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Prediction of Chronic Obstructive Pulmonary Disease Stages Using Machine Learning Algorithms

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ABSTRACT

Identifying chronic obstructive pulmonary disease (COPD) severity stages is of great importance to control the related mortality rates and reduce the associated costs. This study aims to build prediction models for COPD stages and to compare the relative performance of five machine learning algorithms to determine the optimal prediction algorithm. This research is based on data collected from a private hospital in Egypt for the two calendar years 2018 and 2019. Five machine learning algorithms were used for the comparison. The F1 score, specificity, sensitivity, accuracy, positive predictive value, and negative predictive value were the performance measures used for algorithms comparison. Analysis included 211 patients' records. The results show that the best performing algorithm in most of the disease stages is the PNN with the optimal prediction accuracy, and hence, it can be considered as a powerful prediction tool used by decision makers in predicting severity stages of COPD.

KEYWORDS

Classification Algorithms, COPD, Data Mining, Healthcare Data Analytics, Machine Learning

1. INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD) may be defined as a group of progressive lung diseases recognized by emphysema, chronic bronchitis and airflow fettering (Singh et al., 2019). It was estimated that around 30 million people in the US have COPD, with about half of them are unaware of having it. Undiscovered and untreated COPD may lead to faster progression of disease, heart problems, and worsening respiratory infections. Universally, COPD has been considered as a leading cause of higher rates of death. It was reported that 3.17 million deaths were caused by the CODP in 2015 (i.e., 5% of all deaths in that year), (Rodriguez-Roisin et al., 2017). The total costs of lung diseases in the EU (European Union) has been estimated to be about 6% of the total healthcare costs, and COPD was reported as taken the largest percentage (56%) of these costs (Singh et al., 2019). Thus, early diagnosis, controlling and prediction of COPD is of utmost importance for reducing its associated mortality rates and improve its financial consequences. Estimating the disease current stage and predicting the disease progression is one of the most crucial tasks done by clinicians during the patients' treatment journey. With accurate and timely prediction of disease stages, proper interventions and treatment plans may then be applied to prevent disease degradation. Clinicians use the GOLD staging or grading system to decide the severity stage of patients. The grade will affect the treatment a patients receive. The GOLD system checks many things, for example, symptoms, how many times COPD has gotten worse, any times patient had to stay in the hospital because of COPD degradation, results from spirometry (i.e. a test that checks the amount of air and speed that patients can exhale)

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which is based on are based on two measurements: 1) Forced vital capacity (FVC): the largest amount of air patients can breathe out after breathing in as deeply as they can, 2) Forced expiratory volume (FEV-1): shows how much air patients can exhale from their lungs in 1 second.. GOLD stands for the Global Initiative for Chronic Obstructive Lung Disease. The National Heart, Lung, and Blood Institute, National Institutes of Health, and the World Health Organization started it in 1997. The GOLD system defines four grades (stages) of COPD severity, grade1, grade2, grade3 and grade4.

Data mining and machine learning have widely been used in the healthcare sector as an efficient tool for extracting hidden knowledge from available datasets. For example,

