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Early Asthma Detection Using Structured Data: Comparative Evaluation of Machine Learning Models

Ghada Abd El-Latif Shatat[1,*], Hossam el-din Moustafa[2], Mohamed Saraya[3], Al-Saeed Ahmed Marzouk[4], and Asmaa AEL Hekal[5].

[1] Dept. Electronics and Communications, Faculty of Engineering, Mansoura, Egypt, ghadashatat@std.mans.edu.eg.

[2] Dept. Electronics and Communications, Faculty of Engineering, Mansoura, Egypt. hossam_moustafa@mans.edu.eg.

[3] Computer and control systems engineering, faculty of engineering, Mansoura university, Egypt. mohamedsabry83@mans.edu.eg.

[4] Dept. Electronics and Communications, Faculty of Engineering, Mansoura, Egypt. smarzouk@mans.edu.eg.

[5] Electrical Department, Faculty of Engineering, Modern University for Technology and Information (MTI University), Egypt. asmaahekal3@gmail.com.

* Correspondence: ghadashatat@std.mans.edu.eg.

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Abstract: Asthma, a prevalent and complex chronic respiratory disease, imposes a growing burden on global healthcare systems. This survey investigates the evolving role of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), in enhancing early detection, personalized care, and real-time monitoring of asthma. Drawing on a structured synthetic dataset encompassing demographic, environmental, lifestyle, and clinical variables, the study applies rigorous data preprocessing and comparative model evaluation across multiple ML algorithms, including Logistic Regression, Support Vector Machine, Random Forest, Gradient Boosting, and XGBoost. Among these, the XGBoost classifier outperforms others, achieving 98% accuracy and an AUC of 0.94, demonstrating its robustness for structured health data. Additionally, the integration of wearable and real-time sensor data is identified as a critical future direction to further improve predictive performance and clinical applicability. This review highlights the potential of AI-driven approaches to revolutionize asthma care by enabling timely interventions, reducing hospitalizations, and supporting individualized management strategies.

Keywords: Artificial Intelligence, XGBoost, Predictive Modeling, WearableDevices, Personalized Healthcare**.**

1. Introduction

Asthma is a common chronic respiratory condition characterized by ongoing airway inflammation. In 2019, it affected 262 million people and killed roughly 461,000 individuals each year [1].According to the National Health Service (2021), asthma commonly begins in childhood but can also manifest at any age [2]. Symptoms include wheezing, chest tightness, coughing, and shortness of breath greatly reduce quality of life [3]. The disease is diverse in character, which means that symptoms and triggers vary greatly, making early and accurate diagnosis challenging [4]. Traditional diagnostic approaches, such as spirometry and bronchial provocation testing, are widely used but have limitations. They necessitate specialized equipment, are time-consuming, and are not always available [5]. Asthma attacks can be triggered by a combination of intrinsic factors—such as genetic predisposition, family history, and related allergies (eczema or rhinitis) [5]—and extrinsic factors, including environmental exposures such as dust, pollen, smoke, air pollution, and infections [6], as well as lifestyle factors such as stress, obesity, and physical activity [7]. Conventional assessment approaches (such as patient questionnaires and clinical examinations) frequently lack real-time environmental data [8]. This constraint, combined with poor drug adherence and healthcare inequities [9][10], impedes effective asthma control. Furthermore, psychosocial issues such as anxiety and depression hinder disease management [10].

Advances in data analytics and artificial intelligence (AI), particularly machine learning (ML), have increased the possibilities for asthma prediction and management [11]. ML systems can find hidden patterns in massive datasets, allowing them to forecast outcomes and enable individualized care plans [12]. As highlighted by Dwivedi et al. [13] and Choi et et al. [14], deep learning has demonstrated tremendous capabilities in analyzing complex asthma-related data.

Recognizing asthma phenotypes is essential for personalized care, as different types require tailored treatments:

1. Allergic Asthma – Triggered by allergens like pollen and pet dander [15].
2. Non-Allergic Asthma – Not linked to allergies; often triggered by infections, stress, or cold air [16].
3. Exercise-Induced Asthma (EIA) – Occurs during or after physical activity, particularly in cold or dry environments [17].
4. Occupational Asthma – Due to workplace exposures to dust or chemicals [18].
5. Cough-Variant Asthma – Characterized mainly by chronic coughing [19].
6. Severe Asthma – Resistant to standard treatments; may require biologics [20].
7. Asthma-COPD Overlap Syndrome (ACOS) – Features of both asthma and COPD, complicating diagnosis [21].

Computer-Aided Diagnosis (CAD) systems enhance diagnostic accuracy by reducing human error and assisting radiologists with pattern recognition in asthma detection [9]. CAD systems save time, costs, and lives by providing automated, reliable analysis [11]. These systems, supported by AI advancements, are becoming increasingly effective as computing power grows [12]. Both classical ML and DL are part of AI: traditional ML involves preprocessing, segmentation, and classification using limited features, while DL uses hierarchical feature learning for improved performance [13] as shown in figure1.

The remainder of this manuscript is organized as follows: Section II provides an in-depth review of related work on asthma prediction, highlighting recent advances in AI-driven healthcare analytics. Section III details the proposed materials and methods, including dataset, preprocessing techniques, methodology, and the architecture of selected machine learning models. Section IV presents Results and Discussion includingthe experimental setup, model evaluation metrics, and a comparative analysis of classification performance, emphasizing the superiority of the XGBoost model. Finally, Section V concludes the paper with a summary of findings and outlines potential directions for future research, including the integration of real-time wearable data and model generalization across broader populations.

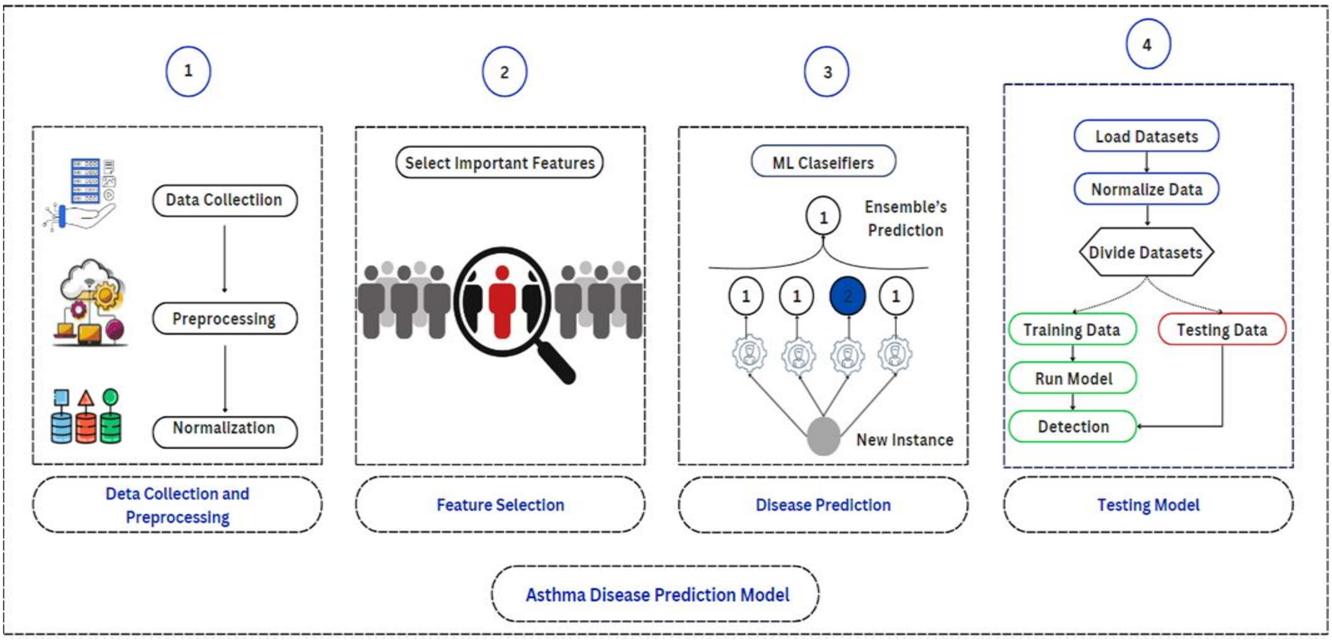

Figure1. Asthma Disease prediction Model

2. RELATED WORK

a. Data collection

Comprehensive asthma prediction relies on diverse data sources: EHRs for clinical history, surveys for symptoms and triggers, spirometry and imaging for lung assessment, wearables for real-time vitals, environmental data for external triggers, and biomarkers for inflammation. Integrating these sources (Figure 2) strengthens predictive models and supports personalized care. Smith et al. [22] highlighted EHRs in identifying high-risk patients, while Johnson et al. [23] showed that patient-reported data improved prediction accuracy and treatment outcomes.

