

A Comparative Analysis of Machine Learning and Deep Learning Models Incorporating Attention Mechanisms for Asthma Prediction

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Abstract

Asthma is a respiratory disease that affects millions of people globally. Early detection can facilitate timely intervention to prevent complications and mortality. If asthma is predicted early and accurately, it will help in timely intervention and effective management. But the conventional method of asthma diagnosis often struggles to understand complex relationships between patient symptoms, triggers, and demographic factors, leading to less accurate predictions. To address this gap, this study carried out a comparative analysis of machine learning and deep learning-based asthma prediction models, introducing the attention mechanism to enhance the deep learning model. With the use of the Kaggle dataset, this study trained three machine learning algorithms, which include a decision tree, a random forest, Extreme Gradient Boosting (XGBoost), and a deep learning Bidirectional Long Short-Term Memory (Bi-LSTM) with an attention layer. The method utilized in this study follows a unique pipeline, which includes the data collection, data preprocessing, exploratory data analysis, model development, model training, and model evaluation based on accuracy, precision, recall, and F1-scores. During the data preprocessing, the study observed data imbalance in the target variable, and the Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the dataset. The result from this study experiment shows that the Bi-LSTM + Attention model outperformed all the compared machine learning models across all evaluation metrics used, by achieving the highest accuracy of 96%, while XGBoost, random forest, and decision tree achieved accuracies of 95%, 94%, and 93%, respectively. The attention mechanism introduced to the BiLSTM model in this study significantly improved the deep learning model's ability to focus on the most relevant features, enhancing interpretability and clinical trust. The findings demonstrate that the attention-enhanced Bi-LSTM model can serve as a reliable component of a clinical decision support system, assisting healthcare practitioners in early asthma detection and risk stratification, thereby enabling timely intervention and improved patient management.

Keywords: Asthma, Prediction, Machine Learning, Deep Learning, Attention Mechanism.

Introduction

Asthma is a chronic respiratory disease with symptoms of frequent wheezing, breathlessness, and tightness of the chest (Sarikloglou et al., 2024). Although Asthma is a non-communicable disease, it poses significant health and economic challenges globally. The detection of Asthma early and accurately is important for its effective management (Hang et al., 2025). The traditional way of detecting Asthma is mostly based on symptom assessment, which may not capture complex and non-linear interactions among environmental, physiological, and behavioural factors that influence asthma (Pavord et al., 2023).

Artificial Intelligence (AI) techniques like Machine Learning and Deep Learning have recently advanced significantly; these advancements have revolutionized medical diagnosis and disease prediction (Soori et al., 2023). Different machine learning algorithms, such as Decision Tree (DT), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), have been utilized by different researchers in the identification of hidden patterns to predict and detect different diseases, and have produced good performance in handling structured clinical data and identifying hidden patterns (Sheth et al., 2022). Also, deep learning models like the Bidirectional Long Short-Term Memory (Bi-LSTM) have also performed well in modeling sequential and contextual dependencies in patient data, when used by different researchers (Da-Silva et al., 2023).

Despite the advancement of these machine learning and deep learning techniques, many existing studies rely only on static symptom assessment and spirometry tests, which fail to adequately capture the complex, nonlinear interactions between patient symptoms, environmental triggers, and demographic factors. Existing machine learning models, while effective for structured clinical data, often treat features independently and lack the capacity to model temporal dependencies inherent in symptom–trigger progression. Also, many deep learning–based asthma prediction studies focus primarily on improving predictive accuracy without addressing the issue of interpretability, which is crucial for clinical trust and adoption. The “black-box” nature of deep learning models limits their usefulness in healthcare settings, where clinicians require insight into which symptoms or triggers contribute most significantly to predictions (Patil et al., 2024). There exists a research gap in developing an asthma prediction framework that simultaneously captures temporal feature relationships and provides interpretable decision-making. This study addresses this gap by integrating an attention mechanism with a Bi-LSTM model, enabling the model to focus on clinically relevant symptom–trigger interactions while improving predictive performance.

This study introduces the attention mechanism interpretability of the Bi-LSTM model by introducing the attention mechanism to the Bi-LSTM model to identify influential features or symptoms contributing to asthma prediction. The introduced attention mechanism not only improves the performance of the model but also provides insight into the decision-making process, which is important for clinical trust and transparency. This study utilized the Kaggle asthma dataset to train three machine learning algorithms, which include DT,

RF, XGBoost, and a deep learning model, which is Bi-LSTM with an attention mechanism. These models were evaluated with the use of standard evaluation metrics, which are accuracy, precision, recall, and F1-scores, alongside confusion metrics to visualize the performance of the models. The main aim of this study is to identify the most effective and interpretable approach for asthma prediction. This study contributes to the growing application of AI in healthcare by demonstrating the ability of an attention-based deep learning model to improve the accuracy and explainability of medical prediction systems.

Literature Review

Bonthada et al. (2024) carried out research that utilized a machine learning approach to improve the reliability of spirometry, which is a major tool for diagnosing asthma. The study utilized the Volume-Time and Flow-Volume graph data to train a machine learning model to detect errors during spirometry tests. The machine learning model was able to achieve 94% accuracy.

Pyingkodi et al. (2023) utilized the machine learning approach for asthma risk prediction. The study utilized the Peak Expiratory Flow Rate (PEFR), indoor particulate matter (PM), and weather data. The study utilized Convolutional Neural Network (CNN) and compared the performance to deep neural networks (DNN), K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). The result shows that the CNN, SVM, and KNN achieved improved accuracy over the DNN.

Ayus et al. (2023) focused on a comparative analysis of machine learning and deep learning algorithms to predict asthma development in children. The study utilized the PRISMA guidelines and collected relevant studies from 2011 to 2021, retrieved from Google Scholar, ScienceDirect, and PubMed. These studies were reviewed carefully, and the results show that the Artificial Neural Networks (ANN) and Support Vector Machines (SVM) outperform other compared algorithms.

Ekpo et al. (2023) focused on the prediction of the air quality index across ten Chinese Cities. Pollutant information containing data (PM_{2.5}, PM₁₀, SO₂, NO₂, CO, and O₃) was collected daily from these cities between 2013 and 2021. The collected dataset was used to train the models after preprocessing. The model used includes RNN, Bi-GRU, BiLSTM, CNN-BiLSTM, Conv1D-BiLSTM, and XGBoost, and was evaluated using MSE, RMSE, MAE, SMAPE, and IA. The conclusion from the study shows that the XGBoost outperforms all other compared algorithms, achieving over 90% accuracy.

Lopez et al. (2023) focused on the application of machine learning and deep learning techniques on asthma prediction. The study utilized data from 2,682 hospitalized patients (777 with asthma, 1,905 with COPD). The study compared the performance of the multilayer perceptron (MLP) with other machine learning models. The result shows that the MLP outperformed the machine learning models, achieving a high accuracy of over 90%.

Haque et al. (2022) carried out research on asthma prediction, using the Fragmented Grid Search (FGS) method. The study utilized the DNN algorithms on the asthma dataset, where different optimization algorithms were also tested. The experimental result shows that the

proposed DNN algorithm with Adam optimizer was able to outperform all other compared algorithms, achieving the best accuracy of 96%.

Soni et al. (2022) utilized a hybrid of Spatial Transformer Network (STN) and CNN to perform lung disease prediction. The study utilized the chest X-ray images collected from the Kaggle NIH Chest X-ray repository. The proposed hybrid model was able to achieve an accuracy of 69%, outperforming the compared vanilla grey model with 67.8% accuracy and the CNN model with 63.8% accuracy.

