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The Design Of An Expert System To Detect The Possibility Of An Asthma Attack In An Environment

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ABSTRACT
Introduction: *Asthma is a chronic breathing problem impacting around 300 million individuals worldwide, with forecasts indicating this figure may increase to around 400 million by 2025. The intricate nature of asthma, influenced by various environmental factors like allergens, pollution, and climatic changes, requires sophisticated forecasting methodologies. This work introduces a novel expert system utilizing Artificial Intelligence (AI) and Machine Learning (ML) methodologies to evaluate and forecast the likelihood of asthma attacks based on real-time environmental factors and personal health information. The research employs sophisticated ML techniques, specifically XGBoost and LightGradient Boosting Machine (lightGBM), to analyze complex datasets comprising patient symptoms and environmental triggers. By integrating advancedalgorithms with rule-based expert knowledge, the system classifies asthma attack risks into high, medium, and low categories. Principal Component Analysis (PCA) was utilized to streamline feature selection, ensuring the most relevant factors are considered while maintaining predictive accuracy.The study's findings demonstrated remarkable predictive performance. XGBoost achieved accuracies of 92% for city day, 93% for city hour, and 93% for patient datasets. LightGBM showed similarly impressive results, with 91% accuracy for city day, 90% for city hour, and a remarkable 97% for patient-specific data. The ensemble model, combining XGBoost and LightGBM, emerged as the most outstanding approach, delivering 99% accuracy for city datasets and a perfect 100% accuracy for patient data.Future developments aim to enhance the system through advanced AI models, improved personalization, real-time data processing, wearable device integration, and potential expansion to predict risks for other respiratory conditions. By continually refining ML algorithms and incorporating comprehensive patient data, this expert system promises to revolutionize asthma management, offering personalized, timely, and accurate predictions that can significantly improve patients' quality of life.*

Keywords: *Asthma prediction, Real-Time Monitoring,Machine Learning,LightGBM,XGBoost.*

INTRODUCTION

The development of an expert system to identify the possibility of an asthma attack in a specific situation is a crucial step in using AI to improve patient care and asthma management. Asthma, a chronic respiratory disorder characterized by airway inflammation and constriction, may be induced by numerous environmental variables, such as allergens, pollutants, and climatic variations [1]. Identifying these triggers and predicting the likelihood of an asthma attack is the top priority for effective preventive measures and timely intervention. The expert system utilizes a combination of knowledge-based rules, ML algorithms, and real-time data analysis to assess environmental conditions and their potential impact on asthma inconvenience. It integrates information on air quality, pollen levels, humidity, temperature, and other relevant parameters to generate predictive models [2]. These models are continuously updated based on new data inputs and refined through feedback mechanisms, ensuring accuracy and reliability.Key components of the expert system include a user-friendly interface for inputting personal health data, a database of asthma-related knowledge and rules, and algorithms for data processing and pattern recognition [3].

The primary goal of the asthma attack expert method is to empower individuals with asthma, healthcare professionals, and caregivers with timely information and actionable insights to minimize the risk of asthma attacks. By providing personalized recommendations, alerts, and preventive strategies, it aims to improve asthma management, reduce emergency hospital visits, and improvethe overall quality of life for people with asthma, and collaborative efforts between medical experts, data scientists, and technology developers are crucial for the successful implementation and continuous improvement of such systems [4].Overall, the design of an expert system for detecting the possibility of asthma attacks in various environments represents a significant advancement in asthma care, leveraging the capabilities of AI to enhance preventive measures, promote patient empowerment, and ultimately improve health outcomes for individuals living with asthma [5].

1.1 Research Motivation

The motivation behind developing an expert system to detect asthma attack possibilities arises from critical concerns in both healthcare and environmental management. Asthma, a widespread chronic respiratory condition affecting millions globally, is characterized by periodic exacerbations triggered by various environmental factors. The unpredictable nature of these exacerbations poses challenges for patients and healthcare providers alike. Leveraging advancements in AIand data analytics, a tailored expert system for asthma management could provide personalized risk assessments based on environmental factors like air quality, pollen levels, temperature, and humidity.The tailored expert system has the potential to empower asthma patients by equipping them with personalized insights to make informed decisions about their activities and environments. By enabling individuals to proactively mitigate asthma triggers in specific settings, such as avoiding outdoor activities during high pollen seasons or optimizing indoor air quality, the system could reduce the frequency and severity of asthma attacks, leading to improved management outcomes and enhanced quality of life.

