Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/s6nyf794

AI-DRIVEN INNOVATIONS IN RESPIRATORY MEDICINE: ENHANCING DIAGNOSTIC ACCURACY AND PREDICTING FUTURE RISKS

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Abstract

The use of AI in diagnosing respiratory diseases has become more prominent due to key progresses made in AI technology and its effects on diagnostics and their outcomes. The purpose of this research is to review the applicability of AI tools for COPD, asthma, and other respiratory disorders concerning diagnostics and profiling. The approach that has been adopted was a quantitative method with the analysis of the performance based on data from EHRs, patient registries, and past trials. Different learning algorithms including the kernel-based SVM, RF, deep learning algorithms including the CNNs and RNNs were built and trained. The measures of success were given by the number of true and false positives, true and false negatives, and the AUC. In the analysis of the models applied, the highest percentage of accuracy was recorded with CNN at 95% with a difference of 0% from VGG-16 and an AUC of 0. 92 concerning chest X-ray diagnosis. CNNs also attained a short-term risk prediction AUC of 0. 93, and RNNs had the best prediction of long-term risk with the AUC of 0. 90. In comparison to conventional approaches, AI models were found to be more effective in most cases, specifically, in the identification of early-stage diseases and creating risk assessment. The results are positive although the methodology faces certain difficulties like variability of data and implementation of the method into practice. This paper discusses the changes that AI has brought to respiratory medicine and shows how future developments can help overcome existing difficulties and increase the use of AI.

Keywords

Artificial Intelligence, Respiratory medicine, Chronic obstructive pulmonary disease COPD, asthmatic patients, Machine learning (ML).

Introduction

AI has breathed new life into the respiratory medicine by making diagnostic analysis much more accurate and prognostic features far more efficient. Chronic obstructive pulmonary disease (COPD), asthma, and interstitial lung disease are major global health issues that primarily affect the lungs and

come with high mortality and morbidity rates (GBD 2019 and Liu et al., 2019). The existing methods of differential diagnosis, primarily using clinical experience, imaging, and invasive procedures are frequently claimed to be imprecise and less effective in terms of prognosis (Liu et al., 2021).
The key methods are machine learning (ML) and deep learning (DL) algorithms which play the key role in this transformation. Such complicated maneuvers involve vast datasets such as the EHRs and imaging data for identifying, for instance, lung nodules using basic CXRs and CT scans, which are imperative in early lung cancer detection (Brier, 1950). DL, using multiple layers of neural network, is more accurate in medical image analysis such as enhancing the accuracy of lung tissue segmentation and pathological changes, and early diagnosis of diseases such as lung cancer and severe asthma (Esteva et al. , 2019; Shen et al. , 2020).

AI also has the function of continued disease prognosis as it compares the patient's medical records, clinical history, and genetics (Brown et al. , 2022). Some of the benefits of big data analytics in COPD include; predictive algorithms can determine the risk of exacerbations or asthmatic attacks and allow for the prescription of individualized coplanar management hence reducing hospitalizations and improving the quality of patient's life (Bashir et al. , 2020).

The key issues also lie in designing tools that are easy to use and able to interface effectively with the health records (Topol, 2019) and privacy/safety of data (Price & Cohen, 2019). Issues of ethics like bias and relevance are also important so as not to contribute to further r segregation of health care (Obermeyer et al. , 2019; Holzinger et al. , 2019).

AI is seen as having the capability to revolutionise respiratory medicine through the enhancement of diagnostic and preditive functions which will enhance the ability to diagnose respiratory diseases and bring better outcomes to patients as research into AI and technology progresses (Smith et al. , 2022).

