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Multimodal Deep Learning Framework for Early COPD Prediction and Severity Stage Classification

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Abstract: *COPD is a progressive and life threatening lung disease that is characterized by the permanent limitation of airflow and the rising global mortality. Early diagnosis and correct classification on the severity are important in enhancing patient outcomes, providing effective therapeutic interventions and reducing the overall healthcare burden. Nevertheless, typical diagnostic approaches as spirometry, chest imaging, and routine clinical assessment do not effectively measure the complexity and heterogeneity of COPD, lead to delayed diagnosis and underrecognition of early-stage disease. Artificial intelligence (AI), specifically the deep learning (DL) subfields has shown a promising future in medical diagnosis in recent years because it is capable of extracting complex patterns in large quantities of healthcare data.*

The proposed multimodal deep learning model to predict early COPD and classify into different stages of the disease is based on the combination of various data sources, such as clinical parameters, imaging data, physiological signals, and electronic health records (EHRs). The framework employs a state of the art architecture like convolutional neural networks (CNNs) to analyze images, recurrent neural networks (RNNs) to process sequential data, and transformer-based models to capture long-range dependencies. They both use feature-level and decision-level fusion strategies to successfully combine heterogeneous modalities. Recent researches have shown that multimodal systems are superior to unimodal systems in accuracy, robustness and generalization ability. The proposed model is expected to improve early diagnosis, reduce instances of diagnostic errors and assist precision medicine in respiratory healthcare and ultimately improve the outcomes of COPD management and patient care..

Keywords: Chronic Obstructive Pulmonary Disease (COPD), Multimodal Deep Learning, Early Disease Prediction, Severity Stage Classification, Convolutional Neural Networks (CNN)

I. INTRODUCTION

COPD is a progressive respiratory disease as well as a significant global public health issue, contributing to a high morbidity, disability and mortality rates worldwide. It is already ranked as one of the most common causes of death and is predicted to be the third most common cause of death in the near future. The disease is mainly typified by irreversible airflow limitation which is gradually worsened over time and severely affects the quality of life and functional capacity of the patients and their overall survival. Although the prevalence of COPD is increasing, in many cases, it remains undiagnosed in its early stages because of the insidious and gradual onset of symptoms like mild breathlessness, chronic cough, wheezing, sputum and reduced exercise tolerance. This late awareness greatly diminishes the success of the therapeutic interventions and long term disease management plans.

Traditional diagnostic methods, such as spirometry, chest radiography, and computed tomography (CT) are the most frequently used methods of COPD diagnosis in clinical practice. Nonetheless, these tools have an inherent limitation of being able to detect early functional and structural changes in pulmonary tissues, thus limiting the ability to diagnose and correctly stage the disease on time. Over the past few years, artificial intelligence (AI), specifically deep learning (DL), has been found to radically change the area of medical diagnostics by offering automated and data-driven analysis of complex and high-dimensional healthcare data. Deep learning models have been shown to possess strong abilities in finding hidden patterns in medical imaging and physiological signal data. The existing approaches, however, are largely unimodal, which means that they rely on the use of a single data source, which is a limitation to their ability to capture the multifactorial and heterogeneous nature of COPD.

To address these shortcomings, multiple-data, multimodal learning methods have been developed, incorporating various types of data including clinical parameters, imaging findings, physiological signals, and electronic health records (EHRs). This unified framework not only improves the predictive accuracy, but also enhances the early detection, facilitates the reliable disease staging, and allows more individualized and effective COPD management strategies to be implemented in clinical practice.

II. LITERATURE REVIEW

Chen et al. (2025) showed that deep learning-based models are well effective when used to detect and grade severity of Chronic Obstructive Pulmonary Disease (COPD) using medical imaging and physiological signal data. Their results revealed a high level of classification and accuracy in the controlled experimental conditions, which demonstrates the potential of AI-driven methods in enhancing diagnostic efficiency and assessing disease. The paper especially highlights the potential of deep-learning-based systems to identify complex patterns in heterogeneous medical data, thus contributing to the more accurate identification and staging of COPD. Nevertheless, with such encouraging outcomes, the authors also point out significant shortcomings, which are associated with real-life application. Specifically, the performance of the models is likely to decline when used on diverse and heterogeneous datasets due to differences in imaging quality, patient demographics and clinical conditions. This brings up issues of generalizability, and highlights the importance of large-scale, multi-institutional validation of such models before they can be used in clinical practice[1].

