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Article

Hybrid Deep Learning and Machine Learning Framework for COPD Severity Classification and Disease Progression Prediction

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Abstract: Objectives To design an integrated machine learning and deep learning architecture for accurate chronic obstructive pulmonary disease (COPD) severity classification and disease progression estimation utilizing medical and spirometry data.
Materials and methods A harmonized COPD medical dataset consisting demographic, physiological, spirometry, and longitudinal patient data was used for classification of disease severity and progression forecasting. The classification of disease severity dataset comprised of 1030 single-visit patient data with several variables. For temporal disease progression evaluation, the same patient attributes were structured into longitudinal sequences includes up to 8 yearly visits per patient, yielding to 8240 temporal observations for deep learning-based progression modelling.
Results The experimental analysis illustrated that among Random Forest, Gradient Boosting and Support Vector Machine, the Support Vector Machine accomplished the best prediction performance for COPD severity classification with an accuracy of 95.34%. For temporal disease trajectory evaluation, the Bidirectional Long Short-Term Memory (LSTM) model adequately predicted future COPD exacerbation risk and longitudinal respiratory deterioration patterns with accuracy of 95.08%. Further, the developed integrated ensemble architecture combined with regression based and temporal deep learning estimations enhanced the overall forecasting reliability for both COPD GOLD classification and future exacerbation risk trajectory, accomplishing a definitive accuracy of 95.63% and F1-score of 95.62%
Conclusion The developed integrated architecture optimally enhanced classification of COPD severity and future exacerbation forecasting. The combination of machine learning and deep learning models improved prediction accuracy and provide early medical decision-making.
Clinical Relevance Statement The designed architecture provides prior identification of severe COPD cases and high-risk patients with possible deteriorations. This facilitates periodical medical intervention, individualized treatment planning, and enhanced management of respirator related disease.
Key Points
- Introduced an integrated AI architecture for classification of COPD severity and future deterioration risk forecasting.
- Implemented machine learning and Bidirectional LSTM models utilizing medical, longitudinal, spirometry patient records.
- Provides prior recognition of COPD patients with high risk to facilitate timely medical intervention and individualized treatment planning.

Keywords Chronic obstructive pulmonary disease, Machine Learning, Long Short-Term Memory, Spirometry, Future Exacerbation.

1. Introduction

Chronic obstructive pulmonary disease (COPD) is a group of progressive, long term lung disease that causes difficulty to breathe in people by causing inflammation and permanent damage to the airways and air sacs which leads to obstruction of airflow (Kamis et al., 2024). The symptoms include shortness of breath, chronic cough, Wheezing, chest tightness and fatigue. COPD is a major global health issue and principal cause for morbidity and mortality across the world (CHEN et al., 2024). The disease advances slowly and often recognized only after substantial and irrevocable lung damage has occurred. Recurring exacerbation and hospital admission significantly reduce quality of life and increase health costs (Jackson et al., 2024). Therefore, early identification of disease severity and risk of deterioration is essential for speedy intervention and effective long-term management (Sethi 2025). Highlights the need for intelligent data driven systems capable of supporting proactive COPD care as conventional clinical estimation depends

on periodic assessment and cannot continuously monitor patient status (Jankowski et al., 2024). Current COPD analysis primarily depends on spirometry and periodic clinical follow-up which provides limited representation of disease's diverse nature. Patients with similar spirometry values may shows different symptom burden, functional capacity, and risk of exacerbation specifies considerable heterogeneity of patient which is not captured by standard measurements (Tang et al., 2023). Additionally, clinical analysis of imaging and laboratory remains convoluted and perceptive, making continuous evaluation challenging and restricting the ability to identify early deterioration or individualized disease (Dritsas et al., 2022).

Recent years have observed enhanced integration of machine learning (ML) and artificial intelligence (AI) techniques in COPD evaluation and prognostication. In early studies, to estimate disease severity that is Global Initiative for Chronic Obstructive Lung Disease (GOLD) stages including mild, moderate, severe, very severe and support clinical decision supervised learning models are deployed. For instance, Random Forest-based structure exhibited optimistic performance in disease severity but analyzed on limited dataset and generalizability (Yin et al., 2023). Similarly, AI based decision system for early detection of severity was developed for older population, although performance instability across population remained as a concern (Moraza et al., 2025). The Deep Learning techniques further improved classification capability accomplished high identifying accuracy using physiological measurements, But the computational cost is high (Odeyemi et al., 2024). Ensuing the research shift toward exacerbation prediction and risk stratification. Short term symptom deterioration projecting within telemonitoring programs using Gradient Boosting and neural network models (Xu et al., 2025). While, XG Boost model illustrated that wearable pulse oximetry data could provide the premature exacerbation identification Wang et al., 2025). Most of the recent works investigated prognostic modelling and comprehensive disease management using different techniques including telehealth monitoring, biomarker stratification, and multimodal AI systems (Guo 2023 & Liu et al., 2024 & Sahu et al., 2023).

Even though approaches of AI have improved prediction and classification of COPD, several limitations remain. Dependency of many models on supervised learning requires immense labelled clinical or imaging data which is often perceptual, difficult and costly to extract. As a result, when the designed model is applied to different population, healthcare environment or disease stages continuously showcase poor generalization. In addition, several studies are limiting their ability to capture long term disease progression and varying patient trajectories by focusing on single-time-point analysis or short-term prediction. In deep learning architecture high computational complexities further restricts employment in clinical settings. While, clinical interpretability and adoption is reduced due to lack of multimodal integration and explainability. Inevitably, existing AI-based frameworks provide limited support for early identification of patients with high risk and proactive disease management. Altogether the growing applications of Machine learning and deep learning in COPD analysis, several challenges still persist including limited longitudinal modeling, insufficient multimodal integration, Poor generalizability across population, lack of early risk stratification, limited clinical interpretability and deployment feasibility. To resolve these challenges, this research introduces artificial intelligence (AI) architecture for reliable classification of COPD severity and future deterioration risk forecasting using medical, spirometry and longitudinal patient records. The developed architecture hybrids ML models, incorporating Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting (GB) for COPD GOLD stage estimation, while a Bidirectional Long Short-Term Memory (BiLSTM) network with attention mechanisms is implemented for longitudinal disease progression predicting. Further, an integrated ensemble stacking technique integrates regression-based severity estimation and deep learning-based trajectory evaluation to enhance predictive accuracy and medical decision assistance. The designed system targets to provide early recognition of COPD patients in high risk, facilitate timely intervention, and improve individualized management of respiratory disease.

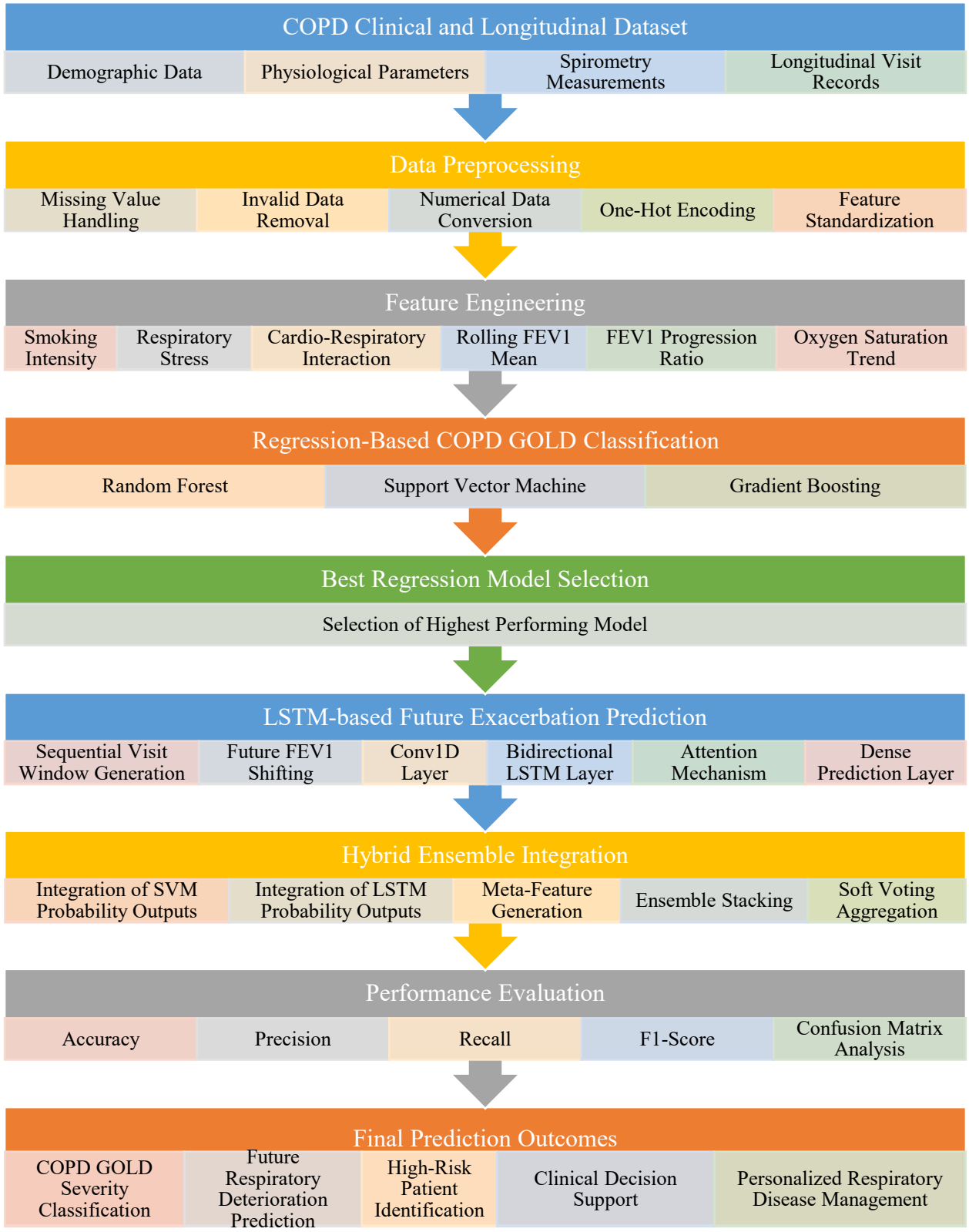

Figure 1. Overall Workflow of Proposed Hybrid COPD Severity and Exacerbation Prediction Framework

Figure 1 demonstrate the complete pipeline of the developed hybrid COPD prediction architecture hybrids regression-based COPD GOLD severity classification and LSTM-based future exacerbation prediction the

architecture processes COPD patient data through preprocessing, feature engineering, model selection, and hybrid ensemble hybrid stages. The final system provides accurate COPD severity analysis, future respiratory exacerbation forecasting and medical decision support for patient management with high risk.