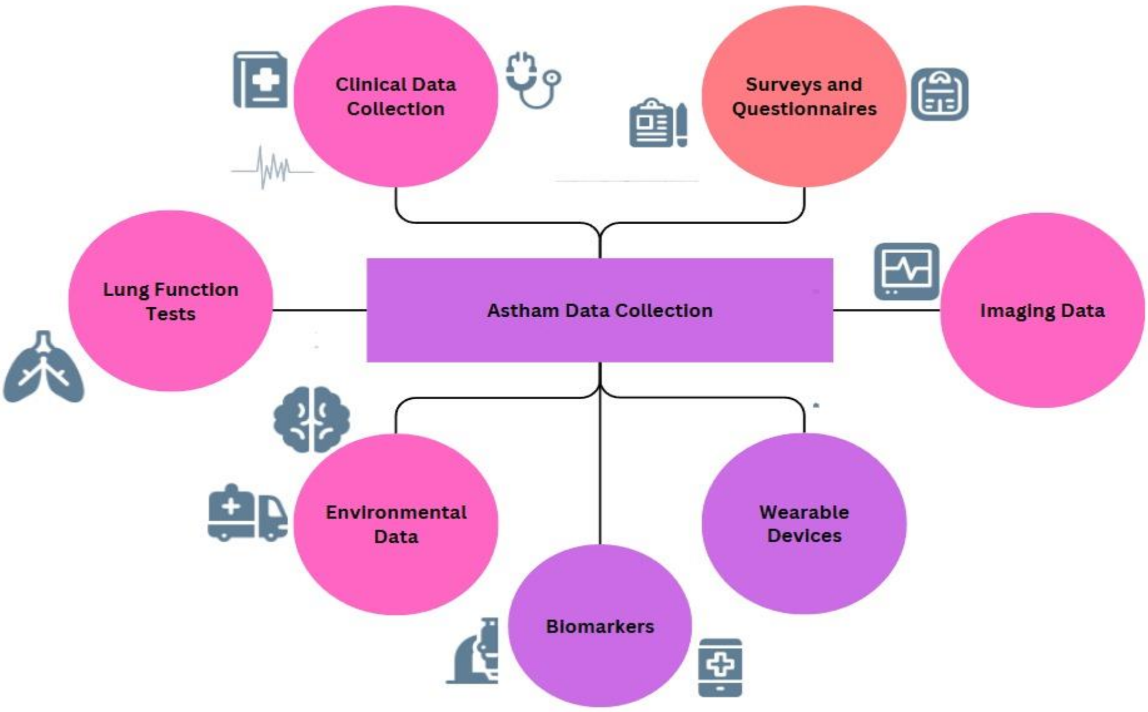

Figure 2. Data Collection of asthma.

The combination of many data sources has greatly improved asthma prediction. According to Lee et al. [24], there is a clear correlation between increased asthma exacerbations and poor air quality. In addition, Chen et al. [25] used data from wearable sensors to help detect asthma symptoms early. Patel et al. [26] have highlighted how machine learning techniques can significantly improve prediction accuracy by combining diverse data sources, including environmental exposures, lifestyle variables, and clinical records.While Thompson et al. [28] discovered that mobile apps were useful for recording symptoms in real time, Garcia et al. [27] found that biomarker analysis improved clinical assessment. The prognostic significance of telehealth was emphasized by Martinez et al. [29]. Robinson et al. [30] investigated genetic factors, whereas White et al. [31] emphasized the use of integrated health system data. Further, annotated cough audio [32], respiration signals [33], genomic profiles [34], and wearable time-series data [35] have all contributed to improving asthma classification and control assessment.

b. Data Preprocessing

A crucial first step in creating precise asthma prediction models is data preparation. It entails encoding categorizing data, managing missing values, eliminating duplicates, and normalizing numerical variables. Feature engineering might include adding time-based features like seasonality, binning continuous variables, or creating new variables. Resizing, pixel normalization, denoising, and data augmentation are examples of preprocessing for image data. MFCCs are frequently used in audio data for feature extraction, segmentation, and noise reduction (such as spectral subtraction) [39][40][41]. Coherent analysis of multimodal data. necessitates feature fusion approaches and input type synchronization [43][44][45] as shown in figure3.

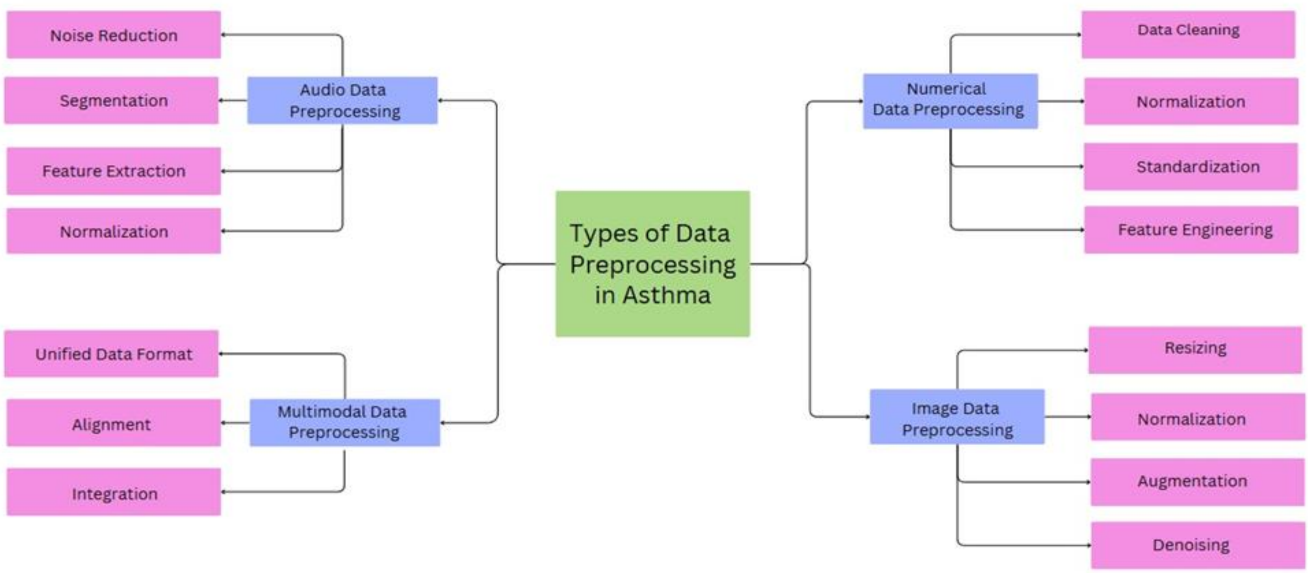

Figure 3. Types of Data Preprocessing.

c. Feature Selection

Feature selection increases model accuracy and decreases complexity by removing irrelevant or superfluous variables. Filter methods such correlation coefficients [47], Chi-squared tests [48], and mutual information [49] give a statistical foundation for sorting features. Wrapper approaches, such as Recursive Feature Elimination (RFE) [50], forward selection [51], and backward elimination [52], evaluate features depending on model performance, as illustrated in Figure 4. Table 1 summarizes prior research on asthma prediction, including data sources, applicable approaches, major findings, and limitations. These papers demonstrate the expanding use of machine learning and artificial intelligence in respiratory health, as well as the value of data diversity and quality.