Mahammad & Kumar (2022) researched asthma prediction using a machine learning approach. The study utilized the decision tree algorithms on datasets collected from data.world and the California Department of Public Health Open Data Portal. The experimental result shows that the proposed decision tree-based model was able to achieve a high outperformance of over 90% accuracy.

Phan et al. (2021) focused on the prediction of sleep disorders among asthma patients. The study utilized both machine learning and deep learning algorithms on a dataset that contains 1 million samples in the Taiwan National Health Insurance Research Database (2002–2010). The machine learning algorithms used include KNN, SVM, and Random Forest, while the deep learning algorithms used include RNN, LSTM, GRU, and CNN. The experimental result shows that the KNN, SVM, Random Forest, RNN, LSTM, GRU, and CNN achieved 0.798, 0.793, 0.813, 0.744, 0.815, 0.782, and 0.951 accuracies, respectively.

Ho et al. (2021) researched asthma prediction using an Optimized Deep Neural Network Regression (DNNR). The study used a dataset containing 1,010 Asthma Control Test (ACT) scores from 10 users. The dataset has ten features, which include five weather (temperature, humidity, air pressure, UV index, wind speed) and five demographics (age, gender, outdoor job, outdoor activity, and location). The experimental result shows that the proposed DNN model achieved 94% accuracy, MAE=0.20, and MSE=0.09.

Based on the studies that have been reviewed in this study, we observed that different machine learning and deep learning models have been utilized for asthma prediction, and none have utilized the attention mechanism for asthma prediction, which has the ability to enhance feature interpretability and model focus. Additionally, we observed that most previous studies often rely on single standalone algorithms, without considering comparative performance analysis between classical machine learning and attention-based deep learning models. This study addresses these gaps by introducing a Bi-LSTM with an Attention mechanism and comparing its predictive performance with machine learning algorithms, which include Decision Tree, Random Forest, and XGBoost models, using a balanced Kaggle dataset.

Table 1: Summary of Related Asthma Prediction Studies

Author (Year)	Algorithm(s) Used	Key Finding	Limitation
Bonthada et al. (2024)	Machine Learning (Spirometry-based model)	Achieved 94% accuracy in detecting errors in spirometry tests using Volume-Time and Flow-Volume data	Focused on spirometry error detection rather than direct asthma prediction
Pyingkodi et al. (2023)	CNN, DNN, KNN, SVM	CNN, SVM, and KNN outperformed DNN in asthma risk prediction using PEFr and environmental data	Did not model temporal symptom progression or feature interpretability
Ayus et al. (2023)	ANN, SVM (Systematic Review)	ANN and SVM consistently outperformed other algorithms for childhood asthma prediction	Review-based study; no experimental validation or interpretability analysis
Ekpo et al. (2023)	RNN, Bi-GRU, BiLSTM, CNN-BiLSTM, XGBoost	XGBoost achieved over 90% accuracy in air quality prediction relevant to respiratory health.	Focused on the air quality index, not direct asthma diagnosis
Lopez et al. (2023)	MLP, Classical ML models	MLP achieved over 90% accuracy in predicting asthma and COPD outcomes	Lacked temporal modeling and attention-based interpretability
Haque et al. (2022)	DNN with Fragmented Grid Search	Optimized DNN with Adam optimizer achieved 96% accuracy	Limited interpretability and absence of an attention mechanism
Soni et al. (2022)	STN + CNN	Hybrid STN–CNN achieved 69% accuracy in lung disease classification from X-ray images	Low accuracy and focused on imaging data rather than clinical features.
Mahammad & Kumar (2022)	Decision Tree	The decision tree model achieved over 90% accuracy for asthma prediction	Single-model approach with limited generalization capability
Phan et al. (2021)	KNN, SVM, RF, RNN, LSTM, GRU, CNN	CNN achieved the highest accuracy (0.951) for sleep disorder prediction in asthma patients	No attention mechanism; task focused on comorbidity rather than asthma prediction
Ho et al. (2021)	Optimized DNN Regression	Achieved 94% accuracy using weather and demographic features	Small sample size and lack of feature-level interpretability
This Study	Bi-LSTM + Attention	Achieved 96% accuracy with improved interpretability and temporal feature learning	Relies on a publicly available dataset; real-time validation needed.

As shown in Table 1, existing studies have demonstrated the effectiveness of both machine learning and deep learning models for asthma-related prediction tasks. However, most prior works either rely on standalone algorithms, lack temporal modeling of symptom–trigger relationships, or fail to address the interpretability challenge associated with deep learning models. Unlike previous studies, this research integrates an attention mechanism with a Bi-LSTM architecture to capture sequential dependencies while providing feature-level interpretability, thereby addressing a key methodological gap in asthma prediction research.

Methodology

The methodology presents a stepwise approach for the developer and the evaluation of the asthma prediction model, incorporating machine learning and deep learning algorithms. The development process follows a unique approach, which includes data collection, data preprocessing, model building, model training, and model evaluation.

Data Collection

This dataset, which was utilized to train the machine learning and deep learning algorithms in this research, was collated from the Kaggle repository, which is a publicly available machine learning repository. The collected dataset contains relevant features to asthma diagnosis with both clinical and demographic features, which include Age, Gender, Symptoms, Triggers, and Diagnosis (0 = No Asthma, 1 = Asthma). The dataset structure and feature description are presented in Table 2.

Table 2: Dataset Sample

Age	Gender	Symptoms	Triggers	Diagnosis
56	Female	Shortness of breath	Dust	0
19	Female	Coughing	Cold air	0
76	Female	Shortness of breath	Dust	0
65	Male	Chest tightness	None	0
25	Male	Chest tightness	None	1
79	Female	No symptom	Dust	1
79	Male	Wheezing	Dust	0
28	Female	Wheezing	Pollen	0
7	Female	Chest tightness	Smoke	0
26	Male	Wheezing	None	0
57	Female	Coughing	Cold air	1
6	Female	Wheezing	Smoke	0
34	Female	Wheezing	Animal dander	0
42	Male	Wheezing	Cold air	1
6	Male	Wheezing	None	0
68	Female	Wheezing	None	0
64	Male	Coughing	Dust	0
25	Male	Shortness of breath	Dust	1
37	Female	Shortness of breath	None	0

Data Preprocessing

This study was performed on the collected dataset. This was done to ensure optimal performance of the machine learning and deep learning model. The data preprocessing process includes:

a. Exploratory Analysis and Correlation

This study conducts a descriptive analysis and visualizations to understand the distribution of the data. During this analysis, this study generated count plots such as Age distribution by diagnosis (Figure 3), Gender vs diagnosis (Figure 4), symptoms vs diagnosis (Figure 5), and Triggers vs diagnosis (Figure 6). These plots were generated to explore the relationships between *Age*, *Gender*, *Symptoms*, and *triggers* with *Diagnosis*. Additionally, this study generated a correlation heatmap (Figure 2) to identify highly correlated features, which may affect the performance of the proposed models, ensuring that there is no multicollinearity issues exist in the dataset.

b. Class Imbalance Analysis and SMOTE

The initial analysis carried out in this study shows that the dataset is slightly imbalanced, as shown in Figure 7. To address the problem of imbalance, which can affect the robustness and general performance of the models, this study utilized the Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic samples for the minority class. Figure 4 shows the diagnosis Distribution after SMOTE, showing the balanced dataset and ensuring that the models do not become biased toward the majority class.

c. Encoding and Feature Preparation

This study encoded the categorical features for the machine learning models with the use of label encoding; these categorical features include Gender, Symptoms, and Triggers. While for the deep learning model, this study creates a new text-based feature by concatenating Symptoms and Triggers. Tokenizer was used to tokenize the text sequence, and was padded to a uniform length for input into the Bidirectional LSTM (Bi-LSTM) model.