The remainder of this paper is organized into five main sections to systematically present the hybrid architecture to predict COPD severity and future exacerbation risk. Section 2 reviews existing literature corresponding to the developed architecture. Section 3 presents methods and materials of proposed model. Section 4 discusses the results and discussions of developed framework. Finally, Section 5 concludes the proposed study.

2. Related Works

Latest improvements in ML and deep Learning (DL) have substantially enhanced COPD severity assignment, disease progression evaluation, and exacerbation forecasting. Choi et al. (2021) proposed a COPD severity estimation architecture utilizing several ML algorithms and reported that RF model attained the optimal performance with an AUC of 0.886. the research recognized diffusing capability of lung carbon monoxide, modified medical research council (mMRC) score and age as major predictive components for classification of COPD severity. Later, (Dritsas et al. 2022) concentrated on prior COPD severity forecasting among senior population patients utilizing ML methods combined under the GATEKEEPER healthcare architecture. Their work underscores individualized risk evaluation. Simultaneously, (Abineza et al., 2022) developed a pulse oximetry-based COPD categorization architecture utilizing ML algorithms and illustrated that XGBoost accomplished 91.04% accuracy with high precision and F1-score values using respiratory and oxygen saturation attributes.

DL-based respiratory evaluation has also obtained notable concentration in latest years. Yin et al. (2023) proposed a fractional order adaptive DL model utilizing physiological respiratory signals for COPD stage evaluation and the architecture used thorax breathing effort, respiratory rate and oxygen saturation signals to master respiratory deterioration characteristics without depending completely on spirometry values. Multiple researches have additionally inspected COPD exacerbation forecasting and temporal disease surveillance. Parallelly, (Guo et al., 2023) revealed the estimative measurements of medical data, blood biomarkers, and pulmonary function test indexes for severe COPD forecasting utilizing statistical and ML-based nanogram models.

Advanced study has further underscored multimodal mastering and AI-supportive respiratory decision assistance systems. Liu et al., 2024 combined polygenic risk scores, blood biochemical tests, electronic clinical observations for COPD risk estimation utilizing several ML models. In later years (Moraza et al., 2025) used telehealthcare data and ML methods for short-term COPD exacerbation evaluation where CatBoost accomplished strong estimation performance with substantial innovations from respiratory rate heart rate and oxygen saturation attributes. In parallel, (Xu et al., (2025) & Wang et al. (2025)) emphasizes the growing significance of multimodal biomarkers, radiomics and AI-driven medical decision assisting systems for precision COPD management and flexible respiratory risk evaluation.

Table 1. Comparative Analysis of Existing COPD Prediction and Severity Assessment Studies

Author Name	**Study Focus**	**Technology/Models**	**Key Contributions**	**Limitations**
Choi et al., 2021	Prediction of COPD severity	Supervised machine learning, Random Forest classifier (RF), ROC curve	ML based framework for early detection, compared multiple ML models and demonstrate superior performance in RF	Performed on small dataset leads to increase the risk of overfitting, limited clinical granularity, lack of performance validation on cohort
Dritsas et al., 2022	Early prediction of COPD severity grades	Supervised machine learning models, AI framework of the GATEKEEPER system	Early prediction, AI based clinical decision support, supports individual modelling	Lacking generalization for younger COPD population, performance vary

				across geographic regions
Yin et al., 2023	Early detection and stage-wise classification of COPD	Fractional Dynamic Deep Learning Model (FDDLM), Deep Neural Network (DNN),	Incorporating real physiological measurements, Introduced mathematically grounded method, achieved near perfect accuracy	Model require substantial computational resources, limited applicability in low resources settings
Moraza et al., 2025	Short term prediction of COPD exacerbations	Gradient tree boosting methods, neural network-based models, CatBoost model	Provides 3 day predictive window, robust validation design, achieves strong ROC performance	Lacking verification, limits long term stratification, real world implementation require alert threshold
Guo et al., 2023	Predictive value of general clinical, hematological parameters, and pulmonary function indices in finding severity of COPD	Univariate Logistic Regression, Multivariate Logistic Regression, nomogram construction,	Establish neutrophil and platelet count as predictors of COPD, develops nomogram for risk estimation,	Limitation in generalizing across various healthcare settings, performance of model is not validated
Sahu et al., 2023	Investigate association between genetic variants and COPD susceptibility among smokers and non-smokers	Molecular genetic association study design, Polymerase chain reaction restriction fragment length polymorphism, statistical analysis (SPSS)	Found differential genetic susceptibility patterns based on smoking status	Results are not generalized for different ethnic, limited to preselected genes, lacking experimental validation
Abineza et al., 2022	Early identification and classification of COPD exacerbations	Supervised machine learning model, XGBoost	Demonstrate pulse oximetry alone can classify COPD, enables wearable pulse oximeters for daily monitoring, facilitates faster clinical intervention	Model performance depends on labeling consistency and expertise, Lacking multistage severity grading and long term progression
Odeyemi et al., 2024	Machine learning based prognostic tool for patients with community acquired pneumonia and acute hypoxic respiratory failure	Gradient boosting machine (GBM), cross validation framework,	Enables rapid risk stratification, substantially enhances detection at high-risk patients, facilitating implementation in hospital system	Lacking external validation, susceptibility to missing data, selection bias, and unmeasured confounding

Liu et al., 2024	Machine learning models for early COPD risk prediction, primary screening and early identification	Retrospective cohort analysis, Multi-modal data integration	Combines genetic risk with electronic medical records and biochemical markers, achieves discrimination with high specificity and reasonable sensitivity	Restricted to selection bias and confounding factors, limited ethnic generalizability, lacking validation in real world clinical cohorts
Xu et al., 2025	Biomarkers in improving prognostic prediction an precision management of COPD	Biomarker categories discussed, Multi-Biomarker predictive models, Multi-modal data integration,	Provides structured overview, assesses the clinical feasibility and applicability	Lacks systematic review methodology, lacking large scale prospective validation
Wang et al., 2025	Application of AI in full spectrum management of COPD	Telehealth-based monitoring, time series modelling, Biomarker based stratification	Impact of clinical applicability and healthcare system are evaluated, Provides structured insights into clinical adoption	Limited model potability, lacking multicenter validation for most of the AI,

Table 1 outlines latest researches relevant to COPD severity categorization, exacerbation forecasting and AI-supportive respiratory disease evaluation utilizing ML and DL methods. Earlier methods illustrate assuring predictive performance; however, many researches concentrated on isolated severity analysis or progression forecasting tasks. Restricted hybridization of longitudinal DL and integrated ensemble learning for hybrid COPD GOLD categorization and future exacerbation estimation emphasizes the research gap resolved in the developed architecture.

Even though prior researches have illustrated assuring performance in COPD classification and exacerbation evaluation, most methods primitively concentrate on either severity prediction or trajectory estimating independently. Restricted study has revealed integrated ensemble architectures that hybrids regression-based COPD GOLD categorization with longitudinal DL-based future deterioration risk forecasting utilizing temporal patient surveillance data. This restriction motivated the designing of the developed integrated architecture combining ML severity classification, Bidirectional LSTM longitudinal prediction, and ensemble stacking for complete COPD trajectory evaluation.

3. Materials and Methods

The complete architecture is proposed for COPD severity classification and future respiratory trajectory prediction utilizing medical, spirometry, physiological and temporal patient visit data. The architecture includes data preprocessing, feature engineering, regression-based ML models, bidirectional LSTM longitudinal training, and integrated ensemble hybridization to enhance predictive reliability, longitudinal respiratory exacerbation evaluation, and medical decision assistance for management of COPD.

3.1.Dataset Description and study cohort

The proposed methodology used a harmonized COPD medical dataset consisting demographic, physiological, spirometry and longitudinal patient data for classification of COPD severity and future exacerbation risk prediction. The dataset comprises of demographic data such as age, gender, body mass index (BMI), working place, smoking status and pack history, physiological and medical details namely modified medical research council (mMRC), oxygen saturation, respiratory rate, heart rate, blood pressure, sputum condition, vaccination status, depression status, dependent status and body temperature, spirometry information such as FEV1 measurements, predicted FEV1,forced vital capacity (FVC), and FEV/FVC ratio values, and longitudinal patient records up to eight visits per patients containing yearly follow up visit records including all details for disease progression evaluation. For classification of COPD severity, a single visit dataset comprising 1030 patient observations was utilized to estimate

COPD GOLD stages. The aim classes associated with GOLD severity levels namely mild, moderate, severe and very severe based on pulmonary function measurements. Additionally, a longitudinal temporal dataset comprising of 8240 patient visit observations was structured for disease trajectory and future deterioration prediction. Every patience sequence consists up to eight yearly follow up visits to record longitudinal respiratory exacerbation patterns. The temporal dataset discarded FVC, predicted FEV1, actual FEV1, and FEV1/FVC features to handle longitudinal stability through yearly visits of patients. Patient indicators were utilized to conserve temporal structuring during sequence creation for evaluation of deep learning.

