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Performance Evaluation of Multi-class Classification based Detection of CoViD-19 using Machine Learning Algorithms

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Abstract: The Corona Virus Disease (CoViD-19) has underscored the need for accurate and rapid diagnostic tools to combat the spread of the virus. Machine learning techniques have shown promise in detecting CoViD-19 from medical imaging data, such as X-rays and CT scans. This study presents a comprehensive evaluation of multi-class classification methods for the detection of CoViD-19 using adverse dataset of medical images. Our research focuses on the development and assessment of machine learning algorithms capable of classifying CoViD-19 cases into multiple categories, including distinguishing CoViD-19 from other respiratory conditions and providing insights into the disease's severity. We utilize a dataset comprising a wide range of chest X-ray and CT scan images obtained from various sources and demographic groups to ensure the robustness of our model. In this study, we explore and compare the performance of several machine learning algorithms, including Decision Tree, Support Vector Machines (SVMs) and Naïve Bayes among others. We also employ data preprocessing techniques, feature selection, and data augmentation to enhance the model's accuracy and generalization capabilities. Furthermore, we present an in-depth analysis of the model's performance metrics, such as Accuracy, Specificity, Precision, Recall, Time, and Error rate to provide a comprehensive evaluation of its diagnostic capabilities. Our results show case the strengths and weaknesses of each algorithm in the context of CoViD-19 detection and multi-class classification. The findings of this research are valuable for healthcare practitioners, researchers, and policy makers involved in the fight against CoViD-19. By identifying the most effective machine learning algorithms and techniques for multi-class classification-based CoViD-19 detection, we aim to contribute to the development of robust and reliable diagnostic tools, ultimately aiding in the early identification and management of CoViD-19cases.

Keywords: CoViD-19, Machine Learning, X-ray, CT scan.

I. INTRODUCTION:

The outbreak of the Coronavirus Disease 2019 (CoViD-19) has posed an unprecedented global health crisis, demanding rapid and accurate diagnostic methods to mitigate its spread. The conventional diagnostic approaches, such as Polymerase Chain Reaction (PCR) testing, while highly accurate, can be time-consuming, resource-intensive, andmay not be available in all settings. Machine learning (ML)algorithms have emerged as a promising tool for CoViD-19 detection, offering the potential for faster and more accessible diagnosis.

Multi-class classification, as a subset of ML techniques, plays a crucial role in CoViD-19 detection by categorizing patients into various classes based on theirCoViD-19 status, suchas 'Positive, ''Negative,' and' Indeterminate. 'Evaluating the performance of these ML algorithms is paramount to ensure their clinical viability and reliability.

This research aims to provide a comprehensive overview of the performance evaluation of multi-class classification-based CoViD-19 detection using various machine learning algorithms.

II. CLASSIFICATION METHODS

Classification methods area set of techniques in machine learning and statistics used to categorize or label data intopredefined classes or categories based on their features orattributes. This field is a fundamental part of supervised learning, where a model is trained on a labeled dataset to make predictions on new, unlabeled data points. Classification methods are used in various applications, including image recognition, spam email detection, medical diagnosis, and more. Classification methods play a vital role in automating decision-making processes and have a useful application in fields like Healthcare, Finance, Natural Language Processing (NLP), and Computer Vision. The selection of the classification algorithm depends on the problem, the nature of the data, and the desired performance metrics. The uniqueness in classification depends on mapping function to a firm output level. Numerous learning classifiers were labelled as Perceptron, Naïve Bayes, Decision Tree, Logistic Regression, Support Vector Machine(SVM). The idea of the work focuses on novel approach of ML for analysis of CoViD-19 data to attain a decent accuracy. Some of the most used classifiers are described as Decision tree, Logistic Regression, Naïve Bayes, SVM. After testing and training the data, various parameters like Precision, Accuracy, Recall, Error rate and Specificity are calculated. The ML algorithms are further classified as:

2.1. DecisionTree:

It's a well-known supervised machine learning algorithm used for regression and classification tasks. It is a versatile and interpretable model that is particularly useful for decision-making processes and understanding the relationships within the data. It belongs to supervised learning [3]. It is used for solving regression and classification problems. The aim of this is to produce a training model that can be used to predict the class.

