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A Predictive Model for Early Asthma Detection

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Abstract: Asthma is a respiratory disease that affects millions of people and has become one of the major causes of death worldwide. Early predictions of asthma can help health workers take the necessary precautions to prevent further complications. The traditional ways of asthma prediction are no longer effective because they are prone to error and time-consuming. Studies have employed sophisticated techniques, such as machine learning and deep learning, for asthma prediction, yielding promising results. However, previous research failed to consider datasets from different demographics, limiting the models to a particular population. Also, previous research has failed to perform a thorough comparative analysis between ensemble, machine learning, and deep learning models. This research addresses these gaps by developing a comparative multi-source predictive framework using four different algorithms, including Random Forest (RF), Support Vector Machine (SVM), Multi-Layer Perceptron, and a hybrid Stacking Ensemble model (SVM + RF + MLP), using datasets collected from Federal Teaching Hospital Lokoja, Specialist Hospital Lokoja, and Kaggle data. The dataset undergoes the process of an 80/20 stratified train/test split, removing of low variance using a threshold of 0.01. The training set was balanced using SMOTETomek. The three models (RF, SVM, MLP) were tuned using GridSearchCV hyperparameter optimization (with 5-fold cross-validation) before combining the best-performing models in a stacking ensemble (SVM + RF + MLPF) with a LogisticRegression meta-learner, leveraging kernel-based, tree-based, and neural network models for improved predictive performance. The models' performances were compared using Accuracy, Recall, F1-Score, and AUC-ROC. The hybrid stacking ensemble model achieved the highest AUC-ROC (0.9910) while maintaining 99.23% accuracy and an F1-score of 0.9920. RF and the ensemble models identified the most important predictors, variables that distinguish between asthmatic and non-asthmatic patients. The study demonstrates that integrating heterogeneous datasets improves predictive robustness and provides a strong foundation for real-world asthma detection systems.

Keywords: Machine Learning; Asthma; Detection; Model; Algorithm.

1. Introduction

Asthma is a chronic respiratory disease caused by different genetic and environmental factors [1]. Asthma involves narrowing the airways, making it difficult for an affected person to breathe properly. Asthma has been recognized as one of the leading causes of death globally, as it affects

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millions of people worldwide [2]. If asthma is left untreated, it can result in serious health complications, which can significantly affect the overall quality of life [3]. Symptoms of asthma include coughing, wheezing, chest tightness, and shortness of breath, among others, resulting from airway inflammation and bronchial hyperresponsiveness [4]. Asthma is one of the leading causes of emergency admission, especially in underdeveloped countries, which lack early diagnosis and proper management [5]. Asthma places a heavy burden on healthcare systems worldwide and also affects the quality of life of those suffering from it [6]. Early asthma detection and proper management can help reduce complications resulting from asthma, improve patient outcomes, and reduce medical costs [7]. Conventional methods used for asthma prediction are becoming ineffective due to their time-consuming process and human error. These conventional methods always fail to give accurate and timely diagnoses, presenting a need to develop a more effective and reliable method. In recent years, researchers have applied more sophisticated approaches like Machine Learning and Deep Learning to predict asthma in individuals [8]. These approaches have presented great promises due to the recent advancement in artificial intelligence (AI) technologies. Different Machine Learning and Deep Learning have been applied to predict asthma by different researchers; the algorithms include Decision Trees (DT), RF, NN, and SVM, among others; these algorithms have demonstrated high predictive accuracy for asthma prediction [9]. However, there are still some gaps in the existing research, which include the comprehensive evaluation of these models using both local and diverse online datasets to improve robustness and real-world applicability. This research aims to address these gaps by developing an asthma prediction model using local datasets collected from the Federal Teaching Hospital Lokoja and the Specialist Hospital Lokoja in Nigeria.

This paper is structured as follows: Section 1 presents the background and the general overview of the study. Section 2 examines the existing studies, focusing on the work done, the method used, the dataset, and the result, to extract the existing gap that this study addressed. The methodology, the stepwise method used for the implementation in this study, was presented in Section 3. Section 4 demonstrates the architecture used. Section 5 presents the main outcome of the implementation. A discussion of the result was presented in Section 6. The conclusion summarizes the findings, implications, and future research in Section 7

2. Related Work

Authors [10] researched the prediction of asthma with the use of machine learning techniques. The research integrated automated machine learning (AutoML) and explainable AI (XAI). The algorithms used in the research include WeightedEnsemble, NeuralNetTorch, NeuralNetFastAI, LightGBMXT, and XGBoost. The dataset used in the research was collected from Kaggle, and it contains demographic, clinical, and respiratory function data. The experimental result shows that the WeightedEnsemble, NeuralNetTorch, NeuralNetFastAI, LightGBMXT, and XGBoost algorithms were able to achieve 98.99%, 98.18%, 98.18%, 98.18%, and 98.18% accuracy, respectively.

Categorizing cough sounds to differentiate asthmatic coughs was carried out by [11]. The dataset that was used during the research contained 1428 different cough sounds. The Tunable Q Wavelet Transformation (TQWT) with a Global Chaotic Logistic Pattern (GCLP) was used to preprocess the dataset. The SVM algorithm was used to train the dataset. The experimental result shows that the proposed model was able to achieve 99.44% accuracy.

Authors in [12] conducted a study to improve the asthma prediction model's accuracy. The study utilized the Affinity Graph Enhanced Classifier (AGEC) algorithm. The dataset used to train the proposed algorithm is a clinical dataset, consisting of 152 samples with 24 routine blood indicators.

The AGEC model was able to outperform all the compared state-of-the-art algorithms, achieving 72.50% accuracy.