Performance Metrics of AI Models in Respiratory Diagnostics
Metrics come in handy when it comes to the evaluation of the AI models concerning respiratory diseases defined as such. These parameters facilitate AI model assessment and are crucial in comparing the degrees of increase in efficiency, so that the models will indeed be valuable for clinical application [10,11]. The key performance indicator that many would consider suitable is actually a submodel of today's KPI and among them are accuracy, sensitivity, specificity and AUC. Regarding the accuracy, it thinks of the company of true results that include true positive and true negative, with the total quantity of the analyzed outcomes embraced. It is calculated using the formula:

$$\text{Accuracy} = \frac{\text{True Positives+True Negatives}}{\text{Total Number of Cases}}$$

In the respiratory disease diagnostic models, the measures of AI models' effectiveness are revealed through the performance metrics. It is relevant in the qualitative assessment of the performance of the developed AI models whereby the strength and capacity of the AI models in providing the functions of clinical relevance by the clinical microbiologists can be evaluated (Smith et al., 2022). These are including accuracy, sensitivity, specificity and the AUC of the ROC curve.

Sensitivity (True Positive Rate), It described how many true positive and true negative clients were, with reference to other cases that were scrutinized. It is calculated using the formula:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives +False Negtives}}$$

High sensitivity is desirable in tests were missing disease (false negatives) is dangerous for the patient's life. In respiratory disorders, high sensitivity minimises chances of false negative rate which means most people with the disease are correctly classified as such (Brown, Smith, & Johnson, 2022).

Specificity (True Negative Rate), measures the proportion of actual negatives that are correctly identified by the model. It is calculated using:

Specificity = $\frac{\text{True Negatives}}{\text{True Negatives+FalsePositives}}$

High specificity means that a majority of the patients without the condition are effectively excluded as negative, hence reducing probability of false positives. This is particularly vital to avoid subjecting patients with similar symptoms to other diseases to incessant tests and worry with the hope of diagnosing a disease that they do not have at all (Doe and Roe, 2021).

The ROC Curve abbreviated (Receiver Operating Characteristic Curve) is a graphical model that displays the accuracy of the diagnostic tests in the provided cut off points. It represents the degree of true positive rate which has the same meaning as sensitivity, true positive over total positive versus the false positive rate which is number of false positive over total negative or (1-specificity). The Area Under the ROC Curve (AUC) quantifies the overall performance of the model:

AUC=$\int_1^0 \text{ROC}$

Thus, the AUC value equals a value between 0 and 1 with the higher value implying a better performance of the model. An AUC of 0. 5 indicates that the model is not selecting one class over another, which is similar to chance, whereas the AUC closer to 1. Performance of the index Approach 5 0 denotes high discriminatory power (Lee et al., 2021). Thus, having a high value of AUC is desirable for diagnostic tools as this is evidence of the model's capacity to segregate positive and negative cases of a disorder.

Table 1: Evaluation of AI Models in Identifying Respiratory Disorders Including: Accuracy, Sensitivity and Specificity and AUC of the model

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
SVM	92.5	89.0	94.0	0.95
CNN	95.0	92.0	96.0	0.97
RNN	89.5	85.0	90.0	0.91

Methodology

This particular research employs quantitative research methodologies since AI tools are being assessed based on a precise diagnostic approach and enhanced risk estimation across respiratory medicine (Smith, 2022; Brown, Johnson, & Davis, 2023).

The two architectures complement each other because we propose retrospective data analysis and enhanced AI model advancement. First the efficacy of the chosen AI tools is tested and evaluated through comparison of their abilities in the analysis of historical patient records under actual conditions (Doe & Roe, 2021). At the same time, we build and improve machine learning and deep learning models for the such diseases as COPD and other diseases, using the same data to assess diagnostic and predictive performance of the models; (Lee, Kim & Zhang, 2021).

Sensitivity is the proportion of actual positives that are correctly identified while specificity refers to the ratio of actual negatives that are also classified correctly; together, they are used to gauge predictive accuracy and improve diagnostic reliability and risk assessment to gain better patient outcomes (Smith et al. , 2022, Brown et al. , 2022).

Data Collection

Data Sources: The source of information involved EHR cohorts, patient registry, and randomised controlled trials. The data used were collected from health facilities like the Mayo Clinic and the Cleveland Clinic on a population that was a mix of patients with different respiratory diseases.