2.2. Logistic Regression

It's a commonly used statistical and machine learning model for binary and multiclass classification tasks. Despite its name, it is primarily used for classification rather than regression. Logistic Regression models the probability that a given input belongs to a particular class, making it particularly useful for problems where the output is a binary outcome (e.g., yes/no, spam/ham) or for multiclass problems where you want to assign data points to one of several classes. It is classified into three categories:

•Binomial will have two probable types of dependent variables, such as1or 0, Pass or Fail, etc.

•Multinomial will have more than two likely unordered types of the dependent variable, such as cats, dogs, or sheep.

•Ordinal will have more than two likely ordered types of dependent variables, such as little, Moderate, or Extreme.

2.3.NaiveBayes:

It's a probabilistic ML algorithm used widely for classification and text categorization tasks. It is based on the Bayes' theorem and makes a "naive" assumption of conditional independence among features, which simplifies the modeling process. Despite its simplicity and the naïve assumption, Naïve Bayes often performs surprisingly well in a wide range of real-world applications, particularly in NLP and spam email detection.

Bayes theorem used for solving problems related to classification. It is primarily used in *text classification* that includes high-dimensional training data. It's a simple and utmost active Classification algorithm which helps in quick predictions based on the fast ML models. It is a probabilistic classifier; to predict the basis of the probability of an object.

2.4. SVM:

It's a powerful supervised ML algorithm that is primarily used for classification and regression tasks. SVMs are known for their efficacy in handling high-dimensional data and for their ability to find complex decision boundaries.

The primary objective of the SVM is to produce the best line which can isolate N-dimensional space into modules, hence it can easily have kept the new data in the correct category in future. This supreme decision boundary is called a hyperplane. SVM indicates the extreme points/vectors that help in creating the hyper plane. The great points are called support vectors, and hence it is labeled as SVM.

3. METHODOLOGY

Data set consists of 240 patient's data with 32 attributes consisting of patient details and their health condition. The symptoms that are considered are Age, Sex, WBC, Dyspepsia, Dyspnea, Hypoxemic, Fatigue, headache, Temperature, Fever, Fever duration, Cough, wheezing, Respiratory failure, Consolidations, diarrhea, anosmia, loss of appetite, nausea, Smoking, History disease1, History disease2, History disease3, CoViD-19 Mingling, Thickens, Ground glass, Ground glass Position, Opacity, pO2, PCR, lymphadenopathy, Pharyngeal swab, CoViD-19(2 class) /Diagnosis (4 Class). For analysis 1 all the 32 attributes are considered. For second analysis only 28 attributes are considered removing pO2, diarrhea, Hypoxemic, WBC attributes are removed, and the models are trained. For third analysis 22 attributes are considered removing some attributes from the attributes considered for analysis 2. The attributes removed are Dyspnea, History disease1, History disease2, History disease3, lymphadenopathy, Pharyngeal swab.

3.1 Block Diagram

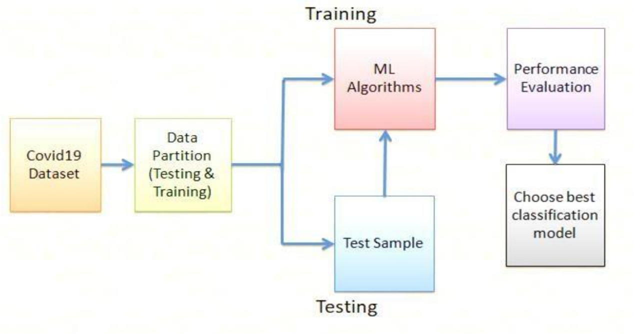

Fig. 1: Trained Model.

The dataset of CoViD-19 which consists of 240 samples issplits into two portions. One for training and another is fortesting. We separated the dataset into training and testingparts under different ratios. The machine gets trained on thetrain data using different classification models and takes the sample data from the test data and checks against the trained models to classify whether the person has CoViD-19 or not. We evaluate the performances like accuracy, precision, error rate, recall, specificity by using the generated confusion matrix. Based on these performance evaluations we choose the best classification method.

3.2 Implementation Steps

The following are the implementation steps of the project mentioned step by step.

Step-1: Collecting raw data of patient's symptoms.

Step-2: Train the data under different ML classifiers.

Step-3: Check accuracy for different test and train ratios.

Step-4: Compare performance of all the classifiers.

Step-5: Reduce attributes that doesn't cause any change to accuracy.