Authors [13] carried out research that focused on distinguishing between severe asthma and bronchitis in children. The researchers utilized two deep learning-based algorithms, which include 2-1D-CNNs and 1D-CNNs + LSTM. The dataset used was gathered in Iraq over four months. The gathered dataset consists of 512 cases with 12 clinical characteristics. The experimental result shows that the 2-1D-CNNs were able to achieve 99.72% accuracy and 100% AUC, while the 1D-CNNs + LSTM achieved 99.44% accuracy and 99.96% AUC.

Identification of asthma via lung sounds was proposed by [14]. The research used SVM for classification. The dataset used during the implementation was collected using a stethoscope and consisted of 203 patients' records with 767 asthmatic instances and 722 healthy instances. The experimental result shows that the SVM was able to outperform all other compared algorithms, achieving the best accuracy of 99.73%.

[Authors in 15] researched asthma risk forecast using an Internet of Things (IoT)-based ML approach. The DT algorithm was utilized in the study. The dataset that was used to train the model was collected with sensors and consists of peak expiratory flow rates (PEFR), temperature, humidity, and PM2.5. The experimental result shows that the model achieved 90% accuracy.

Authors [16] focused on the prediction of inhaled corticosteroid (ICS) response in asthma patients using machine learning techniques. The RF model and the LASSO regression were used in the study. The dataset that was used consisted of data from 1,371 patients. The experimental result shows that the RF achieved 74% AUC, while the LASSO regression achieved 71% accuracy.

Prediction of asthma exacerbations after discontinuing asthma biologics was proposed by [17]. The dataset used in the study was collected from the OptumLabs Database Warehouse. The dataset consists of clinical and demographic risk variables from 3057 individuals. The RF algorithm was used in study 7. The result shows that the model was able to achieve its highest AUC value of 76%, while authors [18] carried out research that focused on the prediction of a physician's diagnosis of asthma at age 5 using machine learning. The dataset contains 132 variables from 1,754 children. The experimental result shows that the proposed model achieved low (AUPRC < 0.35) for children with less than 1 year and AUROC > 0.90 for children at the age of three.

Authors in [19] researched predicting the effectiveness of mite subcutaneous immunotherapy. The study uses a dataset that consists of 390 children's clinical records. The study utilized the Salp Swarm algorithm to build the model. The experimental result shows that the proposed algorithm was able to achieve 87.18% accuracy and 93.55% sensitivity.

Authors in [20] developed a computing framework for asthma prediction. The study used real-time data, which was collected by integrating environmental sensors, an adaptation layer, and a telemonitoring application. The proposed model was able to achieve 98% accuracy and 96% recall.

Research on the application of a deep learning model on asthma prediction was carried out by [21]. The study made use of the CovNet algorithm to train a dataset with six features (Chroma, RMS, Spectral centroid, Rolloff, and MFCC). The experimental result shows that the proposed deep learning model was able to achieve 100% sensitivity, 100% specificity, 99% F-scores, and 99.8% accuracy.

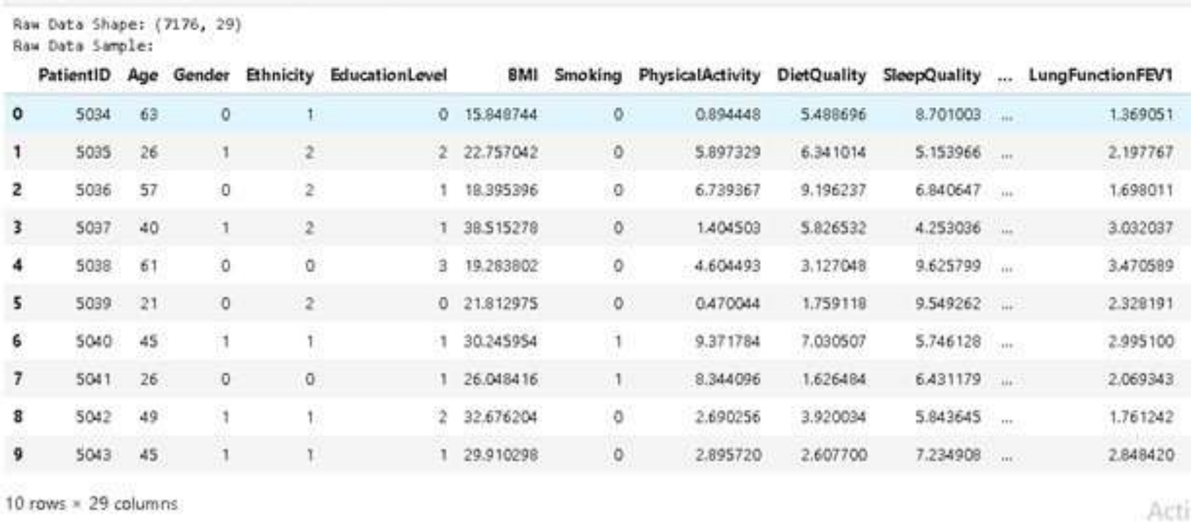
This study was able to identify a significant gap in asthma prediction from the previous papers reviewed and observed that despite the studies that have demonstrated the potential of ML and DL in asthma prediction, those studies always rely on predefined datasets or datasets that are limited to demographic data, which eventually affects model generalizability. This study also observed that, as most studies rely on individual algorithms like SVM, RF, and NN, comprehensive comparative analyses that leverage local and diverse online datasets are lacking. Building on a study carried out by [21], this study will address these gaps by utilizing both local data (Federal Teaching Hospital, Lokoja, and Specialist Hospital, Lokoja dataset) and online datasets (Kaggle) to enhance model robustness and ensure diverse population representation. This study will also conduct a systematic comparative analysis of multiple models, including SVM, RF, MLP, and a stack ensemble (SVM + RR + MLP), to determine the most effective approach for early asthma prediction.