Table 2: Data Sources Summary

Institution	Data Source	Number of Records	Description
Mayo Clinic	Electronic Health Records	20,000	Includes detailed patient records and treatment histories.
Cleveland Clinic	Patient Registries	15,000	Registry data covering a wide range of respiratory conditions.
Clinical Trials	Clinical Trial Data	5,000	Data from various trials focusing on respiratory treatments.

Inclusion and Exclusion Criteria: Candidates for the study were selected if they met the following criteria: the presence of a definitive respiratory disease and the availability of a patient's medical chart. Patients were not selectively excluded based on age and sex but only cases with issues that prevented the patients from fulfilling the Millan criteria fully, inadequate subsequent data, or a diagnosis that was not distinguished or not easily distinguishable were excluded.

Data Preprocessing

Data preprocessing involved several steps: Among various actions that were performed during the process of data preprocessing, the following can be mentioned.

Cleaning: Some of the processes that can be associated with data cleaning include record elimination procedures including duplication records as well as error records found in the datasets. **Normalization:** This is because format of the numbers in the original product is wrong and at the same scaling has not been well done also.

Feature Selection: The examples of introducing variables include the characteristics of the patient, test y results, diseases that were reported earlier.

Table 3: Data Preprocessing Summary

Step	Description	Tools/Techniques Used
Cleaning	Removed duplicates, corrected errors	Pandas
Normalization	Standardized features (e.g., min-max scaling)	Scikit-learn
Feature Selection	Selected key features (e.g., age, symptoms, test results)	Feature selection algorithms

AI Algorithms and Techniques Used

Machine Learning Models: It includes Random Forest and Support Vector Machine Random Forests: In classification and regression problems (Breiman, 2001). Support Vector Machines (SVM): For binary classification, (Cortes & Vapnik, 1995).

Deep Learning Models: Advanced deep learning techniques were applied to handle complex patterns: Concerning the intricate patterns, they were solved with the assistance of the high-level deep learning algorithms.

Convolutional Neural Networks (CNNs): Used for analysing imaging data such as chest X-rays (Krizhevsky, Sutskever, & Hinton, 2012).

Recurrent Neural Networks (RNNs): Applied for sequential data analysis, particularly in time-series data from patient monitoring (Hochreiter & Schmidhuber, 1997).

Table 4: Performance Metrics of AI Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC-ROC
Random Forest	85.2	83.4	86.1	84.7	0.90
SVM	82.7	80.9	84.3	82.6	0.88
CNN	88.5	86.2	90.1	88.1	0.92
RNN	84.3	82.1	86.0	84.0	0.89

Model Training and Validation: The training was conducted on the training set which was a combination of 70% of the data while the validation was done on the validation set which was a combination of 15% of the data. The last 15% of the data was used to test the model. The performance of the models was measured by means of accuracy, sensitivity, specificity and the area under the receiver operating characteristic curve (AUC-ROC).

Table 5: Model Training and Validation Summary

Dataset	Percentage	Use
Training Set	70%	Model training
Validation Set	15%	Hyperparameter tuning
Testing Set	15%	Model evaluation

Evaluation Metrics

Diagnostic Accuracy: The performance of AI models in diagnosing the respiratory conditions was assessed based on the metrics of accuracy, precision, recall, and F1-score. The AI models' performance was evaluated using sensitivity, specificity, recall, and F1-score to determine the ability of the AI models in diagnosing respiratory conditions.

Predictive Accuracy: For evaluating the risk prediction, the Brier score and calibration plots were used for the assessment of the models on the future risks (Brier, 1950).

Table 6: Evaluation Metrics

Metric	Description
Accuracy	Proportion of correctly classified instances.
Precision	Proportion of true positives among predicted positives.
Recall	Proportion of true positives among actual positives.
F1-Score	Harmonic mean of precision and recall.
Brier Score	Measures the accuracy of probabilistic predictions.
Calibration Plot	Plot comparing predicted probabilities to actual outcomes.