Step-6: Now train the new data with different test and train ratios for different classifiers.

Step-7: Compare the performances of obtained new and previous data.

Step-8: Repeat the steps until we get more accuracy with less number of attributes.

3.3 FlowChart

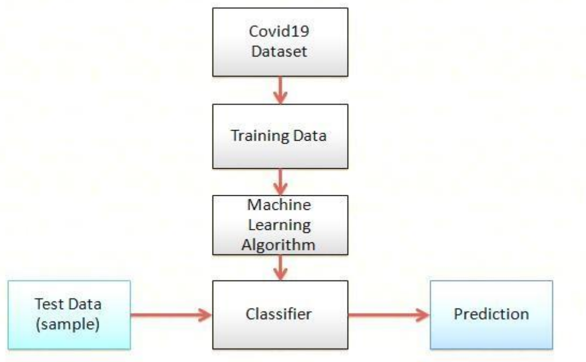

Fig.2: Flow Chart

3.4 Evaluating a Classification model.
3.4.1 Confusion Matrix:

- It provides us with a matrix or table as output and describes it's the performance.
- It is also called the error matrix.
- This matrix gives predicted results in a summarized form, which has a total number of correct and incorrect predictions.

Table3.1: Confusion matrix

	ActualPositive (1)	Actual Negative (0)
Predicted Positive(1)	TruePositive (TP)	FalsePositive (FP)
Predicted Negative(0)	FalseNegative (FN)	TrueNegative (TN)

True Positives (TP)-gives correctly predicted positive values which means the actual class is yes.

True Negatives(TN)-gives correctly predicted negative values which means actual class is no.

False Positives(FP)–Predicted class is yes when actual class is no.

False Negatives(FN)–Predicted class is no when actual class is yes.

3.4.2 Accuracy

It's a one metric for evaluating classification models**.** It is defined as the % of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

$$\textbf{Accuracy}= \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP + FN}}$$

3.4.3 Precision

It is the ratio of correctly predicted positive class to the total predicted positive class.

$$\textbf{Precision}= \frac{\textbf{TP}}{\textbf{TP+FP}}$$

3.4.4 Recall

Recall (Sensitivity) - It is the ratio of correctly predicted positive class to the all observations in actual class-yes.

$$\textbf{Recall}= \frac{\textbf{TP}}{\textbf{TP+FN}}$$

3.4.5 Error rate

Predicted output values is not correct is termed as the error rate. If final values are categorical, the error is stated as an error rate. It is the proportion of cases in which the prediction is wrong.

Error rate=100 – percentage of accuracy

3.4.6 Specificity

It is defined as the proportion of actual negatives, predicted as the negative (or true negative). This implies there will be another proportion of actual negative, which got predicted as positive and could be termed as false positives. It could also be called a false positive rate.

$$\textbf{Specificity}= \frac{\textbf{TN}}{\textbf{TN+ FP}}$$

4. Results

4.1 Analysis for 4 class

Analysis for 32 attributes:

Attributes considered are Age, Sex, WBC, Dyspepsia, Dyspnea, Hypoxemic, Fatigue, headache, Temperature, Fever, Fever duration, Cough, wheezing, Respiratory failure, Consolidations, diarrhea, anosmia, loss of appetite, nausea, Smoking, History disease1, History disease2, History disease3, CoViD-19 Mingling, Thickens, Ground glass,

Ground glass Position, Opacity, pO2, PCR, lymphadenopathy, Pharyngealswab, Diagnosis.

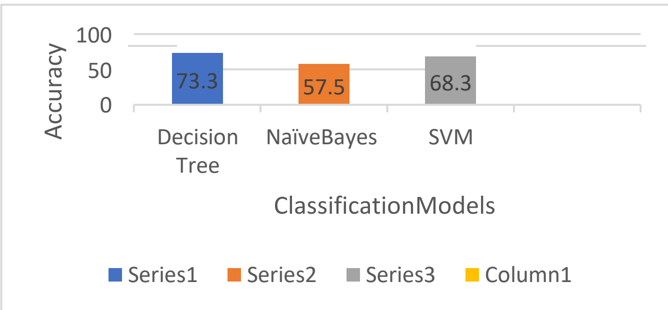

Fig.3: Graphical representation of Accuracy of Machine Learning Algorithms for 32 attributes