(Yu et al., 2010) classified and predicted diabetes patients using SVM. (Magnin et al., 2009) employed SVM to classify Alzheimer's disease using brain anatomical MRI. PRNNs, DTs, NB have been used by (Dessai et al., 2013) for predicting heart diseases. (Cao et al., 2013) predicted HBV-induced liver cirrhosis using MLP algorithm. Concerning COPD related studies, (Guillamet et al., 2018) applied clustering algorithms to EMRs to determine relevant phenotypes of COPD. There are also many studies that compared predictive models based on their predicted output (Demir, 2014; Futoma et al., 2015 and Austin,2007). However, most of these studies suffer from poor prediction quality, as the Area Under the Curve (AUC) ranged from 0.57 to 0.74, with only one excepted study of (Coleman et al., 2004), who reported an AUC value of 0.83. (Amarala et al., 2012) evaluated the performance of different ML algorithms in developing a COPD classifier using forced vacillation measurements. Their results outweighed the performance of KNN, SVM and ANNs. While in their later study (Amarala et al., 2015), KNN and RF classifiers were suggested to have accurate diagnosis of early obstruction of respiratory. (Wang et al., 2020) were the first to use classification models to identify AECOPD on a large scale. However, to the best of our knowledge, prediction of COPD severity stages has not yet been investigated. In this work, we aim to develop prediction models of different COPD severity stages and analyse and compare the performance of different ML algorithms to identify the optimal prediction algorithm. Five different ML algorithms have been evaluated, namely: Support Vector Machine (SVM), Naïve Bayes (NB), Boosted Decision Tree (BDT), Probabilistic Neural Networks (PRNN), and Logistic Regression (LR). The choice of these algorithms was based on their characteristics diversity (Kuncheva, 2014) and their popularity in research (Wu et al., 2019; Nijeweme-d'Hollosy et al., 2018; Prashanth et al., 2016 and Cui et al., 2018). We hypothesize that the application of the mentioned algorithms may be used in the prediction of COPD severity stages and hence it will add value for the management of COPD.

The main contribution of our work is as follows:

1. Evaluating suitable machine learning algorithms for COPD severity stages prediction among five classifiers (i.e., SVM, NB, BDT, PRNN and LR).
2. Finding the optimal algorithm for COPD severity stages prediction.

2. MATERIAL AND METHODS

2.1 Dataset

Data has been collected from a private hospital in Egypt for the two calendar years 2018 and 2019. Data contains information about all COPD admitted patients which includes lots of information such as: hospitalization data, demographics, clinical tests' results, diagnosis, signs, treatment procedures etc. however, personal information such as name, address and so forth are all omitted to keep patients' privacy. The dataset used in the analysis consisted of 211 COPD Egyptian patients and contained 24 variables (10 numerical, 14 categorical).

2.2 Data Processing

There were 23 input features and one output feature (the disease stage) were extracted from the data. Table 1 represents detailed description of the data. There have been around 6% missing values in the dataset. Statistically speaking, missing values that are smaller than 5% of the data may be dropped from the analysis without a significant effect on the results. However, for higher percentages, it is usually handled by imputation (replacement). Missing values were handled by replacing with mode for categorical data and by mean for numerical data. Data normalization has then been applied to data using z-score to ensure elimination of amplitude differences and features variations. Pre-analysis has been applied to a training dataset to check for class imbalance. It was found that the class distribution is slight skewed in different classes. However, the bias was relatively small to be considered as an imbalanced class problem and this can be justified by the nature of the data as normally patients are distributed among the different severity stages nearly equal with no certain bias to a specific severity stage. Data processing is further illustrated in Fig. 1.

PaCO2: measures the partial pressure of carbon dioxide from arterial blood; PO2: measures the partial pressure of oxygen from arterial blood; FEV1:measures the forced expiratory volume in 1 second; FVC: measures the forced vital capacity; Difficulty of cough: measures the difficulty of coughing with E for easy and H for hard; Sleep Quality: measures the quality of patients sleep, with B for bad and N for normal; Supine position: measures if the patient can lie in supine position or not, with N for no and Y for yes; Activity Capability: measures the effect of physical activity on the patients' symptoms, with B for bad effect of worsening only one symptom and W for a worse effect of worsening at least two symptoms.

2.3 Supervised Machine Learning

2.3.1 Support Vector Machine (SVM)

Support vector machines are one of the most robust machine learning algorithms used for data analysis, classification and regression (Chen et al., 2008). It can be applied for both linear and nonlinear datasets (Aljahdali and Hussain, 2013). SVM starts with a set of training data samples, with each sample characterized as belonging to one of two classes, an SVM training algorithm builds a supervised model that assigns new samples to one class or the other. SVM training procedure tries to find a decision boundary to maximize the margin. New samples are then mapped into that same space and predicted to belong to a certain class. Kernel methods are utilized in the mapping of new samples. In the current study, two kernel functions were employed: linear and radial basis functions. The other two SVM parameters are C and γ whose values range from 0 to 150 and from 0 to 30 respectively.