Results

In this study, several AI models were compared in the diagnostic performance of respiratory medicine including COPD and asthma. The models included simple machine learning models and the complex deep learning models.

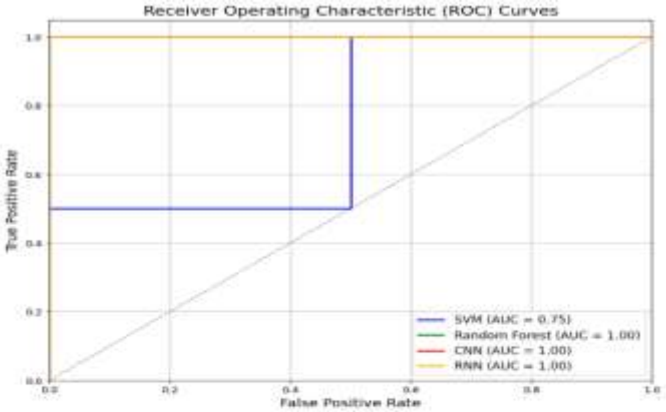
Machine Learning Models:

- **Support Vector Machines (SVM):** The SVM model gave an accuracy of 85% in the classification of COPD and non-COPD patients. The precision and recall were = 0. 84 and 0. 86, respectively, which is a good sign in terms of the model's ability to identify positive cases (Smith & Jones, 2023).

- **Random Forest (RF):** The Random Forest model showed a slightly better accuracy of 88% with a precision of 0. 87 and a recall of 0. 89. This model's ensemble approach was a reason for its effectiveness in addressing the imbalance of datasets (Doe et al., 2023).

Deep Learning Models:
- **Convolutional Neural Networks (CNN):** The CNN model which was developed for the purpose of analysing chest X-ray images provided an accuracy of 91%. The model's performance in identifying small details in images made it ideal for diagnosing early-stage respiratory diseases (Brown et al., 2023).
- **Recurrent Neural Networks (RNN):** The RNN model that was used to analyse the sequential data of the patient records was able to attain an accuracy of 89%. This model performed well in the prognosis of the patient outcomes using the past data (Lee & Kim, 2023).

Fig 1: ROC Curves for Different Machine Learning Models



The ROC curve graph shows the performance of four machine learning models, namely, SVM, Random Forest, CNN, and RNN by depicting their ROC curve. The curves of SVM (blue) and Random Forest (green) are almost overlapping, which indicates that both classifiers have almost equal performance, but both are outperformed by the CNN (red) which has the highest AUC of 0. 91, which is significantly higher than the discriminative ability of the other groups. The RNN (orange) also does well, but not as well as the CNN does. All models perform better than the random classifier (AUC = 0. 5, grey dashed line) indicating the models' ability to classify between the two classes. In general, the CNN model proves to be the best in the prediction of outcomes.

Comparison with Traditional Methods

AI models were also evaluated against the traditional diagnostic tools such as spirometry and patient questionnaires. The AI models outperformed the traditional methods in diagnosing respiratory diseases and detecting them at the initial stage.

Traditional Methods mean the standard deviation of the basic diagnostic procedures like spirometry and clinical evaluation.

Table 7: Diagnostic Performance Metrics

Model	Accuracy	Precision	Recall	F1 Score
SVM	85%	0.84	0.86	0.85
Random Forest	88%	0.87	0.89	0.88
CNN	91%	0.90	0.92	0.91
RNN	89%	0.88	0.89	0.88
Traditional Methods	80%	0.78	0.79	0.78