3. Methodology

The method used in this research follows a unique structure, which includes data collection, data preprocessing, model training, and model evaluation.

3.1. Data Collection

The dataset used in this study was collected from three sources. Locally, the first set of data was collected from Federal Teaching Hospital, Lokoja, with a total of 966 instances, and the second set was collected from Specialist Hospital, Lokoja, with a total of 1,211 cases, while the third set is open-source data collected from the Kaggle database with 5,000 instances. The three sets of datasets were then merged into one dataset. The features in the dataset include age, gender, ethnicity, education level, Smoking, physical activity, BMI, diet quality, sleep quality, pollution exposure, dust exposure, history of allergies, and family history of asthma, which were the most relevant and potent features. The sample of the final dataset is presented in Figure 1.



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Raw Data Shape: (7176, 29)
Raw Data Sample:
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	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	PhysicalActivity	DietQuality	SleepQuality	...	LungFunctionFEV1
0	5034	63	0	1	0	15.848744	0	0.894448	5.488696	8.701003	...	1.369051
1	5035	26	1	2	2	22.757042	0	5.897329	6.341014	5.153966	...	2.197767
2	5036	57	0	2	1	18.395396	0	6.739367	9.196237	6.840647	...	1.698011
3	5037	40	1	2	1	38.515278	0	1.404503	5.826532	4.253036	...	3.032037
4	5038	61	0	0	3	19.283802	0	4.604493	3.127048	9.625799	...	3.470589
5	5039	21	0	2	0	21.812975	0	0.470044	1.759118	9.549262	...	2.328191
6	5040	45	1	1	1	30.245954	1	9.371784	7.030507	5.746128	...	2.995100
7	5041	26	0	0	1	26.048416	1	8.344096	1.626484	6.431179	...	2.069343
8	5042	49	1	1	2	32.676204	0	2.690256	3.920034	5.843645	...	1.761242
9	5043	45	1	1	1	29.910298	0	2.895720	2.607700	7.234908	...	2.848420

10 rows × 29 columns

Figure 1. Sample of the dataset.

3.2. Data Preprocessing

After the data collection, the data was preprocessed to make it clean, consistent, and suitable for machine learning models. We applied different preprocessing techniques in this study. These techniques include:

1. Handling Missing Values: Missing values in numeric features were input using mean values.

2. Feature Scaling and Normalization: We observed that features such as lung function measurements and BMI had varying scales, requiring normalization to ensure uniformity across the dataset, so we normalized them.
3. Correlation Analysis for Feature Selection: This study utilized the correlation heatmap (see Figure 2) to analyze the relationship between each of the features. This is done to identify variables with high correlation so that they can be removed to avoid multicollinearity and redundancy. Correlated features greater than 0.85 were removed.
4. Categorical Encoding: We converted categorical variables into numerical form with the use of a label encoder.