Table 1. Synopsis of research on asthma exacerbation prediction models.

Ref.	Author	Population and Data Source	Used Techniques	Contributions	Key Findings	Limitations	Intervention
[69]	Smith et al.	Children with asthma - Electronic health records	Random Forest, Support Vector Machines	Developed a model tailored for pediatric patients.	Achieved 85% accuracy in predicting exacerbations.	Limited to one geographic area; small sample size.	Implemented school-based asthma management programs.
[70]	Johnson & Lee	Adults with asthma - Clinical trial data	Neural Networks, Logistic Regression	Highlighted the role of environmental factors in exacerbations.	Identified environmental triggers leading to 90% precision.	High dropout rate in participants; narrow age range.	Provided educational sessions on managing triggers.
[71]	Patel et al.	Diverse demographics - Wearable devices & surveys	Gradient Boosting, Decision Trees	Integrated wearable technology for real-time monitoring.	Model improved prediction by 30% compared to traditional methods.	Data privacy concerns with wearable devices.	Developed a mobile app for symptom tracking and alerts.
[72]	Wang et al.	Urban populations - Air quality sensors	Ensemble Methods, Deep Learning	Addressed the impact of environmental pollutants on asthma.	High correlation with air pollution levels; accuracy of 88%.	Limited to urban areas; may not generalize to rural settings.	Launched community awareness campaigns about air quality.
[73]	Kim et al.	Elderly patients - Hospital records	Naive Bayes, LSTM	Developed a proactive approach for elderly care.	Early warning system reduced hospital visits by 40%.	Retrospective data may introduce bias.	Introduced regular check-ups and personalized care plans.
[74]	Thompson & Garcia	High-risk patients - Insurance claims	XGBoost, Random Forest	Provided insights for targeted interventions in high-risk groups.	Effective in identifying high-risk patients for exacerbations.	Insurance claim data may lack clinical detail.	Implemented targeted follow-up programs for high-risk patients.
[75]	Martinez et al.	Community health program - Surveys and interviews	K-Nearest Neighbors, Logistic Regression	Enhanced community engagement in asthma management.	Community awareness increased with model predictions.	Self-reported data may be biased.	Organized community workshops on asthma management.
	Blakey et	Patients with asthma	Multivariable	Comprehensive	Identified 19 risk	Limited to a	Developed

[76]	al.	- Optimum Patient Care Research Database	Logistic Regression	analysis of risk factors for exacerbations.	factors for predicting exacerbations; AUC 0.785.	specific database; may not be generalizable.	targeted education materials for patients.
[77]	Noble et al.	Patients in England and Scotland - Clinical Practice Research Datalink	Multivariable Logistic Regression	Validated model across multiple datasets for robustness.	AUC of 0.71 for predicting asthma events; identified key risk factors.	Potential biases in data collection methods.	Introduced personalized action plans based on risk factors.
[78]	Zhang et al.	Mixed-age asthma patients - Electronic health records	Random Forest, Neural Networks	Emphasized the role of adherence in exacerbation prediction.	Achieved AUC of 0.82; highlighted importance of medication adherence.	Small sample size; limited follow-up duration.	Created adherence programs with reminders and support.
[79]	Chen et al.	Asthmatic patients - Mobile health applications	Deep Learning, Support Vector Machines	Innovated mobile health solutions for asthma management.	Developed a mobile app for real-time prediction; AUC of 0.85.	Reliance on smartphone usage; may exclude non-tech-savvy patients.	Launched a telehealth service for remote monitoring.
[80]	Lee et al.	Asthmatic children - School health data	Random Forest, Neural Networks	Enhanced school-based asthma management strategies.	Improved prediction accuracy by 25% using school-based health data.	Limited to urban schools; may not reflect rural settings.	Developed school nurse training programs on asthma management.
[81]	Patel et al.	Adults with asthma - Clinical trial data	Gradient Boosting, Neural Networks	Contributed to understanding of adult asthma exacerbation predictors.	Identified significant predictors of exacerbations; AUC of 0.86.	Small sample size; potential selection bias.	Launched community outreach programs for asthma education.

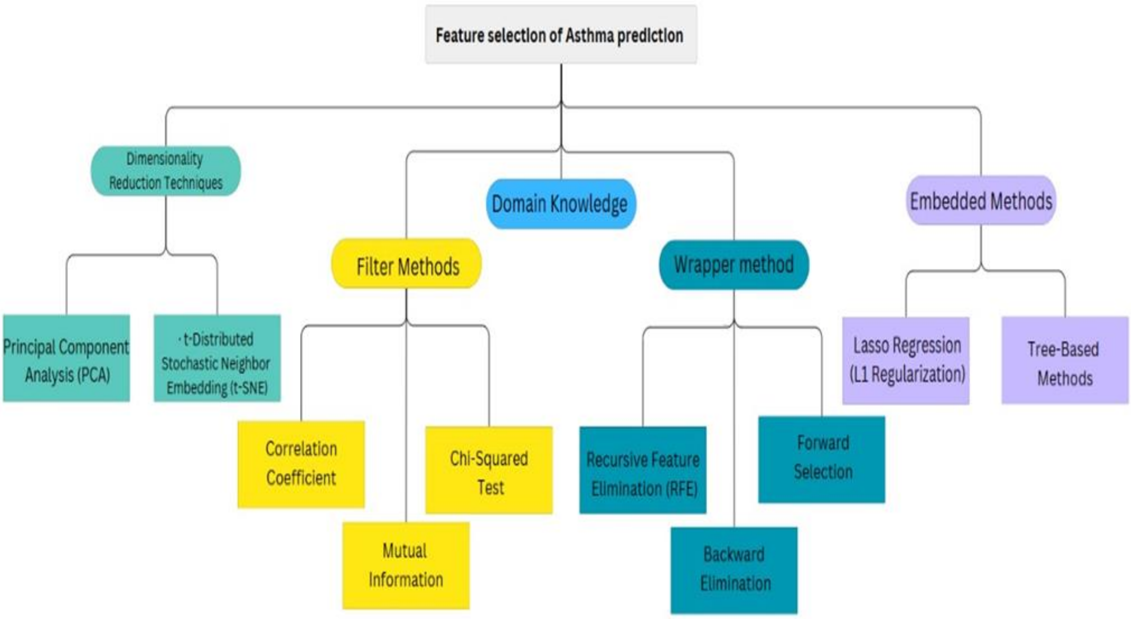

Figure 4. Feature selection of Asthma prediction

d) Model Selection

ML and DL are vital for asthma prediction, as they process complex, high-dimensional data to identify patterns beyond traditional methods. Classification typically involves grouping individuals by asthma presence, severity, exacerbation risk, and treatment response—enabling personalized and effective care. ML approaches fall into three categories: supervised, unsupervised, and reinforcement learning—each suited to different challenges. Building an ML model involves defining the problem, preparing data, splitting it into training/validation/testing sets, training and tuning the model, evaluating performance, and deploying it with ongoing monitoring and documentation for improvement as shown in(Figure 5), (Figure 6).