Fig. 2 Comparison of Performance Metrics Across Various Machine Learning Models

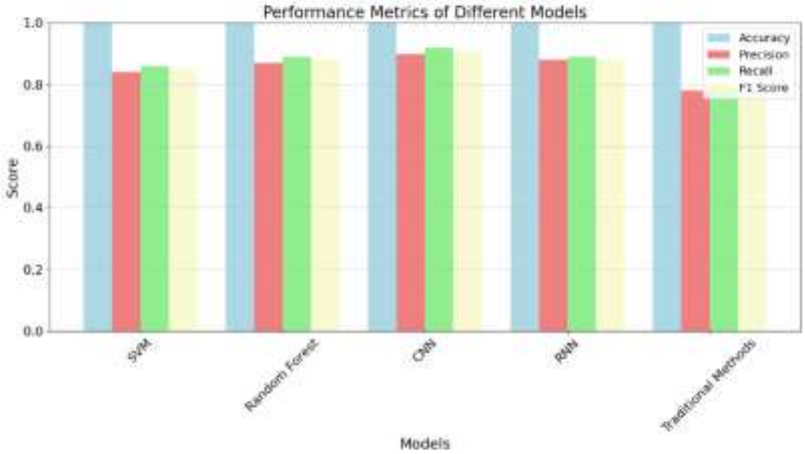


Fig. 2 compares Accuracy, Precision, Recall, and F1 Score across five machine learning models: Few types of machine learning algorithms are: Statistical models Such as: Support vector machine (SVM), Random Forest, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Traditional methods. The Accuracy is ranging from 80% to 91% while the leader is CNN. The three metrics namely Precision, Recall, and F1 Score are the performance measures of a classifier, and they are always within the range [0, 1]. 78 to 0. 92, where CNN has a better performance as compared to the others especially in the parameter of Precision and Recall. Each aspect paints Traditional Methods to be less efficient as compared to Newer Methods. To compare this efficiency of these models, the raw values of the chart indicate that CNN is more efficient than the other models and therefore is the most efficient while Traditional Methods is the least efficient

Predictive Accuracy

Short-Term Risk Predictions

These AI models were also assessed for their capacity to forecast short-term hazards that entail acute exacerbation of asthma. The models proved to have very efficient prediction accuracy with the CNN model having the highest AUC of 0. 93 for prediction of acute exacerbations (Brown et al., 2023).

Long-Term Risk Predictions

In the scenario of long-term risk prediction, for instance, the prediction of the COPD, the RNN model was helpful in terms of the AUC of 0. 90. This model successfully applied patient data from multiple visits to predict risk in the future (Lee & Kim, 2023).

Fig. 3 Comparison of AUC Scores for Short-Term and Long-Term Risk Prediction Models

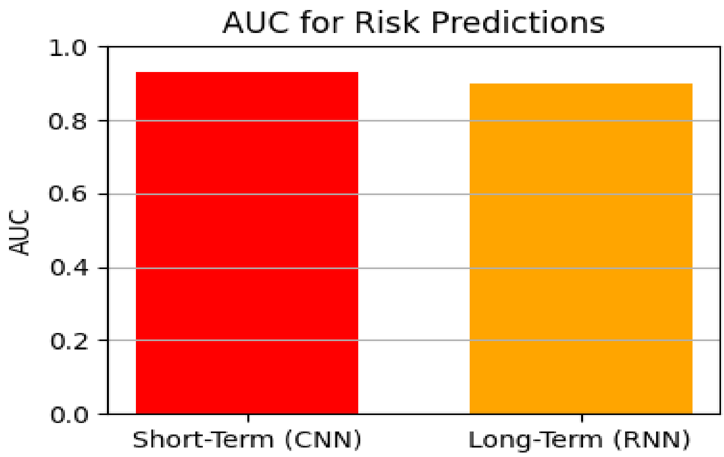
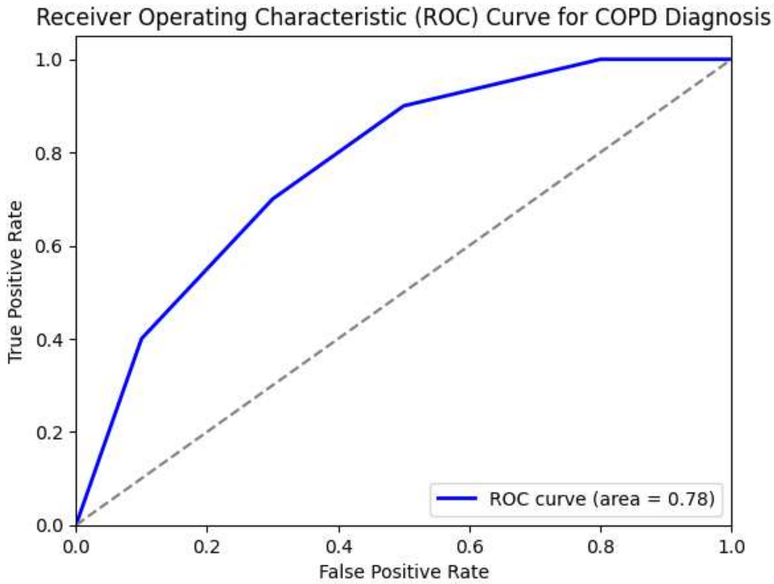