2.3.2 Naïve Bayes (NB)

The Naïve Bayes algorithm is considered to be the most popular, simple and fast machine learning algorithm. It is based on the Bayes probability theorem for predicting the class of a given unknown dataset. It assumes complete independency between different features in its effect on the final output (Chaovalitwongse et al., 2011). Different assumption may be made for feature distributions. In our study, we employed the Gaussian Naïve Bayes algorithm in building the predictive model.

2.3.3 Boosted Decision Tree (BDT)

The Boosted decision Tree algorithm idea is based on building a robust classifier by combining a set of linear weaker classifiers (Lombardo et al., 2015). It is a kind of learning method in which trees in lower levels correct the errors in trees in upper levels in an iterative manner.

2.3.4 Probabilistic Neural Network (PNN)

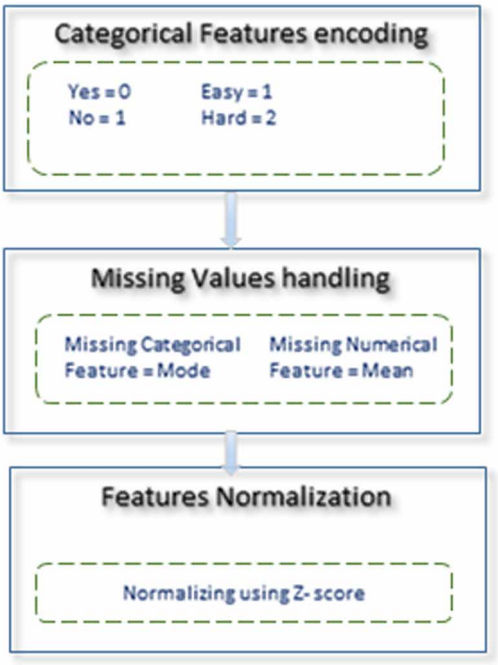
Probabilistic Neural Networks were first introduced by Donald F. Specht in 1990 as a radial basis function neural network that replaced the sigmoid activation function normally used in neural networks