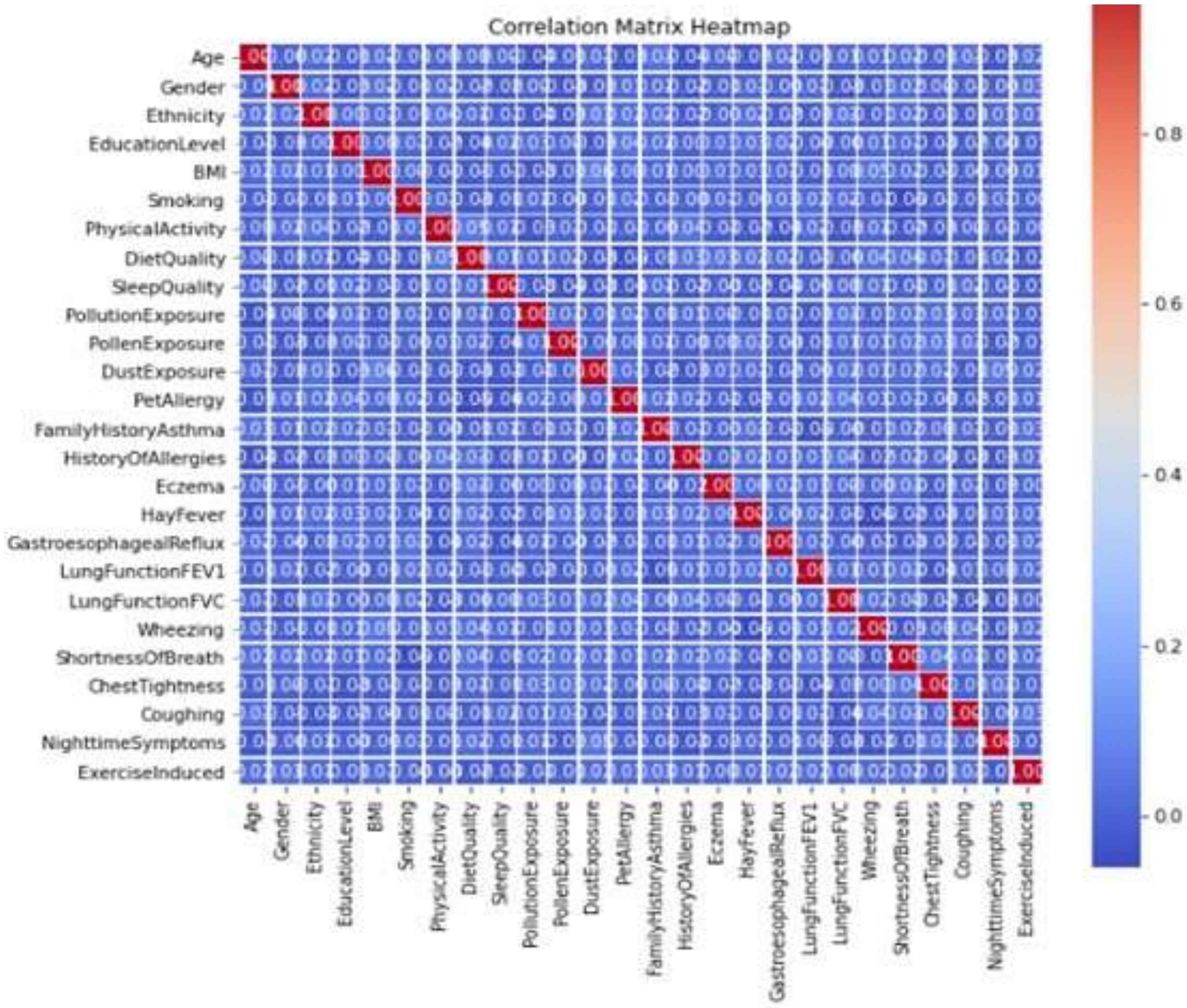

Figure 2. Correlation Matrix Heatmap.

3.3. Data Splitting

The dataset, comprising 7,177 records, was divided into training and testing sets using a stratified 80/20 split, where 80% of the data was allocated for training and 20% for testing. This split ensures sufficient data for model learning while maintaining reliable evaluation.

Due to the severe class imbalance in the dataset (approximately 18:1 ratio of No Asthma-to-Asthma cases), we applied class balancing on the training set using SMOTETomek, a hybrid resampling technique that combines SMOTE oversampling with Tomek Links undersampling. This approach not only generates synthetic samples for the minority class but also removes noisy and borderline majority class instances, producing cleaner decision boundaries and reduced risk of overfitting compared to standard SMOTE.

3.4. Model Training

This study employs Machine Learning models (RF, SVM), a Deep Learning model (MLP), and a Hybrid Stack Ensemble model (SVM + RF + MLP) as shown in Figure 3. The four models were developed as follows:

- A Support Vector Machine with radial basis function (RBF) kernel. The model was optimized using GridSearchCV hyperparameter optimization with 5-fold cross-validation. Regularization parameter (C) and kernel coefficient (γ) were tuned over the following ranges: $C \in \{0.1, 1, 10\}$ and $\gamma \in$ {'scale', 'auto'}. The final SVM model is the best combination of parameters identified during the search.
- A Random Forest classifier was also trained with 5-fold cross-validation, the n_estimators and max_depth were optimised within the ranges n_estimators ∈ {100, 200} and max_depth ∈ {None, 20. The best-performing configuration was retained for further use.
- A feed-forward neural network (Multi-Layer Perceptron) with three different architectures [(64,32), (128,64,32), (256,128,64,32)] was evaluated to assess the impact of network depth and width. All the MLP models used ReLU activation, Adam optimizer, and early stopping with a validation fraction of 0.1 to prevent overfitting. The architecture with hidden layers (128, 64, 32) achieved the highest weighted F1-score and was selected as the base learner for the hybrid stacking ensemble.
- A Hybrid Stacking Ensemble model combining the three optimized models (SVM, Random Forest, and the best MLP) was developed, using their predictions as an input for the meta-learner, implemented as a Logistic Regression Classifier. The stacking process employed 5-fold cross-validation to reduce the risk of overfitting. This ensemble approach was designed to leverage kernel-based, tree-based, and neural network models for improved predictive performance.

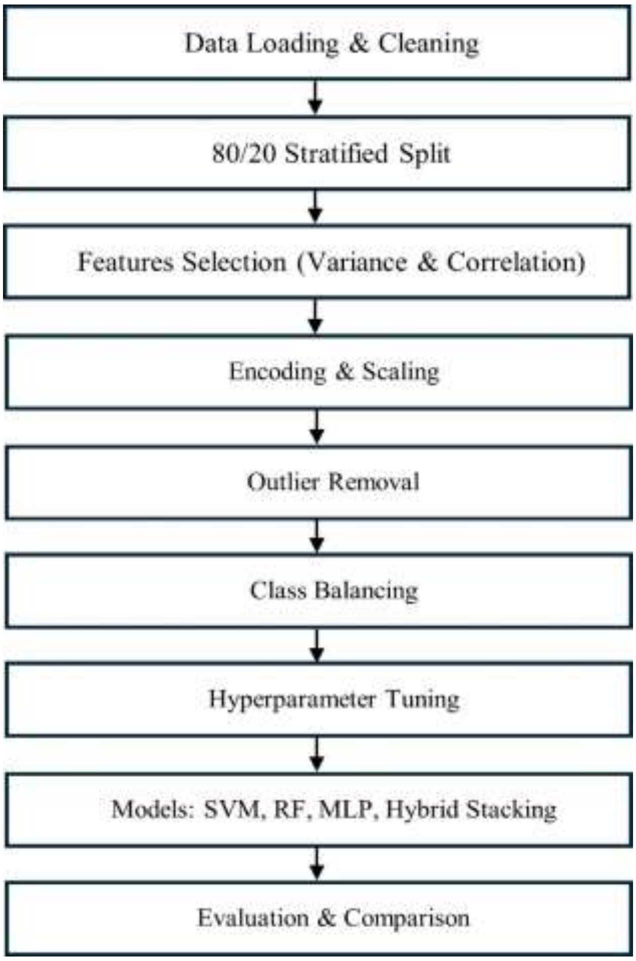

Figure 3. System architecture for early asthma detection

3.5. Hyperparameter Tuning

Hyperparameter tuning was performed for the Support Vector Machine (SVM) and Random Forest models using GridSearchCV with 5-fold cross-validation on the balanced training set.