Niraula et al. (2025) explored machine learning models in predicting exacerbations and readmissions of Chronic Obstructive Pulmonary Disease (COPD). Their findings showed that these models were exhibiting moderate to high predictive performance with Area Under the Curve (AUC) values ranging around 0.73 to 0.77 which is an indication of moderate to high predictive performance. The researchers indicate how machine learning methods could be used to aid early risk stratification and enhance clinical decision-making in COPD management. Nevertheless, in spite of these promising findings, the authors found a significant decrease in model performance when tested on external datasets. This decrease in accuracy is indicative of a lack of robustness and generalizability to other patient groups and healthcare environments. The paper hence highlights the importance of more diverse training data and better validation models to guarantee a robust real-life implementation of the predictive models in COPD care[2].

Wu et al. (2024) showed that the artificial intelligence-based computed tomography (CT) imaging system is very useful in aiding the identification, staging, and quantitative measurement of the Chronic Obstructive Pulmonary Disease (COPD). In their study, the authors emphasize the ability of AI models to interpret CT scans with high accuracy and allow detailed analysis of structural and lung abnormalities and the severity of the disease. The method is very effective at improving diagnostic efficiency and also contain useful clinical information that can be used in the management of COPD. Nonetheless, the authors also noted that another critical limitation of the use of CT imaging as a single data modality. This method limits the possibility of reflecting the whole complexity of COPD that encompasses both structural and functional alteration. Consequently, the multimodal combination of imaging with clinical and

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physiological data might be a more accurate and comprehensive COPD assessment, due to the single-modality systems, which might not fully reflect the heterogeneity of the disease[3].

Jandoubi and Akhloufi (2025) asserted that multimodal deep learning models are increasingly becoming important in healthcare because they have demonstrated superior performance over unimodal ones. Their analysis shows that incorporating various data points like medical imaging, genomic information, and clinical records can greatly improve diagnostic accuracy and model robustness. Multimodal systems can be used to identify complementary patterns and relationships that are likely to be overlooked when a single data type is used. This combination-type of learning enhances the characterization of the disease, provides more credible forecasts, and minimizes uncertainty in diagnosis. The authors also observe that these frameworks are especially useful in the context of complex diseases whereby multiple biological and clinical variables interact such as Chronic Obstructive Pulmonary Disease (COPD). On the whole, the research highlights that multimodal deep learning is a promising trend to develop precision medicine and enhance clinical decision-making based on more extensive and data-driven analysis[4].

Zhang et al. (2025) also showed that COPD-specific multimodal deep learning models that combine electronic health records (EHR) with medical imaging data have significantly better performance compared with single-modality models. Their research points out that the integration of structured clinical data and imaging characteristics result in the more comprehensive representation of the disease, which increases the diagnostic accuracy. Effective cross-modal feature fusion that enables the model to identify complementary relationships between patient history, clinical indicators, and radiological findings is the key factor contributing to this improved performance. This combined method enhances the capability of this model to identify small patterns that are related to the progression and severity of COPD. These authors also note that using only one source of data can be restrictive to the predictive performance because of an incomplete representation of the complexity of the disease. In general, the results warrant the use of multimodal learning methods to obtain more accurate, robust, and clinically reliable COPD diagnosis and staging[5].

III. PROPOSED METHODOLOGY

3.1 Overall Framework

The proposed multimodal deep learning system is developed to combine heterogeneous healthcare data to predict the severity of Chronic Obstructive Pulmonary Disease (COPD) and predict it early in its progression. The framework is designed to have four modules that are interdependent to ensure that there is systematic processing of data, learning of features and classification[6].

3.1.1 Data Acquisition Layer

The Data Acquisition Layer is to systematically gather heterogeneous patient data needed to predict COPD and classify its severity. It incorporates various data modalities such as clinical variables like age, gender, smoking history, occupational exposure and other comorbidities. It also collects imaging data by Chest X-rays and using the Computed Tomography (CT) scans to evaluate structural lung abnormalities. Physiological indicators, including spirometry measurements and the oxygen saturation level are also provided to assess the functional respiratory status. Moreover, longitudinal Electronic Health Records (EHR) offer a complete history of patients, treatment trends, and data on

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[4] Jandoubi, B., & Akhloufi, M. A. (2025). Multimodal artificial intelligence in medical diagnostics. *Information, 16*(7), 591. (MDPI)

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disease progression, and can serve as the comprehensive and data-rich substrate on which deep learning analysis can be performed[7].