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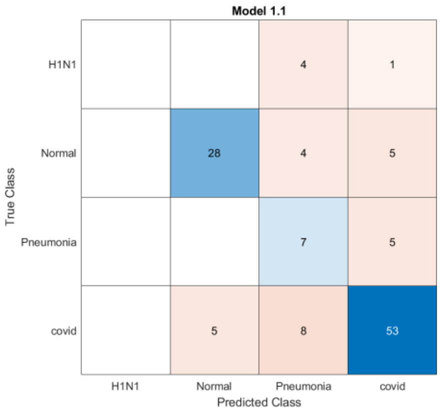

Fig.4: Confusion Matrix for Decision tree of 32 attributes

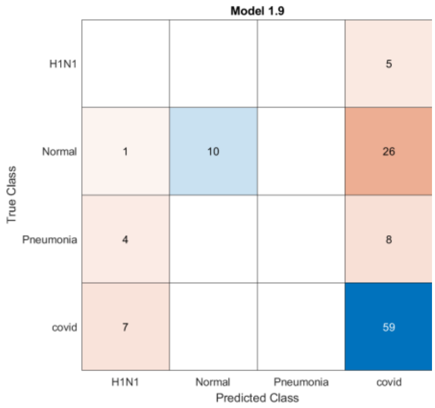

Fig.5: Confusion Matrix for Naïve Bayes of 32 attributes

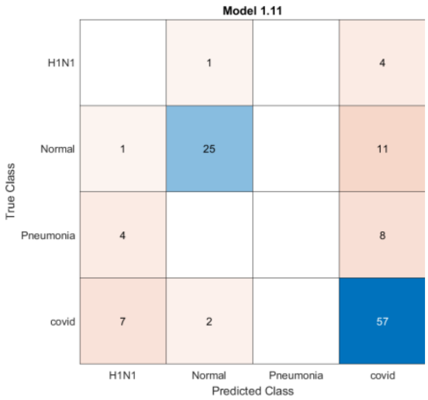

Fig.6: Confusion Matrix for SVM of 32 attributes

The parameter values obtained for 32 attributes of type 4 Class are listed in table 4.16, 4.17, 4.18, 4.19.

Table 1: Analysis for 32 attributes of type 4 Class for decision tree

Test: Train	DecisionTree											
	FineTree						MediumTree					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	66.7	70.7	86.6	5.0	0.76	33.3	66.7	70.7	86.6	26	0.68	33.3
20:80	73.3	93.2	86.1	26	0.67	26.7	72.9	72.1	77.1	30	0.76	27.1
30:70	85.7	80.7	79.7	10	0.75	14.3	71.4	85.7	79.7	23	0.78	28.6
40:60	72.1	71.6	70.4	23	0.64	27.9	72.9	72.1	71.6	15	0.85	27.1
50:50	87.6	82.5	88.2	15	0.75	12.4	69.2	81.6	82.5	10	0.75	30.8

Table2: Analysis for 32 attributes of type 4 Class for CoarseTree, Linear SVM

Test: Train	DecisionTree						SVM					
	CoarseTree						LinearSVM					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	62.5	72.3	86.6	6.07	0.79	37.5	73.3	93.2	86.1	26	0.78	26.7
20:80	72.9	72.1	77.1	29.4	0.68	27.1	85.7	80.7	79.7	10	0.63	14.3
30:70	71.4	85.9	79.7	23	0.83	28.6	72.1	71.6	70.4	23	0.78	27.9
40:60	72.9	72.1	71.6	11	0.79	27.1	87.6	82.5	88.2	15	0.61	12.4
50:50	69.2	81.2	82.5	16	0.75	30.8	66.7	70.7	86.6	5.0	0.83	33.3

A-Accuracy, P-Precision, R-Recall, T-Time(sec),S -Specificity, E-Errorrate

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Table 3:Analysis for 32 attributes of type 4 Class for SVM

Test: Train	SVM											
	QuadraticSVM						CubicSVM					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	72.9	72.1	77.1	30	0.87	27.1	72.9	72.1	77.1	29.4	0.69	27.1
20:80	71.4	85.7	79.7	23	0.79	28.6	71.4	85.9	79.7	23	0.75	28.6
30:70	72.9	72.1	71.6	15	0.68	27.1	72.9	72.1	71.6	11	0.88	27.1
40:60	69.2	81.6	82.5	10	0.78	30.8	69.2	81.2	82.5	16	0.83	30.8
50:50	66.7	70.7	86.6	26	0.79	33.3	62.5	72.3	86.6	6.07	0.79	37.3