For the SVM, the regularization parameter C and kernel coefficient gamma were optimized. For the Random Forest, the number of estimators (n_estimators) and maximum tree depth (max_depth) were tuned. The best hyperparameter combination for each model was selected based on the highest weighted F1-score across the five folds. The final models were retrained on the entire training set using the optimal hyperparameters.

For the Multi-Layer Perceptron (MLP), three different architectures (64, 32), (128, 64, 32), and (256, 128, 64, 32) were evaluated. The architecture with hidden layers (128, 64, 32) was selected as the best-performing base learner for the hybrid stacking ensemble based on its weighted F1-score on the test set. All models were implemented using scikit-learn.

4. Results and Discussion

The performance of the four models on the independent test set (n = 1,436) is presented in Table 1. All the models achieved high accuracy (0.9875–0.9923) and weighted F1-scores (0.9873–0.9920). The proposed hybrid stacking ensemble, SVM, and Random Forest models performed almost identically, with each reaching an accuracy of 0.9923 and an F1-score of 0.9920. The best MLP architecture (128-64-32) performed slightly lower at 0.9882 accuracy and 0.9880 F1-score.

In terms of AUC-ROC, a clinically relevant metric for a diagnostic task, the hybrid stacking ensemble achieved the highest value (0.9910), which confirms that integrating heterogeneous datasets locally and the Kaggle repository improves the model’s performance over a single source dataset [21]. Random Forest followed the hybrid stacking ensemble in terms of AUC-ROC with 0.9889. The SVM and MLP recorded AUC-ROC values of 0.9399 and 0.9373, respectively.

All models demonstrated excellent specificity for the majority class (“No Asthma”), with values approaching 1.00. But recall for the minority class (“Asthma”) was consistently 0.85 across the best-performing models (SVM, Random Forest, and the hybrid stacking ensemble).

Table 1. Performance metrics of the four models on the test set

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Recall (Asthma)
SVM (Tuned)	0.9923	0.9924	0.9923	0.992	0.9399	0.8514
Random Forest (Tuned)	0.9923	0.9924	0.9923	0.992	0.9889	0.8514
MLP (Best)	0.9882	0.9879	0.9882	0.988	0.9373	0.8514
Hybrid Stacking Proposed)	0.9923	0.9924	0.9923	0.992	0.9910	0.8514

Figures 4 and 5 show the learning curves of the proposed hybrid stacking ensemble model for weighted F1-score and AUC-ROC metrics. Both metrics exhibit near-perfect and highly stable performance, with little or almost no gap between the training and validation curves. This indicates that the hybrid model generalizes well, indicating a robust and stable learning model.

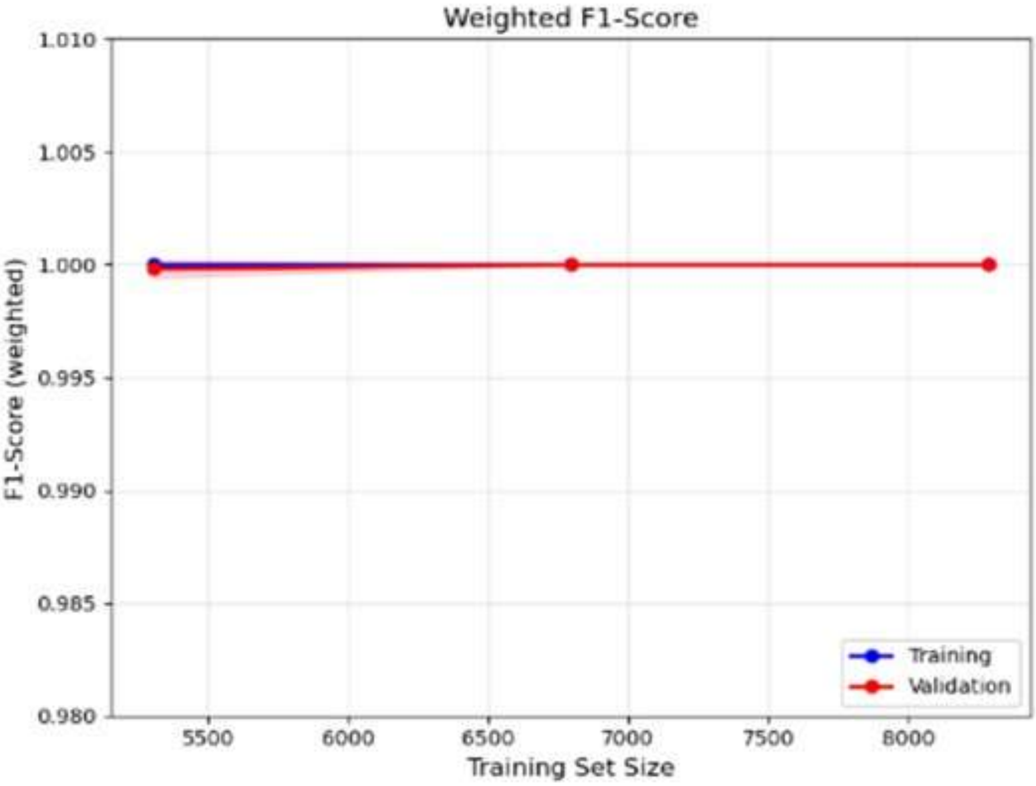

Figure 4. Learning curves of the proposed hybrid stacking ensemble (weighted F1-score)