Moreover, deploying such a system could yield valuable insights for public health efforts. By elucidating the relationship between environmental exposures and asthma exacerbations, the system could inform targeted interventions and policies aimed at reducing the burden of asthma on both individual and population levels. The interdisciplinary approach at the intersection of healthcare, environmental science, and AIholds profound implications for improving asthma management and public health outcomes.The development of an expert system for asthma attack prediction thus represents a promising avenue for research. By harnessing healthcare, environmental science, and AI, the initiative has the potential to drive transformative advancements in asthma care, benefiting individuals, healthcare systems, and society as a whole. It underscores the importance of interdisciplinary collaboration in addressing complex healthcare challenges and highlights the role of technology in facilitating personalized and proactive approaches to disease management. Overall, the endeavour holds significant promise for improving the lives of millions affected by asthma worldwide while advancing by understanding of the complex interplay between environmental factors and respiratory health.

OBJECTIVES

The primary objective of this research is to initiate a fundamental change in the way asthma care is approached.

- Expert system to continuously monitor the presence or absence of asthma triggers (environmental and physiological) in an environment.
- Expert system to predict the risk of an asthma attack.
- Expert systems provide a reliable means for better management of asthma by predicting the correct prophylactic dose to prevent an asthma attack.
- Expert System solves the problem by warning asthma patients about the risk of possible attack if they stay in the environment.

METHODS

The research methodology chapter for designing an expert system to detect the possibility of having an asthma attack in an environment has been structured around key components. This research uses both patient symptom data (e.g., breathing difficulty, coughing) and related environmental data (e.g., air pollution levels) to develop ML models using XGBoost and LightGBM to predict different levels of asthma attack risk, such as high, medium, or low. After model performance evaluation, an expert system is built that combines MLpredictions with rule-based logic defined by domain experts allowing nuanced risk assessment. Rules include symptoms, pollutant levels, and ML-predicted risks, among other factors. The final asthma attack risk assessment integrates an evidence-based ML model with knowledge-based expert system rules to enhance comprehensive and accurate predictions. This methodology combines data with domain expertise to detect the

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possibility of having asthma attacks. This all-inclusive method ensures better predictive accuracy by combining ML capabilities with expert domain knowledge.

3.1 Problem Formulation

Multiple constraints exist that make it difficult to model the complex relationships between patient symptoms, individual health profiles, and environmental triggers to make accurate, customized asthma attack risk assessments. These include a lack of patient and environmental-specific data, difficulty in developing personalized ML models capturing exacerbation patterns in detail seamlessly merging model-based predictions with knowledge-based expert systems, and assessing the performance of integrated systems. Overcoming these problems involves collecting patient symptoms and environmental data using research methodology involving cleaning and feature selection stages before building a model using XGBoost and LightGBM. This involves such activities as computing performance metrics, improving models, and incorporating knowledge-based expert systems that use defined rules derived from clinical experts. Finally, the approach combines expert rules with ML model predictions to better understand the risks and make better predictions by using both the AI's capabilities and human expertise.

3.2 Proposed Methodology

This study has created an expert system that can be used for predicting individual asthma attack risks in open environments by combining patient symptoms and environmental data. XGBoost and LightGBM are ML models which employ user-specific data as well as air quality (pollution levels), to predict three categories of risk: high, medium, or low. These predictions are then combined with rule-based reasoning provided by domain experts considering the symptoms, pollution levels, and other factors to produce a nuanced risk assessment. It is a unique approach because it combines predictive analysis informed by data with insight from experts to enable accuracy and personalized early warnings about potential asthma attacks, hence enabling the affected patients to take preventive measures accordingly. In figure 4, it depicts how the operation takes place through a diagrammatic representation called the proposed layout. Finally, the below steps have been provided to explain the process flow of the proposed methodology.

