Classifier in the Context of COVID-19

To streamline the computation of prior and posterior probabilities, two tables, namely the frequency table and the likelihood table, can be employed. These tables are very importantin determining the prior and posterior probabilities. The frequency table records the frequency of labels for each feature. In this particular study, the Naïve Bayes classifier utilizes multiple features. Table 5.1 illustrates an example of such multiple features.

Table 5.1: Displays the Various Features Employed in the Classification of COVID-19

Sl.No.	Symptoms
1	Fever
2	Tiredness
3	Dry Cough
4	NoneExperiencing
5	Sore Throat
6	Diarrhea
7	Runny Nose
8	Difficulty in Breathing
9	Nasal Congestion

Now, to put the aforementioned equation (1) into action, we can automatically apply it to the COVID-19 dataset. In this process, we have extracted the initial 25 data points from the dataset. The resulting probabilities associated with the symptoms are presented in Table 5.2.

Table 5.2:The Probabilities Associated with the Symptoms

Sl.No.	Symptoms	Yes	No	P(yes)	P(no)
1	Fever	20	5	20/25	5/25
2	Tiredness	19	6	19/25	6/25
3	Dry Cough	21	4	21/25	4/25

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4	NoneExperiencing	10	15	10/25	15/25
5	Sore Throat	22	3	22/25	3/25
6	Diarrhea	18	7	18/25	7/25
7	Runny Nose	21	4	21/25	4/25
8	Difficulty in Breathing	22	3	22/25	3/25
9	Nasal Congestion	21	4	21/25	4/25
		174	**51**		

For example, the probability of occurring COVID-19 given that the symptom is fever, P (probability=fever | occurrence=yes) =20/25. Also, we have to find the class probabilities P(y) from above table 5.2.
For example, P (occurrence=yes) =174/ 225 and P (occurrence=no) = 51/ 225
So, the probability of occurring of COVID-19 is given by:
P (yes| occurrence) = P (Fever | yes) * P (Tiredness | yes) * P (Dry Cough | yes)* P (None Experiencing | yes)* P (Sore Throat | yes)* P (Diarrhoea | yes)* P (Runny Nose | yes)* P (Difficulty in Breathing | yes)* P (Nasal Congestion | yes) * P (yes) / P (current occurrence)
P(yes|occurrence)=20/25 *19/25*21/25*10/25*22/25*18/25*21/25*22/25*21/25*174/225 / 1
P (yes | occurrence) = 0.0621
The probability of not occurring of COVID-19 given by:
P (no | occurrence) = P (Fever | no) * P (Tiredness | no) * P (Dry Cough | no)* P (None Experiencing | no)* P (Sore Throat | no)* P (Diarrhoea | no)* P (Runny Nose | no)* P (Difficulty in Breathing | no)* P (Nasal Congestion | no) * P (no) / P (current occurrence)
P (no | occurrence) = 5/25 *6/25*4/25*15/25*3/25*7/25*4/25*3/25*4/25*51/225 / 1
P (no | occurrence) =0.000749
Since P (Yes | occurrence)> P (No | occurrence)
So, the prediction that COVID-19 occurs is ‘Yes’.

6. COVID-19 Classification using Random Forest Classifier

The Random Forest (RF) classification approach was originally introduced by Leo Breiman in 2001. It is a supervised learning algorithm that creates an ensemble of decision trees using the "bagging" technique. By combining multiple learning models, the overall performance is improved.
Random Forest is an ensemble classifier that merges several decision trees and makes predictions based on majority voting. It offers advantages over individual decision trees by addressing the issue of overfitting. As decision trees grow deeper, they tend to overfit, resulting in low bias and high variance.

The Random Forest classification process involves several steps:
1. Training Dataset Conversion: The training dataset is transformed into a bootstrapped dataset, employing random sampling with replacement.

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2. Decision Tree Construction: A decision tree is constructed using the bootstrapped dataset. Bootstrapping involves random selection, allowing the same value to be chosen multiple times.
3. Output Generation: Each decision tree generates its output.
4. Voting Phase: This final phase of the Random Forest method involves voting or pooling. It determines the correct and incorrect features of each tree in the forest. The decision tree for COVID-19 Random Forest classification is depicted in Figure 6.1.