Table 1. Detailed data enumeration

Dataset Description					
Attribute	**Type**	**Values**			
		Grade1	**Grade2**	**Grade3**	**Grade4**
Age	Numerical	70.07(7.78)	72.09(6.78)	73.08(9.17)	73.09(8.18)
Gender	Categorical	F-42(42%) M-68(68%)	F-20(33.39%) M-40(66.61%)	F-10(29%) M-25(71%)	F-3(19%) M-13(91%)
Smoking History	Categorical	N- 20(20%) Y- 80(80%)	N-10(17%) Y-50(83%)	N- 5(14%) Y-30(86%)	N-0(0%) Y-16(100%)
Respiratory rate	Numerical	19.23(1.95)	19.99(1.89)	22.89(2.69)	25.52(2.79)
Pulse rate	Numerical	83.73(9.91)	85.14(8.18)	95.23(9.18)	109.23(10.38)
Diastolic blood pressure	Numerical	76.96(8.26)	78.06(9.18)	78.76(9.08)	79.16(10.42)
Systolic blood pressure	Numerical	120.37(11.94)	122.64(13.29)	124.33(9.94)	125.71(10.44)
Potential of hydrogen	Numerical	7.19(0.07)	7.58(0.03)	7.87(0.02)	7.99(0.06)
$PaCO_2$	Numerical	46.35(9.71)	48.12(10.70)	48.75(10.01)	49.15(09.11)
PO_2	Numerical	76.02(21.14)	78.11(20.03)	79.41(22.06)	79.28(19.15)
FEV1/FVC	Numerical	89.77(9.14)	64.35(10.62)	41.17(8.14)	15.12(13.84)
FEV1predicted	Numerical	90.30(9.06)	63.42(11.05)	40.72(8.19)	14.12(12.55)
Diabetes	Categorical	N- 72(72%) Y- 28(28%)	N- 46(77%) Y-14(23%)	N- 26(74%) Y -9(26%)	N- 12(75%) Y - 4(25%)
Hypertension	Categorical	N- 61(61%) Y- 39(39%)	N-41(68%) Y-19(32%)	N-25(71%) Y-10(29%)	N-12(75%) Y- 4(25%)
Fever	Categorical	N- 70(70%) Y -30(30%)	N-37(61.7%) Y -23(38.3%)	N-21(60%) Y -14(40%)	N-9(56.3%) Y-7(43.7%)
Cough	Categorical	N- 12(12%) Y- 88(88%)	N- 11(18%) Y- 49(82%)	N- 6(17.2%) Y-29(82.8%)	N-0(0%) Y- 16(100%)
Wheezing	Categorical	N-61(61%) Y-39(39%)	N- 27(45%) Y- 33(55%)	N-5(14.3%) Y- 30(85.7%)	N- 1(6%) Y- 15(94%)
Sputum	Categorical	N-76(76%) Y-24(24%)	N- 42(70%) Y- 18(30%)	N-26(74.3%) Y- 9(25.7%)	N- 13(81%) Y- 3(19%)
Difficulty of cough	Categorical	E-37(37%) H-63(63%)	E-21(35%) H-39(65%)	E-9(26%) H-26(74%)	E-0(0%) H-16(100%)
Sleep Quality	Categorical	B-23(23%) N-77(77%)	B-19(32%) N-41(68%)	B-8(23%) N-27(77%)	B-14(87.5%) N-2(12.5%)
Supine position	Categorical	N-75(75%) Y-25(25%)	N-49(82%) Y-11(18%)	N-29(82.8%) Y-6(17.2%)	N-15(94%) Y-1(6%)
Chest Pain	Categorical	N- 79(79%) Y- 21(21%)	N- 41(68%) Y -19(32%)	N- 25(71%) Y -10(29%)	N- 8(50%) Y -8(50%)
Activity Capability	Categorical	B-71(71%) W-29(29%)	B-48(80%) W-12(20%)	B-26(74.3%) W-9(25.7%)	B-15(94%) W-1(6%)

(Specht, 1990). The idea of the PNN algorithm is based on the kernel Fisher discriminate analysis algorithm (Melhem et al., 2017). The algorithm has four main layers: input, pattern, summation

Figure 1. Data Processing Procedure



and decision. Each neuron in the pattern layer employs a radial basis function as its own activation function. In our study, this function was assumed to be Gaussian.

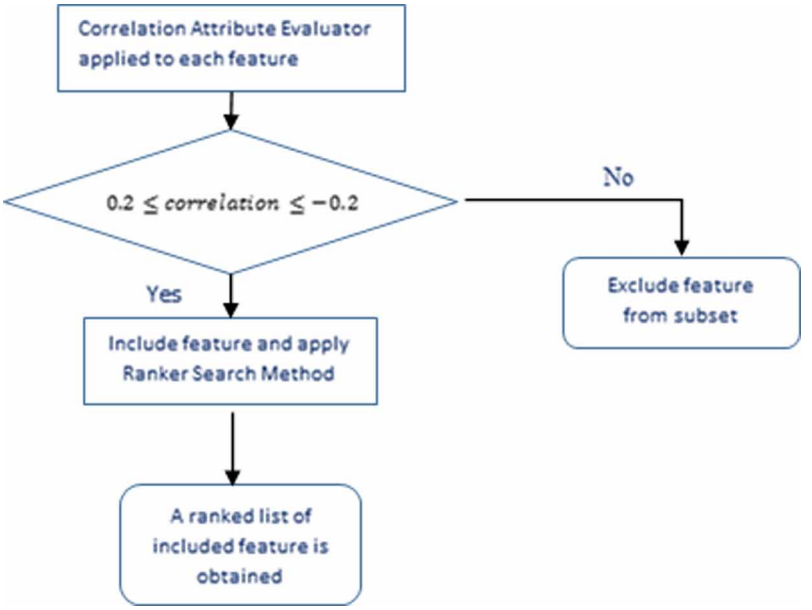
2.3.5 Logistic Regression (LR)