Model Development

This study developed two categories of models, which are

1. Classical Machine Learning Models, including decision trees, random forests, and XGBoost.
2. Deep Learning Model, which is the Bi-LSTM integrated with an Attention Mechanism. This study integrated the attention layer to assign different weights to the features, which allows it to focus on the most relevant symptoms and triggers influencing asthma diagnosis.

Model Training and Evaluation

The training of the models was done with 80% of the dataset, and the remaining 30% was used for the models' evaluation with the use of stratified sampling to preserve class distribution. This study utilized scikit-learn to train the machine learning models and *TensorFlow/Keras* to implement the deep learning model. After the model training, the model was further evaluated based on accuracy, precision, recall, and F1 scores. The

classification reports and confusion matrices were also generated to visualize the performance of each model. Additional plots were generated for the Bi-LSTM + Attention model to visualize training and validation accuracy and loss across epochs. This helped monitor convergence and detect overfitting.

Architecture Diagram

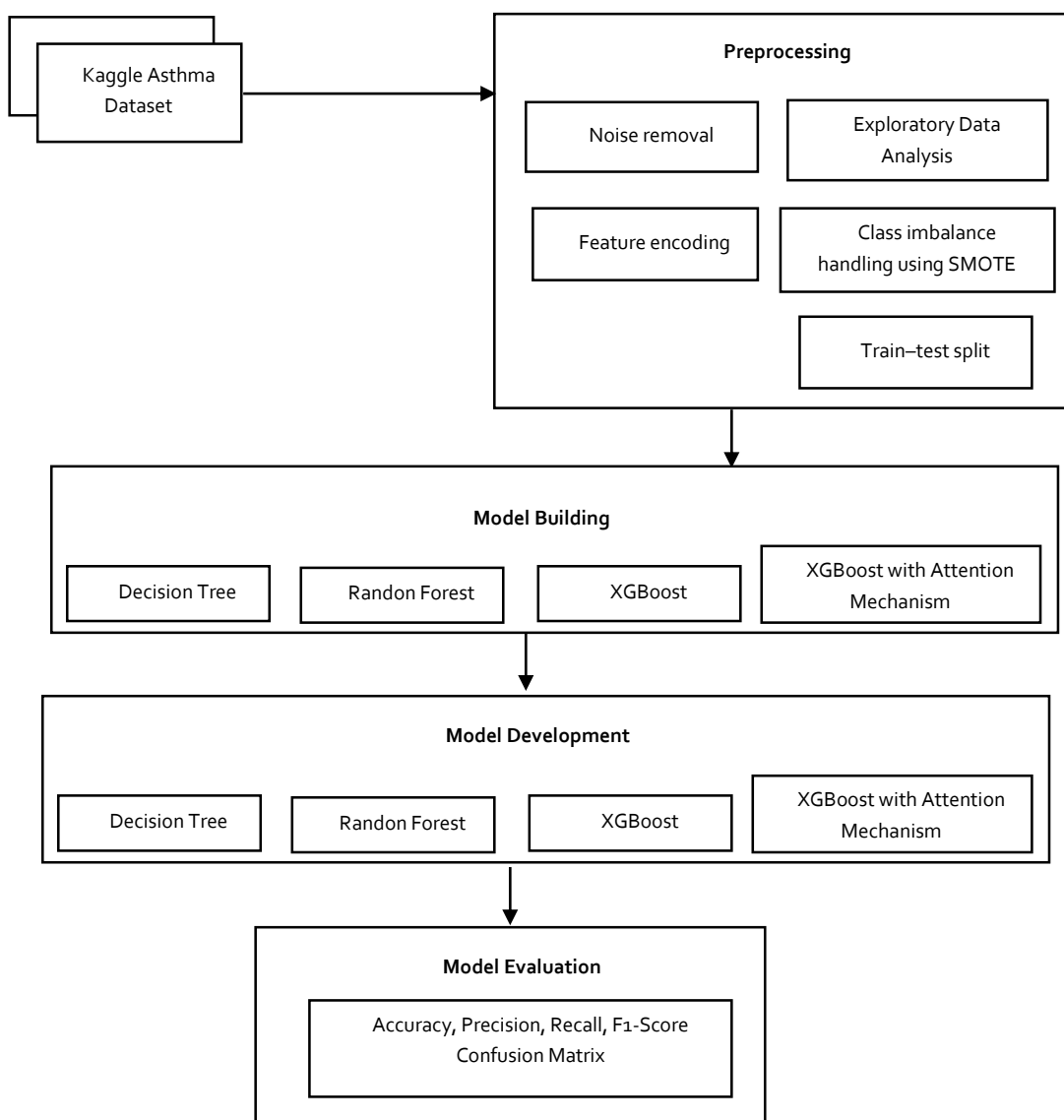


Figure 1: Proposed Asthma Prediction Architecture

Results

The result section presents the results obtained from the experiment on the developed machine learning and deep learning models for asthma prediction.

Exploratory Data Analysis

The correlation matrix for the encoded dataset is presented in Figure 2, revealing a moderate relationship between the features, suggesting that symptom patterns and exposure triggers are key determinants in predicting asthma disease. The relatively low correlations between each feature show that there is no multicollinearity, which ensures that all the features contribute independently to model learning.

The plot showing the Age Distribution by Diagnosis is presented in Figure 3. This plot shows that asthma is more common among younger age groups and decreases with age, aligning with the epidemiological evidence that asthma often occurs in early life and may decrease over time. Figure 4 presents the plot showing Gender vs Diagnosis, showing that asthma occurs slightly more in women than in men, aligning with clinical reports that asthma susceptibility can be influenced by hormonal and immunological factors. The plot showing the Symptoms vs Diagnosis is presented in Figure 5, showing that individuals with constant coughing, wheezing, or tightness of the chest are more likely to be diagnosed with asthma. Similarly, Figure 6, showing the plot of Triggers vs Diagnosis, shows that individuals exposed to dust, cold air, and smoke are more likely to be diagnosed with asthma, underscoring the environmental component of asthma onset and exacerbation.