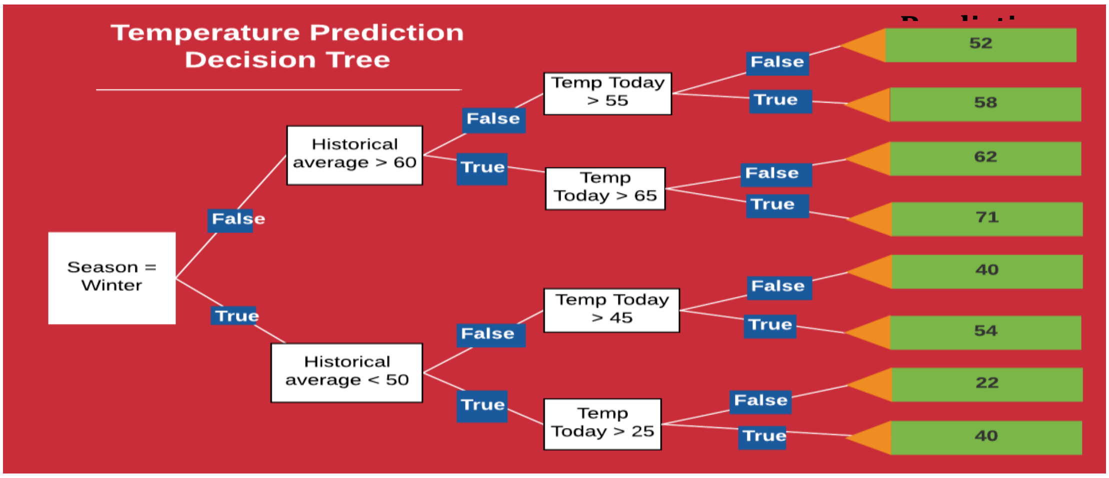

Figure 6.1: Decision Tree Used in the Classification of COVID-19 Through The Random Forest Method

By utilizing decision trees, we can construct a random forest. A potential issue with a single large and deep decision tree is the risk of overfitting, where the tree essentially memorizes the training set, similar to how a person might memorize an eye chart.
The purpose of Random Forest is to mitigate overfitting. It achieves this by creating random subsets of features and building smaller, shallower trees using these subsets. The sub-trees are then combined to form the Random Forest. One drawback of Random Forest is that it can be slow when executed on a single process, but it can be parallelized to improve efficiency. The operational principle of Random Forest is depicted in Figure 6.2.

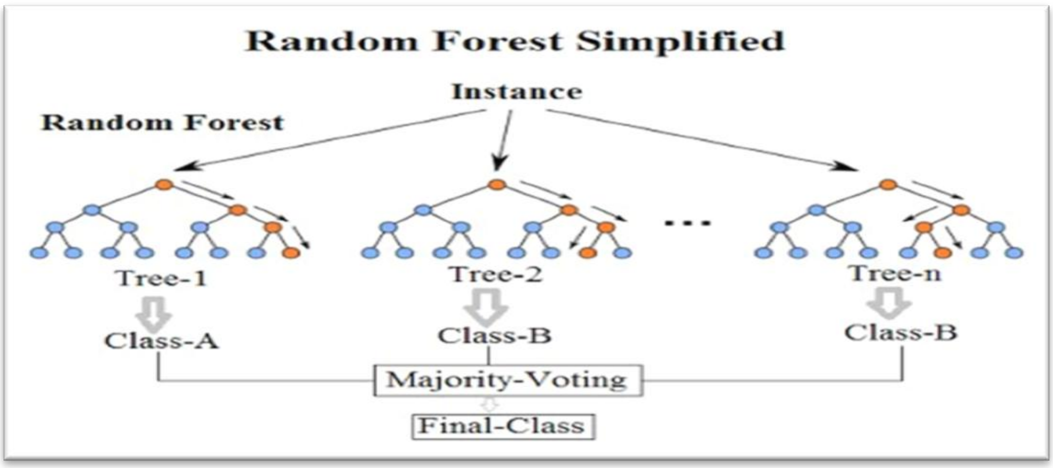

Figure 6.2: The Underlying Working Principle and Structure of the Random Forest

7. Implementation

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The implementation of COVID-19 classification was carried out using Python with Machine Learning techniques. The successful completion of this paper involved the practical application of the implemented Machine Learning model.