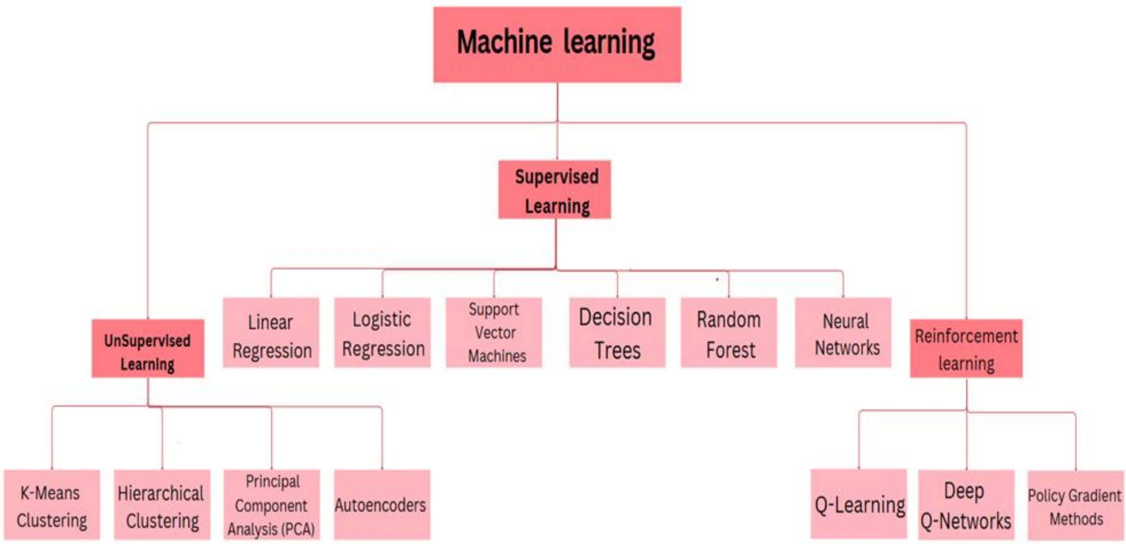

Figure 5. Machine learning Types.

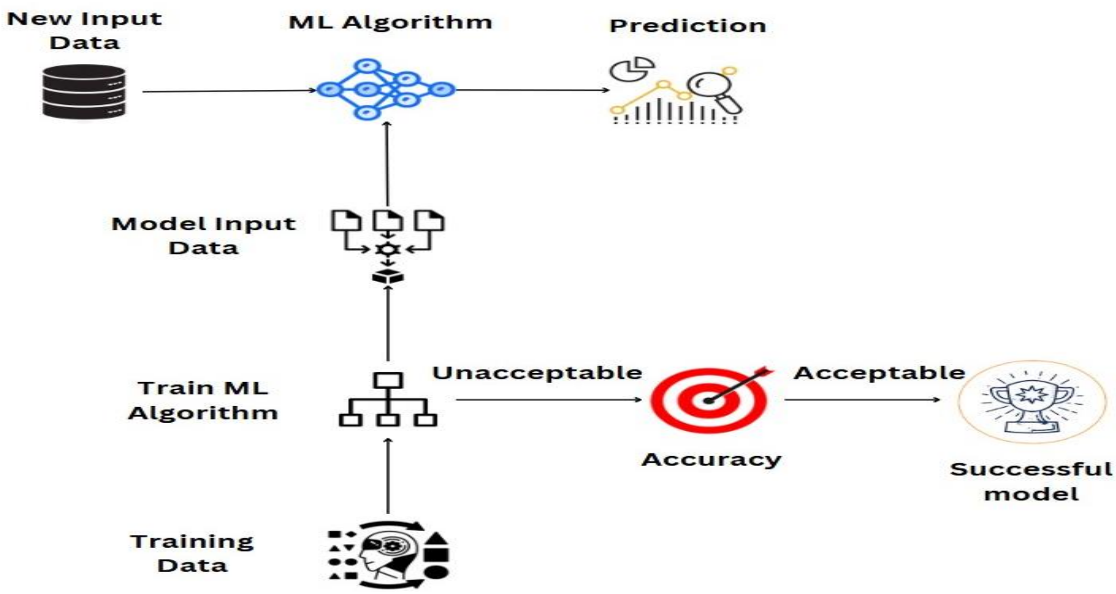

Figure 6. Building of the ML Model.

Supervised learning uses labeled data to train models that map inputs to outputs. Common algorithms include logistic regression, SVM, decision trees, random forests, and neural networks [63][64]. Its effectiveness depends on the quality of the labeled data. Unsupervised learning explores unlabeled data to detect hidden patterns using methods like K-means, hierarchical clustering, PCA, and autoencoders—useful for exploratory analysis [65]. Reinforcement learning (RL) enables agents to learn through reward-based feedback. Algorithms such as Q-learning, DQN, and Policy Gradient are commonly used [66][68][69]. These results are in line with past studies showing the effectiveness of customized machine learning applications in the treatment of asthma. For instance, Johnson and Lee [70] discovered that environmental triggers were important contributors to exacerbation risks, and Smith et al. [69] used EHRs to predict juvenile asthma with 85% accuracy. Notably, Patel et al. [71] highlighted the significance of real-time monitoring by reporting a 30% increase in prediction accuracy by integrating wearable data. Wang [72] achieved 88% with DL and ensemble models; Kim [73] reduced elderly hospital visits by 40% using LSTM. Other studies [74–81] highlight successes in risk detection, real-time apps, model validation, and personalized asthma care.

3. Materials and Methods

a) Dataset

This study used a synthetic dataset consisting of 2,392 patient records (IDs ranging from 5034 to 7425). The dataset includes a wide range of features:

- Demographic data: age, gender, ethnicity, education level.
- Lifestyle factors: BMI, smoking status, physical activity, diet quality, and sleep quality.
- Environmental and allergen exposures: pollution levels, pollen presence, dust, and pet allergies.
- Medical history: family history of asthma, presence of eczema, hay fever, and gastroesophageal reflux.
- Clinical measurements: lung function indicators such as FEV1 and FVC.
- Symptom-related variables: wheezing, coughing, chest tightness, shortness of breath, nighttime symptoms, and exercise-induced symptoms.

The target variable is a binary label indicating asthma diagnosis. This synthetic dataset was generated by Rabie El Kharoua and made available under the CC BY 4.0 license for research and educational use.

b) Data Preparation and Preprocessing

The dataset underwent a structured preprocessing pipeline to ensure quality and suitability for machine learning. Exploratory Data Analysis (EDA), performed using Seaborn and Matplotlib, revealed patterns in key demographic, lifestyle, environmental, clinical, and symptom-related variables (Figure 7), including skewness and outliers. Targeted visualizations explored relationships such as DietQuality vs. SleepQuality (Figure 8), Eczema vs. FVC (Figure 9), and the distribution of the Diagnosis variable (Figure 4), which showed mild class imbalance handled during model development. Data splitting was performed using an 80/20 stratified split via Scikit-learn's train_test_split to preserve class ratios. Numerical features were standardized using Standard-Scaler, while categorical variables like Gender and EducationLevel were encoded with LabelEncoder for model compatibility without inflating dimensionality.