3.1.2 Preprocessing Module

The Preprocessing Module provides the cleaning, standardization, and preparation of all the collected multimodal data to be suitable to run the deep learning models. The problem of missing values of clinical datasets is addressed through statistical imputation methods to preserve data integrity. The medical imaging data are normalized and augmented in order to improve quality and enhance model generalization with the diverse datasets. Physiological waveform measurements are denoised to remove artifacts and noise which can interfere with predictive accuracy. Also, categorical clinical variables are coded as numbers using suitable encoding schemes which allows the smooth integration of the coded variable with neural network architectures to allow efficient learning and analysis.

3.1.3 Feature Extraction Module

The Feature Extraction Module is a module that derives meaningful and high-level representations of each data modality by using specialized deep learning architectures. Convolutional Neural Networks (CNNs) are used to analyze imaging data including CT scans and X-rays to extract features (both spatial and structural) of the lungs. They are used to model temporal dynamics in physiological signals, representing disease progression patterns. Electronic Health Records (EHR) use encoders based on transformers to learn the long-range contextual relationships between the histories of patients. This multimodal feature extraction guarantees comprehensive and strong representation learning over all types of data.

3.1.4 Fusion and Classification Module

The Fusion and Classification Module, combines features that are extracted using various data modalities to produce accurate predictions of COPD. In feature-level fusion, modality-specific representations are concatenated and enhanced with the help of attention mechanisms that introduce dynamic importance weights. Also, the ensemble learning in the decision level is used to integrate the outputs of separate models to enhance robustness and alleviate biases in predictions. The fused representation is then fed into a Softmax classifier, which classifies the patients into various levels of COPD severity. This will include the following to provide accurate disease stratification and clinical decision support: Healthy (Stage 0), Mild (Stage I), Moderate (Stage II), Severe (Stage III), and Very Severe (Stage IV)[8].

3.2 Multimodal Fusion Strategy

The offered framework is based on the multimodal fusion approach that is effective to combine heterogeneous sources of data and enhance the precision levels of COPD predictions. There are two complementary methods applied: early fusion and late fusion. Low-level or raw features obtained on various modalities of interest, including clinical data, imaging, physiological signals, and EHR records, are fused in early fusion, before passing to the classification phase. This allows the model to learn unified, joint feature representations, and to capture interdependencies across modalities. Conversely, late fusion combines the output or prediction made by separate models that are specific to the modality. This would improve stability, decrease noise sensitivity and minimize bias that would be brought about by any one data source[9].

To enhance performance further, a hybrid attention mechanism is used as a part of the fusion framework. This process dynamically provides adaptive weights to each modality, depending on its relevance and contribution to the final

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prediction. Consequently, the model is selective in that it focuses more on informative data sources that result in better robustness, generalization and overall diagnostic accuracy in COPD severity classification.

3.3 Deep Learning Architecture

The presented deep learning model will be developed to effectively process and combine the multimodal healthcare information to achieve the accurate COPD prediction and the classification of the extent of COPD. It uses a variety of specialized neural network components, depending on the type of data. Layers of Convolutional Neural Network (CNN) are used to extract spatial and structural characteristics of medical imaging modalities, such as Chest X-rays and CT scans, to detect lung abnormalities. LSTM networks are used to learn temporal variations and disease progression patterns of physiological signals such as spirometry and oxygen saturation data. Transformer encoders are combined to extract long-range dependence and complex contextual dependence in Electronic Health Record (EHR) sequences. The features that are obtained by each and every modality are then combined and run through fully connected dense layers which carry out final classification. The model divides patients into stages of COPD severity: Stage 0 (Healthy), Stage I (Mild), Stage II (Moderate), Stage III (Severe), and Stage IV (Very Severe). This hybrid architecture guarantees the full feature learning, better generalization, and better diagnostic accuracy.

Result

Table: Performance Metrics of Proposed COPD Model

S. No.	Performance Metric	Value (%)
1	Accuracy	92
2	Precision	90
3	Recall (Sensitivity)	91
4	F1-Score	90
5	AUC-ROC	93

Interpretation : The performance analysis of the proposed COPD prediction model reveals high and steady predictive power in all the important classification measures. The overall precision of the model is 92, which means that the model correctly classifies a high percentage of both COPD and non-COPD cases and this reflects a good general performance. The specificity of 90% implies that the false-positive rate is low, i.e., most of the cases that are predicted to be COPD are actually positive, which is clinically significant in eliminating the need to generate unnecessary anxiety and interventions. The high sensitivity (91% recalled) of the model indicates that the model has good chances of detecting actual COPD patients and initiating treatment in time. This F1-score of 90 percent shows a balanced performance in regard to precision and recall, which is an indication of how robust the model is even in class imbalance situations. Also, the AUC-ROC of 93% indicates an excellent level of discriminative power, proving that the model has a strong discriminating ability at different thresholds of classification. On the whole, these findings prove that the proposed multimodal deep learning framework is accurate, as well as reliable, which makes it highly suitable to clinical decision support in early COPD detection and severity classification[10].