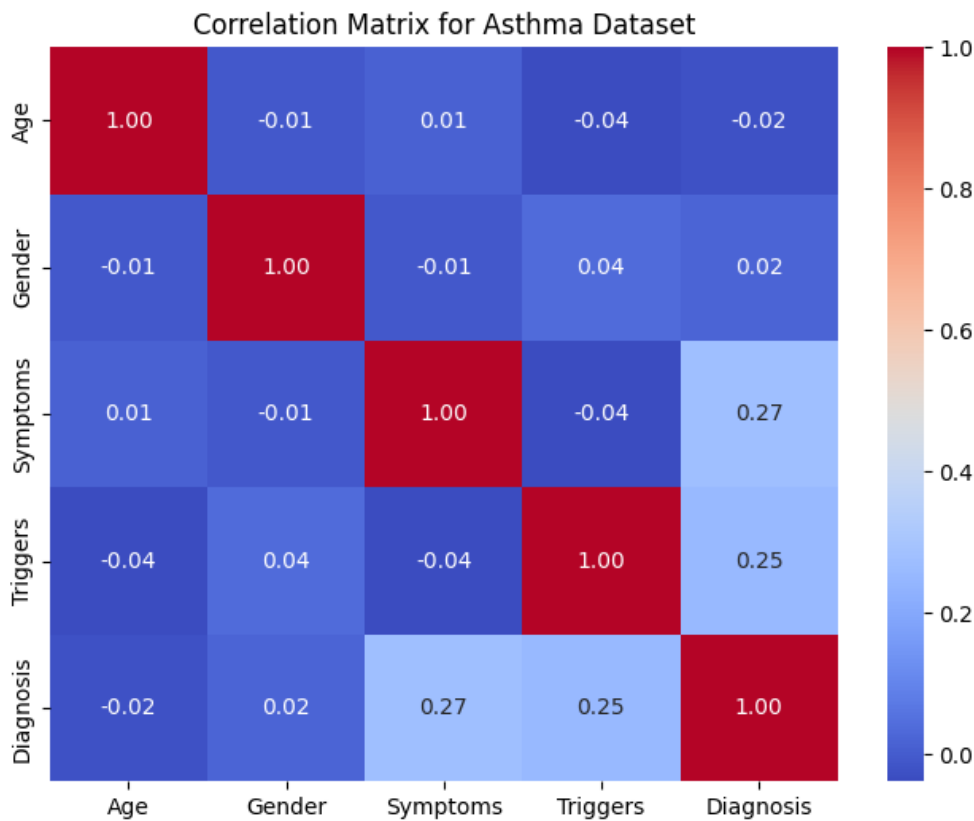


Figure 2: Correlation Matrix

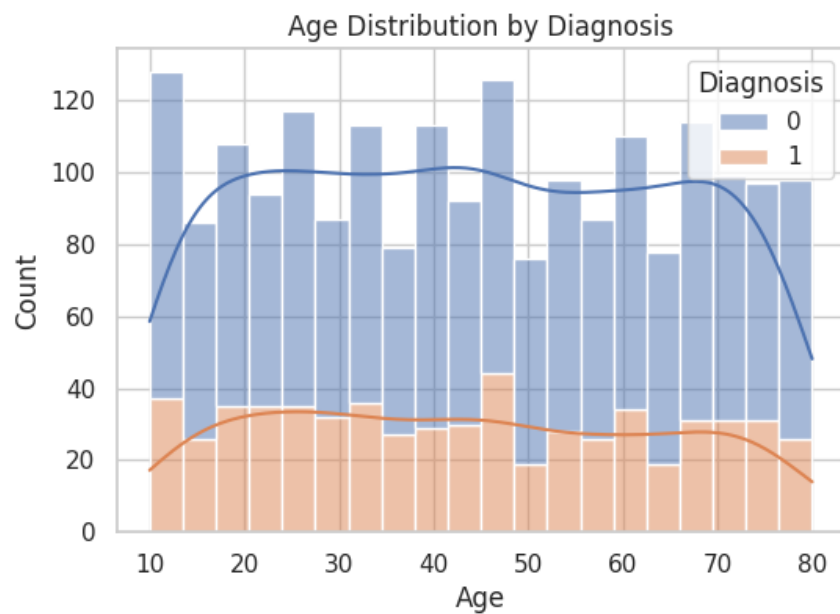


Figure 3: Age Distribution by Diagnosis

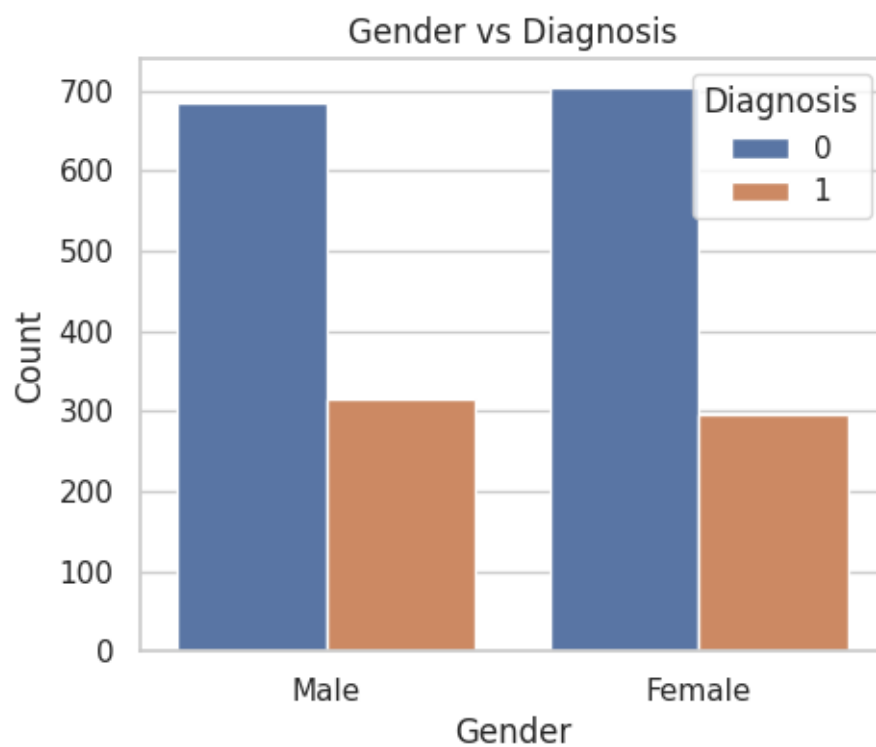


Figure 4: Gender vs Diagnosis

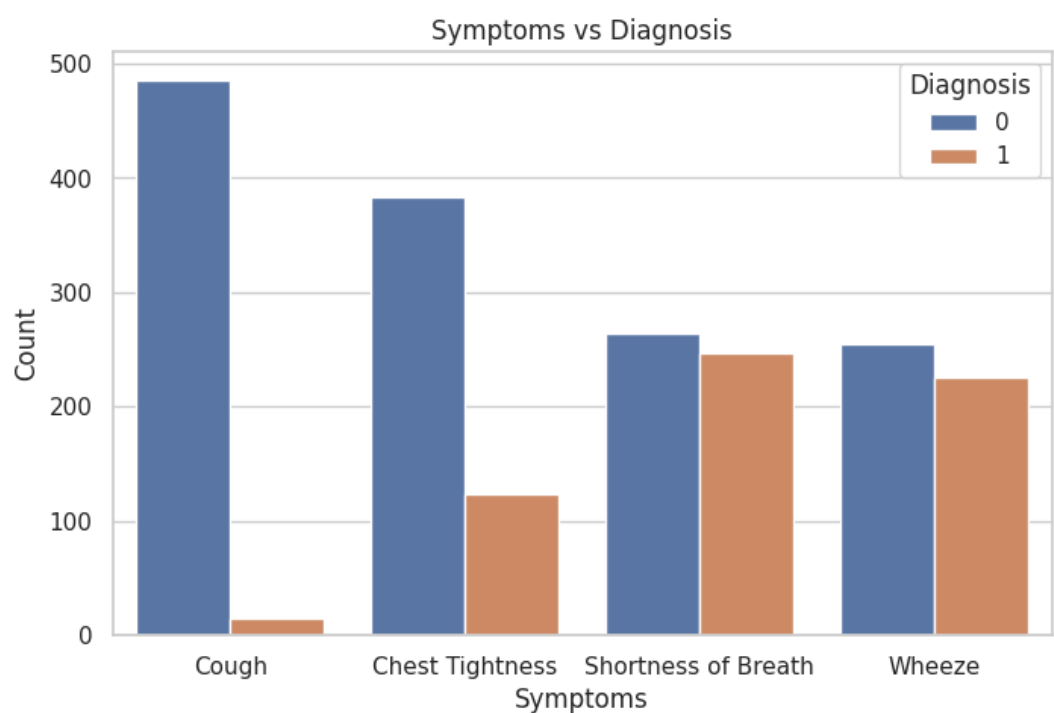


Figure 5: Symptoms vs Diagnosis

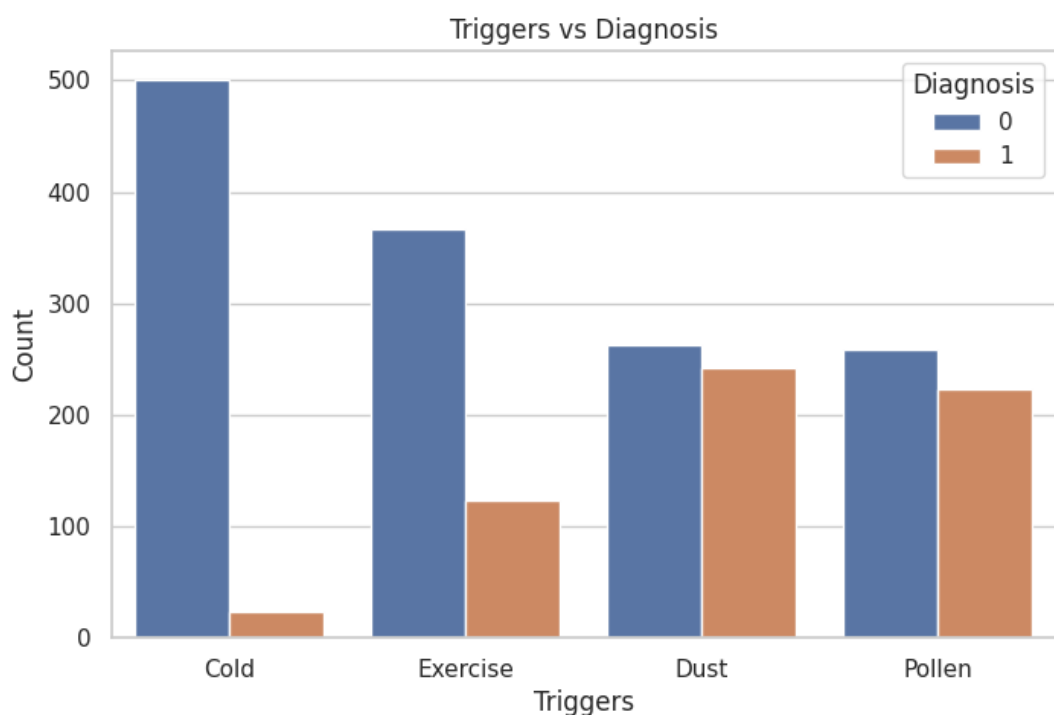


Figure 6: Triggers vs Diagnosis

Data Imbalance and Balancing

The diagnosis distribution before SMOTE is presented in Figure 7, showing that there is data imbalance between "No Asthma" (0) and "Asthma" (1) classes. This study applied the

SMOTE to address the data imbalance in order to prevent the model's bias toward the majority class. After applying the SMOTE, the second diagnosis distribution was carried out after SMOTE, as presented in Figure 8, demonstrating a balanced class distribution, which ensures fairness and robustness during model training.

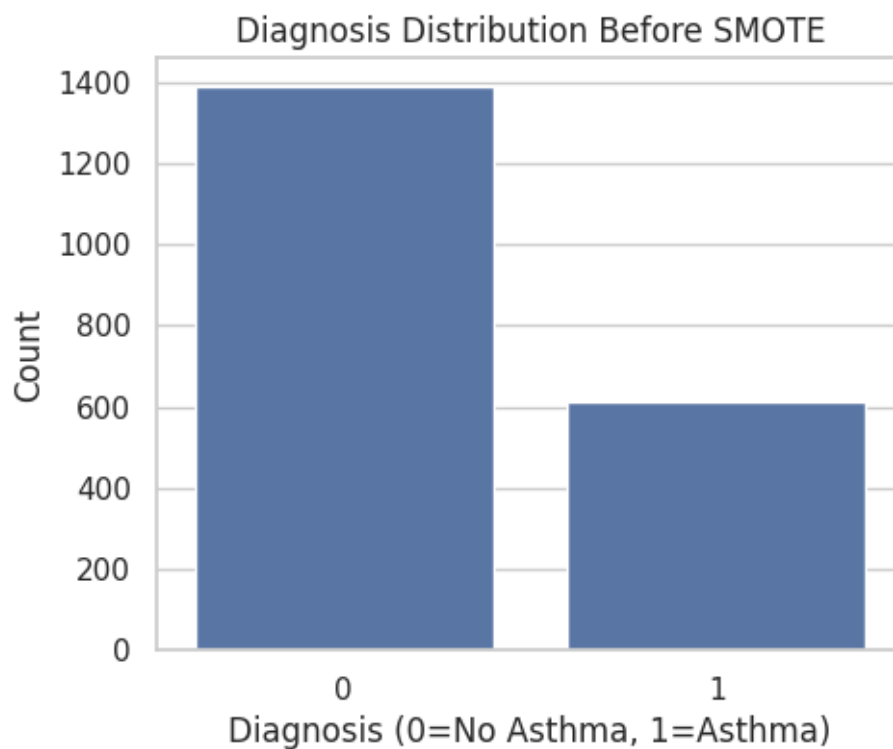


Figure 7: Diagnosis distribution before SMOTE