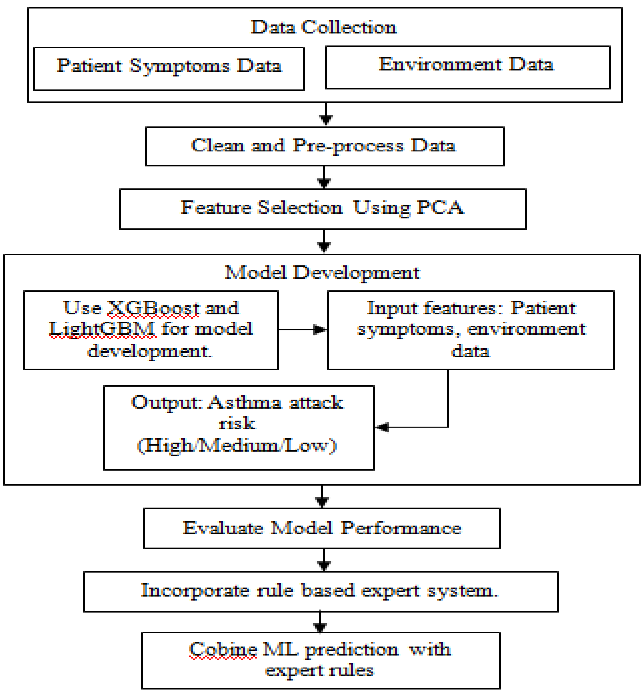

Figure 3. 1: Proposed Methodology

Step 1: Data Collection

- **Patient Symptom Data:** Gather information on asthma symptoms considering from asthma disease dataset.

- **Environmental data:** Considering a comprehensive look at air quality across 28 diverse Indian cities.

Step 2: Data Preprocessing
This step includes removing all missing values and outliers from the data collected. Numerical features should be standardized or normalized.

Step 3: Feature Selection Using PCA
PCA is now employed for feature selection, which allows forshrinking the dimensions of the dataset.This leads to the selection of only the most relevant features and better model efficiency.

Step 4: Model Development
- **ML Model:** DevelopanML model by a combination of XGBoost and LightGBM. They can work with complex relationships in data, thus making them suitable for classification tasks.
- **Input Features:** Patient symptom data and environment data are both used as input features for the model.
- **Output:** The output of the model is whether asthma attack risk is high, medium, or low.

Step 5: Model Evaluation
- **Evaluate Model Performance:** Accuracy, precision, recall, and F1-score are evaluation metrics that can be used to determine if the ML model performs well or not.
- **Model Refinement:** Based on evaluation results, refine the model so that it can further improve its predictive capabilities.

Step 6: Expert System
An expert system incorporates rule-based logic and ML predictions to give a more comprehensive risk assessment.
- **Define rules based on expert knowledge:**
  - IF PM10 levels > 50ug/m^3 OR CO levels > 5ug/m^3, THEN Asthma attack risk is HIGH.
  - IF Difficulty-in-Breathing = Yes OR Dry-Cough = Yes, THEN Asthma attack risk is HIGH.
  - IF None_Symptoms = Yes BUT ML model predicts HIGH risk based on Age, Gender, Severity factors, and Pollutant levels THEN Asthma attack risk is HIGH.
  - IF Sore-Throat = Yes AND ML model predicts LOW risk based on patient factors and Pollutant levels, THEN Asthma attack risk is MEDIUM.
  - IF No symptoms are present AND the ML model predicts LOW risk, THEN Asthma attack risk is LOW.

Step 7: Combine ML Model Predictions with Expert Rules
Finally, the ML model predictions should be integrated with the rules from an expert system to give a final risk assessment. This approach takes advantage of ML's strengths and domain expertise to provide more accurate and comprehensive predictions.

RESULTS

The creation of an expert system to assess the likelihood of an asthma attack in a specific environment involves a systematic approach, leading to meaningful outcomes through a series of essential steps. The data collection phase involved gathering patient symptom data from an asthma disease dataset and environmental data from air quality indices across 28 diverse Indian cities. This comprehensive approach ensured that both patient health indicators and environmental factors were considered. During data preprocessing, missing values and outliers were removed, and numerical features were standardized to ensure data consistency and reliability.
PCA was used for feature selection to decrease the dimensions of the dataset and keep only the most relevant features. This process improved the efficiency and effectiveness of the model. The model development phase used a combination of LightGBM and extreme gradient boosting (XGBoost) to leverage their ability to handle complex data relationships. Patient symptoms and environmental data were used as input features, with the model outputting risk levels of asthma attacks categorized as high, medium, or low.