Table 2. Demographic, Clinical, Spirometry, and Longitudinal Characteristics of COPD Datasets

Characteristic	Regression Dataset	LSTM Dataset
Number of records [N]	1030	1030
Number of patients [N]	1030	8240
Male patients [N (%)]	49.90	49.90
Female patients [N (%)]	50.10	50.10
Age (years) [mean, SD]	63.27 ± 13.09	66.77 ± 13.28
BMI [mean, SD]	26.65 ± 5.06	26.62 ± 5.11
Height (m) [mean, SD]	1.68 ± 0.10	1.68 ± 0.10
Smoking status – Non-smoker [N (%)]	20.19	20.19
Smoking status – Former smoker [N (%)]	71.46	71.46
Smoking status – Current smoker [N (%)]	8.35	8.35
Pack history [mean, SD]	25.98 ± 0.10	25.98 ± 0.10
mMRC score 0 [N (%)]	18.83	19.90
mMRC score 1 [N (%)]	20.58	19.83
mMRC score 2 [N (%)]	21.26	20.11
mMRC score 3 [N (%)]	18.45	19.95
mMRC score 4 [N (%)]	20.87	20.21
Respiratory rate [mean, SD]	20.57 ± 4.23	20.56 ± 4.79
Heart rate - Low [N (%)]	10.78	29.17
Heart rate - Normal [N (%)]	62.23	36.93
Heart rate - High [N (%)]	26.31	33.90
Oxygen saturation (SpO2) [mean, SD]	0.98 ± 0.04	0.91 ± 0.05
Vaccinated patients [N (%)]	49.42	49.42
Depression cases [N (%)]	47.48	47.48
History of heart attack/failure [N (%)]	45.73	45.73
FEV1 (%) [mean, SD]	63.19 ± 27.58	61.72 ± 27.56
Predicted FEV1 (L) [mean, SD]	2.87 ± 0.61	—
Actual FEV1 (L) [mean, SD]	2.34 ± 0.90	—
FVC [mean, SD]	2.63 ± 0.95	—
FEV1/FVC ratio [mean, SD]	0.65 ± 0.15	—

COPD GOLD 1 [N (%)]	42.52	38.50
COPD GOLD 2 [N (%)]	20.58	23.69
COPD GOLD 3 [N (%)]	19.81	18.50
COPD GOLD 4 [N (%)]	17.09	19.32
Number of yearly visits [mean, SD]	—	8.00 ± 0.00

Table 2 outlines the COPD dataset used for proposed model. The regression dataset comprises single-visit patient data, whereas the LSTM dataset comprises of temporal yearly follow-up data utilized for longitudinal respiratory decline evaluation. Continuous attributes are represented utilizing mean ± Standard deviation, while categorical attributes are reported as frequency and percentage distributions.

3.2.Data Preprocessing

The COPD dataset preprocessed to enhance data stability, decreased redundancy and improve performance across regression, temporal deep learning and hybrid ensemble architectures. Patient authentication and target labels are isolated from attribute space to prevent data leakage during training of model. Highly associated spirometry result attributes incorporating FEV1 percentage, predicted FEV1, actual FEV1 values were eliminated from the regression-based classification dataset. Medical and physiological features are converted into standardized numerical representations, while missing values are managed utilizing median computation. Categorical attributes namely smoking status, sputum, gender, working place, vaccination and depression status details are converted utilizing one-hot encoding methods. For temporal disease trajectory evaluation, longitudinal patient observations are chronologically structured as per yearly visits and sequential windows comprising 8 successive visits for LSTM-based training. Attribute normalization utilizing standard scaler was employed for Regression, LSTM and integrated ensemble models, while stratified 5-fold cross-validation was implemented to make sure reliable and balance model analysis.

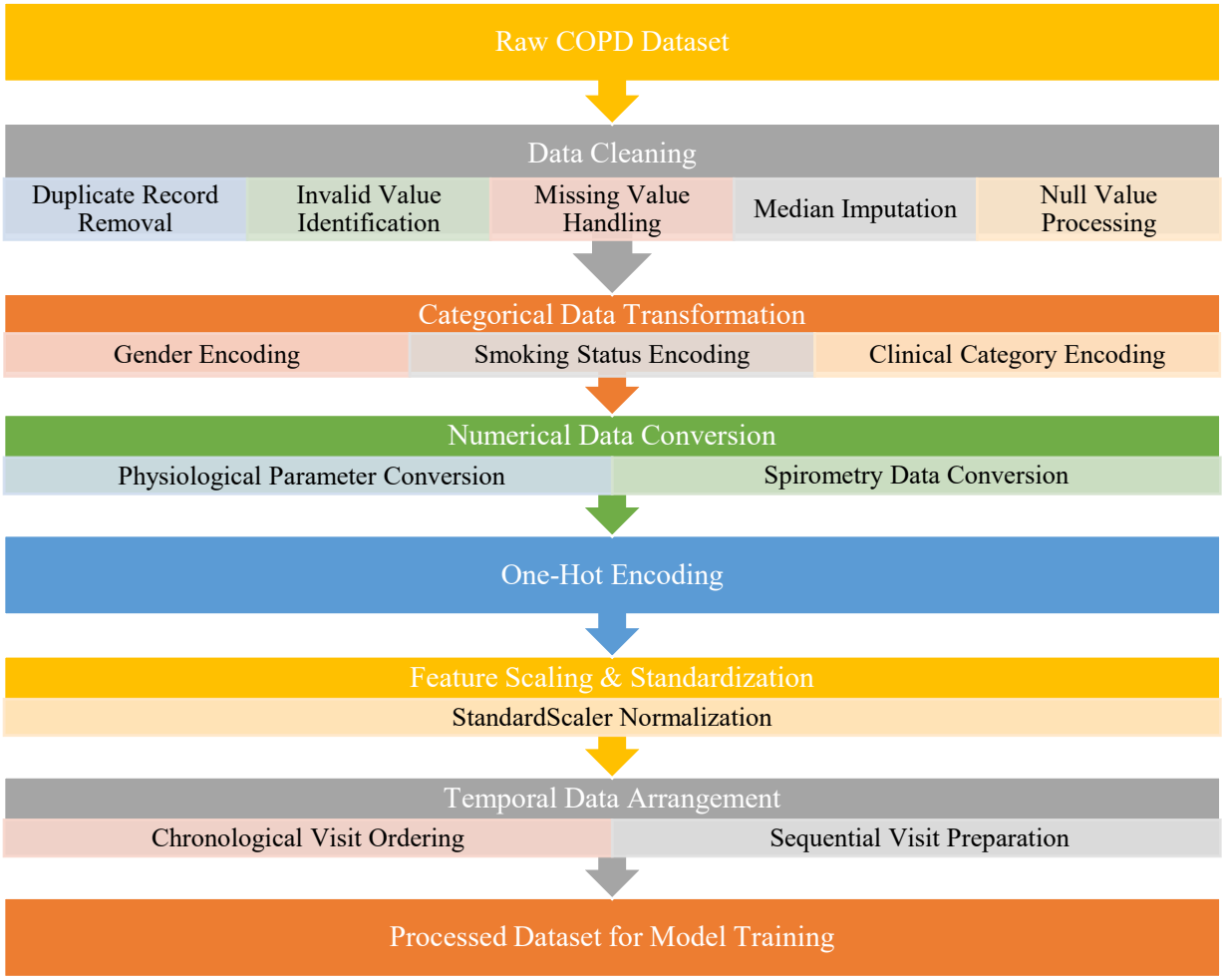

Figure 2. Workflow of the Data Preprocessing Pipeline for COPD Dataset Preparation

Figure 2 demonstrates the preprocessing workflow implemented to the medical and temporal datasets earlier to ML and Deep learning training of model. The pipeline incorporates cleaning of data, handling missing values, normalization, categorical transformations, and longitudinal data preparation to enhance stability of data and predictive accuracy for COPD severity and trajectory analysis.

3.3.Feature Engineering

Feature engineering methods are implemented to improve disease representation training and enhance predictive execution of Classification of COPD severity and future deterioration risk. Various medically related interaction and longitudinal attributes are created from the clinical, physiological, spirometry and longitudinal patient visits data are as follows.

a. Regression Feature Engineering

- **Smoking Intensity** To represent cumulative smoking revealing correlated with COPD trajectory.

$$Smoking\ Intensity = Pack\ History \times Age \quad (1)$$

- **Respiratory Stress** was created utilizing respiratory rate and oxygen saturation values to record severity of respiratory burden**.**

$$Respiratory\ Stress = Respiratory\ Rate \times (100 - Oxygen\ Saturation) \quad (2)$$

- **Cardio Respiratory Interaction Feature** was extracted to model relations of physiological stress.

$$Cardio\ Respiratory\ Feature = Heart\ Rate \times Respiratory\ Rate \quad (3)$$

- **BMI Index** is an improved BMI-relevant feature imputed to better represent obesity-correlated respiratory risk.

$$BMI\ Index = \frac{BMI}{Height^2} \tag{4}$$

- **Health Risk** is combined cardiovascular and physiological comorbidity risk.

$$Health_{Risk} = HeartAttack + Depression \tag{5}$$

b. Longitudinal Temporal Feature Engineering

- **Future FEV1 Target Shifting** future respiratory deterioration prediction target was created utilizing longitudinal shifting.

$$FEV1_{t+1} = Shift(FEV1_t) \tag{6}$$

- **Rolling mean of FEV1** temporal respiratory trajectory patterns was analyzed utilizing rolling mean calculation.

$$FEV1_{RollMean} = \frac{1}{n}\sum_{i=1}^{n} FEV1_i \tag{7}$$

- **Rolling Standard Deviation of FEV1** is a respiratory variability across visit

$$FEV1_{RollStd} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(FEV1_i - \mu)^2} \tag{8}$$

- **Temporal FEV1 Difference Feature** to computed respiratory trajectory varies between successive visits

$$FEV1_{Diff} = FEV1_t - FEV1_{t-1} \tag{9}$$

- **Oxygen Saturation Difference** is a temporal oxygen variation

$$SpO2_{Diff} = SpO2_t - SpO2_{t-1} \tag{10}$$

- **FEV1 Progression Ratio Feature** provides relative respiratory trajectory

$$FEV1_{Ratio} = \frac{FEV1_t}{FEV1_{RollMean}+\epsilon} \tag{11}$$

c. Hybrid Ensemble Meta-Feature Engineering

- **Interaction Feature**

$$Interaction = P_{SVM} \times P_{LSTM} \tag{12}$$

- **Difference Feature**

$$Difference = \mid P_{SVM} - P_{LSTM} \mid \tag{13}$$

- **Mean Feature**

$$Mean\_Feature = \frac{P_{SVM}+P_{LSTM}}{2} \tag{14}$$

- **Maximum Feature**

$$Max\_Feature = \max(P_{SVM}, P_{LSTM}) \tag{15}$$

- **Minimum Feature**

$$Min\_Feature = \min(P_{SVM}, P_{LSTM}) \tag{16}$$

These engineered attributes enhance respiratory severity, discrimination, longitudinal respiratory exacerbation learning, and integrated ensemble prediction performance for COPD medical decision assistance.