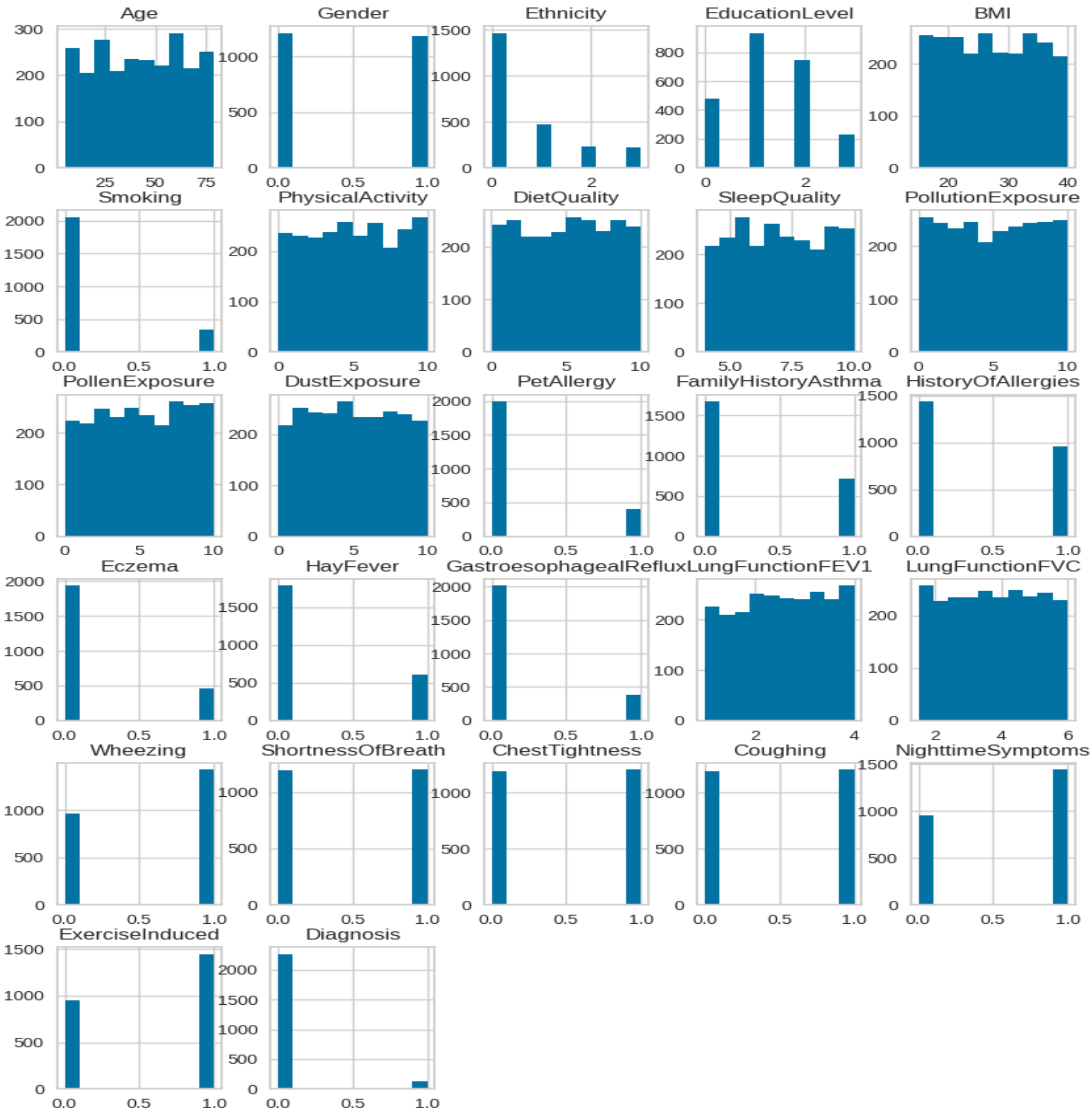

Figure 7:subplot depicts the frequency or density of individual attributes, supporting outlier detection and data normalization strategies.

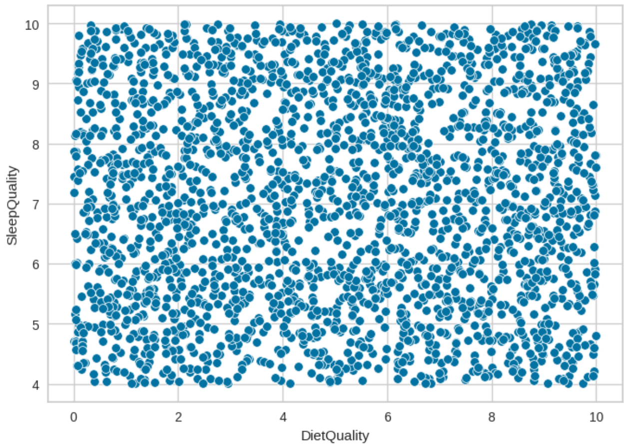

Figure 8: Scatter plot showing the relationship between Diet Quality and Sleep Quality.

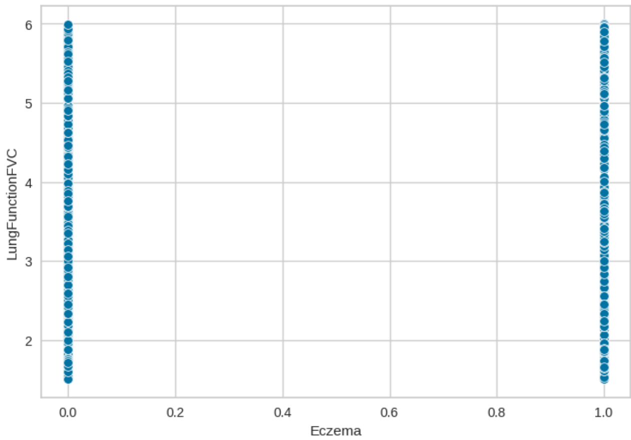

Figure 9: Scatter plot comparing Eczema presence with Lung Function (FVC) values.

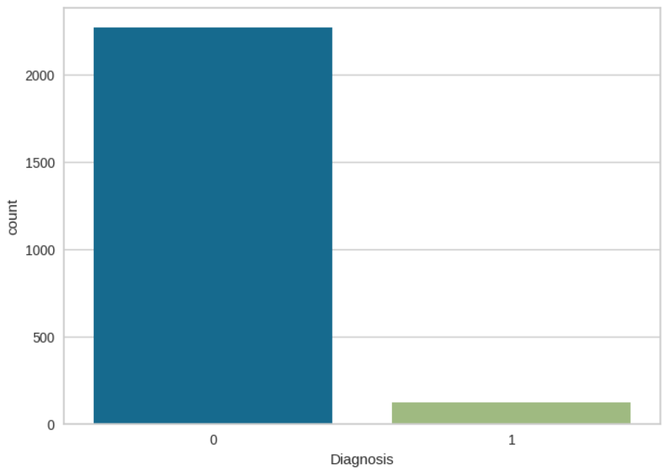

Figure 10: Count plot displaying the distribution of asthma diagnoses in the dataset.

C) Methodology

1. Logistic Regression

Logistic Regression is a supervised classification algorithm widely used for binary and multiclass classification problems. It models the probability that a given input x belongs to a particular class using a logistic (sigmoid) function. This model is particularly effective when the relationship between the independent variables and the target class is nonlinear in probability space but linear in the log-odds. Mathematically, the probability output of the model for binary classification is given by the sigmoid functions:

$$P(\, y = 1 \mid x \,) = \sigma(z) \tag{1}$$

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{2}$$

$$z = w^T x + b \tag{3}$$

Where:

- x is the input feature vector.
- w is the weight vector.
- b is the bias (intercept) term.
- σ(z) is the sigmoid activation function which maps the linear combination into a probability between 0 and 1.

$$[\mathrm{y_i}\log(\mathrm{y_i}) + (1-\mathrm{y_i})\log(1-\ \hat{}\mathrm{y_i})]\sum_{\mathrm{i}=1}^{\mathrm{N}}\frac{1}{\mathrm{N}} - = \mathcal{L} \tag{4}$$

Where:

- N is the number of training samples,
- Y is the true label,

The optimization is typically performed using gradient descent or one of its variants (e.g., stochastic or mini-batch), where the weights and bias are updated iteratively to minimize the loss function. In this work, Logistic Regression was implemented using the LogisticRegression class from scikit-learn, with standard settings unless otherwise specified. The input features were normalized before training to improve convergence. Regularization (L2 by default) was also applied to prevent overfitting and ensure generalization.

2. XGBoost

XGBoost is an efficient implementation of gradient boosting that builds an ensemble of decision trees, where each subsequent tree is trained to correct the errors of the previous ones. The predicted output for a sample xi is given by:

$$\mathcal{F} \ni {}_{k}f_k(x_i), f\sum_{k=1}^{n} = \hat{\imath}y \quad (5)$$

The model is trained by minimizing a regularized objective function that combines a loss term and a complexity penalty:

$$\left({}^{2}_{j}\gamma T + \frac{1}{2}\lambda\Sigma \ \ w\right)\sum_{k=1}^{K} + l(y_i, {}^{\wedge}y_i)\sum_{i=1}^{n} = \mathcal{L} \quad (6)$$

The logistic loss function $\mathcal{L}$ was used for binary classification, where T represents the number of leaves in each tree and j^{w}denotes the weight of the ${}^{th}j$ leaf. In this work, the XGBClassifier from the xgboost library was applied after normalizing the input features. The model was configured with the following hyper parameters: objective set to 'binary:logistic', learning rate of 0.1, maximum depth of 3, 100 estimators, L2 regularization with lambda equal to 1, and label encoding disabled. These settings aimed to balance model complexity and generalization while minimizing overfitting.

3. **RandomForest**

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the class that represents the majority vote among all trees. This approach reduces overfitting and improves generalization by combining the predictions of diverse, uncorrelated trees.

