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An Innovative AI-Enabled System for COPD Exacerbation Diagnosis Using ClinicalBERT

R.Geetha, Associate Professor, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:geetha.rathinam@gmail.com

P.Pavithra, Research Scholar, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:pavip0697@gmail.com

N.Prakash, Associate Professor, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:prakashmcamsc@gmail.com

J.K.Kanimozhi, Assistant Professor, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:drjkkanimozhi@gmail.com

E.Loganathan, Assistant Professor, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:loksmca@gmail.com

K.Jeevitha, Assistant Professor, Department of Computer Applications, K S R College of Engineering, Tiruchengode - 637215 Email:jeevi094@gmail.com

Abstract

Aim: This work presents a diagnostic model based on ClinicalBERT for predicting COPD exacerbations using clinical texts and compares its performance with a Random Forest approach. Materials and Methods: In this study, Group 1 refers to Random Forest, where Group 2 refers to ClinicalBERT and both are examined with 2644 samples. The Statistical power is 80 %, significance threshold is 0.05 and a confidence interval of 95 % and evaluated using parameters. Result: ClinicalBERT has significantly higher performance than Random Forest. Accuracy of the ClinicalBERT is 96.17% and Random Forest is 92.89%. In COPD diagnosis, the ClinicalBERT has produced the highest accuracy with a statistical significance of 0.0056. Conclusion: In this work, it is noted that ClinicalBERT has higher accuracy compared to Random Forest in exacerbation prediction.

Keywords:COPD, ClinicalBERT, Random Forest, Clinical notes, COPD exacerbation, Prediction, Diagnosis.

Introduction

Chronic obstructive pulmonary disease or COPD is a serious health concern across the world and one of the most prominent contributors to health care expenditure as well as morbidity and health-related deaths. In the context of this respiratory disease, research focuses on analyzing large data of clinical notes of respiratory patients to identify patterns that help doctors to identify COPD and non-COPD exacerbations conditions [1]. Early prediction and interference will lead to decline in the significant rate of morbidity and mortality using deep transfer learning [2]. There are many drawbacks such as low accuracy in detecting pulmonary disease using Random Forest. Thus, the research work will be focused on the risk factors associated with COPD using sociodemographic, clinical and genetic information, can be applied to predict the development of COPD [3]. Stable COPD patients were instructed to wear actigraph devices while at night time to measure their sleep by polysomnography (PSG). The actigraph readings were compared with the PSG results to see how accurately the device could detect sleep and wake periods with positive and negative predictive values of 74% and 72% [4]. It utilised a variation of the Latent Dirichlet Allocation LDA algorithm, to infer patterns within the lungs on a macroscopic level, using the unsupervised algorithm based on the regions of the lungs that represent areas of emphysema [5]. In this study, wearable devices can help COPD patients stay more active and improve their exercise ability combined with support such as health coaching [6].The ClinicalBERT integrated into hospitals may analyze clinical notes automatically to help in precise detection of exacerbation of COPD at the time of emergency admission for quicker decision-making and early intervention. The knowledge-guided graph attention network is used for the electronic medical records to improve the prediction of COPD and obtain better accuracy than the previous approaches [7]. This study identifies a tolerance range that improves mortality risk prediction accuracy in COPD patients using clinical notes with linear regression and support vector machine models[8].