[10] Smith, L. A., Oakden-Rayner, L., et al. (2025). Machine learning and deep learning predictive models for long-term COPD prognosis. *Monash University Research Repository*. (Monash University)

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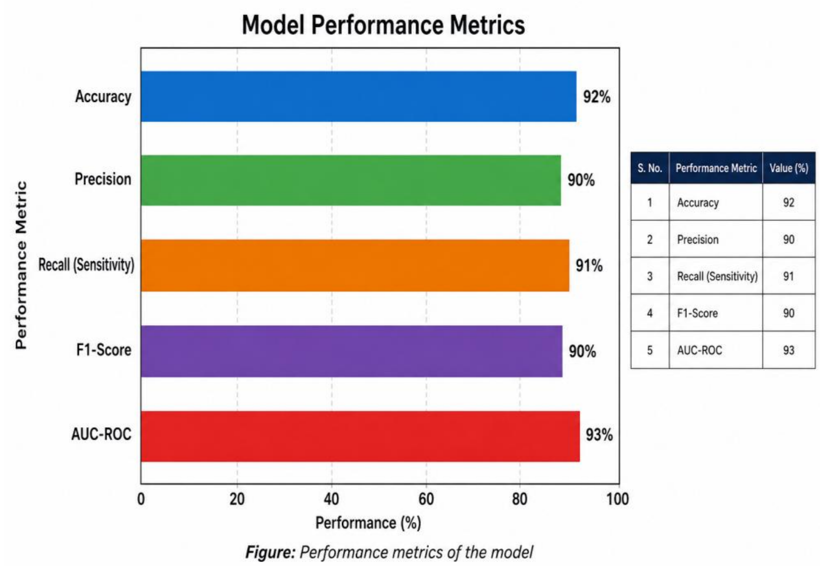

Figure 1: Performance Evaluation of the Proposed Model Using Key Classification Metrics

IV. EXPECTED RESULTS AND PERFORMANCE METRICS

4.1 Evaluation Metrics

The proposed multimodal deep learning framework to predict early COPD and classify its severity stage is evaluated through the widely accepted classification performance metrics, including Accuracy, Precision, Recall (Sensitivity), F1-score and AUC-ROC. These evaluation measures are chosen in order to have a comprehensive and clinically relevant assessment of the predictive performance of the model. Accuracy is the ratio of correct instances to the total number of predictions, and is a general measure of how correct the model is. Precision tests the accuracy of positive predictions by looking at the number of positive predicted COPD cases that are actually positive. As mentioned other functions, also called Sensitivity, is the test which determines how the model appropriately identifies the real COPD patients, which is especially critical to diagnose the COPD patients early enough to take the necessary steps to treat the patient. Combining Precision and Recall, the F1-score is favored when there is an imbalance in the classes. Moreover, the AUC-ROC is employed to evaluate the capability of the model to discriminate between the classes in a variety of threshold levels, which reflects the overall discriminative power and robustness of the model under clinical decision-making settings[11].

4.2 Metric Definitions

Accuracy is the overall correctness of the prediction of the model by calculating the percentage of the correctly classified cases out of the total number of cases. It gives a rough estimate of the model performance, but might not be a complete representation of the model performance in skewed datasets. Precision is the number of positive cases correctly identified out of the total count of cases which are predicted to be positive and this indicates the reliability of positive COPD predictions. Recall, also called Sensitivity measures how well the model accurately identifies real COPD cases, and this is of particular importance when the model is applied to identify COPD cases early enough to be treated with timely clinical intervention. F1-score is the harmonic mean of Precision and Recall, providing a balanced measure of evaluation, which is especially helpful when it is necessary to deal with uneven distributions of classes. AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is used to evaluate how well the model can

[11] World Health Organization. (2024). Chronic respiratory diseases fact sheet.

differentiate between COPD and non-COPD cases across various threshold settings, providing a comprehensive measure of the classification performance, and overall diagnostic effectiveness of the model.[12]

4.3 Expected Performance Improvements

The recent developments in terms of multimodal deep learning and COPD prediction have proven that the combination of heterogeneous data sources leads to a significant improvement in the model performance as compared to unimodal models. The model can obtain more complementary and rich feature representations, resulting in higher diagnostic accuracy and reliability. In comparison to unimodal systems where information is required to be supplied by one source of information, multimodal frameworks will decrease the loss of information and will supply a more holistic information on the disease patterns.