Table4: Analysis for 32 attributes of type 4 Class for Kernel Naïve Bayes

Test:Train	KernelNaïveBayes					
	A	**P**	**R**	**T**	**S**	**E**
10:90	66.7	76.5	83.3	6.5	0.68	33.3
20:80	57.5	85.7	77.2	15.7	0.72	42.5
30:70	64.5	79.6	88.7	21.5	0.64	35.5
40:60	59.8	89.5	75.3	14.5	0.76	40.2
50:50	63.2	77.1	81.5	29.5	0.66	36.8

A-Accuracy, P-Precision, R-Recall, T-Time(sec), S-Specificity, E-Errorrate

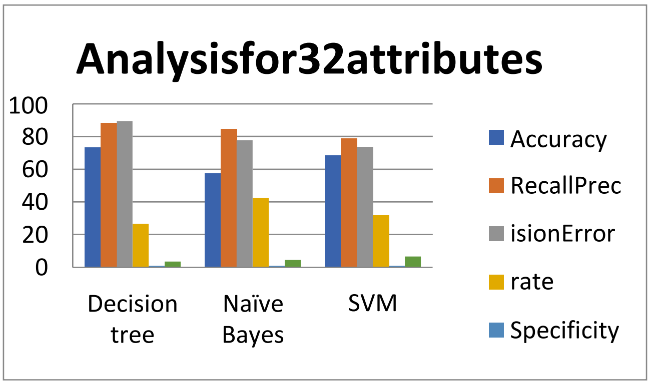

Fig.7:Analysis parameters for 32 attributes

Analysis for 28 attributes:

Attributes considered are Age, Sex, Dyspepsia, Dyspnea, Fatigue, headache, Temperature, Fever, Fever duration, Cough, wheezing, Respiratory failure, Consolidations, anosmia, loss of appetite, nausea, Smoking, History disease1, History disease2, History disease3, CoViD-19 Mingling, Thickens, Ground glass, Ground glass Position, Opacity, PCR, lymphadenopathy, Pharyngealswab, Diagnosis.

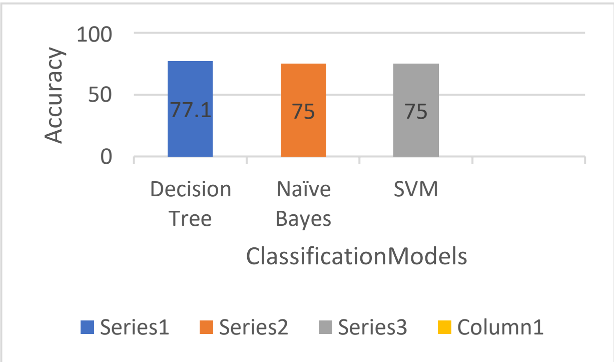

Fig. 8: Graphical representation of Accuracy of MachineLearning Algorithmsof28 attributes.