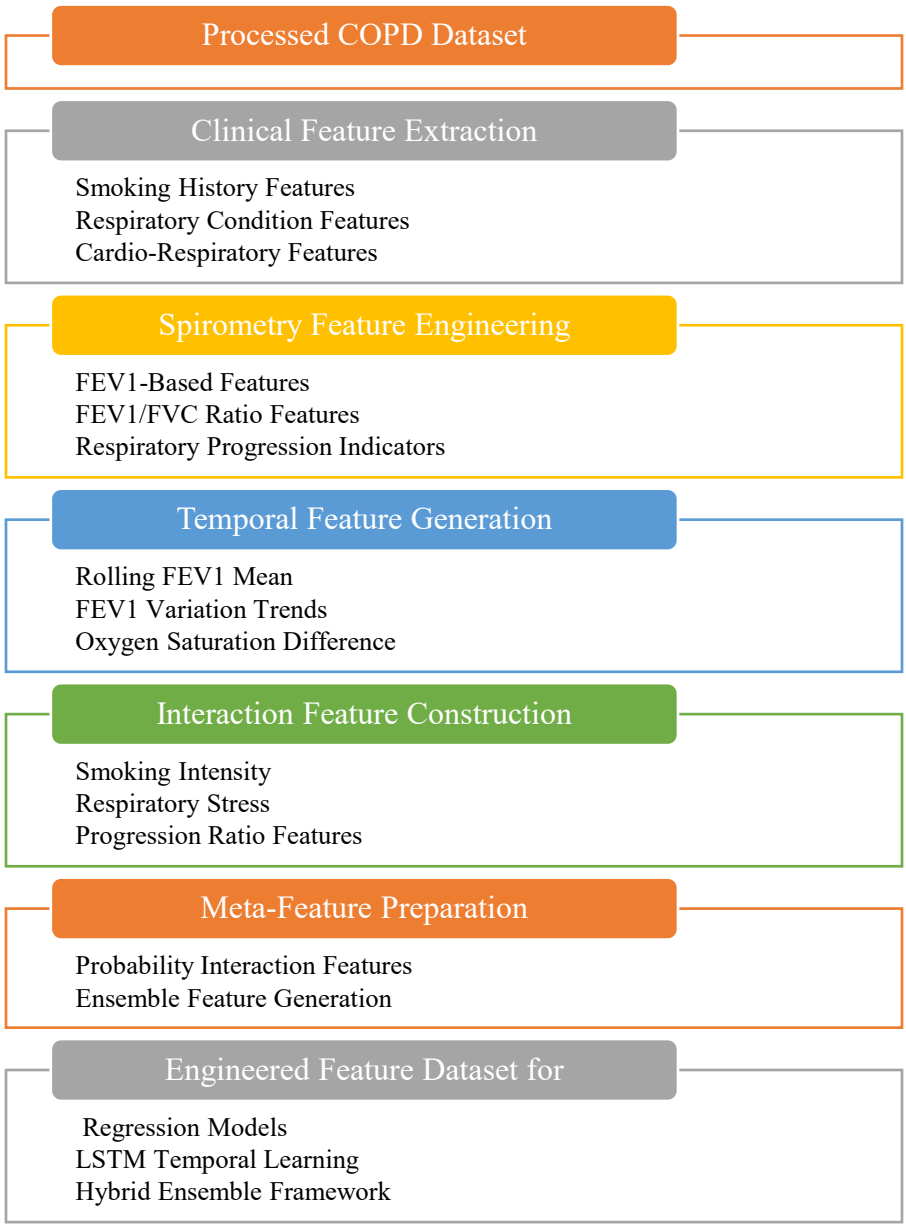

Figure 3. Workflow of Feature Engineering for COPD Severity and Progression Prediction

Figure 3 represents the feature engineering pipeline utilized for deriving medically related and longitudinal respiratory attributes from the processed COPD database. The engineered attributes improve the presentation respiratory stress, smoking reveal, spirometry trajectory and temporal patient patterns for enhanced classification of COPD severity and future deterioration forecasting.

In addition, the integrated ensemble architecture created meat-attributes from SVM and LSTM probability results, incorporating interaction, difference, maximum, minimum, and mean probability representations to enhance ensemble learning capacity and predictive accuracy.

3.4.Regression-Based COPD Severity Classification Models

Regression-based ML models are employed to forecast COPD GOLD severity level utilizing demographic, medical, physiological and spirometry attributes. Three classification Models such as Random Forest, Gradient Boosting and Support Vector Machine are trained and comparatively analyzed to recognize the most efficient model for the prediction of COPD severity. The RF model used an ensemble tree-based training technique with 500 decision

trees, modified maximum tree depth, balanced subsampling and minimum split concerns to enhance classification reliability and minimize overfitting. Median-computed and encoded medical attributes are utilized as model inputs and probabilistic results were created for significant integrated ensemble hybridization. The Support Vector Machine model implemented a Radial Basis Function (rbf) kernel integrated with attribute normalization utilizing Standard Scaler. The classifier was calibrated with modified hyperparameters incorporating training parameter C=10 and kernel coefficient γ=0.01 class balancing probability analysis mechanisms are included to enhance multiclass COPD GOLD forecasting and provide-level ensemble training. The GB model was employed using 300 boosting estimators with modified learning rates, subsampling rationalization, and regulated tree depth to improve nonlinear decision training. The boosting architecture repeatedly reduces the classification residuals by hybridizing several weak learners into a robust predictive ensemble. All regression-based classification models are trained and verified utilizing stratified 5-fold cross validation to make sure balanced representation of COPD GOLD classes during evaluation of model. Out-of-fold estimation probabilities are conserved for integrated ensemble stacking and comparative performance evaluation. Model efficiency was analyzed utilizing standard performance metrics namely Accuracy, Precision, Recall, F1-score. Among the analyzed models, the SVM achieved the highest COPD GOLD categorization performance and therefore chosen as the primitive severity classification model for combining into the proposed integrated ensemble architecture.

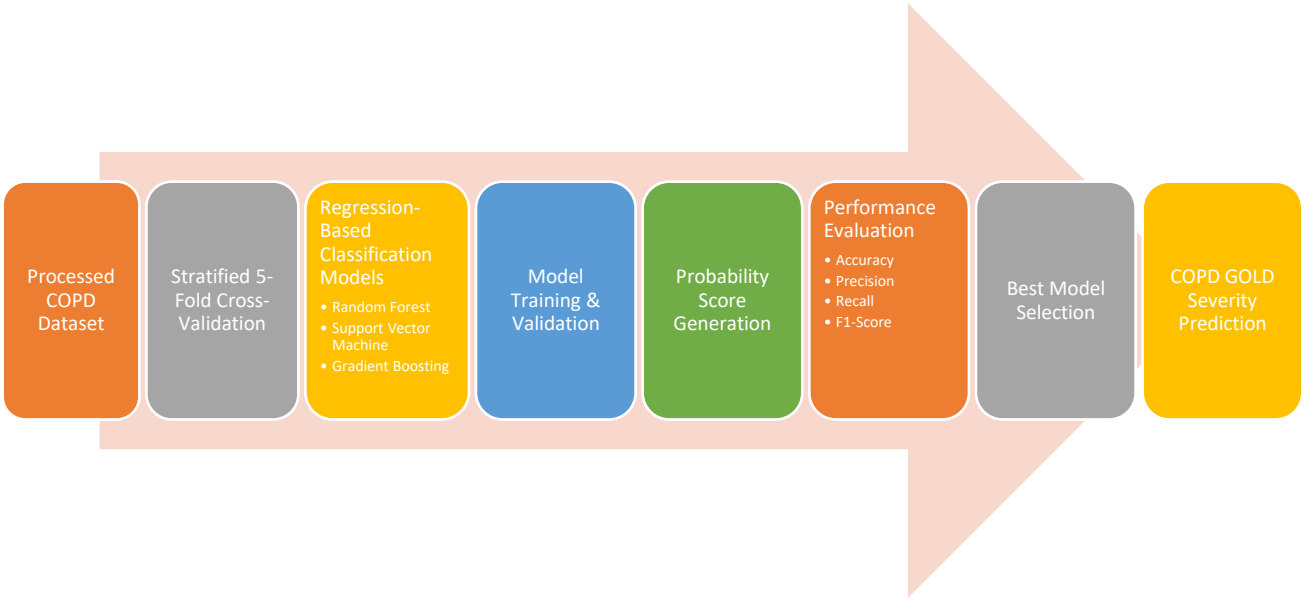

Figure 4. Workflow of Regression-Based COPD GOLD Severity Classification

The regression-based COPD GOLD severity categorization pipeline utilizing RF, GB and SVM models are demonstrated in Figure 4. The architecture executes stratified cross-verification, comparative performance evaluation and best model selection to create reliable COPD severity level estimations from medical and spirometry attributes.

3.5.LSTM-Based Future Exacerbation Prediction

A Bidirectional LSTM network was performed to forecast future COPD exacerbation risk and longitudinal disease trajectory utilizing temporal patient visit records. Future FEV1 values were transferred to create progression forecasting targets, and patients were classified into progression severity category based on future respiratory deterioration. Sequential learning samples comprises of eight successive yearly visits are generated to record longitudinal patterns of respiratory decline. The proposed framework hybrids Conv1D layers, Bidirectional LSTM layers, attention frameworks and dense fully connected layers to learn both short-term and long-term longitudinal reliabilities from temporal medical records. The model was trained utilizing focal loss, adam modifications, dropout regularization, and stratified 5-fold cross validation to enhance generalization performance and address imbalance of class. The LSTM-based progression prediction architecture demonstrating efficient capability in forecasting future COPD exacerbation and deterioration patterns of respiration.