8. Results and Discussions

This section provides a complete overview of the COVID-19 classification model proposed in this study, along withaccurate results and comparative analysis.

8.1 Evaluation Metrics

Throughout the study, various evaluation metrics such asRecall, Precision, accuracy,and F1-score were computed. These metrics were derived using the confusion matrix, which serves as the basis for computing the aforementioned parameters.

True positive (TP): correctly predicted positive class data points.

False positive (FP): negative class data points predicted as a positive class. True negative (TN): correctly predicted negative class data points.

False negative (FN): negative class data points predicted as a positive class.

P: total positive class data points.

N: total negative class data points.

True positive rate (TPR) = TP/P

False positive rate (FPR) = FP/N

Performance measures are defined using the following equations: The equations are shown in Figure 8.1.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})},$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})},$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})},$$

$$\text{F} - \text{measure} = \frac{2 * \text{precision} * \text{recall}}{(\text{precision} + \text{recall})}.$$

Figure 8.1: The Equations Used for Calculating Performance Measures

Table 8.1 presents the overall accuracy results and comparisons based on the experiments conducted in this research.

Table 8.1:The Accuracy Results and Comparisons Obtained From The Experiments Conducted In This Research.

Sl.No.	**Number of Patients Records**	**Naive Bayes (NB)-Accuracy in Percentage**	**Random Forest (RF)-Accuracy in Percentage**
1	3,16,800	87.39%.	87.47%

Figure 8.2 and Figure 8.3 depict the confusion matrices for the Naive Bayes and Random Forest algorithms respectively, in the context of COVID-19 classification.

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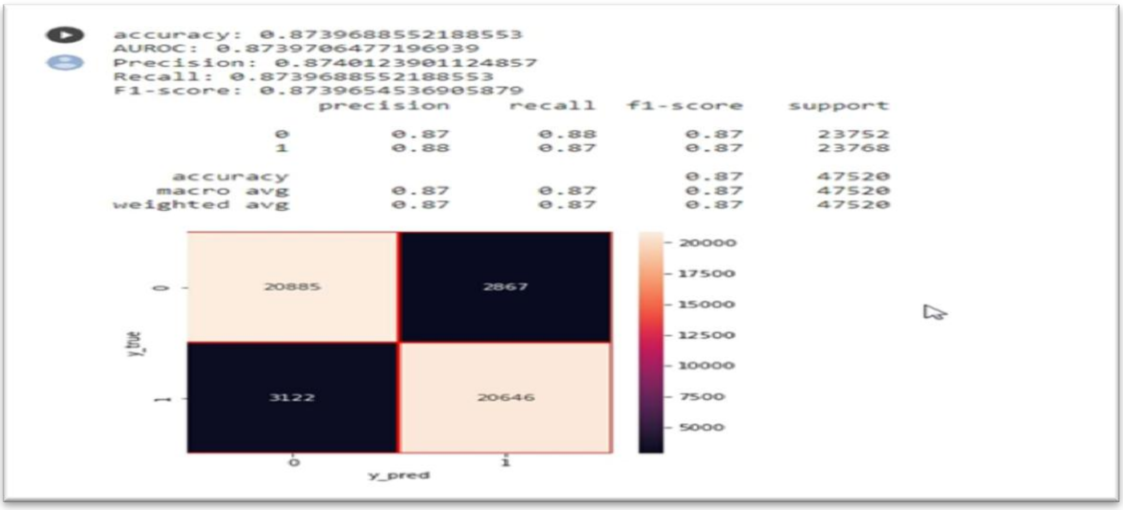

Figure 8.2: The Confusion Matrix Obtained Fromthe Implementation of the Naive Bayes Algorithm