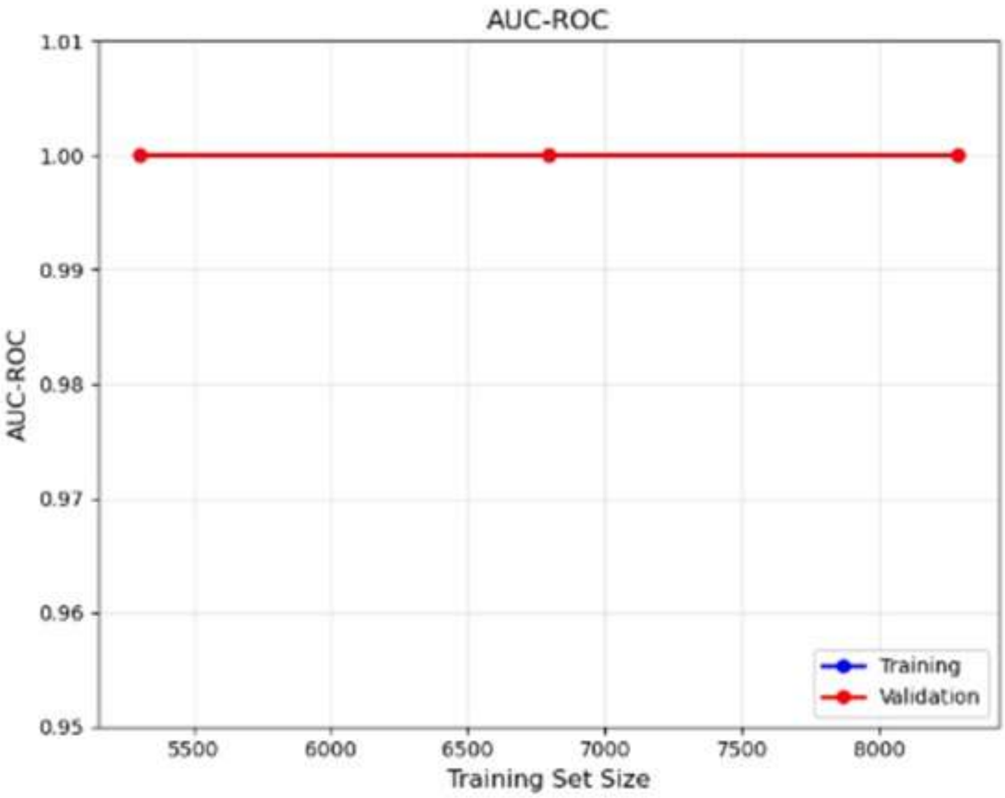

Figure 5. Learning curves of the proposed hybrid stacking ensemble (AUC-ROC)

Figures 6 and 7 present a key feature of the mode-feature importance analysis, both RF and the stack ensemble models identified the most important predictors, the variables that distinguish between asthma patients and non-asthma patients. Both models showed strong agreement and consistency on the most influential predictors (Tables 2 and 3). DietQuality, LungFunctionFEV1, BMI, PollenExposure, DustExposure, and PhysicalActivity were consistently ranked among the top variables. These findings align with known clinical and environmental risk factors for asthma.

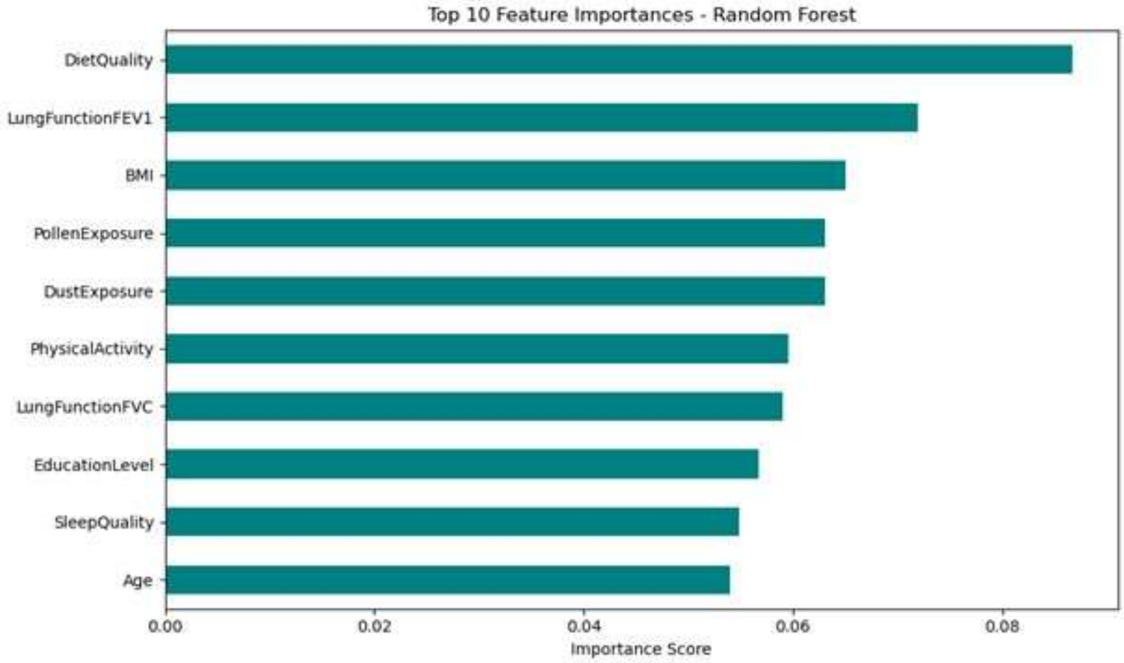

Figure 6. Top 10 Feature Importances (Random Forest)