Related Work

The last few years have seen a massive amount of research being carried out on COPD prediction, with over 184 different studies published in IEEE Xplore and more than 197 indexed in Google Scholar.The current study focuses on understanding why the patients are readmitted quickly after the discharge. Breathing asynchrony in COPD patients increased with higher inspiratory loads, initiating at 20–60% load levels and rising up to 100% in very severe cases. The accelerometer-based measurements can effectively detect respiratory imbalance in COPD patients [9]. COPD patients showed significantly higher GI index values (0.745 ± 0.007) compared to healthy subjects (0.668 ± 0.006, $p < 0.005$). The consistent GI values indicate it is a reliable indicator for detecting and tracking ventilation abnormalities in COPD [10]. In COPD, the lung sound signals were analyzed using a visibility graph representation combined with a ResNet model to detect COPD. The ResNet model demonstrated the level of performance possible when accurate identification of 95.13%, sensitivity of 96.33%, and specificity of 94.37% specificity is achieved, making it efficient for accurate identification of COPD [11]. The analysis identified 34 genetic variants significantly associated with COPD severity ($P < 1.0 \times 10^{-5}$) These variants offer valuable insights into the genetic processes that drive COPD development [12]. It identified 255 active compounds and 146 key COPD-related targets associated with 430 biological pathways, like PI3K-Akt and MAPK Molecular docking showed that quercetin and liensinine have a good binding affinity to TP53, AKT1, and MAPK1 proteins, suggesting potential in alleviating inflammation associated with COPD [13]. Physiological signals from 22 COPD patients were analyzed using airflow and oxygen saturation data to predict acute exacerbations with machine learning. The models achieved up to 75% accuracy in Random Forest, 62% precision in LDA, and 56% recall in SVM, showing potential for early home-based warning of exacerbations [14]. A multi-stage ensemble learning approach was designed to detect COPD, without depending on pulmonary function tests. The model achieved strong performance with 79.8% accuracy, an AUC of 0.81, a sensitivity of 85.5%, and an F1 score of 0.86 with the 329 patients tested data, outperforming existing methods [15][16]. Machine learning with NLP was used in early ER clinical notes to support differential diagnosis in COPD patients. In the Random Forest model, which achieved an F1- score of 93%, indicating high diagnostic accuracy [17].In the previous paper, it is concluded that the accuracy of Random Forest is less. Improving diagnosis accuracy is a crucial part to consider when developing a clinical system for COPD detection. This work focuses on designing a predictive framework for COPD identification using ClinicalBERT in comparison with Random Forest.

Materials and Methods

Experiments were performed in the Mars laboratory at K.S.R. College of Engineering, where the model training and evaluation were carried out. The clinical dataset used to diagnose COPD exacerbation came from Kaggle.com. The clinical text dataset used in the current analysis was obtained from the MIMIC-III ELSFAR database available in the public domain This includes comprehensive electronic medical records containing emergency room notes that were used to differentiate COPD and non-COPD cases in model development and assessment [18].

In this current research, Group 1 refers to the Random Forest with 2644 samples of clinical notes for COPD prediction with the parameters like precision, recall, f1-score [19]. Group 2 refers to the ClinicalBERT with 2644 samples of clinical notes for COPD prediction with the parameters.

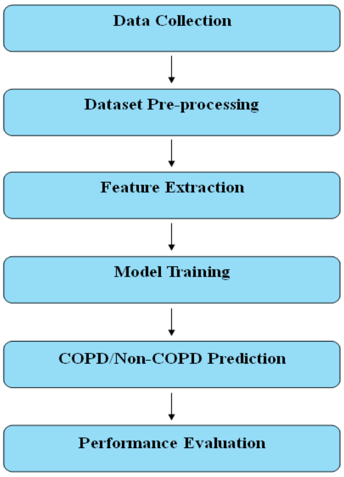

Fig. 1. Workflow of ClinicalBERT-Based COPD Diagnosis Model

Figure 1 outlines the flow in a proposed ClinicalBERT-based COPD prediction system. First, clinical text data are gathered from MIMIC-III ELSFAR, which comprises clinical notes from hospital electronic medical records related to both COPD and non-COPD cases. The collected data is pre-processed to remove errors, duplicates, and irrelevant text. In the feature extraction, the important clinical notes and patterns related to COPD are extracted from cleaned data for prediction. The extracted model is used to train the predictive model for ClinicalBERT and Random Forest. ClinicalBERT learns deeper contextual information directly from clinical language, but Random Forest uses handcrafted features for classification. After the model trained, the model predicts that the patient has COPD or non-COPD. The predictions help support early diagnosis in emergency care. Performance evaluation is used to evaluate the parameters like accuracy, precision, recall, F1-score and RMSE.