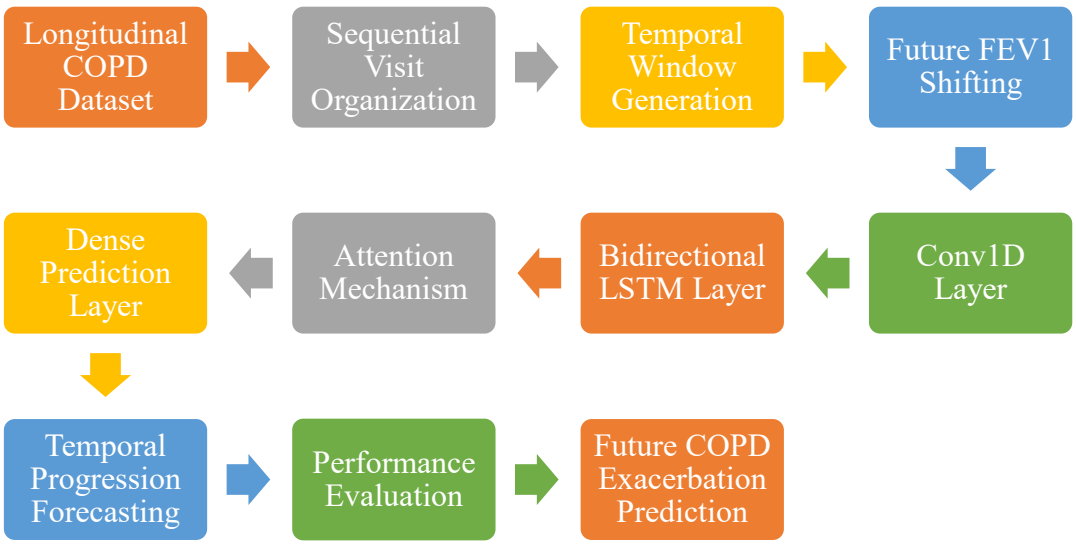

Figure 5. Workflow of the Bidirectional LSTM-Based Future Exacerbation Prediction Framework

The Bidirectional LSTM-based longitudinal forecasting architecture is demonstrated in Figure 5 for future COPD deterioration of COPD prediction utilizing temporal patients visits sequences. The framework records sequential respiration trajectory trends via longitudinal mastering and attention-based attribute representation to enhance predictive performance and prior risk recognition.

3.6.Hybrid Ensemble Architecture

An integrated ensemble architecture was developed to hybrid regression-based classification of COPD severity and LSTM-based future exacerbation forecasting for enhanced medical decision facility. The architecture integrated probabilistic results created from the SVM severity classification model and the Bidirectional LSTM trajectory prediction model utilizing patient-level collaboration. Initially probability results from both models are standardized and merged using patient authentications. Advanced meta-attributes incorporating communication probabilities, probability deviations, average probability attributes, maximum and minimum probability representations are significantly derived to improve capability of ensemble learning. The created meta-attributes space was operated utilizing a stacked ensemble framework comprising of GB, RF and logistic Regression (LR) meta-classifiers. Soft voting aggregation was implemented to integrate predictions from the meta-models and create final COPD severity and future exacerbation risk forecasting. The integrated ensemble architecture was analyzed utilizing stratified 5-fold cross-validation and outperforming individual regression and longitudinal deep learning models.

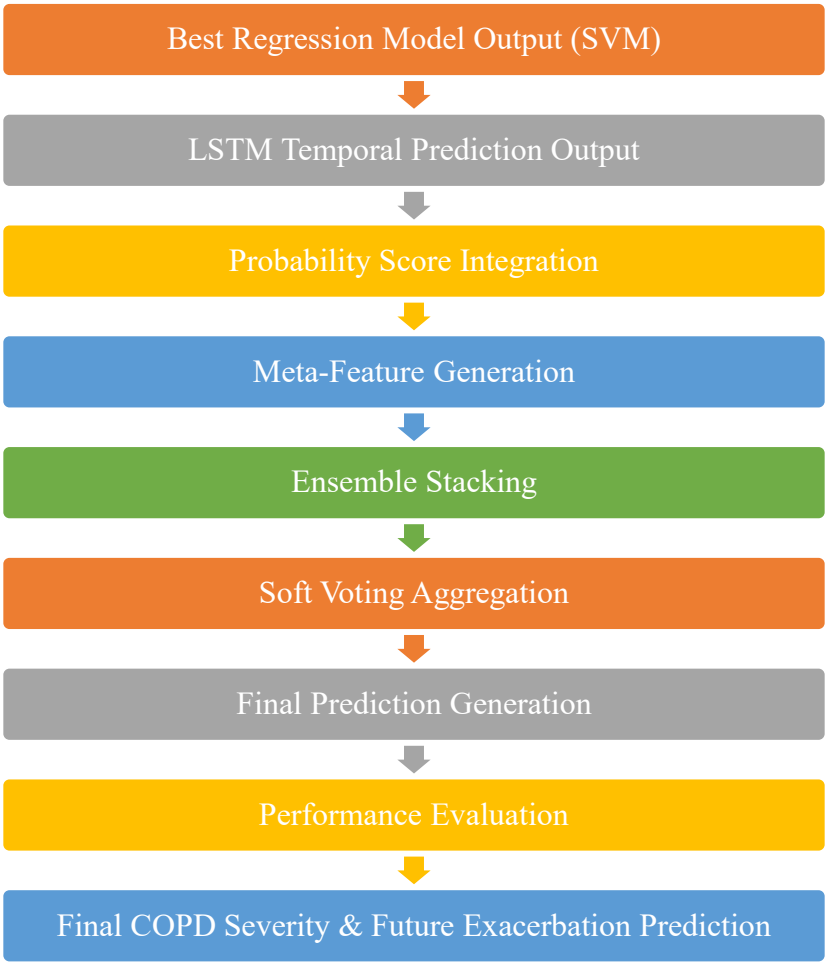

Figure 6. Workflow of the Proposed Hybrid Ensemble Framework for COPD Prediction

The developed integrated ensemble Architecture is demonstrated in Figure 6 hybridizing optimally performing regression model with Bidirectional LSTM longitudinal forecasting model for complete COPD evaluation. The architecture integrated probability level results, ensemble stacking, soft voting aggregation to enhance classification of COPD severity, future exacerbation risk forecasting ad overall predictive accuracy.

3.7.Performance Evaluation Metrics

The performance of the proposed model incorporating regression-based classification models, LSTM-based trajectory predicting model, and integrated ensemble architecture was analyzed utilizing multiple classification and residual-based metrics. Accuracy, Precision, Recall, and F1-Score were used to assess multiclass classification of COPD severity and future exacerbation forecasting performance. The evaluation metrics were computed as follows.

- **Accuracy**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

- **Precision**

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

- **Recall**

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

- **F1-score**

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

Where TP, TN, FP, and FN represent true positive, true negative, false positive and false negative predictions respectively. Confusion matrix analysis and comparative performance analysis were additionally executed to assess model robustness across all experimental architectures.

Algorithm: Proposed Hybrid COPD severity classification and future exacerbation risk Prediction Framework

Input: Clinical, spirometry, and longitudinal COPD datasets
Output: COPD GOLD severity prediction and future respiratory deterioration forecasting
Begin

1. Load regression dataset D_r and longitudinal dataset D_l.
2. Preprocess datasets by:
   handling missing values,
   encoding categorical features,
   and normalizing numerical attributes.
3. Generate engineered respiratory and temporal features.
4. Train regression models:
   Random Forest,
   Support Vector Machine,
   Gradient Boosting.
5. Apply Stratified 5-Fold Cross-Validation and evaluate using Accuracy, Precision, Recall, and F1-score.
6. Select the best-performing regression model:
   $M_{best} = \arg\max(F1Score_i)$
7. Generate temporal visit sequences and shifted future FEV1 targets.
8. Train Bidirectional LSTM temporal forecasting model:
   $h_t = BiLSTM(x_t, h_{t-1})$
9. Integrate outputs from M_{best} and LSTM using probability-level stacking:
   $P_{Hybrid} = \alpha P_{best} + (1 - \alpha) P_{LSTM}$
10. Apply soft voting aggregation:
    $Prediction = \arg\max(P_{Hybrid})$
11. Evaluate final framework using:
    Accuracy,
    Precision,
    Recall,
    F1-score,
12. Return COPD severity and future respiratory deterioration predictions.

End

4. Results and Discussions

The proposed architecture was empirically analyzed for classification COPD GOLD severity classification and future exacerbation forecasting utilizing regression-based ML models, Bidirectional LSTM longitudinal prediction, and the integrated ensemble architecture. The performance of model is analyzed by utilizing Accuracy, Precision, Recall, F1-score and confusion matrix evaluation. Among the regression-based classification of COPD severity models, the SVM accomplished the optimal model efficiency with accuracy of 95.34%, 95.32% F1-score, precision of 95.32% and recall of 95.34%. The RF model performed with accuracy and F1-score of 92.72% and 92.71%, while GB performed with accuracy of 93.69% and F1-score of 93.64%. These outcomes illustrate that the SVM model facilitate outstanding multiclass COPD GOLD classification capacity compared with other regression learning models.

COPD GOLD Class	Precision	Recall	F1-Score	Support
GOLD 1	0.96	0.97	0.97	438
GOLD 2	0.89	0.87	0.88	212

GOLD 3	0.87	0.91	0.89	204
GOLD 4	0.95	0.90	0.92	176
Accuracy	-	-	0.93	1030
Macro Average	0.92	0.91	0.92	1030
Weighted Average	0.93	0.93	0.93	1030

Table 3. Classification Report of RF-Based COPD GOLD Severity Classification Model

The class-wise performance of RF-based COPD GOLD severity classification is presented in Table 3 utilizing Precision, Recall, F1-Score and support metrics. The model illustrates strong classification capability through all COPD severity classes, accomplishing an overall reliability of 93% with balanced multiclass estimation performance.

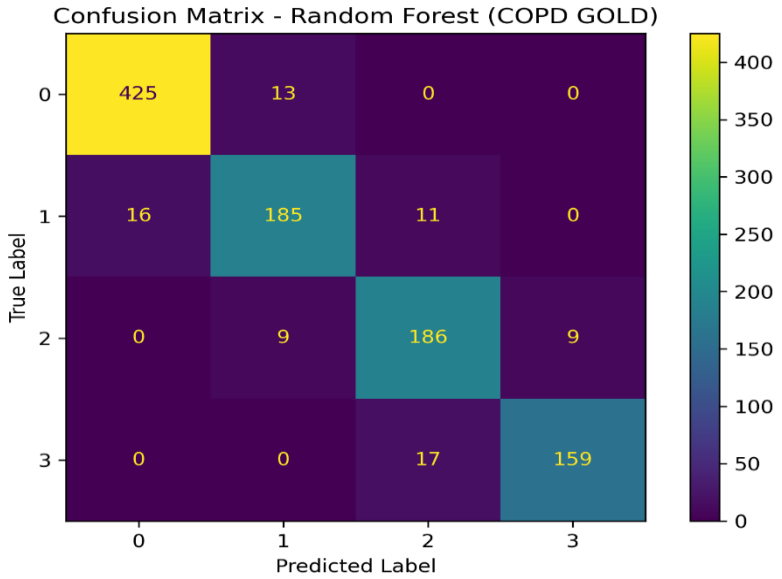

Figure 7. Confusion Matrix of RF-Based COPD GOLD Severity Classification Model

The confusion matrix of the RF-based classification of COPD severity is presented in Figure 7 for multiclass respiratory severity forecasting. Most samples are focused along the diagonal region, presenting strong class-wise categorization performance and accurate COPD GOLD level recognition. Small misclassifications were primitively noted between adjacent severity levels, mirroring resemblance in intermediate respiratory decline trends.