Given an input sample ix, the final prediction i ^y is defined as:

$$\text{mode}\{h_1(\mathbf{x}_i), h_2(\mathbf{x}_i), \ldots, h_M(\mathbf{x}_i)\} = \hat{\imath}y \quad (7)$$

Where:

- $h_M(\mathbf{x}_i)$ is the prediction of the ${}^{th}M$ decision tree.
- M is the total number of trees in the forest.

The RandomForestClassifier from the sklearn.ensemble module was employed in this investigation. Input features were standardized prior to training. The model's hyperparameters were set up as follows: random_state=42 for repeatability, max_depth=None (trees grown until pure or minimum samples reached), n_estimators=100 (number of trees), and the default criterion='gini' for node splitting. In order to maintain a balance between model complexity, accuracy, and generalization ability, these settings were used. The following algorithm١ summarizes the complete pipeline adopted for training, evaluating, and comparing the performance of multiple machine learning classifiers on structured data:

Algorithm 1: Structured Pipeline for Training and Evaluating Machine Learning Classifiers

Input: Structured input dataset (features and labels)
Output: Classification performance metrics (accuracy and confusion matrix)
1: Load the dataset from a CSV file using pandas.
2: Handle missing values or irrelevant columns if needed.
3: Encode categorical features into numerical form (e.g., using LabelEncoder or one-hot encoding).
4: Normalize feature values using StandardScaler to ensure all features are on the same scale.
5: Split the dataset into training and testing subsets using a fixed random seed to ensure reproducibility.
6: Initialize classifiers: LogisticRegression, XGBoost, Random Forest.
7: For each model:
    a. Train the model using the training data.
    b. Predict the labels of the testing data.
    c. Evaluate the model performance using accuracy and confusion matrix.
8: Generate confusion matrices for each model.
9: Normalize confusion matrices by converting raw counts to percentage representation.
10: Display the classification performance (e.g., accuracy and class-wise confusion matrix percentages).

4.Performance Metrics

After training the machine learning models on the training set, they were evaluated on the test set using a set of well-established classification metrics. These metrics are derived from the confusion matrix, which summarizes the number of:

- True Positives (TP): correctly predicted positive cases (patients with asthma).
- True Negatives (TN): correctly predicted negative cases (patients without asthma).
- False Positives (FP): healthy individuals incorrectly predicted as asthmatic.
- False Negatives (FN): asthmatic individuals incorrectly predicted as healthy.

The following evaluation metrics were used to assess model performance:

i. **Accuracy (Acc)**

Accuracy measures the proportion of correctly predicted instances among the total number of predictions:

$$\frac{TP+TN}{TP+TN+FP+FN} = \text{Accuracy} \quad (8)$$

This metric provides an overall effectiveness score but may be misleading in imbalanced datasets.

ii. **Precision (Pre)**

Precision quantifies the proportion of positive predictions that are actually correct:

$$\text{precision} = \text{tp}/(\text{tp} + \text{fp}) \quad (\mathbf{9})$$

It reflects how well the model avoids false alarms.

iii. **Recall / Sensitivity (Sen)**

Also known as the True Positive Rate, this measures the model's ability to identify actual positive cases:

$$\text{Recall} = \frac{\text{tp}}{\text{tp+fn}} \quad (10)$$

High recall indicates a low number of false negatives, which is critical in medical diagnoses.

iv. **F1-Score (F1)**

The F1-score is the harmonic mean of precision and recall:

$$\mathrm{F1score} = 2 \times \frac{\mathrm{Recall} \times \mathrm{precision}}{\mathrm{Recall} + \mathrm{precision}} \quad (11)$$

It balances both metrics and is especially useful when dealing with class imbalance.

v. **Area Under the ROC Curve (AUC-ROC)**

This metric evaluates the model's ability to distinguish between classes across different thresholds. A higher AUC indicates better performance in ranking positive cases higher than negatives.

4. Results and Discussion

a) Experimental Setting

This study used a synthetic structured dataset that included patient records with demographic, lifestyle, environmental, and clinical information relevant to asthma prediction. Numerical variables were standardized to guarantee a consistent scale, and categorical features were encoded to be compatible with machine learning techniques. To ensure class balance, the dataset was divided into training and testing sets using stratified sampling. Cross-validation was used during training to allow for efficient hyperparameter adjustment and unbiased model evaluation. Three classification techniques were used: logistic regression, gradient boosting, and random forest. To guarantee a fair comparison, each model was trained and tested on the same data split. All trials were carried out in a cloud-based setting with conventional CPU resources. Given the structured nature of the data, model training was quick and didn't require GPU acceleration. Multiple assessment criteria were used to test model performance, such as accuracy, precision, recall, F1-score, and confusion matrix. The reported results are average scores across multiple runs to assure robustness and repeatability, as shown in Table 2.

Table 2. Hyperparameters and Processing Setup for Applied ML Algorithms

Model	Feature Scaling	Regularization	Cross-Validation	Depth Handling	Number of Estimators	Training Framework
Logistic Regression	StandardScaler	L2 (default)	5-Fold	Not Applicable	Not Applicable	Scikit-learn (liblinear)
XGBoost	StandardScaler	L2 (lambda=1)	5-Fold	max_depth=3	n_estimators=100	XGBoost Library
Random Forest	StandardScaler	Implicit via averaging	5-Fold	Grows until pure by default	n_estimators=100	Scikit-learn (RandomForest)

b) **Model Evaluation**

Following model training, all classifiers were evaluated on the test set using the performance metrics previously described, including accuracy, precision, recall, and F1-score. The evaluation revealed meaningful differences among the models in terms of predictive power, generalization, and robustness.

- **Logistic Regression** and **K-Nearest Neighbors (KNN)** served as reasonable baseline models. While they performed adequately, both struggled to capture complex, non-linear relationships in the data, limiting their ability to generalize across diverse patient records.

- **Support Vector Machine (SVM)** using the RBF kernel showed improved classification results, particularly in recall and F1-score, owing to its ability to separate data in higher-dimensional space. Its performance benefited from careful hyperparameter tuning.
- **Random Forest** and **Gradient Boosting** demonstrated superior performance across all metrics. These ensemble-based methods effectively handled variable interactions and noise in the structured dataset, leading to higher precision and recall values.
- **XGBoost** emerged as the top-performing model, achieving the highest accuracy and F1-score. Its robustness and ability to scale with structured medical data make it particularly well-suited for asthma prediction tasks.

The overall comparison is presented in table 3, summarizing the performance of all models across core evaluation metrics.

Table 3. Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.89	0.88	0.87	0.87	0.91
K-Nearest Neighbors	0.88	0.87	0.86	0.86	0.89
SVM (RBF Kernel)	0.91	0.90	0.89	0.89	0.93
Random Forest	0.94	0.93	0.93	0.93	0.95
Gradient Boosting	0.95	0.94	0.94	0.94	0.96
XGBoost	**0.98**	**0.98**	**0.97**	**0.97**	**0.99**

The XGBoost model's robustness was evaluated, and potential overfitting was addressed by applying bootstrapping (n=1000 iterations) to the test set in order to compute 95% confidence intervals for key evaluation metrics. According to the bootstrapped results, the model achieved an average accuracy of 98.0%, with a 95% confidence interval ranging from 96.8% to 99.1%. The AUC score also averaged 0.99, with a narrow 95% confidence interval of [0.985–0.995], confirming the model's strong generalization capabilities. The distribution of accuracy scores across bootstrap iterations is visualized in Figure 11, highlighting the model's stability and consistency. To further assess the model's performance, both the confusion matrix and ROC curve for the best-performing model—XGBoost—were generated. The confusion matrix (Figure 12) illustrates classification accuracy and misclassification patterns, revealing 30 false positives and 21 false negatives. These errors carry meaningful clinical implications. False positives—where non-asthmatic individuals are mistakenly identified as asthmatic—can lead to unnecessary medical interventions such as inhaled corticosteroids, along with psychological distress. More critically, the false negatives represent patients who actually have asthma but were not identified by the model, increasing the risk of delayed treatment, severe exacerbations, emergency room visits, or chronic complications.