Logistic Regression is a special kind of nonlinear classification models. It is mainly used for binary dependent variables such as dead or alive, infected or non-infected, stage 1 or not, etc. (Brydon et al., 2019 and Amin et al., 2018). Its main aim is to find a sigmoid function to link the right label of the classification task to the result of the linear model. One of the main advantages of LR is the associated probability of each predicted data sample label which is quite beneficial in decision support applications.

2.4 Feature Selection

In order to avoid any bias during the comparison of the involved machine learning algorithms, the filter method has been employed as our feature selection method. Weka has been employed as our analysis software. Weka divides feature selection process into two parts: 1) attribute evaluator and 2) search method. Attribute evaluator evaluates each attribute in the context of the output class while the search method attempts to find the optimal combination of features to select. In this study, the Correlation Attribute Evaluator was used, which is based on the Pearson's correlation coefficient between the feature and the output class. Features whose correlation is near to +1or -1 are included, while values near 0 are omitted, our cut-off value was set to 0.2/-0.2. The Correlation Attribute Evaluator requires the use of the Ranker Search Method which sorts the evaluated features in a ranked list. Feature selection process is further illustrated in Fig. 2.

Figure 2. Feature Selection Process



2.5 Model Assessment

Prediction models has been evaluated using different metrics that has been applied previously in various studies (Tapak et al., 2019 and Dwivedi, 2018). However, in this study, the F1 score, specificity, sensitivity, accuracy, positive predictive value and negative predictive value were the performance measures used for algorithms comparison. Some of these measures can be estimated based on the confusion matrix entries (see Table 2).

The sensitivity estimates the rate of COPD patients that are correctly predicted in the right stage and can be calculated using the following formula:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

The specificity measures the rates of normal COPD patients that are correctly predicted as normal, and is calculated by the following formula:

Table 2. Confusion matrix

Confusion Matrix		
True Label	**Predicted Label**	
	Positive	Negative
Positive	TP	FN
Negative	FP	TN

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

Positive predictive value is calculated using the formula:

$$\text{PPV} = \frac{TP}{TP + FP}$$

Negative predictive value is calculated using the formula:

$$\text{NPV} = \frac{TN}{TN + FN}$$

Accuracy is calculated using the formula:

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

2.6 Model Construction

Weka3.8.5 was chosen for the implementation of prediction models (Garner, 1995 and Ozcift & Gulten, 2011). Weka (Waikato Environment for Knowledge Analysis) is an open source software developed at the University of Waikato, New Zealand and issued under the GNU General Public License. As the fact of our relatively small dataset, a stratified 10-fold cross- validation was employed to measure the performance of prediction models: the overall dataset was randomly divided into 10 subsets, and each subset was then used as a testing set while the remaining subsets were used as training sets. Cross validation is a widely used technique in machine learning models (Wu et al., 2019). LR has been usually used as a baseline model in comparison with other machine learning models in the healthcare literature (Feng et al., 2019), hence, in this study, LR was serving as our baseline model for comparison.

3. RESULTS

As illustrated in Table 1, age for grade 1 patient has an average value of 70.07 with SD 7.78, while for grade 2 its average is 72.09 and ranges from 72.09 - 6.78 to 72.09 + 6.78. Other descriptive statistics of other features can be concluded from Table1 as well. For example, smoking history for the grade 1 patients is 80% positive and 20% negative while for grade 2 it was 17% negative and 83% positive. It can be concluded from the descriptive statistics in the table that certain features are highly correlated with the disease grade (output class). For example, features like FEV1/FVC, FEV1predicted, Fever, Cough, Wheezing, Sputum, Difficulty of cough, Supine position, Chest Pain, Activity Capability are highly correlated to the COPD grade while other features don't have a sound significance on the disease severity stage.