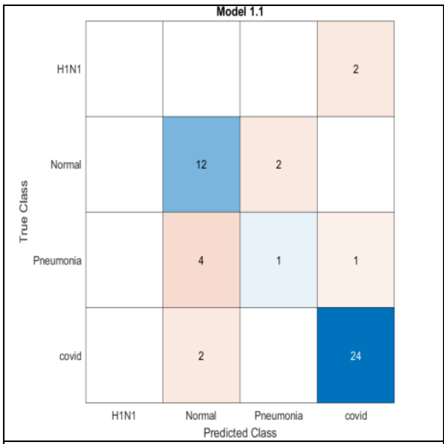

Fig.9:Confusion Matrix for Decision tree of 28 attributes

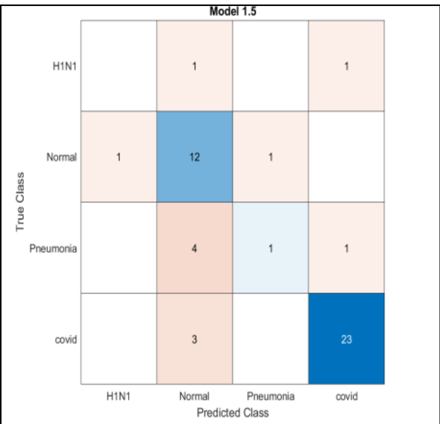

Fig.10: Confusion Matrix for Naïve Byes of 28 attributes

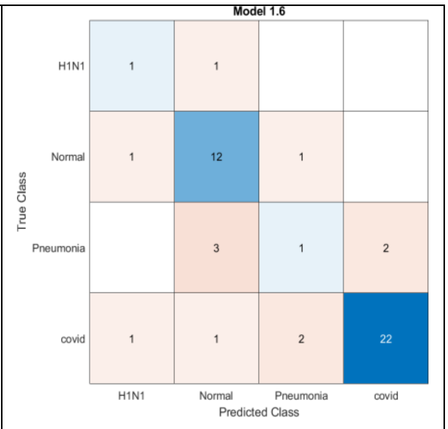

Fig.11: Confusion Matrix for SVM of 28 attributes

The parameter values obtained for 28 attributes of type 4 Class are listed in table 4.20, 4.21, 4.22, 4.23.

Table5: Analysis for 28 attributes of type 4 Class for decision tree

Test: Train	DecisionTree											
	FineTree						MediumTree					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	71.2	84.5	76.5	7.5	0.76	28.8	71.2	84.5	76.5	8.7	0.78	28.8
20:80	77.1	87.4	89.7	22	0.87	22.9	77.1	87.4	89.7	25	0.66	22.9
30:70	75	77.1	82.5	10	0.65	25	75	87	89	16	0.78	25
40:60	75	81.5	74.5	21	0.64	25	75	81	74.3	15	0.85	25
50:50	73.2	79.6	86.6	27	0.75	26.8	73.2	79.6	86.6	27	0.65	26.8

Table6: Analysis for 28 attributes of type 4 Class for Coarse Tree, Linear SVM

Test: Train	DecisionTree						SVM					
	CoarseTree						LinearSVM					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	71.2	84.5	76.5	6.2	0.69	28.8	77.1	87.4	89.7	22	0.68	22.9
20:80	77.1	87.5	76.5	26	0.68	22.9	75	77.1	82.5	10	0.73	25
30:70	75	77.1	87.5	16	0.73	25	75	81.5	74.5	21	0.88	25
40:60	74	87.6	74	22	0.89	26	73.2	79.6	86.6	27	0.71	26.8
50:50	73	79	86	27	0.65	27	71.2	84.5	76.5	7.5	0.73	28.8

A-Accuracy, P-Precision, R-Recall, T-Time(sec), S-Specificity, E-Error rate

Table 7: Analysis for 28 attributes of type 4 Class for SVM

Test: Train	SVM											
	QuadraticSVM						CubicSVM					
	A	P	R	T	S	E	A	P	R	T	S	E
10:90	77.1	87.4	89.7	25	0.87	22.9	77.1	87.5	76.5	1.24	0.69	22.9
20:80	75	87	89	16	0.79	25	75	77.1	87.5	0.8	0.75	24
30:70	75	81	74.3	15	0.68	25	74	87.6	74	0.73	0.88	26
40:60	73.2	79.6	86.6	27	0.68	26.8	73	79	86	0.76	0.83	27
50:50	71.2	84.5	76.5	8.7	0.79	28.8	71.2	84.5	76.5	0.8	0.79	28.8

Table 8: Analysis for 28 attributes of type 4 Class for Kernel Naïve Bayes

Test:Train	KernelNaïveBayes					
	A	P	R	T	S	E
10:90	73.3	62.5	7.8	7.5	0.68	26.7
20:80	75	81.2	89.5	16.8	0.76	25
30:70	69	77	76	27	0.66	31
40:60	64	75	76	14	0.87	36
50:50	55.5	69.5	88.3	24.5	0.77	44.5

A-Accuracy, P-Precision, R-Recall, T-Time(sec), S-Specificity, E-Error rate

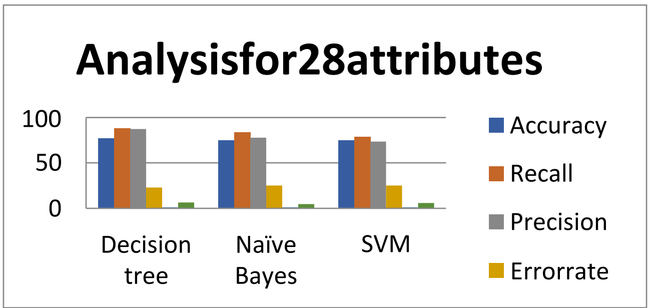

Fig.12: Analysis parameters for 28 attributes

Analysis for 22 attributes:

Attributes considered are Age, Sex, Dyspnea, Fatigue, headache, Temperature, Fever, Fever duration, Cough, wheezing, Respiratory failure, Consolidations, anosmia, loss of appetite, nausea, Smoking, CoViD-19 Mingling, Thickens, Groundglass, Groundglass Position, Opacity, PCR, Diagnosis.

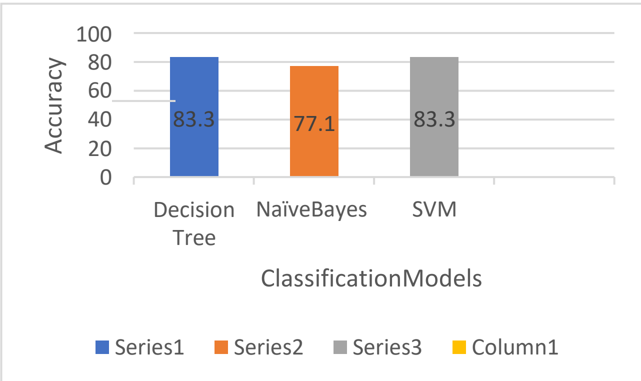

Fig. 13: Graphical representation of Accuracy of Machine Learning Algorithms of 22 attributes.

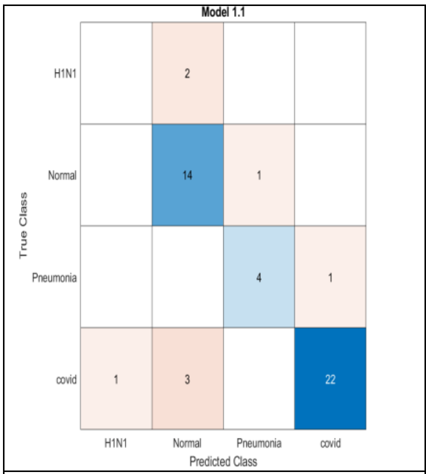	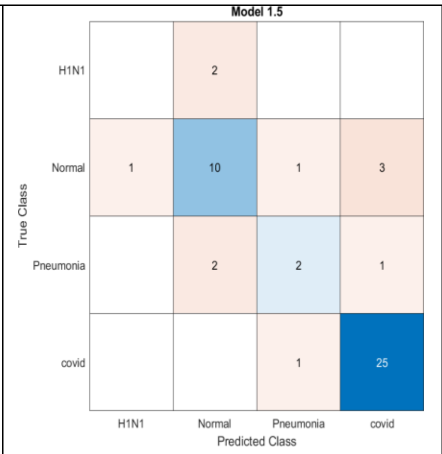	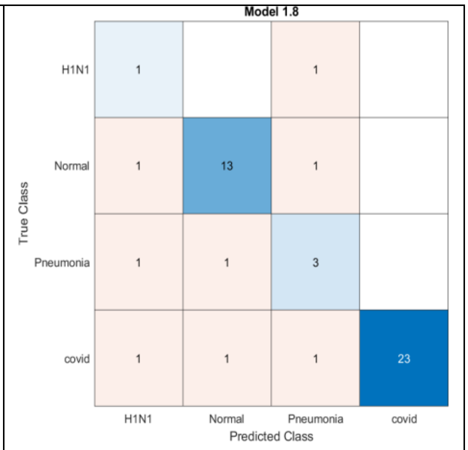
Fig. 14: Confusion Matrix for Decision tree with 22 attributes	Fig. 15: Confusion Matrix for NaïveBayes with 22 attributes	Fig.16: Confusion Matrix for SVM with 22 attributes

The parameter values obtained for 22 attributes of type 4 Class are listed in table 4.24,4.25,4.26,4.27.