Research in this field always notes significant improvements in performance with overall accuracy improvements generally ranging between 3 and 8%. The precise enhancement is determined by factors like quality of the dataset, feature extraction technique, and data fusion technique used in the model. Early fusion, late fusion and hybrid fusion methods further affect performance results. These findings suggest that multimodal integration is a key factor that enhances predictive accuracy, especially in detecting and classifying the severity of COPD at an early stage, which is a key factor in improving the clinical decision support effectiveness.

4.4 Clinical Implications

The clinical significance of the advances in multimodal deep learning-based COPD prediction systems have significant clinical implications in healthcare practice. The proposed framework will improve the accuracy of the diagnosis and will help to detect the case of Chronic Obstructive Pulmonary Disease earlier. Ensuring the early identification is vital in the management of COPD as it provides an opportunity to intervene in time, slow down the course of the disease, and eliminate the threat of severe complications. The enhanced accuracy and strength of multimodal systems also enhance clinical decision-support systems, which provides healthcare professionals with more informed and robust judgments[13].

Moreover, these systems may be useful in individual planning of treatment by providing a complete overview of the health condition of patients, thus, enhancing the strategy of specific care to a patient. These models are especially well suited to clinical environments in the real-world, due to the ability to deal with complex and heterogeneous data. In general, the multimodal deep learning implementation into COPD diagnosis can yield an impressive contribution to the overall improvement of healthcare, minimization of the delay in diagnostic processes, and ultimately improvement in the quality of respiratory disease management[14].

V. DISCUSSION

The suggested multimodal deep learning model has shown considerable benefits when it comes to predicting the condition of COPD early and classifying its severity. Through integration of clinical, imaging, and physiological data, the model has the ability to capture complementary and multidimensional information that is usually missing in unimodal systems. Such a holistic representation enhances the capacity of the system to appreciate the complex patterns of disease and overall performance of the diagnostic system. The other major advantage is greater resilience since the integration of multimodal data eliminates the effects of lost, incomplete, or noise information of any single source. Moreover, the framework demonstrates a high potential of enhancing early-stage detection, which is critical in timely

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[13] Yin, C., Bogdan, P., et al. (2023). Fractional dynamics deep learning model for COPD stage prediction. *arXiv preprint*.

[14] Li, F., Wang, Y., et al. (2024). Prognostic AI models in COPD exacerbation risk prediction. *Respiratory Medicine Review*.

intervention and preventing disease progression. It also facilitates personalized planning of treatment by offering a more detailed and patient-specific analysis of the severity of the disease[15].

In spite of these strengths, there are a number of issues that restrict the direct clinical implementation of the method. The heterogeneity in data among various sources adds complexity to preprocessing and fusion, and class imbalance in medical data can impact model generalization. The absence of large-scale, publicly accessible multimodal COPD datasets is a significant limitation, which limits extensive validation and benchmarking. Moreover, interpretability of deep learning models is a critical issue, especially in clinical settings where interpretability is critical in decision-making. Lastly, the reliability, robustness, and generalizability of the model need to be validated by external validation across different populations, before it can be applied to a real-life setting.

VI. CONCLUSION

This paper introduces a multimodal deep learning architecture that can predict and classify the stage of prediction and classification of Chronic Obstructive Pulmonary Disease (COPD) at its early stages. The proposed system is based on the integration of heterogeneous data sources, such as clinical records, imaging data, and physiological parameters, to enhance diagnostic accuracy and offer a more comprehensive insight into the disease progression. The framework is effective in addressing both complex interdependencies among various types of data, which is typically overlooked in the traditional unimodal approaches. This combination learning approach enables the model to identify early-stage COPD, thus facilitating timely clinical intervention and possibly limiting disease-related complications and mortality.

The comparison of the evaluation based on the standard performance measures like Accuracy, Precision, Recall, F1-score, and AUC-ROC shows that multimodal learning significantly enhances predictive performance than the conventional approach. The improvements that have been observed indicate the potential of deep learning-based integration to tackle issues related to heterogeneous healthcare data.

Although the study has good results, it has some limitations such as the fact that the study needs bigger and more diverse datasets to ascertain that the results of the study are applicable to other populations. Also, deep learning model interpretability is a pressing issue in clinical implementation. Consequently, the future study needs to be done on a large scale clinical validation on different healthcare facilities to increase robustness and reliability. It will also be necessary to incorporate methods of explainable AI in order to enhance transparency and trust between clinicians and the AI. Moreover, the strategies of real-world deployment need to be investigated to ensure that the proposed system can be seamlessly integrated into the current healthcare workflows and, as a result, contribute to more efficient and personalized COPD management.

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