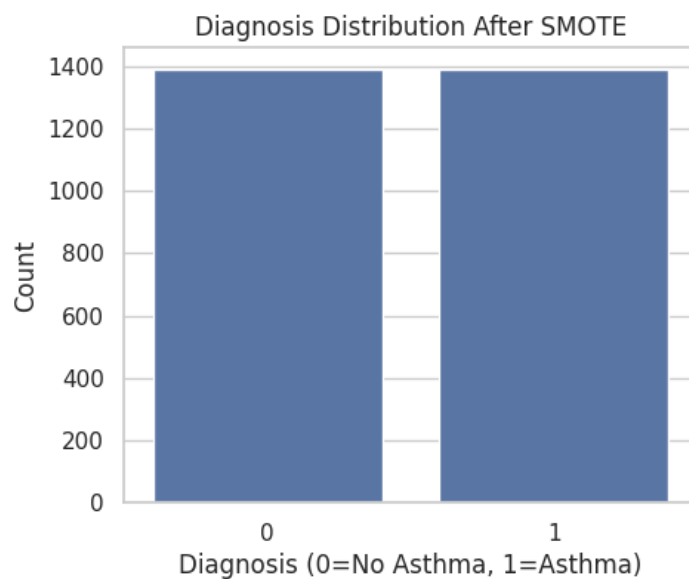


Figure 8: Diagnosis distribution after SMOTE

Model Training and Evaluation

This study developed and evaluated four different predictive models, including three machine learning models (decision tree, random forest, and XGB) and one deep learning model (Bi-LSTM with Attention). These models were trained on 80% of the pre-processed dataset, and the remaining 20% was used to evaluate the performance of the models based on their oaccuracy, precision, recall, and F1-score.

Decision Tree Model

The classification report for the decision tree model is presented in Table 3, while the confusion matrix is presented in Figure 9. The result shows that the decision tree model achieved an accuracy of 93%, precision of 94%, recall of 90%, and F1-score of 92%, showing its effectiveness in capturing the general pattern. However, the model’s moderate recall shows that it has a few misclassifications in positive asthma cases.