Table 9: Analysis for 22 attributes of type 4 Class for decision tree

Test: Train	DecisionTree											
	FineTree						MediumTree					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	71.9	89	88	6	0.76	28.1	71.7	89.9	88	22	0.78	28.3
20:80	83.3	81.6	90.5	16	0.67	16.7	80.6	84.5	80	18	0.66	19.4
30:70	72	84	86	15	0.75	28	72	84.5	86.6	21	0.88	28
40:60	79	77.1	91.7	21	0.64	21	75	77.1	91	10	0.65	25
50:50	75	79.6	86.6	27	0.65	25	73.2	79.6	86.6	27	0.75	26.8

Table 10 Analysis for 22 attributes of type 4 Class for Coarse Tree, Linear SVM

Test: Train	DecisionTree						SVM					
	CoarseTree						LinearSVM					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	71.7	89.7	88.3	10.6	0.69	28.3	71.9	89	88	6	0.78	28.1
20:80	77.1	81.6	87	21	0.78	22.9	83.3	81.6	90.5	16	0.63	16.7
30:70	72	84	86	16	0.83	28	72	84	86	15	0.88	28
40:60	77	87.6	74	22	0.79	23	79	77.1	91.7	21	0.71	21
50:50	73	79	86	27	0.65	27	75	79.6	86.6	27	0.63	25

A-Accuracy, P-Precision, R-Recall, T-Time(sec), S-Specificity, E-Error rate

Table11: Analysis for 22 attributes of type 4 Class for SVM

Test: Train	SVM											
	QuadraticSVM						CubicSVM					
	A	**P**	**R**	**T**	**S**	**E**	**A**	**P**	**R**	**T**	**S**	**E**
10:90	71.7	89.9	88	22	0.67	28.3	71.7	89.7	88.3	10.6	0.99	28.3
20:80	80.6	84.5	80	18	0.79	19.4	77.1	81.6	87	21	0.85	22.9
30:70	72	84.5	86.6	21	0.88	28	72	84	86	16	0.98	28
40:60	75	77.1	91	10	0.78	25	77	87.6	74	22	0.83	23
50:50	73.2	79.6	86.6	27	0.69	26.8	73	79	86	27	0.79	27

Table12: Analysis for 22 attributes of type 4 Class for Kernel NaïveBayes

Test:Train	KernelNaïveBayes					
	A	**P**	**R**	**T**	**S**	**E**
10:90	73.3	80.9	75.2	8.5	0.86	26.7
20:80	77	81	89	17	0.67	23
30:70	71	78	73	26	0.89	29
40:60	77	69	81	19	0.76	23
50:50	69	77	89	15	0.67	31

A-Accuracy, P-Precision, R-Recall, T-Time(sec), S-Specificity, E-Error rate

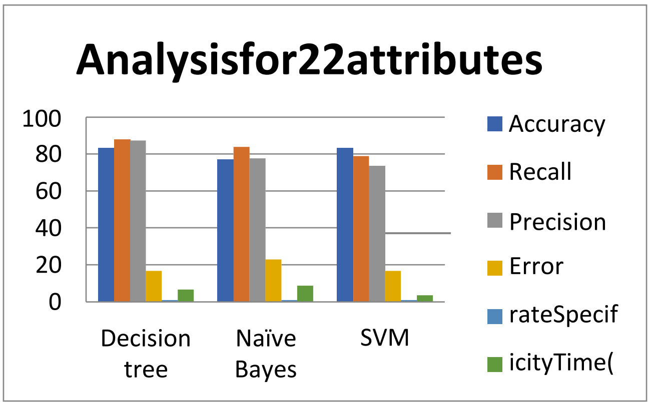

Fig. 17:Analysis parameters for 22 attributes

Conclusion:

From the experimental results it is observed that for fourclass models with 32 attributes, Kernel Naïve Bayes gives good specificity of 77.5% and precision of 68.3% and Fine tree gives the accuracy of 73.3% and recall of 87.3%. For 28 attributes, Kernel NaïveBayes gives precision of 75%, Linear SVM gives recall of 79% and Fine tree gives the accuracy of 77.1% and specificity of 89.2%. For 22 attributes, Kernel Naïve Bayes gives accuracy of 77.1%, Fine tree gives the accuracy of 83.3% and precision and recall with 78.9% and 82.3% respectively. Here it is proved that with less no of attributes we can detect the CoViD-19 with good accuracy of 83.3% and precision of 78.9% for Fine Tree Classifier.

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