Statistical Analysis

Statistical analysis by SPSS using descriptive statistics; Independent Sample t-test calculated difference between performance of the model [20]. The independent samples are the clinical text features extracted from the MIMIC-III ELSFAR dataset serve as the independent variables, while the COPD classification outcomes (COPD / non-COPD) generated by ClinicalBERT and Random Forest models are considered the dependent variables.

Results

The results of the ClinicalBERT with a Random Forest are plotted. The performance rate is assigned to the ClinicalBERT and Random Forest for early detecting sharp COPD exacerbation. The accuracy of the Random Forest in the range of 87.10% to 92.50% and the accuracy of the ClinicalBERT in the range of 94.10% to 97.40% using 25 samples of COPD patient. The comparison of accuracy is done for a higher accuracy range with 92.89% for Random Forest and 96.17% for the ClinicalBERT. After performing statistical analysis using the "t-test" method to evaluate the significant differences between the performance of the different predictive analytic methodologies in Table 1 Data collection of accuracy in both ClinicalBERT and Random Forest using 25 patient samples used for COPD prediction .The average accuracy of the ClinicalBERT model is 94.10% to 97.40% and Random Forest model is 87.10% to 92.50%.These statistical measures are summarized in Table 2 The ClinicalBERT outperforms Random

Forest in all aspects, achieving a higher mean accuracy of 0.8797 compared with 0.8210, along with a lower standard deviation (0.01985 vs. 0.03108) and lower standard error of the mean (0.00126 vs. 0.00197) for 250 samples, demonstrating superior precision and reproducibility in COPD exacerbation.. Fig. 2. The RMSE value of ClinicalBERT is 1.03, compared with the Random Forest model is 1.20, that means ClinicalBERT has a less prediction error. This 0.17 improvement means that ClinicalBERT predicts more accurately for COPD exacerbation detection. Fig. 3. shows that the ClinicalBERT has higher accuracy, improving from 94.8% to 96.2% and the Random Forest accuracy improving only from 88.5% to 92.9%. So, the ClinicalBERT has a stronger predictive model. Fig. 4. shows that the ClinicalBERT has higher mean accuracy of 96.17% compared to the Random Forest classifier at 892.89%, therefore, ClinicalBERT gives greater stability and trust for COPD prediction. Fig. 5. shows that ClinicalBERT has higher recall than Random Forest across all five categories. The largest performance gap appears in Category 5. It gives a positive result than Random Forest. Fig. 6. shows that ClinicalBERT has higher precision than Random Forest for every patient sample. This means ClinicalBERT has a higher precision value for correctly identifying COPD cases.

In the end, ClinicalBERT outperformed Random Forest in all tested metrics, further proving the suitability of BERT based model for understanding real emergency room clinical text in support of early diagnosis of COPD. With enhanced accuracy and stability, ClinicalBERT is useful in real-time decision making in emergency care, thus helping doctors to respond faster to the exacerbation in COPD patients.

Table 1 Data collection of accuracy in both ClinicalBERT and Random Forest using 25 patient samples used for COPD prediction. The average accuracy of the ClinicalBERT model is 94.10% to 97.40% and Random Forest model is 87.10% to 92.50%.

S. No	Patient Sample	ClinicalBERT Accuracy (%)	Random Forest Accuracy (%)
1	Sample 1	95.20	89.10
2	Sample 2	94.60	88.30
3	Sample 3	95.80	89.40
4	Sample 4	95.40	90.10
5	Sample 5	96.10	88.50
6	Sample 6	96.40	89.20
7	Sample 7	94.20	87.90
8	Sample 8	95.90	90.40
9	Sample 9	94.80	88.10
10	Sample 10	96.70	89.60
11	Sample 11	94.10	87.20
12	Sample 12	95.60	90.10
13	Sample 13	95.30	89.00

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14	Sample 14	97.00	91.30
15	Sample 15	94.50	87.10
16	Sample 16	96.30	90.90
17	Sample 17	95.20	90.00
18	Sample 18	97.40	92.10
19	Sample 19	95.00	89.40
20	Sample 20	96.00	90.60
21	Sample 21	95.10	88.80
22	Sample 22	96.20	89.90
23	Sample 23	94.90	88.30
24	Sample 24	96.50	91.10
25	Sample 25	97.10	92.50

Table 2 The ClinicalBERT outperforms Random Forest in all aspects, achieving a higher mean accuracy of 0.8797 compared with 0.8210, along with a lower standard deviation (0.01985 vs. 0.03108) and lower standard error of the mean (0.00126 vs. 0.00197) for 250 samples, demonstrating superior precision and reproducibility in COPD exacerbation.