Table 3: Decision tree classification report

Class	Precision	Recall	F1-Score	Support
0	0.93	0.98	0.95	278
1	0.94	0.83	0.88	122
Accuracy	—	—	0.93	400
Macro Average	0.94	0.9	0.92	400
Weighted Average	0.93	0.93	0.93	400

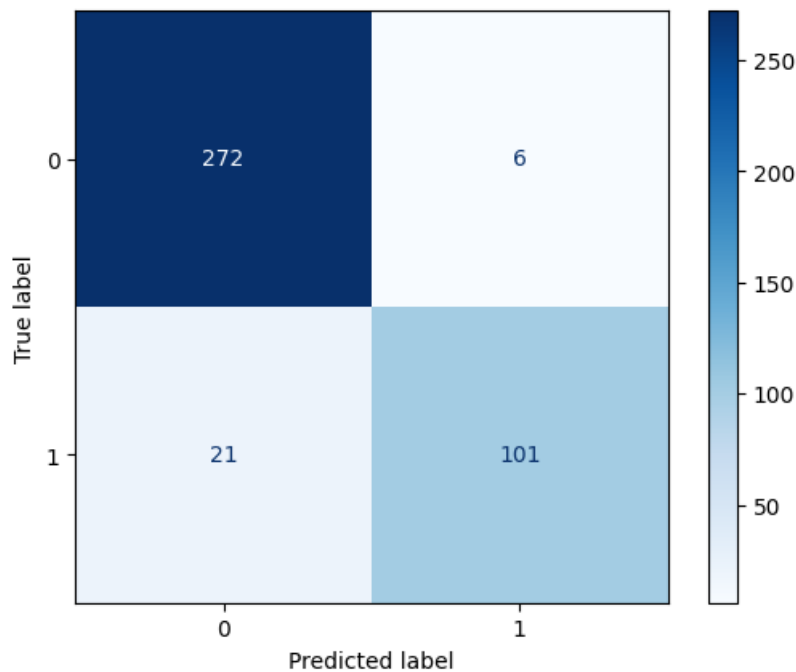


Figure 9: Decision tree confusion matrix

Random Forest Model

The classification report for the random forest model is presented in Table 4, while the confusion matrix is presented in Figure 10. The result shows that the random forest model achieved 94% accuracy, 94% precision, 92% recall, and 93% F1-score, which demonstrates random forest robustness through ensemble averaging, reducing overfitting, and enhancing generalization.

Table 4: Random Forest classification report

Class	Precision	Recall	F1-Score	Support
0	0.94	0.97	0.96	278
1	0.94	0.86	0.9	122
Accuracy	—	—	0.94	400
Macro Average	0.94	0.92	0.93	400
Weighted Average	0.94	0.94	0.94	400

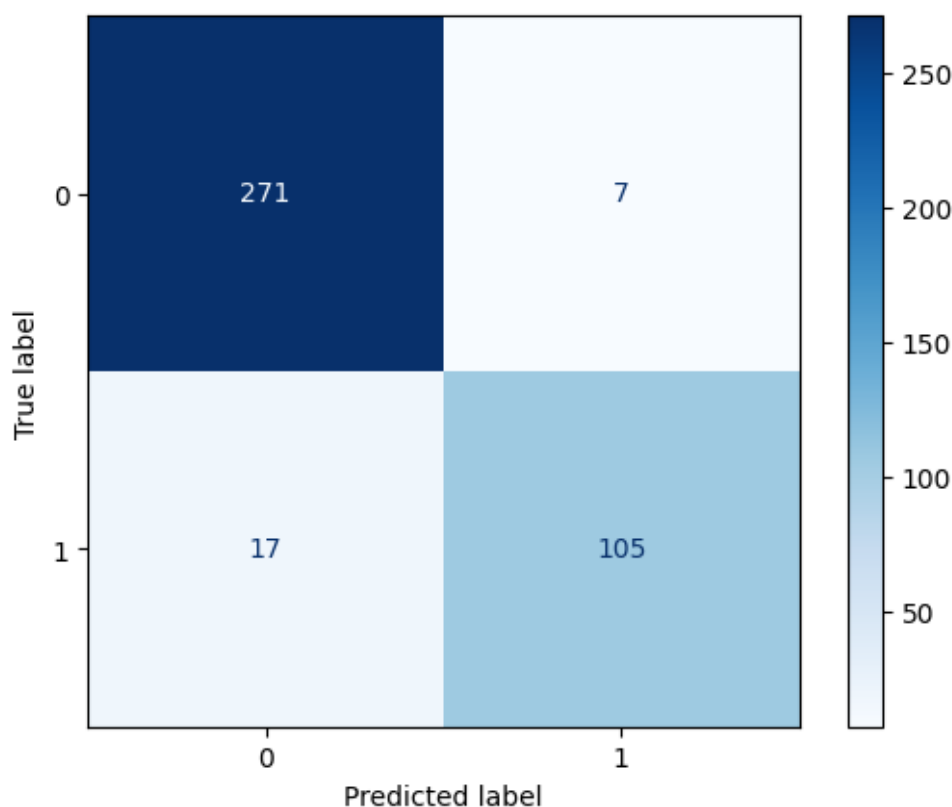


Figure 10: Random Forest Confusion Matrix

XGBoost Model

Figure 5 presents the classification report for the XGBoost model, while Figure 11 presents the model's confusion matrix. The result shows that the XGBoost model achieved 95%

accuracy, 95% precision, 93% recall, and 94% F1-score. This result shows the effectiveness of the gradient boosting framework in optimizing feature contributions and handling nonlinear patterns better than the compared traditional machine learning models.

Table 5: XGBoost Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.95	0.98	0.96	278
1	0.96	0.88	0.91	122
Accuracy	—	—	0.95	400
Macro Average	0.95	0.93	0.94	400
Weighted Average	0.95	0.95	0.95	400