- **Based on environmental parameters**

Case 1: High Asthma Risk predicted based on environmental parameters as shown in table 4. 5.

Table 4. 1: High asthma risk predicted based on environmental parameters

	Key /parameter	Value
Input	Enter city	Delhi
output	Air Quality Index (AQI)	214
	PM2.5 in ug/m^3	156
	CO level in ug/m^3	15
	Pollution estimation (High/ Medium/ Low)	High
	Asthma risk prediction for Delhi	High

Themodel predicts a high asthma risk in Delhi due to elevated environmental parameters: an AQI of 214, PM2.5 at 156, and CO level at 15. These values indicate poor air quality, leading to a high estimated pollution level and, consequently, a high risk of asthma, particularly for those with respiratory sensitivities.

Case 2: Moderate Asthma Risk predicted based on environmental parameters as shown in table 4. 6.

Table 4. 2: Moderate asthma risk predicted based on environmental parameters

	Key /parameter	Value
Input	Enter city	Agra
Output	Air Quality Index (AQI)	143
	PM2.5 in ug/m^3	71
	CO level in ug/m^3	7
	Pollution estimation (High/ Medium/ Low)	Medium
	Asthma risk prediction for Agra	Medium

The model predicts a moderate asthma risk in Agra based on the given environmental parameters. With an AQI of 143, $PM_{2.5}$ concentration of 71, and a CO level of 7, the pollution estimation is categorized as medium. These levels suggest that while the air quality is not optimal, the risk of asthma is moderate, indicating a need for cautious monitoring, particularly for individuals with existing respiratory conditions.

Case 3: Low Asthma Risk predicted based on environmental parameters as shown in table 4. 7.

Table 4. 3: Low Asthma Risk Predicted based on environmental parameters

	Key /parameter	Value
Input	Enter city	Ahmedabad
output	Air Quality Index (AQI)	45
	PM2.5 in ug/m^3	42
	CO level in ug/m^3	4
	Pollution estimation (High/ Medium/ Low)	Low
	Asthma risk prediction for Ahmedabad	Low

The model predicts a low asthma risk in Ahmedabad based on the environmental parameters. With an AQI of 45, PM2.5 concentration of 42, and a CO level of 4, the pollution estimation is classified as low. These values indicate relatively good air quality, resulting in a low predicted risk of asthma, making the environment generally safer for individuals with respiratory conditions.

Case 1: High Asthma Risk predicted based on individual patient as shown in table 4. 8.

Table 4. 4: High asthma risk predicted based on individual patient

	Key /parameter	value
Input	Are you experiencing Asthma symptoms (Yes/No)	Yes

	Do you have difficulty in breathing? (Yes/No)	Yes
	Do you have a dry cough? (Yes/No)	Yes
	Do you have a Sore throat? (Yes/No)	No
	Enter city	Delhi
	Entergender (Male =1; Female=0)	1
	Age	35
Output	AQI	201
	Asthma risk	High

The model predicts a high asthma risk for an individual patient based on personal health parameters. A 35-year-old male from Delhi, has reported experiencing asthma symptoms, difficulty in breathing, and a dry cough, though no sore throat was noted. With an AQI of 201 in Delhi, which indicates poor air quality, the model assesses the overall asthma risk as high. This suggests that the patient's symptoms and conditions in their location contribute to a significant risk of asthma exacerbation.
Case 2: Moderate Asthma Risk predicted based on individual patient as shown in table 4. 9.