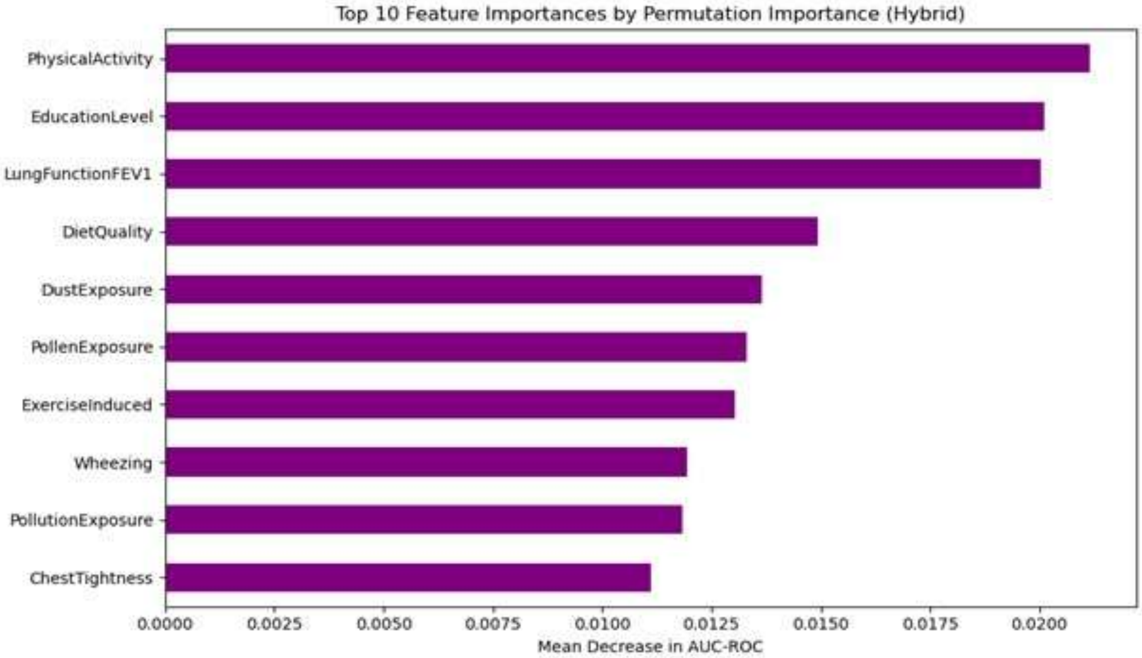

Figure 7. Top 10 Features Importance (Hybrid Ensemble)

Table 2. Top 10 most important features (Random Forest)

Features	Score
DietQuality	0.086748
LungFunctionFEV1	0.071887
BMI	0.065042
PollenExposure	0.063090
DustExposure	0.063061

PhysicalActivity	0.059551
LungFunctionFVC	0.059050
EducationLevel	0.056741
SleepQuality	0.054873
Age	0.054037

Table 3. Top 10 features by permutation importance (Hybrid Stacking)

Feature	**AUC-ROC**
PhysicalActivity	0.021160
EducationLevel	0.020121
LungFunctionFEV1	0.020042
DietQuality	0.014918
DustExposure	0.013641
PollenExposure	0.013315
ExerciseInduced	0.013029
Wheezing	0.011946
PollutionExposure	0.011829
ChestTightness	0.011107

4.1. Model Evaluation

The confusion matrices for the best-performing models (SVM, Random Forest, and Hybrid Stacking) in Figures 8-10 followed a consistent pattern; they all achieved near-perfect classification of the majority class (“No Asthma”), with specificity approaching 100%. But for true asthma cases, 85% of true asthma cases were identified, resulting in approximately 11 false negatives out of 74 actual positive cases.