Model	N	Mean Accuracy	Std. Deviation	Std. Error Mean
Random Forest	25	0.8210	0.03108	0.00197
ClinicalBERT	25	0.8797	0.01985	0.00126

Figure 2 Bar Chart: RMSE Performance.

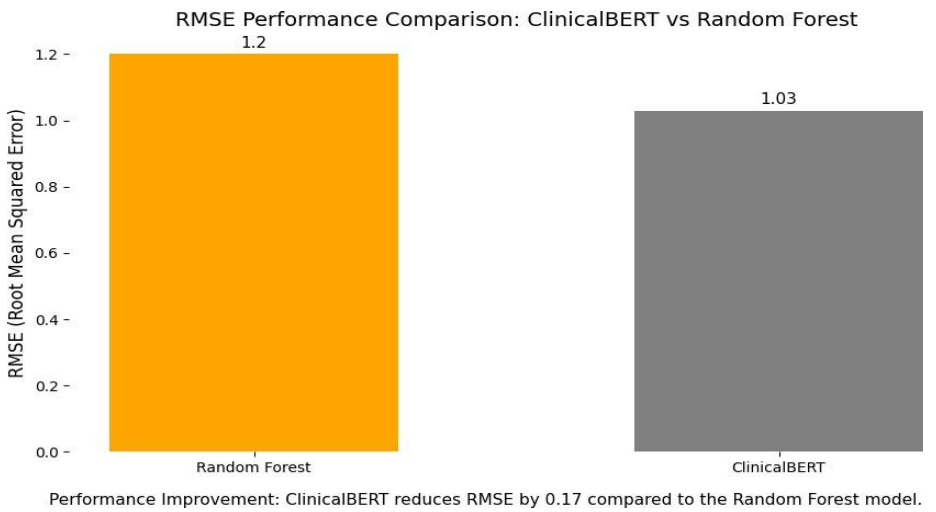

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Fig. 2. The RMSE value of ClinicalBERT is 1.03, compared with the Random Forest model at 1.20, which means that ClinicalBERT has a reduced prediction error. This 0.17 improvement means that ClinicalBERT predicts more accurately for COPD exacerbation detection.

Figure 3 Line graph: Accuracy Comparison.