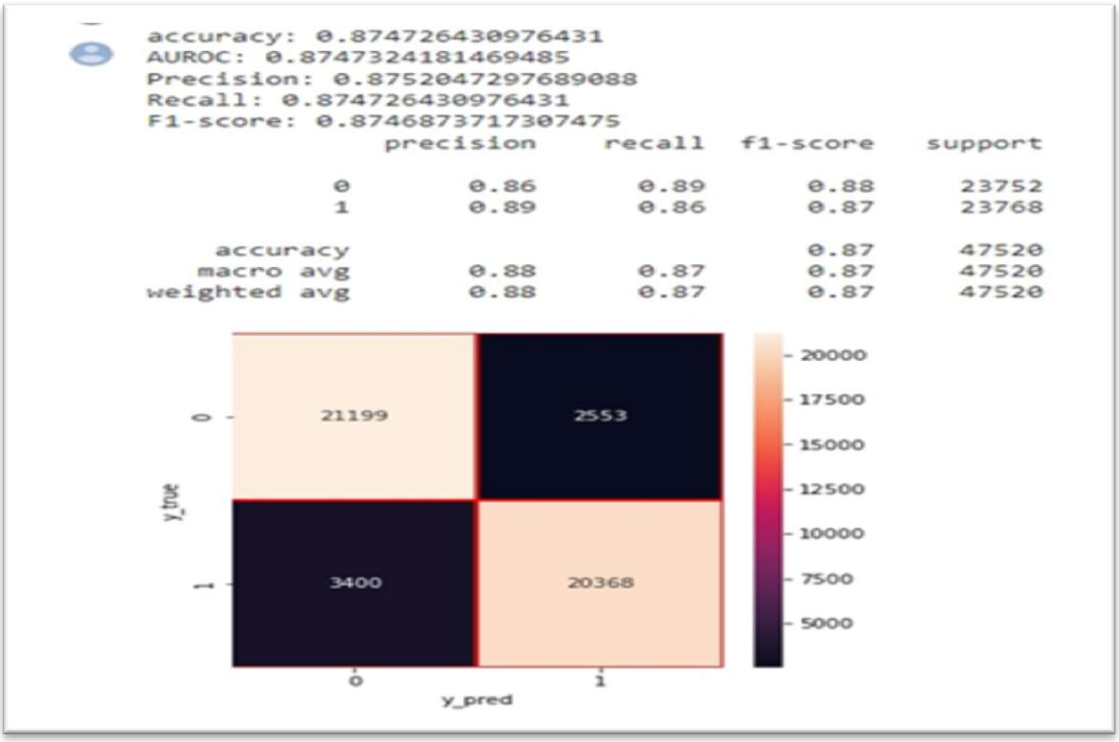

Figure 8.3:The Confusion Matrix Resulting Fromthe Utilization of the Random Forest Algorithm

9. Conclusion

This study introduces an approach to classify and predict COVID-19 utilizing the Naive Bayes and Random Forest classifiers. The Naive Bayes classifier achieved a classification accuracy of 87.39%, while the Random Forest classifier achieved an accuracy of 87.47%. Based on the findings presented in Table 8.1, it can be finalized that the Random Forest classifier outperforms the Naive Bayes classifier in terms of COVID-19 classification accuracy.

References

[1] ZuZJiangMXuPChen W et al.,(2020) Corona Virus disease 2019(COVID-19) a perspective from china radiology 296(2): 15-25
[2] Worldometer COVIS Live update29 June 2021 Available online:https://www.worldometer.info/coronovirus/ (accessed on 29 June 2021)
[3] https://www.worldometers.info/coronavirus/
[4] https://www.worldometers.info/coronavirus/#countries
[5] Sugandh Bhatia and JyoteeshMalhotra (2021) “Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV 2021)" IEEE Xplore Part Number: CFP21ONG-ART; 978-0-7381-1183-4.
[6] Nehal A. Mansour, Ahmed I. Saleh, Mahmoud Badawy, Hesham A. Ali (2022) "Journal of Ambient Intelligence and Humanized Computing (2022)" Volume 13 Pages: 41–73.
[7] L. J. Muhammad, Ebrahem A. Algehyne, Sani Sharif Usman, Abdulkadir Ahmad, ChinmayChakrabortyandI. A. Mohammed (2021) "SN Computer Science (2021)" 2:11.
[8] H Zakiyyah and S Suyanto (2020) “2nd International Conference on Science & Technology (2020 2nd ICoST)-Journal of Physics: Conference Series" 1844 (2021) 012002.

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