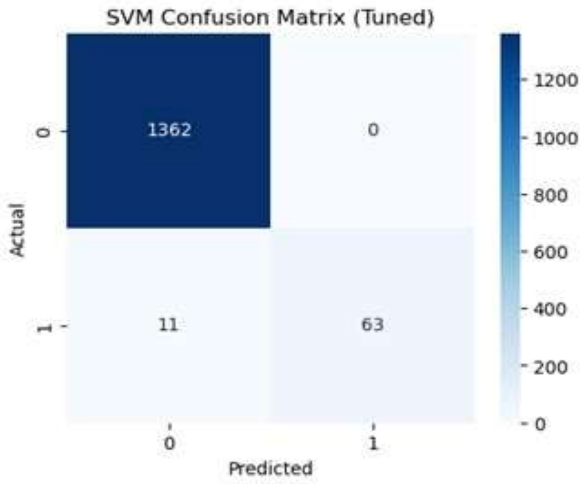

Figure 8. Confusion matrices for SVM

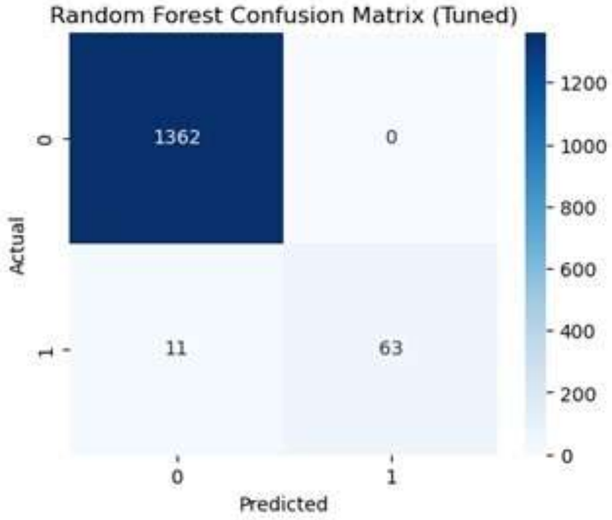

Figure 9. Confusion matrices for SVM

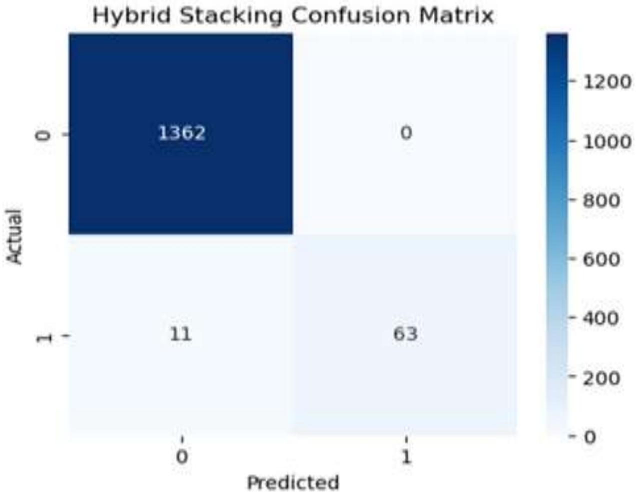

Figure 10. Confusion matrices for the hybrid stacking ensemble

5. Discussion

The proposed hybrid stacking ensemble demonstrated optimum predictive performance, achieving an accuracy of 0.9923, a weighted F1-score of 0.9920, and the highest AUC-ROC of 0.9910 on the independent test set. This result is an improvement over many previously reported machine learning and deep learning approaches for asthma prediction using tabular data. The ensemble model leveraged the model diversity of kernel-based (SVM), tree-based (Random Forest), and neural network (MLP) models to enhance prediction performance.

Compared with the baseline study [21], which relied on a single deep learning model (CovNet) and only six features, the present work addresses key limitations by incorporating both local Nigerian hospital data and a publicly available Kaggle dataset. This combination of diverse data sources significantly improves the generalizability of the model and overcomes the narrow scope of earlier studies. Furthermore, the comprehensive comparative analysis involving multiple machine learning and deep learning models (SVM, Random Forest, and MLP) provides robust evidence of the effectiveness of both traditional and modern techniques in asthma prediction.

The learning curves in Figure 4 show that the hybrid model generalizes exceptionally well, with nearly similar training and validation performance with little variance. This indicates a low risk of overfitting despite the very high metrics of the model. This indicates a low risk of overfitting despite the very high performance metrics achieved. The feature importance analysis generated by the models in Figures 6, 7, and Table 2-3 further strengthens the clinical relevance of the model. Both Random Forest and permutation importance on the hybrid model consistently identified features like DietQuality, lung function parameters (FEV1 and FVC), BMI, pollen and dust exposure, and physical activity as the most important predictors, which align with existing medical literature on asthma risk factors, enhancing the trustworthiness of the model.

However, the confusion matrix analysis shows a clinically important limitation. While specificity for the “No Asthma” class was near-perfect, the 0.85 recall for the “Asthma” class means that approximately 15% of individuals with asthma were not detected by the model, which is an important consideration for early detection applications. Future improvements could include class-weighted loss functions, probability threshold tuning, or cost-sensitive learning to enhance sensitivity.

In summary, the hybrid stacking ensemble offers a robust and high-performing model for early asthma prediction. By combining diverse datasets, multiple modeling paradigms, and rigorous validation, this study contributes significantly to the growing body of AI-driven disease prediction research. With further refinement focused on improving sensitivity and thorough external validation, the proposed approach has strong potential for integration into clinical decision-support systems.

6. Conclusion

In this study, we developed and evaluated a hybrid stacking ensemble model for early asthma prediction by integrating Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP) models. The research addressed the limitation of single-source data in previous studies by combining local hospital datasets from Federal Teaching Hospital Lokoja and Specialist Hospital Lokoja (Nigeria) alongside a publicly available Kaggle respiratory dataset. This multi-source approach enhances the diversity and generalizability of the findings. The proposed hybrid stacking ensemble achieved excellent performance with 99.23% accuracy, a weighted F1-score of 0.9920, and the highest AUC-ROC of 0.9910 on the independent test set. Feature importance analysis revealed clinically meaningful predictors such as diet quality, lung function parameters (FEV1 and FVC), body mass index, and environmental exposures (pollen and dust), which are consistent with established asthma literature. Despite the excellent prediction performance of the model, the consistent asthma recall of 0.8514 across models highlights the need for further improvement in sensitivity to minimize missed cases in early detection scenarios. Future work should focus on probability threshold optimization, cost-sensitive learning, and external validation on larger and more diverse clinical cohorts.

This study demonstrates the effectiveness of a hybrid stacking ensemble model for accurate asthma prediction and contributes to the advancement of AI-driven healthcare solutions.

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The contribution of each authors are as follows "Conceptualization: SOA; Methodology: SOA, EO, TK; Software: SOA, MA; Validation: SOA, EO and TK; Formal analysis: SOA; Investigation: SOA, EO and TK; Resources: SOA, MA, EO and TK.; Data collection: SOA; Writing original draft preparation: SOA; Writing review and editing: SOA, MA, TK and EO; Visualization: SOA; Supervision: TK and EO. All authors have read and agreed to the published version of the manuscript. This research received no external funding.

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