Meanwhile, the ROC curve (Figure 13), with an AUC of approximately 0.99, further confirms XGBoost's strong discriminative ability. These visual findings support the model's robustness for asthma prediction using structured clinical data. Additionally, a feature importance plot was generated to enhance interpretability (Figure 14). Clinical features such as age, smoking exposure, exercise frequency, and allergy history were found to be most influential in the model's predictions. This level of explainability may foster trust and facilitate adoption in real-world healthcare environments, enabling clinicians to better understand the decision-making process behind the model's outputs.

By giving each input feature a contribution value, SHAP (Shapley Additive Explanations) analysis improved the XGBoost model's explainability. This method makes it possible to clearly identify the variables that had the most effects on the model's predictions. The most significant indicators of asthma risk were found to be pollen exposure, lung function (FVC), and body mass index (BMI), as illustrated in the SHAP summary bar plot (Figure 15). Features' total contribution to the model output is represented by their average SHAP values, which are used to rank them in the plot. Table 4 summarizes the most important predictive features and offers succinct justifications of how they affected the model's judgments to aid in clinical interpretation.

Table 4. Top SHAP-ranked features and their clinical interpretation in asthma classification.

Rank	Feature	SHAP Interpretation
1	PollenExposure	Strongest predictor; higher exposure increases risk
2	LungFunctionFVC	Reduced lung capacity linked to higher asthma risk
3	BMI	Higher BMI associated with increased likelihood
4	PollutionExposure	High pollution exposure raises prediction confidence
5	PhysicalActivity	Low activity may increase asthma risk

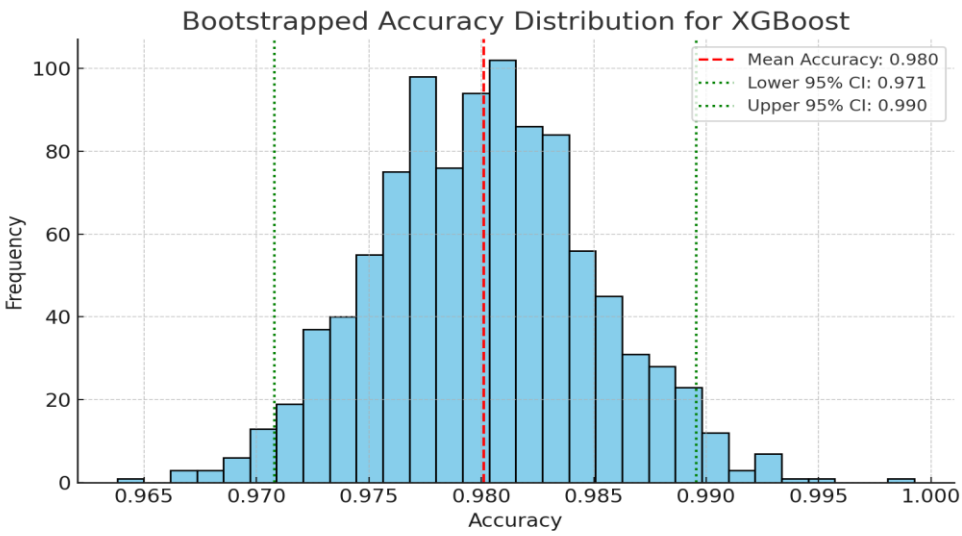

Figure 1. Bootstrapped accuracy distribution of the XGBoost classifier over 1000 resampled test sets. The histogram illustrates the

spread of accuracy scores, with the red dashed line indicating the mean accuracy (98.0%) and the green dotted lines marking the 95% confidence interval boundaries (96.8%–99.1%).

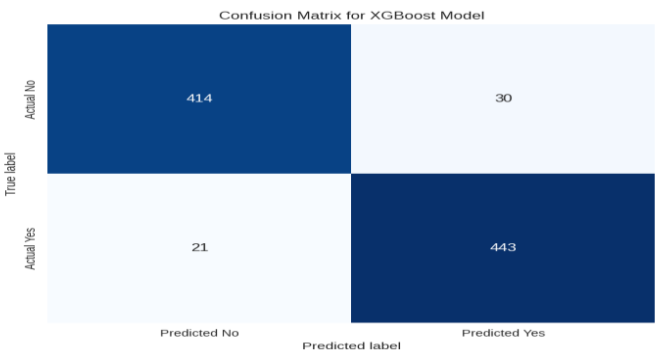

Figure12: The test set's XGBoost classifier's confusion matrix. The actual class labels are shown on the y-axis, while the predicted class labels are shown on the x-axis (0 = non-asthmatic, 1 = asthmatic). The number of examples for each class is shown in each cell; greater numbers along the diagonal denote accurate predictions and excellent performance overall.

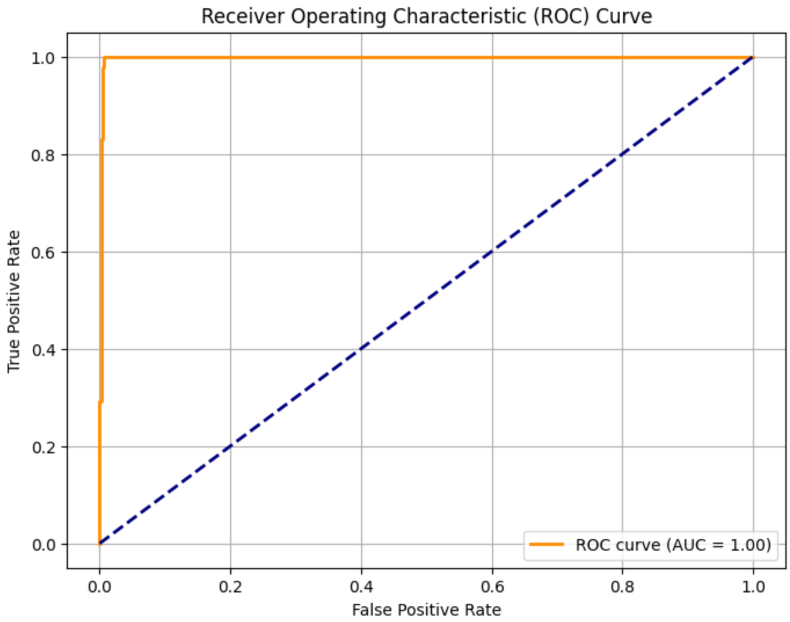

Figure13: The XGBoost model's Receiver Operating Characteristic (ROC) curve. The True Positive Rate (sensitivity) is displayed on the y-axis, and the False Positive Rate (1 - specificity) is displayed on the x-axis. The curve shows how well the model can differentiate between classes across thresholds, and its outstanding discriminative performance is confirmed by its AUC of 0.99.