According to our implemented feature selection procedure, only 10 features were selected as the most significant features, while the remaining 13 features were excluded from the analysis.

Five algorithms were applied for the prediction of COPD grade. The summary of the comparison between the performances of each algorithm is presented in Table 3, 4, 5 and 6 in terms of mean $\pm$

SD for the six performance measure discussed earlier. Results indicated that PNN and SVM outperforms the three other algorithms for grade 1 prediction in terms of the six performance measures. While BDT gives more accurate results for grade 2 prediction in terms of accuracy (82%) and F1 score (84%). On the other hand, it was found that PNN is superior to the four other algorithms in predicting severity stage for grade 3 and grade 4 COPD patients.

4. DISCUSSION

In this study, five different machine learning algorithms were evaluated for predicting the severity stage of COPD patients. Filter methods (i.e. attribute evaluation and ranker search) have been applied as a feature selection technique to find the best set of features to include in our models. The applied models have been compared according to different performance measure (i.e. sensitivity, specificity, accuracy, F1 score, PPV and NPV). To the best of the author knowledge, this is the first study predicting COPD severity through machine learning algorithms.

Results have been illustrated in Tables 3, 4, 5 and 6. Results showed that PNN is the most efficient algorithm in predicting severity stage of COPD patients. Being able to identify the disease stage in the right time would greatly help in the early treatment of patients and avoiding the degradation of the patient's health. In addition, it would significantly reduce associated costs and mortality rates.

In this study, Correlation Attribute Evaluator was used as the main feature selection technique. It assigns a weight to each feature based on the Pearson's correlation between the feature and the output class. Features whose correlation is close to +1 or -1 have been included while features whose correlation is close to 0 have been omitted with a cut-off value of 0.2/-0.2. For example, FEV1/FVC

Table 3. The five prediction models for grade 1 patients

Comparison of performance measures for the five prediction models for grade 1 patients.					
	Baseline Model	**SVM**	**NB**	**BDT**	**PNN**
Sensitivity	0.64(0.21)	0.84(0.18)	0.81(0.22)	0.79(0.21)	0.83.8(0.21)
Specificity	0.66(0.23)	0.80.9(0.12)	0.69(0.23)	0.79(0.19)	0.81.2(0.22)
PPV	0.67(0.18)	0.73(0.11)	0.62(0.21)	0.70(0.18)	0.73.5(0.23)
NPV	0.61(0.14)	0.89(0.10)	0.79(0.18)	0.86(0.11)	0.89(0.09)
Accuracy	0.68(0.08)	0.81(0.14)	0.75(0.15)	0.79(0.13)	0.81(0.12)
F1 Score	0.69(0.11)	0.83(0.03)	0.74(0.11)	0.76(0.08)	0.83.5(0.09)

Table 4. The five prediction models for grade 2 patients

Comparison of performance measures for the five prediction models for grade 2 patients.					
	Baseline Model	**SVM**	**NB**	**BDT**	**PNN**
Sensitivity	0.66(0.20)	0.85(0.19)	0.75(0.23)	0.79(0.21)	0.79(0.11)
Specificity	0.65(0.21)	0.76(0.11)	0.73(0.21)	0.83(0.19)	0.85(0.22)
PPV	0.68(0.17)	0.76(0.12)	0.72(0.20)	0.76(0.18)	0.77(0.21)
NPV	0.60(0.15)	0.81(0.10)	0.80(0.18)	0.89(0.11)	0.90(0.09)
Accuracy	0.62(0.09)	0.78(0.13)	0.70(0.16)	0.82(0.13)	0.80(0.11)
F1 Score	0.69(0.09)	0.79(0.04)	0.64(0.09)	0.84(0.08)	0.81(0.02)