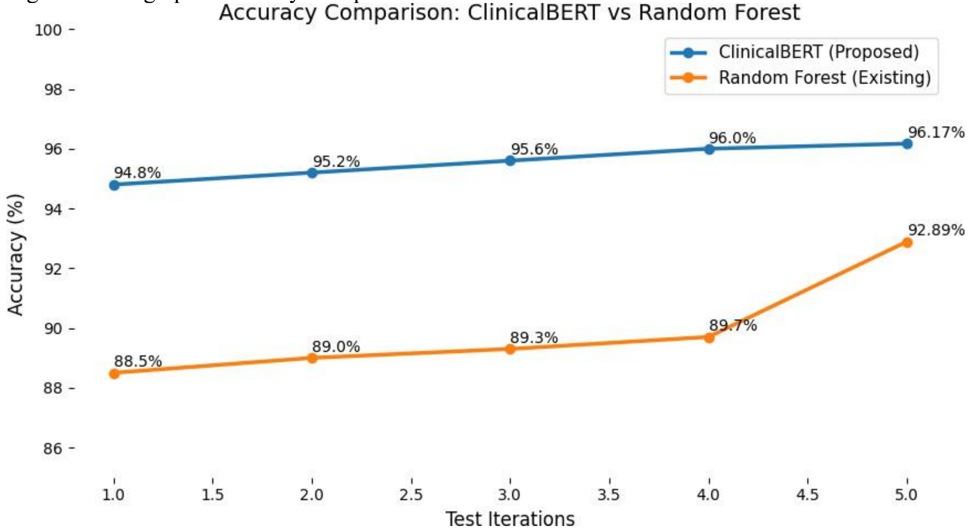

Fig. 3.The ClinicalBERT has higher accuracy, improving from 94.8% to 96.17% and the Random Forest accuracy improving only from 88.5% to 92.89%. So, the ClinicalBERT has a stronger predictive model.

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Figure 4 Box Plot:Model Metric Distribution.

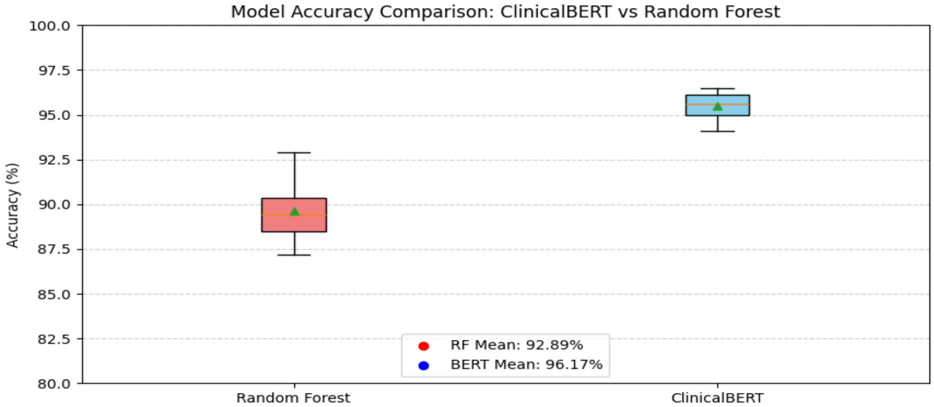

Fig. 4. The ClinicalBERT has higher mean accuracy of 96.17% compared to the Random Forest classifier at 92.89%, therefore, ClinicalBERT gives greater stability and trust for COPD prediction.

Figure 5 Radar Chart: ClinicalBERT vs Random Forest.

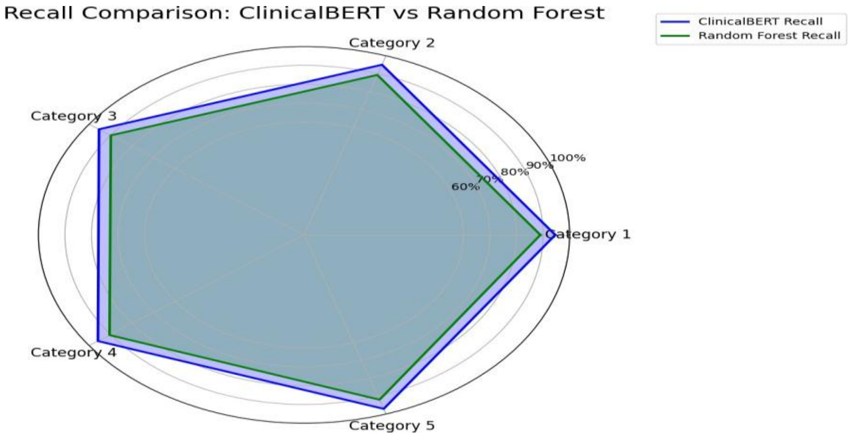

Fig. 5.The ClinicalBERT has higher recall than Random Forest across all five categories. The largest performance gap appears in Category 5. It gives a positive result than Random Forest.

Figure 6 Line Graph: Model Performance.