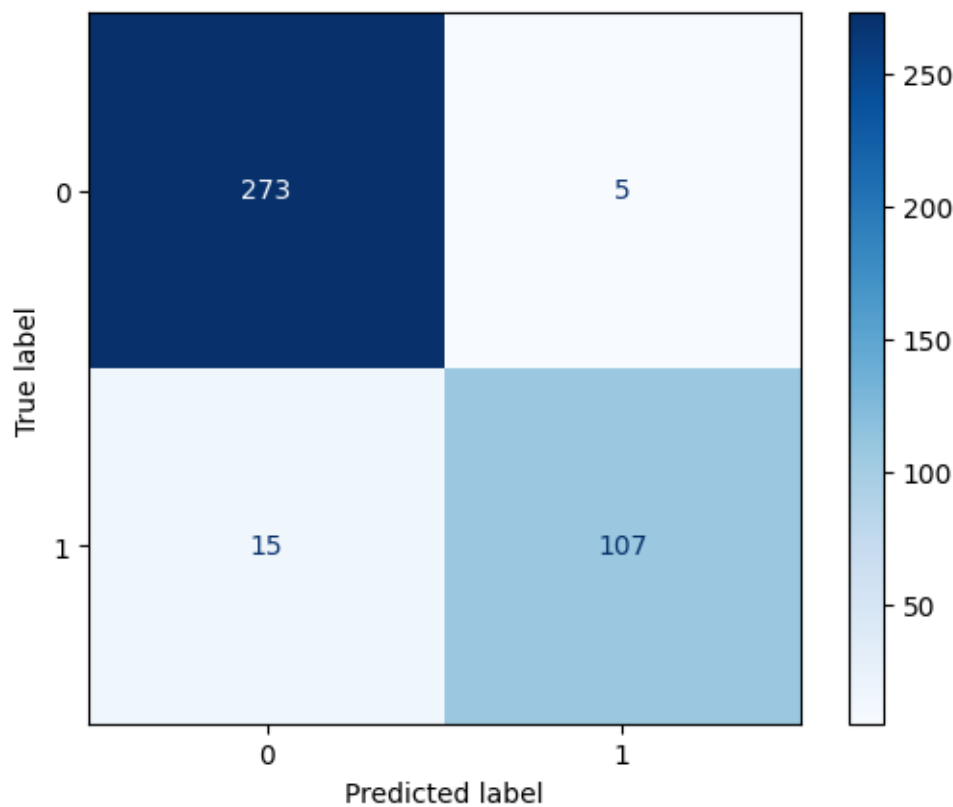


Figure 11: XGBoost Confusion |Matrix

Bi-LSTM with Attention Mechanism

The experiment carried out with the deep learning method utilized the Bi-LSTM model integrated with the attention mechanism. The purpose of the attention mechanism is to capture temporal dependencies and prioritize significant features. The deep learning model architecture is presented in Table 6, showing the embedding, Bi-LSTM, and attention layers, which enable context-aware learning from the textual symptom trigger sequences. The training history for the deep learning-based Bi-LSTM model over 15 epochs is

presented in Table 7, showing an increase in accuracy and a decrease in loss as the number of epochs increases, demonstrating that the model is learning well. The training and validation accuracy curves are presented in Figure 12, showing consistent improvement over each epoch with minimal overfitting, while the training and validation loss curve is presented in Figure 13, demonstrating steady convergence, indicating successful learning of the underlying feature representations.

The Bi-LSTM + attention layers model final evaluation was done with the use of a classification report (Table 8) and a Confusion matrix (Figure 14), revealing the superior performance over the compared machine learning algorithms. The Bi-LSTM + attention layers were able to achieve 96% accuracy, 96% precision, 94% recall, and 95% F1-score. The attention mechanism that was introduced played a crucial role by dynamically assigning higher weights to relevant symptom trigger combinations, which improves the model's predictive capability.

Table 6: Bi-LSTM + attention model architecture

Layer Name	Layer Type	Output Shape	Number of Parameters
Input Layer	InputLayer	(None, 10)	0
Embedding	Embedding	(None, 10, 32)	160,000
Bi-LSTM	Bidirectional LSTM	(None, 10, 128)	49,664
Attention	Attention	(None, 128)	138
Dense Layer	Dense	(None, 32)	4,128
Dropout	Dropout	(None, 32)	0
Output Layer	Dense	(None, 1)	33
Total	—	—	213,963
Trainable Parameters	213,963		
Non-Trainable	0		
Model Size	835.79 KB		

Table 7: Bi-LSTM + attention training history over 15 epochs

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.6538	0.6595	0.6719	0.578
2	0.7518	0.5184	0.9187	0.4146
3	0.9102	0.3702	0.9187	0.3043
4	0.9125	0.3149	0.9187	0.276
5	0.905	0.3208	0.9187	0.2807
6	0.9064	0.3178	0.9187	0.2779
7	0.9169	0.2886	0.9187	0.2651
8	0.9143	0.2781	0.9187	0.2462
9	0.9069	0.2676	0.9187	0.2092
10	0.9154	0.2043	0.9187	0.19
11	0.9184	0.2333	0.9625	0.1852

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
12	0.9629	0.1965	0.9625	0.1825
13	0.9515	0.2365	0.9625	0.1853
14	0.9595	0.2049	0.9625	0.18
15	0.9609	0.1866	0.9625	0.1798

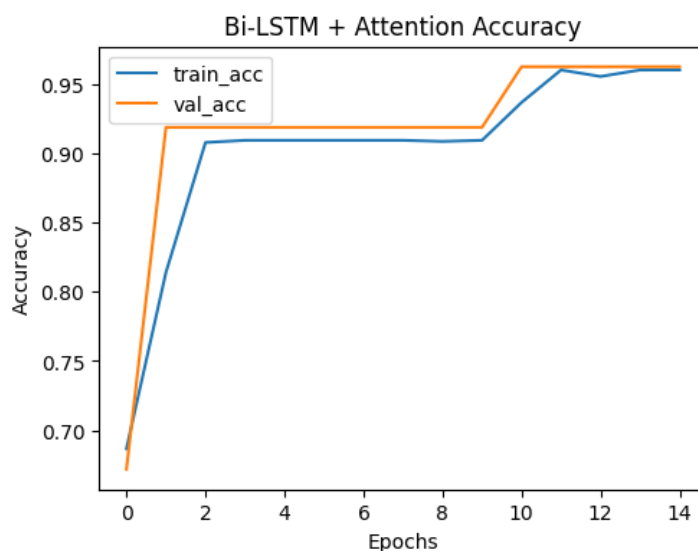


Figure 12: Bi-LSTM+ attention training accuracy and validation accuracy curve

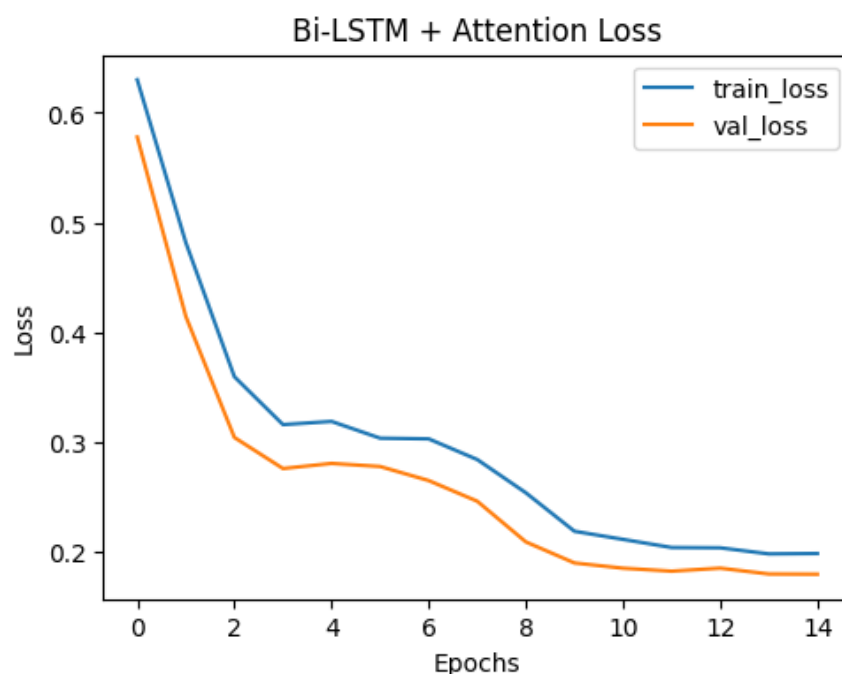


Figure 13: Bi-LSTM + attention training loss and validation loss curve

Table 8: Bi-LSTM + attention classification report

Class	Precision	Recall	F1-Score	Support
0	0.95	0.99	0.97	278
1	0.97	0.89	0.93	122
Accuracy	—	—	0.96	400
Macro Average	0.96	0.94	0.95	400
Weighted Average	0.96	0.96	0.96	400