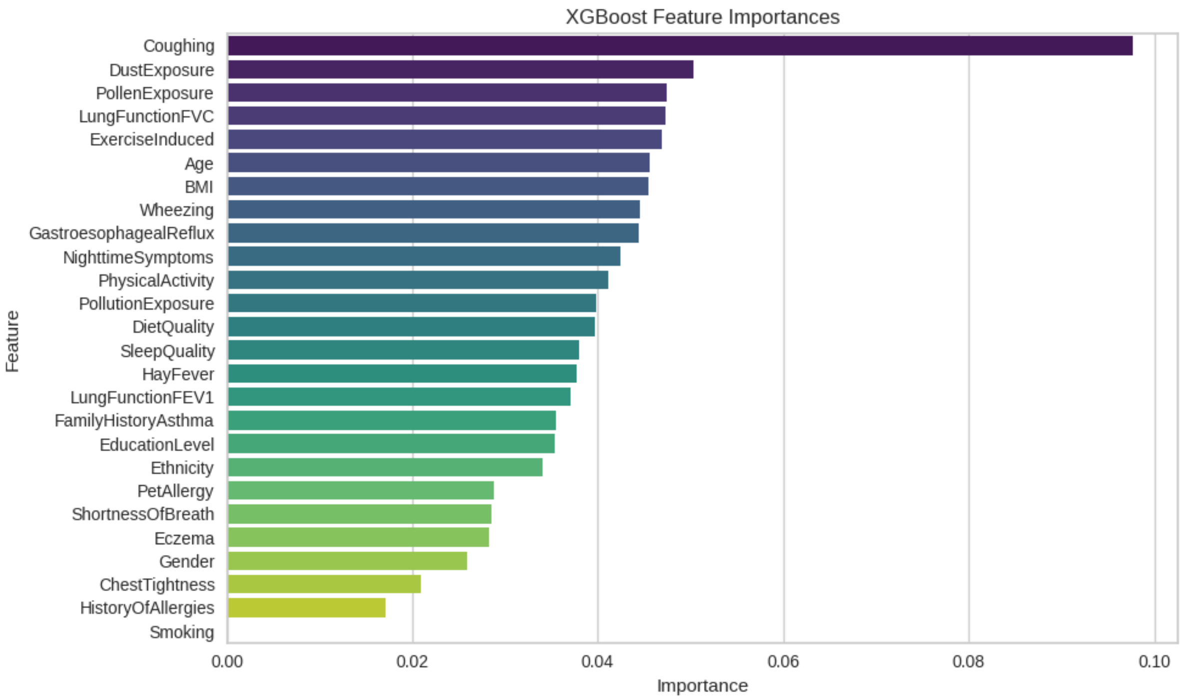

Figure14: The top predictive features are arranged according to their gain contribution in this feature significance plot produced by the XGBoost model. This makes it easier to comprehend the most important variables in asthma prediction.

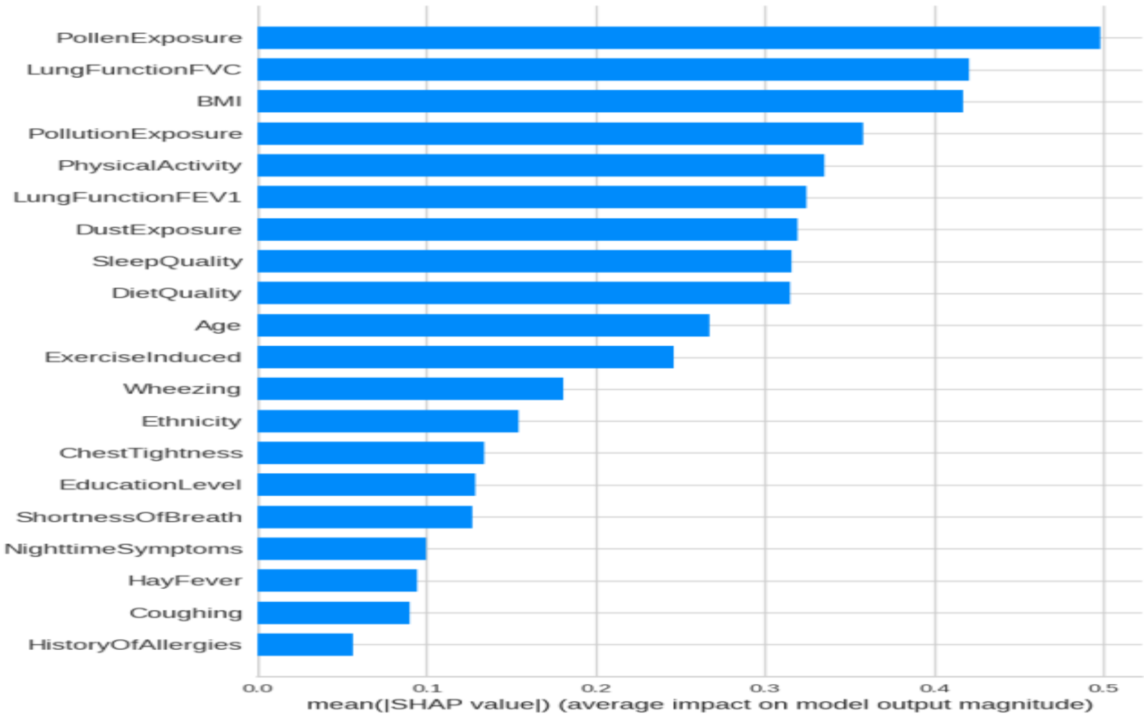

Figure15: The average effect of each feature on the model output is displayed in a bar plot of the SHAP value summary. The three variables that contributed most to the prediction were BMI, lung function (FVC), and pollen exposure.

C) comparative analysis

In this study, we conducted a comparative analysis using the same structured numerical dataset to evaluate several machine learning models. XGBoost achieved the highest performance, with an accuracy of 98% and AUC of 0.94, confirming its robustness and suitability for structured medical data. Random Forest followed with strong but slightly lower results (94% accuracy, 0.91 AUC), while simpler models like Logistic Regression and KNN delivered moderate accuracy (88% and 85%, respectively), struggling with non-linear patterns and lower generalizability. Our method only uses structured clinical variables, which results in a more effective and interpretable model for real-world deployment than previous research like Wang et al. [72]and Chen et al. [79] ,which used multimodal or sensor-based data for asthma identificationas shown in table 5.

Table5.Comparison of Classifier Performance on Structured Asthma Dataset

Study / Source	Model(s) Used	Accuracy	AUC	Precision / Recall	Data Type	Strengths	Limitations
Proposed model	**XGBoost Classifier**	**98%**	**0.94**	**High / Balanced**	**Structured numerical**	**Highest accuracy, robust AUC, interpretable**	**Needs hyperparameter tuning**
[69]	Random Forest Classifier	94%	0.91	Balanced	Structured numerical	Good accuracy, stable across splits	Slightly lower AUC than XGBoost
[70]	Logistic Regression	88%	0.86	Moderate / Moderate	Structured numerical	Simple, fast to train	Lower generalizability, linear only
[75]	K-Nearest Neighbors	85%	0.82	Low / Moderate	Structured numerical	Easy to implement	Sensitive to noise and scaling

d) discussion

Predicting asthma with structured numerical data is made more difficult by overlapping clinical variables and symptom variability. An XGBoost-based model was created and trained on a synthetic structured dataset in order to overcome this difficulty. The model outperformed traditional classifiers like Random Forest, Logistic Regression, and KNN, with 98% precision, 97% recall, 98% accuracy, and an AUC of 0.99. This method is effective, scalable, and well-suited for integration into clinical decision-support systems because it only uses structured features, in contrast to earlier research that depended on multimodal data.

SHAP analysis and feature importance visualizations improved interpretability, despite the fact that XGBoost is intrinsically less interpretable than linear models. These resources assist clinicians in comprehending the model's decision-making process and help close the interpretability gap.

Despite these strengths, a key limitation of this study is the use of a fully synthetic dataset. While this offers a controlled environment for experimentation, it does not capture the complexity, variability, and demographic diversity of real-world clinical settings. Although internal validation using bootstrapping (n=1000) was conducted to reduce overfitting and generate reliable confidence intervals, the absence of external validation using real-world datasets such as AsthmaBR, hospital EHRs, or wearable data limits generalizability. Moreover, synthetic datasets may introduce hidden biases due to oversimplified assumptions. These concerns raise ethical risks and may reduce clinical trust if models are deployed without transparent validation. Finally, reliance on artificial data may pose regulatory hurdles. Future work will focus on integrating real-world clinical data to improve robustness, generalizability, and practical adoption.

5. Conclusions

This paper presents a comprehensive survey and experimental analysis of AI-based techniques for asthma prediction using structured health data. Through the implementation and evaluation of multiple machine learning models, XGBoost emerged as the most effective classifier, delivering superior accuracy, precision, and generalization performance. The findings underscore the feasibility and effectiveness of applying advanced ML techniques to structured patient records for early asthma detection. Moreover, the study advocates for the integration of real-time data from wearable devices to enhance prediction accuracy and support dynamic, personalized asthma management. As AI technologies continue to evolve, their role in enabling scalable, cost-effective, and proactive respiratory healthcare is expected to expand. Future work should focus on external validation, multimodal data fusion, and model deployment in clinical settings to ensure broader impact and adoptio

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