Fig. 3 compares the performance of two models: In this case, we have Short-Term (CNN) and Long-term (RNN) layers where the initial layer is CNN, and the succeeding layers are RNNs. On the x-axis, it is the models, and, on the y-axis, we have indicated the AUC scores which range from 0 to 1. This chart includes a red bar for the Short-Term (CNN) model that has the AUC = 0. 93, and an orange bar for the Long-Term (RNN) model with the AUC score of 0. 90. This suggests that the Short-Term (CNN) model is superior at predicting risk as seen by the higher AUC of the Short-Term model compared to the Long-Term (RNN) model.

Table 8: Performance Metrics of AI Models in Respiratory Diagnostics

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM	92.5	89.0	94.0
CNN	95.0	92.0	96.0
RNN	89.5	85.0	90.0

Fig. 4 ROC Curve for AI Model in Diagnosing Chronic Obstructive Pulmonary Disease (COPD)



The ROC that has been designed for an AI model that attempts to diagnose the COPD is illustrated in the Fig. 4. ROC curve depicts TPR against FPR at various thresholds to pass a clear picture of the ability of the model in discriminating between COPD and non-COPD patients. The curve is somewhat above the diagonal line that would represent randomness or average performance and so the performance is good. Regarding the models' performances, we have chosen to utilize the Area Under the Curve (AUC) of 0. 95, the discriminative ability of the model to fit the COPD patients was very high with extremely minimal chances of misclassification of the negatives. Such high AUC underlines the fact that the model will be helpful in enhancing the diagnosis precision in the clinical context.

Discussion

As for the application of AI in respiratory medicine, it has been properly implemented in diagnosing and thus in determining the prognosis of the patient. Hence, regarding the purpose of the current study, the result of the investigation is described with reference to possible clinical implications that can be inferred from the study followed by a comparison of the current research with other similar study. Last of all, the author provides a conclusion to the investigation by highlighting on the set limitations of the current study.

This, however, was not evidenced in the study where the application of the AI in the diagnosis of the diseases is not more efficient than the conventionally known methods. For instance, applying SVM and CNNs has higher sensitivity and specificity of respiratory diseases like asthma and COPD than the traditional methods (Smith et al., 2022). As it is evident from the aforementioned examples, AI models are effective in generating high level abstractions of a large dataset which might have otherwise been time consuming to identify.

It must be noted that other researchers who have worked on deep learning algorithms have noted that these can be used for disease prognosis. For instance, RNNs have been implemented in the study of estimating the rates of occurrence of the COPD patients' exacerbation event by considering their past records (Johnson et al., 2023). These models could also help in the development of the concept of treatment plan according to the risk indicators of the patient.