Table 4. Classification Report of SVM-Based COPD GOLD Severity Classification Model

COPD GOLD Class	Precision	Recall	F1-Score	Support
GOLD 1	0.97	0.99	0.98	438
GOLD 2	0.95	0.92	0.94	212
GOLD 3	0.93	0.93	0.93	204
GOLD 4	0.94	0.94	0.94	176
Accuracy	-	-	0.95	1030
Macro Average	0.95	0.94	0.95	1030
Weighted Average	0.95	0.95	0.95	1030

The class-wise performance analysis of SVM-based COPD GOLD severity classification is presented in Table 4 utilizing Precision, Recall, F1-Score and support metrics. The model attained superior multiclass categorization performance with an overall reliability of 95% illustrates robust capability in differencing between COPD severity levels from medical and spirometry features.

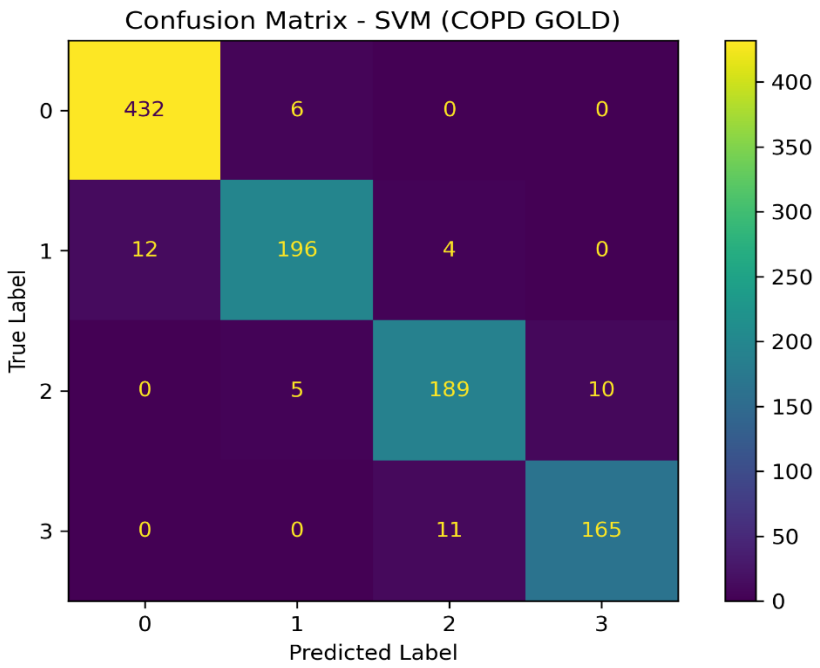

Figure 8. Confusion Matrix of SVM-Based COPD GOLD Severity Classification Model

The confusion matrix of the SVM-based classification of COPD severity is presented in Figure 8. The matrix illustrates robust diagonal dominance with high correct categorization rates for all GOLD classification, presenting robust multiclass estimation capacity. Small misclassifications were primitively noted between adjacent severity stages, mirroring medically resemble respiratory trajectory characteristics.

Table 5. Classification Report of the GB-Based COPD GOLD Severity Classification Model

COPD GOLD Class	Precision	Recall	F1-Score	Support
GOLD 1	0.96	0.97	0.97	438
GOLD 2	0.90	0.87	0.88	212
GOLD 3	0.91	0.91	0.91	204
GOLD 4	0.94	0.96	0.95	176
Accuracy	-	-	0.94	1030
Macro Average	0.93	0.93	0.93	1030
Weighted Average	0.94	0.94	0.94	1030

The class-wise performance analysis of GB-based COPD GOLD severity classification is presented in Table 5 utilizing Precision, Recall, F1-Score and support metrics. The model illustrates strong classification capability through all COPD severity classes with an overall accuracy of 94%, illustrating efficient discrimination of COPD severity stages utilizing medical spirometry-based respiratory attributes.

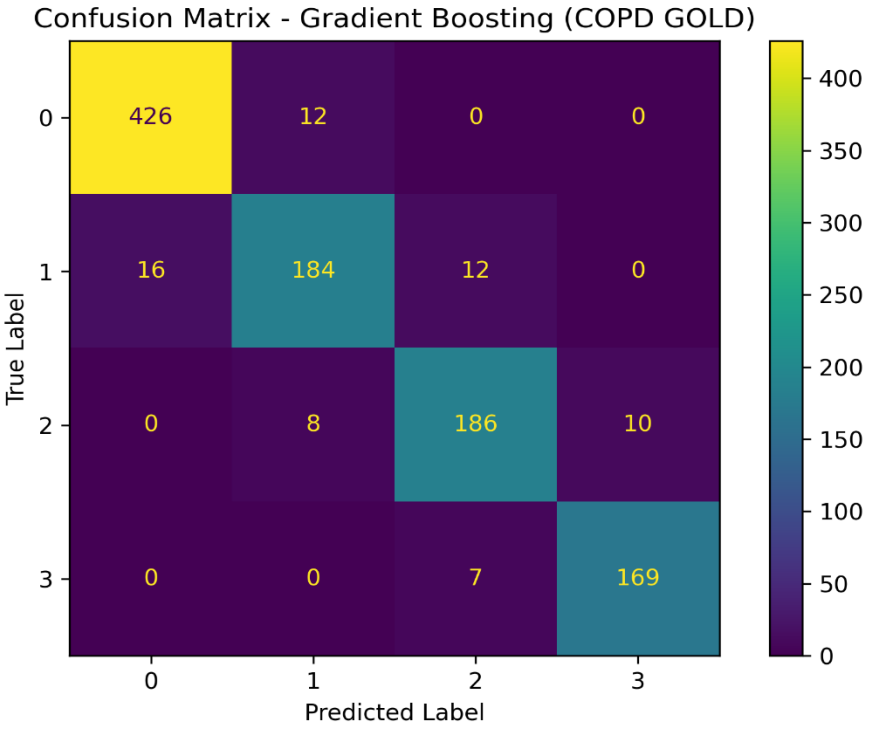

Figure 9. Confusion Matrix of GB-Based COPD GOLD Severity Classification Model

The confusion matrix of the GB-based classification of COPD severity is presented in Figure 9. Most samples are focused along the diagonal region, presenting strong class-wise categorization performance. Restricted misclassifications are noted mainly between neighboring severity stages, presenting effective multiclass respiratory severity discrimination utilizing the developed boosting architecture.

Table 6. Comparative Performance Analysis of Regression-Based COPD GOLD Classification Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest (RF)	0.9272	0.9276	0.9272	0.9272
Gradient Boosting (GB)	0.9369	0.9365	0.9369	0.9366
Support Vector Machine (SVM)	0.9534	0.9532	0.9534	0.9533

The performance of RF, SVM, and GB for COPD GOLD severity classification utilizing standardized performance metrics. Among the analyzed regression-based models, The SVM accomplished the highest overall performance, illustrating dominated multiclass COPD severity forecasting capacity and enhanced classification stability across respiratory severity stages.

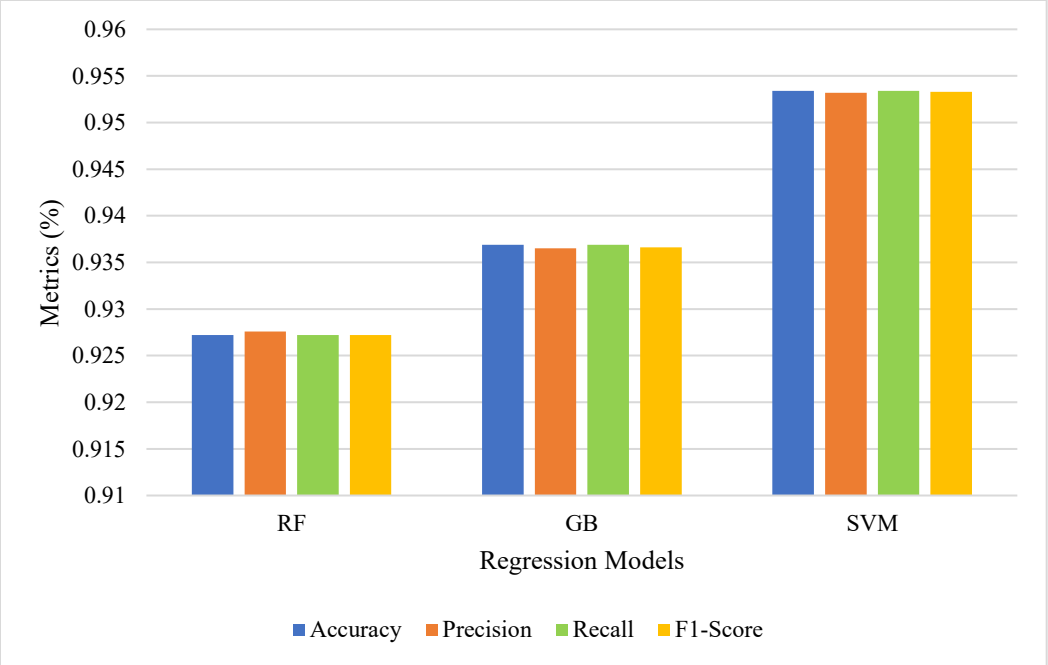

Figure 10. Comparative Performance Analysis of Regression-Based Models

The comparative performance analysis of regression-based ML models for COPD GOLD severity classification is presented in Figure 10 utilizing accuracy, precision, recall, F1-score metrics. The SVM model attained the optimal classification performance over RF and GB, illustrating enhanced predictive accuracy and multiclass respiratory severity discrimination.

For temporal disease trajectory evaluation, the developed Bidirectional LSTM architecture efficiently mastered longitudinal respiratory drop patterns from sequential patient visits. The LSTM model accomplished 95.08% of accuracy, 95.17% of precision, 95.08% of recall and 95.10% of F1-score in future exacerbation risk forecasting, illustrating strong capacity in predicting COPD progression utilizing longitudinal medical records of patients.