Table 5. The five prediction models for grade 3 patients

Comparison of performance measures for the five prediction models for grade 3 patients.					
	Baseline Model	**SVM**	**NB**	**BDT**	**PNN**
Sensitivity	0.62(0.22)	0.84(0.20)	0.84(0.22)	0.79(0.21)	0.85(0.09)
Specificity	0.69(0.22)	0.76(0.17)	0.63(0.23)	0.83(0.19)	0.83.7(0.21)
PPV	0.66(0.19)	0.71(0.11)	0.52(0.21)	0.76(0.18)	0.79(0.22)
NPV	0.63(0.14)	0.89(0.09)	0.89(0.18)	0.89(0.11)	0.89.4(0.11)
Accuracy	0.64(0.08)	0.82(0.12)	0.70(0.15)	0.81(0.13)	0.83(0.12)
F1 Score	0.68(0.10)	0.80(0.05)	0.64(0.11)	0.78(0.08)	0.81(0.19)

Table 6. The five prediction models for grade 4 patients

Comparison of performance measures for the five prediction models for grade 4 patients.					
	Baseline Model	**SVM**	**NB**	**BDT**	**PNN**
Sensitivity	0.64(0.21)	0.85(0.19)	0.84(0.22)	0.79(0.21)	0.85.2(0.11)
Specificity	0.68(0.21)	0.78(0.12)	0.63(0.23)	0.83(0.19)	0.84(0.2)
PPV	0.67(0.17)	0.72(0.11)	0.52(0.21)	0.76(0.18)	0.79(0.13)
NPV	0.62(0.15)	0.88(0.11)	0.89(0.18)	0.89(0.11)	0.90(0.12)
Accuracy	0.69(0.08)	0.78(0.12)	0.70(0.15)	0.81(0.13)	0.82(0.12)
F1 Score	0.67(0.11)	0.79(0.03)	0.64(0.11)	0.78(0.08)	0.80(0.08)

has a correlation value of -0.89.12 which means that the severity stage is highly indicated with the value of the patient's FEV1/FVC. While, the correlation between patient's PH level and the stage of the disease is only 0.15, and hence it was omitted from further analysis in our models. Therefore, clinicians should pay more attention for symptoms like Fever, Cough, Wheezing, Sputum, Difficulty of cough, Supine position, Chest Pain, Activity Capability and spirometry tests like FEV1/FVC, FEV1predicted, as they are highly correlated to the current COPD severity stage of the patient.

However, our study still has some limitations. First, our dataset has been collected over a two years timespan and from one hospital which would negatively affect the generalization of our models. Hence, the implementation of our findings and results to other health centres still needs further investigation. Second, only five algorithms have been considered for comparison in our study, other machine learning algorithms may be more accurate and efficient in predicting severity stage of COPD patients.

Thus, we plan in our future research to include datasets from more than one health centre and include different machine learning algorithms for analysis and comparison.

5. CONCLUSION

This paper investigates the prediction of COPD severity stages which has not yet been investigated to the best of the authors knowledge. In this work, we aimed to develop prediction models of different COPD severity stages and analyse and compare the performance of different ML algorithms to identify the optimal prediction algorithm. Five different ML algorithms have been evaluated. The choice of these algorithms was based on their characteristic's diversity and their popularity in research. We

hypothesize that the application of the mentioned algorithms may be used in the prediction of COPD severity stages and hence it will add value for the management of COPD. The paper contribution is twofold. First, we evaluate suitable machine learning algorithms for COPD severity stages prediction among five classifiers (i.e., SVM, NB, BDT, PRNN and LR). Second, we tried to find the optimal algorithm for COPD severity stages prediction.

In conclusion, our study results confirm the superiority of PNN over other algorithms in predicting the severity stage of COPD patients. Furthermore, our study could find the optimal feature set to be included in machine learning algorithms used for predicting COPD severity stages. The proposed models would greatly assist in predicting the severity stage of COPD patients and hence prevent disease degradation and save costs and lives. Future work will include datasets covering larger timespan and collected from different health centre.

DECLARATION OF COMPETING INTEREST

The author declares no conflict of interest.

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