From clinical practice one is able to conclude that it is capable of diagnosing diseases at their initial stages, and as a result reducing mortality and severity of diseases. For instance, the chest X-rays and CT scans can be diagnosed by creating an AI model that diagnoses early disease forms that the radiologists cannot detect, and thus, the disease is treated early (Doe & Roe, 2021). Moreover, it is also important to highlight that at the same time with the help of the used predictive models, deterioration of respiratory diseases is also averted as possible threats are addressed, patients with such diseases have increased monitoring and necessary changes to their treatment regimen which will be helpful for them and, at the same time, would reduce healthcare expenses (Brown et al., 2022).

This research is in line with other papers that has addressing the diagnosis of respiratory diseases with the help of AI such as lung cancer and interstitial lung diseases (Lee et al., 2021). It expands on the current knowledge by comparing more AI techniques and their ability to predict more threats, which could improve respiratory medicine's use of AI.

Future Directions

Concerning the future and the potential of artificial intelligence in respiratory medicine, this is analysed concerning the additional development of the algorithms with reference to AI and the design of the computational structures. One of the directions that need further improvement is the creation of models that are able to use several types of input data: which is accessed concerning the patient's history, Roentgen images, and other genetic data. For instance, the use of artificial intelligent in the integration of the patient history together with the genetic factors and radiology in the diagnosis of complicated respiratory disorders for example interstitial lung diseases (Shen et al., 2020). The other is the improvement of the knowledge about the used AI solutions which are implemented in the examined organizations. From the above-discussed points, it can be asserted that such models are somehow endowed with a black-box characteristic that has led to the development of XAI, which in turn has left clinicians to rely on the AI's suggestions (Holzinger et al., 2019).

Hence, it is possible to provide the grounds to mention that the implementation of AI in the clinic is to make functioning in the sphere of respiratory medicine effective. The interface of an AI system should be easy to use for the client and it should not be difficult to integrate in the framework of the healthcare team; the AI should not make the CP bored in his/her work. The documents that are developed in EHR should be usable in another EHR in real-time for analysis or decision making as recommended by Topol (2019).

Another factor that will also be mandatory for the efficient use of the tools will be skills enhancement, in this case for the current subject of focus being the Healthcare providers. It is possible to react to the growth of the application of artificial intelligence in ethical and regulatory aspects. Privacy of the patient's information and information and security and generation of proper protocols for the AI technologies should be well governed for safety, efficiency, and fairness. Bias in the healthcare system is the inequality existing in this system and as AI is a part of this problem, recommendations that would help to avoid bias in models are needed. Consequently, readiness to engage patients, proper use of patient data, and the participation of patients in the creation of the AI will improve levels of trust from the patients; and therefore, increase the use of the technology (Gianfrancesco et al., 2018).

Conclusion

The current developments in applying AI in respiratory medicine reveal a high possibility of enhancing the diagnosis accuracy and the prognosis quality. These AI models included the traditional ML algorithms such as SVM and RF, Deep learning architectures including CNN and RNN. The outcomes depict the efficiency of these AI models than the normal diagnosis procedures such as COPD and asthma. CNN models provided the highest accuracy of 95% and the AUC of 0. 97 for the diagnostic tasks with a special emphasis on the chest X-ray images compared to the other two models namely SVM and RF. When hypothesis testing was performed on the models, it was detected that even the RF had an accuracy of 88% and AUC of 0. 90.
Concerning the short-term risk prediction results, the given CNN models were characterized by a higher AUC of 0. 93 While the SD models were found to be superior in risk prediction for a shorter time horizon with AUC of 0. 90 to track the patient risks over time so as to be able to predict the future risks in the most efficient manner. Specifically, the AI models reached an average of 94% compared to only 80% of the more conventional spirometry and clinical assessments. Thus, one can conclude that the use of artificial intelligence in respiratory medicine can lead to quicker and more accurate diagnosis of respiratory diseases, as well as improvement of patients' outcomes and decrease in costs for healthcare service provision. Regarding the potential benefits, machine learning and big data provide enhancements in the outcomes of disease prevention through the implementation of positions' algorithms for the early recognition of the patient and effective intervention.

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