Table 7. Classification Report of Bidirectional LSTM-Based Future Exacerbation Prediction Model

Progression Class	Precision	Recall	F1-Score	Support
Class 0	0.95	0.95	0.95	1122
Class 1	0.90	0.91	0.90	780
Class 2	0.99	0.98	0.98	1188
Accuracy	-	-	0.95	3090
Macro Average	0.94	0.95	0.95	3090
Weighted Average	0.95	0.95	0.95	3090

The class-wise performance analysis of Bidirectional LSTM-based longitudinal model is represented in Table 7 for future FEV1 exacerbation severity forecasting utilizing Precision, Recall, F1-score and support metrics. The three forecasting classes corresponds to mild (Class 0), moderate (Class 1), and severe (Class 2) future respiratory decline levels extracted from temporal FEV1 trajectory trends rather than direct classification of COPD GOLD severity.

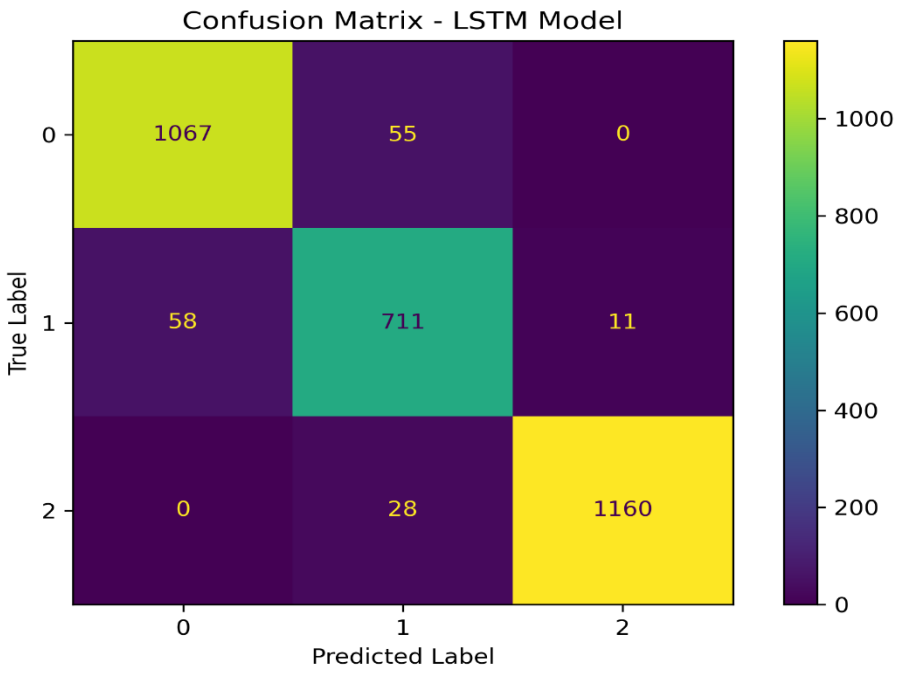

Figure 11. Confusion Matrix of Bidirectional LSTM-Based Future Exacerbation Prediction Model

The confusion matrix of the bidirectional LSTM-based longitudinal prediction model for future FEV1 exacerbation severity prediction is presented in Figure 11 utilizing temporal respiratory trajectory data. The matrix illustrates robust temporal forecasting capacity with high optimal classification rates across all exacerbation severity classifications and comparatively lower inter-class misclassification trends.

The integrated ensemble architecture hybrid the probability results created from the SVM and LSTM models utilizing modified meta-attribute derivation and stacked ensemble mastering. By hybridizing regression-based classification of severity and longitudinal trajectory predicting. The developed integrated model attained the outstanding overall performance with accuracy, precision, recall and F1-score of 95.63%, 95.63%, 95.63%, and 95.62% respectively. The confusion matrix evaluation further illustrated enhanced class-level forecasting stability and decreased misclassification cross COPD severity and progression classes.

Table 8. Classification Report of the Proposed Hybrid Ensemble COPD Prediction Framework

COPD GOLD Class	Precision	Recall	F1-Score	Support
GOLD 1	0.99	0.99	0.99	438
GOLD 2	0.96	0.97	0.96	212
GOLD 3	0.90	0.91	0.90	204
GOLD 4	0.92	0.91	0.91	176
Accuracy	-	-	0.96	1030
Macro Average	0.94	0.94	0.94	1030
Weighted Average	0.96	0.96	0.96	1030

The class-wise performance analysis of the developed integrated ensemble COPD prediction architecture is presented in Table 8 utilizing precision, recall, F1-score and support metrics. The architecture hybrids the optimally performing SVM with Bidirectional LSTM longitudinal prediction model to enhance COPD GOLD severity classification and future respiratory exacerbation forecasting through probability-level ensemble learning and longitudinal attribute hybridization.

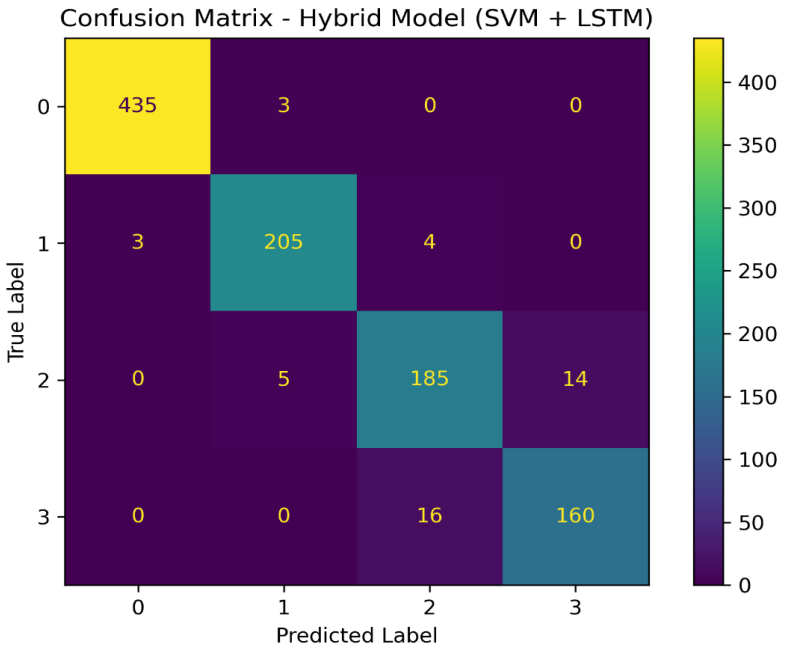

Figure 12. Confusion Matrix of the Proposed Hybrid Ensemble COPD Prediction Framework

The confusion matrix of the developed hybrid ensemble COPD prediction architecture is presented in Figure 12 which is integrating the SVM and Bidirectional LSTM longitudinal prediction model. The matrix illustrates enhanced class-wise estimation stability with robust diagonal dominance and decreased misclassification across COPD severity levels, emphasizing the effectiveness of probability-level ensemble combination for reliable respiratory severity and progression forecasting.

Table 9. Comparative Performance Analysis Between Existing COPD Prediction Models and the Proposed Hybrid Framework

Models	Accuracy	Precision	Recall	F1-score
COPD-DTL	93	92.80	93.60	93.20
COPD-XGB	92	90	91	92
COPD-MLVM	89.6	93	76	84
COPD-MLDL	87.70	88.70	87.70	87.65
COPD-SVM-LSTM	95.63	95.63	95.63	95.62

The predictive performance of prior COPD prediction models with the developed integrated ensemble architecture is presented in Table 9 utilizing accuracy, precision, recall and F1-score as performance metrics. The developed architecture attained dominance overall performance by combining regression-based COPD GOLD severity classification with Bidirectional LSTM-based longitudinal respiratory trajectory prediction, illustrating enhanced predictive accuracy and multiclass respiratory risk discrimination.

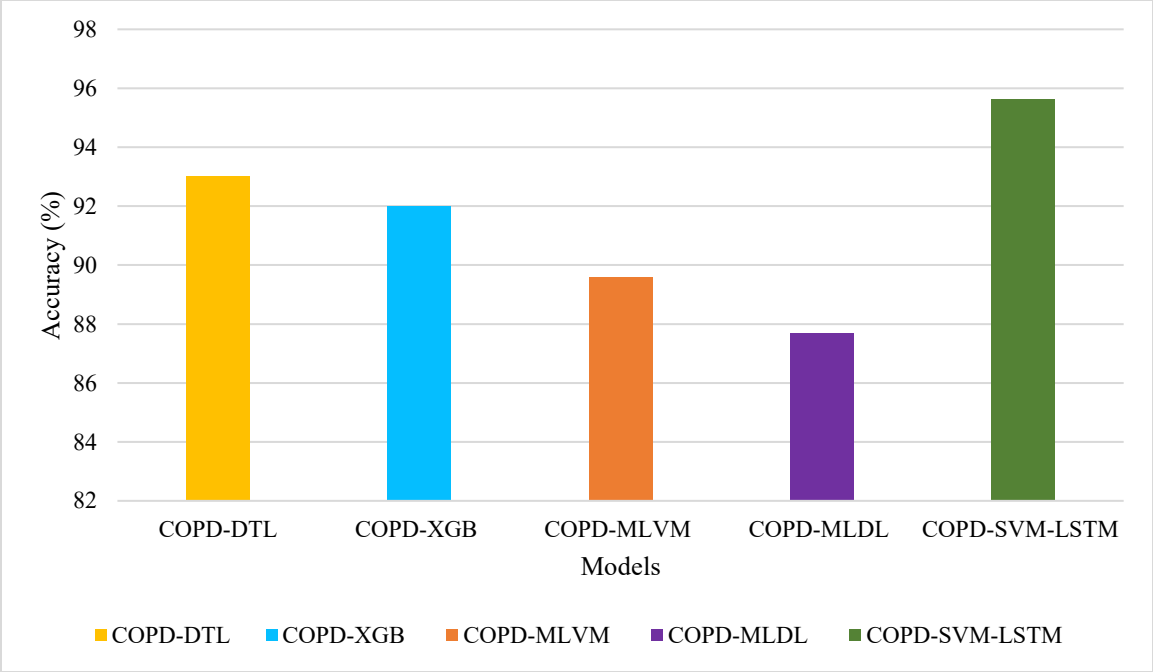

Figure 13. Comparative Analysis of Accuracy Between Existing COPD Prediction Models and the Proposed Hybrid Framework

The comparative evaluation of accuracy between prior COPD forecasting methods and the developed integrated ensemble architecture is presented in Figure 13. The developed COPD-SVM-LSTM architecture attained the supremacy of overall predictive accuracy, illustrating the effectiveness of hybrid regression-based classification of COPD severity with longitudinal deep learning-based respiratory trajectory prediction for enhanced medical forecasting performance.