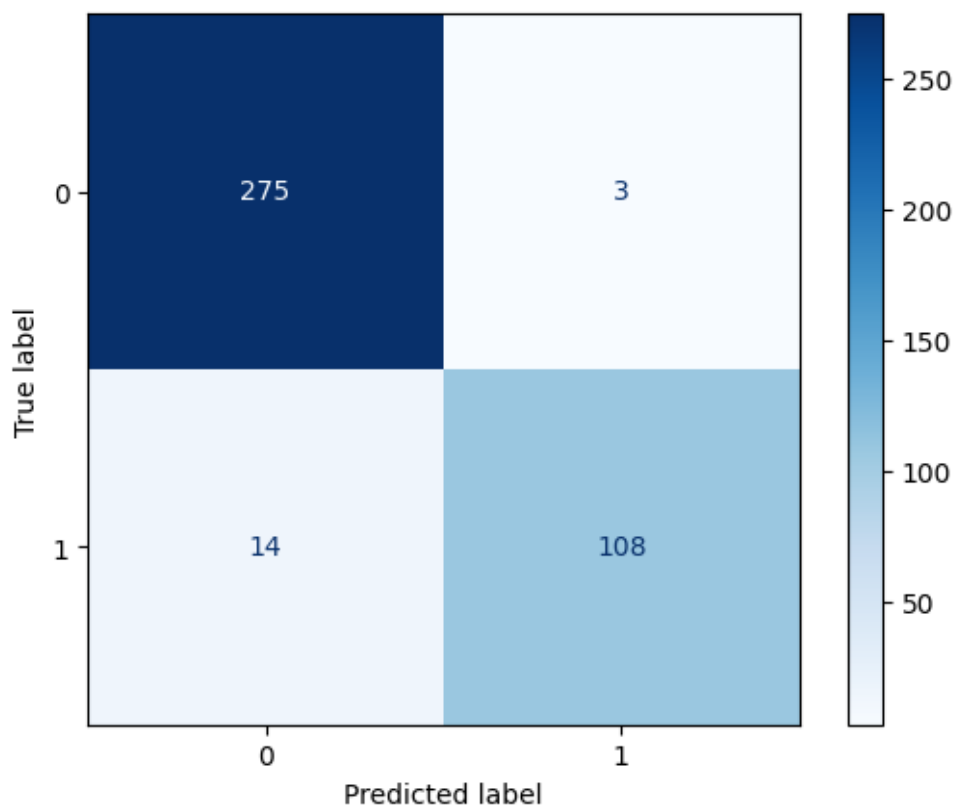


Figure 14: Bi-LSTM + attention confusion matrix

Comparative Analysis of Model Performance

The summary of the model's performance is presented in Table 9, showing the detailed comparison between the developed models in terms of accuracy, precision, recall, and F1-scores.

Table 9: Model's Performance

	Accuracy	Precision	Recall	F1-scores
Decision Tree	93%	94%	90%	92%
Random Forest	94%	94%	92%	93%
XGBoost	95%	95%	93%	94%

		Accuracy	Precision	Recall	F1-scores
Bi-LSTM Attention	+	96%	96%	94%	95%

From the table, it is observed that the deep learning-based Bi-LSTM + Attention model was able to outperform all the compared machine learning models, confirming deep learning with attention mechanisms in capturing complex, nonlinear patterns in symptom trigger sequences. The ensemble models, like the XGBoost and the random forest, also demonstrated strong and consistent performance across all evaluation metrics used, showing their reliability for structured health data.

Discussion

The experimental results from this study show that while traditional machine learning models are efficient at analyzing clinical data, deep learning models with an attention mechanism produce more accurate and reliable models with better contextual understanding of clinical data. The BI-LSTM with an attention mechanism outperformed the other compared algorithms, achieving the highest performance across all evaluation metrics used, with 96% accuracy, 96% precision, 94% recall, and 95% F1-score. This superior performance underscores its strength in correctly identifying asthma-positive cases, an essential requirement in medical diagnosis to minimize false negatives. Ensemble models such as XGBoost and the random forest also demonstrated strong and consistent performance across all evaluation metrics used, with XGBoost achieving 95% accuracy, 95% precision, 93% recall, and 94% F1-score, and the random forest achieving 94% accuracy, 94% precision, 92% recall, and 93% F1-score, showing their reliability for analyzing structured health data. The decision tree performed the least, but still maintained good performance across all evaluation metrics used, with 93% accuracy, 94% precision, 90% recall, and 92% F1-score, demonstrating machine learning's ability to analyze structured health data.

Comparison with Existing Studies

The superior performance of the Bi-LSTM with Attention model in this study aligns with recent findings in respiratory disease prediction literature. For instance, Haque et al. (2022) reported a 96% accuracy using an optimized deep neural network for asthma prediction, while Lopez et al. (2023) demonstrated the effectiveness of deep learning models in predicting asthma-related hospital outcomes with accuracies exceeding 90%. Unlike traditional ensemble models such as XGBoost, which rely on static feature representations, the Bi-LSTM architecture captures sequential and contextual dependencies within symptom–trigger combinations. The attention mechanism further enhances this capability by dynamically assigning higher weights to clinically relevant

features, enabling the model to focus on dominant asthma indicators such as wheezing, persistent coughing, and environmental triggers like dust and cold air.

While XGBoost achieved a competitive accuracy of 95%, its tree-based structure lacks temporal awareness and interpretability at the feature interaction level. The attention-enhanced Bi-LSTM model not only improved predictive accuracy by 1% but also provided insights into feature importance, addressing a key limitation of many existing deep learning approaches in healthcare. These findings suggest that attention-based deep learning models offer a more suitable framework for asthma prediction tasks involving complex symptom progression patterns.

Conclusion

This study successfully developed a comparative analysis framework for asthma prediction using three machine learning algorithms, including a decision tree, a random forest, XGBoost, and a deep learning algorithm (Bi-LSTM) integrated with an attention mechanism. These algorithms were trained on a Kaggle asthma dataset and evaluated individually using accuracy, precision, recall, and F1-score, and were visualized using a classification report and a confusion matrix. The results were compared to identify the most accurate and interpretable approach for predicting asthma occurrence. The experimental results show that all the models performed excellently, with accuracies ranging from 93% to 96%, and are reliable for predicting asthma occurrence. Among the machine learning models, the XGBoost model performed best. Its excellent performance is due to its efficient gradient boosting framework. However, when comparing all the algorithms used, including the deep learning Bi-LSTM with attention model, we observed that the deep learning-based Bi-LSTM with attention model outperformed all the compared machine learning models, achieving the best performance across all evaluation metrics, with 96% accuracy, 96% precision, 94% recall, and 95% F1-score. The outstanding performance of the Bi-LSTM + attention model was greatly influenced by the integration of the attention mechanism, which significantly enhanced the model's interpretability by highlighting the most influential features, such as specific symptom-trigger interactions that contributed to asthma prediction.

Findings from this research show that while traditional ensemble models like random forest and XGBoost are powerful for asthma prediction from structured clinical data, the integration of an attention mechanism with a deep learning model offers superior ability in capturing complex and contextual patterns in structured clinical data. This study validates the importance of integrating attention mechanisms with deep learning algorithms for improved prediction accuracy and transparency in healthcare AI systems. This study provided a comparative analysis of different machine learning models and a deep learning model to guide future research in selecting optimal predictive algorithms for respiratory disease diagnosis. Future work can focus on the expansion of the size of the dataset with more diverse demographic and environmental features, integrating real-time sensor data,

and deploying the model as an intelligent clinical decision-support tool for early asthma detection and management.

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