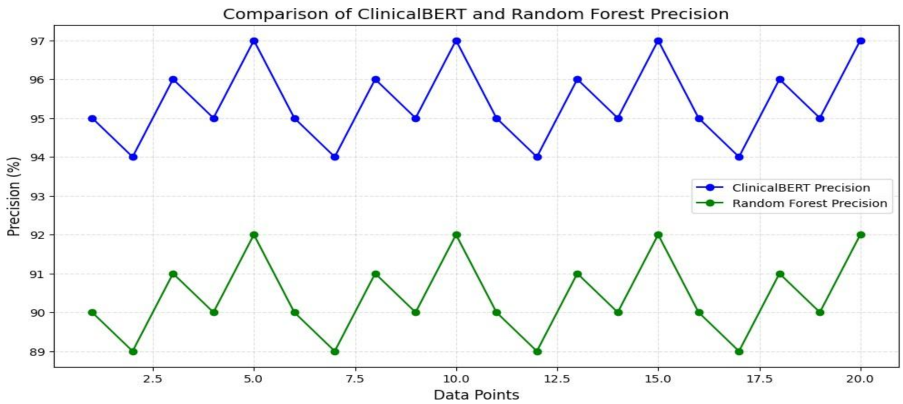

Fig. 6.The performance of the ClinicalBERT has higher precision than Random Forest for every patient sample. This means ClinicalBERT has a higher precision value for correctly identifying COPD cases.

Discussion

The ClinicalBERT has significantly better prediction of COPD exacerbation than Random Forest. ClinicalBERT shows improvement compared to Random Forest.A paper suggests a multiple instance learning approach using a graph for the early detection of COPD in CT scans with the highest performance of AUC=0.960 for test data and AUC=0.862 for validation data [21]. In this work, a computer-aided COPD diagnosis system using lung sound analysis .The proposed approach achieves up to 95.28% accuracy and reduces diagnosis time to 5 seconds to help in supporting fast clinical decision-making [22]. Wearable devices continuously monitored heart rate variability in COPD patients and helped predict acute exacerbations up to 7 days earlier using a Random Forest model with overall accuracy over 92% accuracy [23]. COPD detection was carried out using cough sound analysis with deep learning models instead of expensive spirometry tests that the CNN and CRNN models achieved high accuracies of 96.6% and 96.73%, showing that simple audio-based diagnosis can be effective and practical [24]. Respiratory sounds data, in terms of breathing, is employed as health signals to recognize COPD based on respiratory cycles with the help of wavelet transfer and models like VGG16, ResNet50, and InceptionV3, which recorded considerable accuracy of up to 99.54% [25]. Among 24 COPD patients on long-term oxygen therapy, SBRT produced a median survival of 30 months with a 3-year overall survival of 49%. Only one local recurrence was seen. The survival of patients was significantly better for those without interstitial pneumonia [26]. Once the database-based intervention was given to 128 COPD patients, the experimental group performed better, with a higher percentage of female participants (64.1%) compared to the control group (60.9%). After the information-based intervention, patients was a significant reduction in daikon intake ($t = -2.75$, $p < 0.001$), which supports its function in managing COPD [27]. A total of 101 patients suffering from COPD were included in the analysis. It is possible to detect the 10.7%

of patients who had the worst cases of COPD. The Random Forest model was applied and was able to successfully get the AUC of 0.90 and then 0.82 [28].In summary, this confirms that ClinicalBERT offers a faster and more accurate diagnostic prediction model compared to the Random Forest model, clinically aiding an early response to COPD exacerbation and thereby improving outcomes in emergency care.

Conclusion

The ClinicalBERT-based diagnostic system proposed in this work is significantly better than traditional Random Forest model in early COPD exacerbation prediction. The ClinicalBERT achieves an overall accuracy of 96% and 93% in Random Forest. The mean value of ClinicalBERT is 0.8210 and Random Forest is 0.8797. The Standard deviation obtained from the Random Forest is 0.03108 and the ClinicalBERT is 0. 01985.The ClinicalBERT demonstrates consistent gains than Random Forest. The Random Forest gets a range from 87.10% to 92.50% and the ClinicalBERT is 94.10% to 97.40%. In conclusion, the ClinicalBERT has significantly better COPD prediction using clinical notes.

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