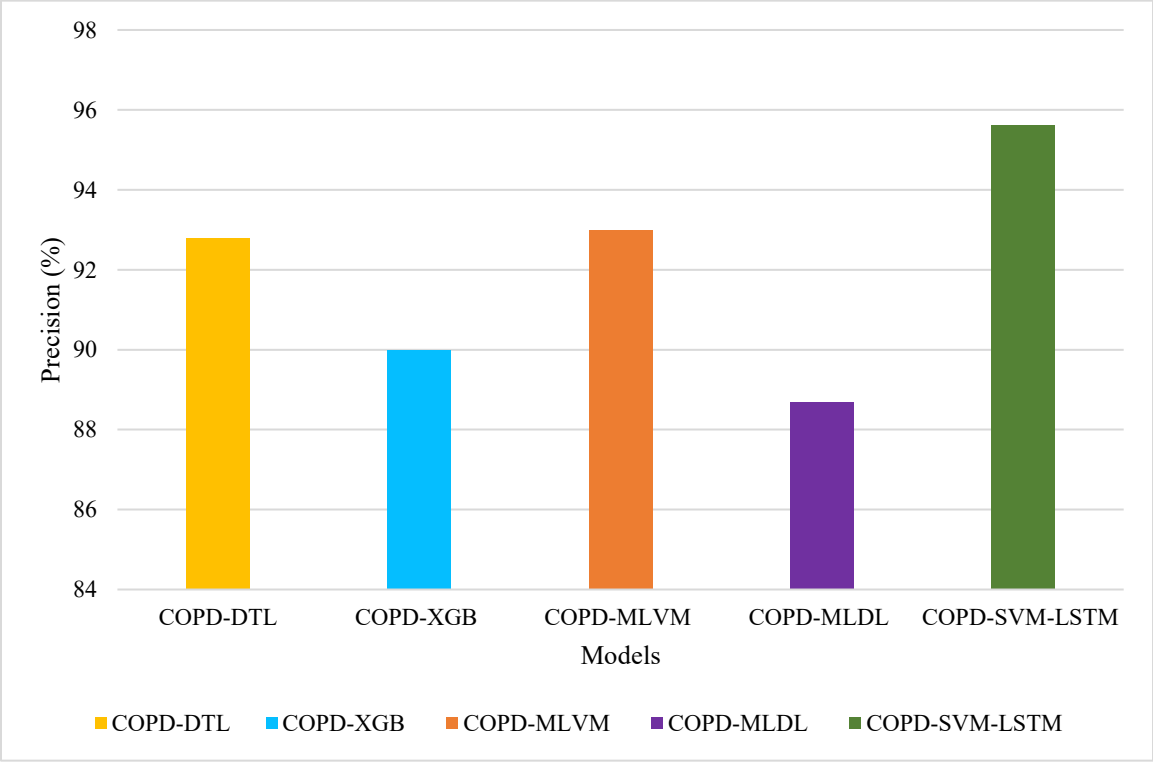

Figure 14. Comparative Analysis of Precision Between Existing COPD Prediction Models and the Proposed Hybrid Framework

The comparative evaluation of precision between prior COPD forecasting methods and the developed integrated ensemble architecture is presented in Figure 14. The developed COPD-SVM-LSTM architecture attained the supremacy precision performance, revealing enhanced prediction stability and deceased false-positive respiratory classification of severity through hybrid regression and longitudinal deep learning-based ensemble learning.

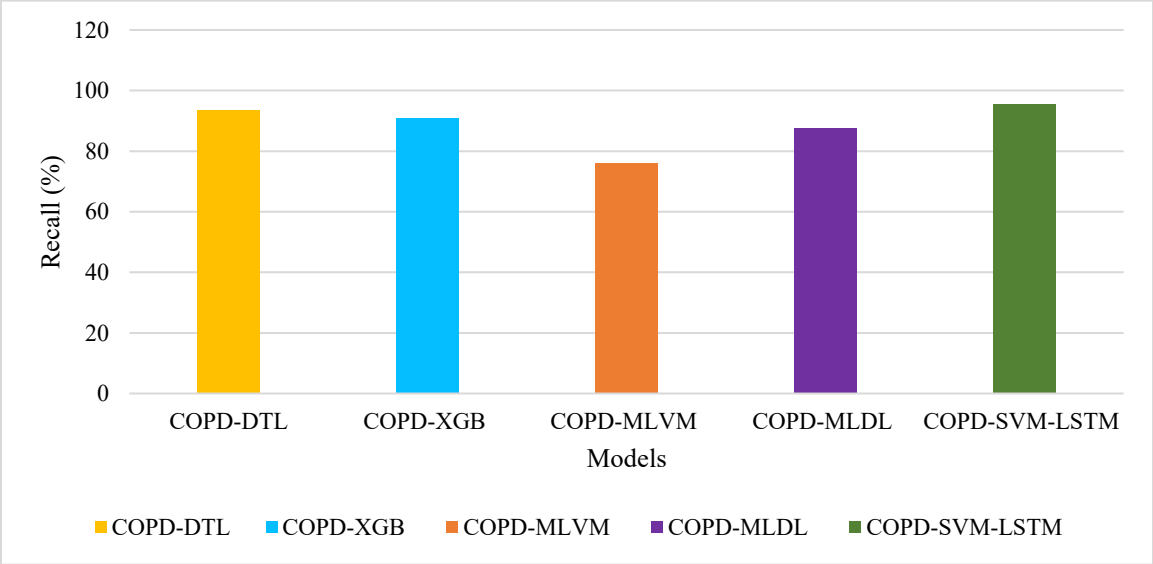

Figure 15. Comparative Analysis of Recall Between Existing COPD Prediction Models and the Proposed Hybrid Framework

The comparative evaluation of recall between prior COPD forecasting methods and the developed integrated ensemble architecture is presented in Figure 15. The developed COPD-SVM-LSTM architecture attained the supremacy in recall performance, illustrating improved capability in correctly recognizing COPD severity and respiratory exacerbation cases with decreased false-negative forecasting.

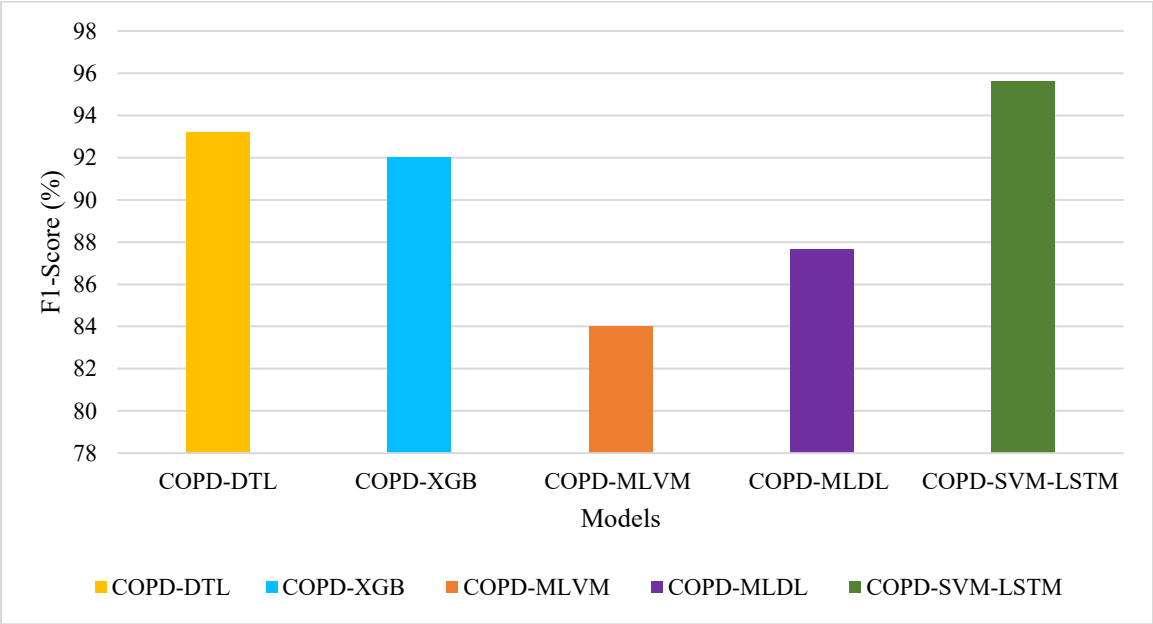

Figure 16. Comparative Analysis of F1-Score Between Existing COPD Prediction Models and the Proposed Hybrid Framework

The comparative evaluation of F1-score between prior COPD forecasting methods and the developed integrated ensemble architecture is presented in Figure 16. The developed COPD-SVM-LSTM architecture attained the supremacy in F1-score, presenting balanced precision and recall performance with enhanced multiclass respiratory severity classification and longitudinal trajectory forecasting capability.

Overall, the empirical outcomes ensures that the developed integrated architecture efficiently enhances COPD severity assignment and future exacerbation forecasting by combining ML-based classification and Deep learning-based longitudinal prediction methods.

5. Conclusion

The developed integrated AI-architecture hybrids the best-performing regression-based classification of COPD severity model with a Bidirectional LSTM-based future exacerbation forecasting architecture utilizing demographic, physiological, spirometry and temporal patient records. Among the analyzed regression models, The SVM accomplished the highest COPD GOLD classification performance and was combined with longitudinal deep learning architecture via ensemble stacking and meta-attribute mastering. The developed integrated architecture efficiently enhanced predictive accuracy for both classification of COPD severity and future respiratory drop prediction. Empirical outcomes illustrated strong performance with improved classification stability and decreased misclassification across COPD trajectory classes. Overall, the architecture facilitates an effective medical decision support method for early recognition of COPD patients at high-risk, providing timely assistance, individualized disease management, and adaptive respiratory progression surveillance. The proposed architecture also introduces a strong base for advanced exacerbation risk evaluation and modified treatment response estimation using temporal patient surveillance and therapeutic trajectory patterns.

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