Table 4. 5: Moderate risk predicted based on individual patient

	Key /parameter	Value
Input	Are you experiencing Asthma symptoms (Yes/No)	Yes
	Do you have difficulty in breathing? (Yes/No)	Yes
	Do you have a dry cough? (Yes/No)	No
	Do you have a Sore throat? (Yes/No)	No
	Enter city	Agra
	Entergender (Male =1; Female=0)	0
	Age	28
Output	AQI	146
	Asthma risk	Medium

The model predicts a moderate asthma risk for a 28-year-old female from Agra who has asthma symptoms and difficulty breathing. With an AQI of 146 in Agra, the model assesses her overall risk as a medium, indicating a significant but not severe risk.
Case 3: Low Asthma Risk predicted based on individual patient as shown in table 4. 10.

Table 4. 6: Low asthma risk predicted based on individual patient

	Key /parameter	Value
Input	Are you experiencing Asthma symptoms (Yes/No)	No
	Entercity	Ahmedabad
	Air Quality Index (AQI)	45
	PM2.5 in ug/m^3	42
	CO level in ug/m^3	4
Output	Pollution estimation (High/ Medium/ Low)	Low
	Asthma risk prediction for Ahmedabad	Low

The model predicts a low asthma risk for a patient in Ahmedabad who has not reported any asthma symptoms. The environmental parameters, including an AQI of 45, a $PM_{2.5}$ level of 42, and a CO level of 4, indicate low pollution levels. Consequently, the overall asthma risk is assessed as low, suggesting that both the patient's health status and the environmental conditions pose minimal risk for asthma.
Model evaluation was conducted using metrics such as recall, precision, accuracy, and f1-score, ensuring robust performance assessment. Based on these assessments, the model was improved to boost its predictive capabilities. Then, an expert system was integrated, combining rule-based logic and ML predictions to conduct

a thorough risk assessment. Specific rules were established based on expert knowledge to assess asthma attack risk considering pollutant levels and patient symptoms. A combined ML model was used with expert rules to provide a final risk assessment. This hybrid approach leveraged the strengths of ML and domain expertise, leading to more accurate and comprehensive predictions. The expert system effectively crossed the gap between data-driven insights and practical knowledge, demonstrating its potential in proactive asthma attack prevention and management.

4.6.1 ML Model

This study uses a combination of XGBoost and LightGBM, both gradient-boosting frameworks, as a machine-learning model. These frameworks are excellent at handling complex relationships in data, which makes them very suitable for the classification task of predicting asthma attack risk.

4.6.2 EVALUATION PARAMETERS

In this section, evaluation metrics are discussed in detail.

(i) Accuracy

Accuracy is a metric that quantifies the ratio of correct predictions to the total number of predictions made. It is calculated using the formula:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.1}$$

Where,

True positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)

A higher accuracy value signifies that the model correctly predicts a large proportion of instances. However, accuracy might not be the most suitable metric for evaluating model performance with imbalanced datasets, as it does not account for the distribution of different classes.

(ii) Precision

It quantifies the ratio of accurate positive forecasts to all positive predictions, including both TP and FP.

$$Precision(P) = \frac{TP}{TP+FP} \tag{4.2}$$

It calculated the amount of appropriately identified positive instances among all the projected positive outcomes. High accuracy refers to the ability to minimize the occurrence of FP.

(iii) Recall

It, sometimes referred to as sensitivity, quantifies the ratio of appropriately predicted TP to the total number of real positive outcomes, including TP and FN.

$$Recall\ = \frac{TP}{TP+FN} \tag{4.3}$$

Recall indicates how well the model identifies true positive cases. Higher recall indicates a lower number of FN.

(iv) F1-Score

It is a statistical measure that calculates the harmonic average of recall and precision. It serves as a unified metric that considers both recall and precision, striking a balance between the two factors.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4.4}$$

The F1-score is a valuable metric when there is a requirement for maintaining an equilibrium between precision and recall. It is especially beneficial when the available data indicates an imbalance.

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4.6.3 Ensemble model

The ensemble model shows the accuracy by combining LightGBM and XGBoost models. Figure 4. 7 shows the performance metrics of an ensemble-voting classifier on the 'cityday' dataset. Metrics include Accuracy of 0.998, Recall of 0.976, Precision of 0.962, and F1 score of 0.971. The model demonstrates strong overall performance, with scores indicating effective prediction capabilities and a balanced approach to true positives and negatives.

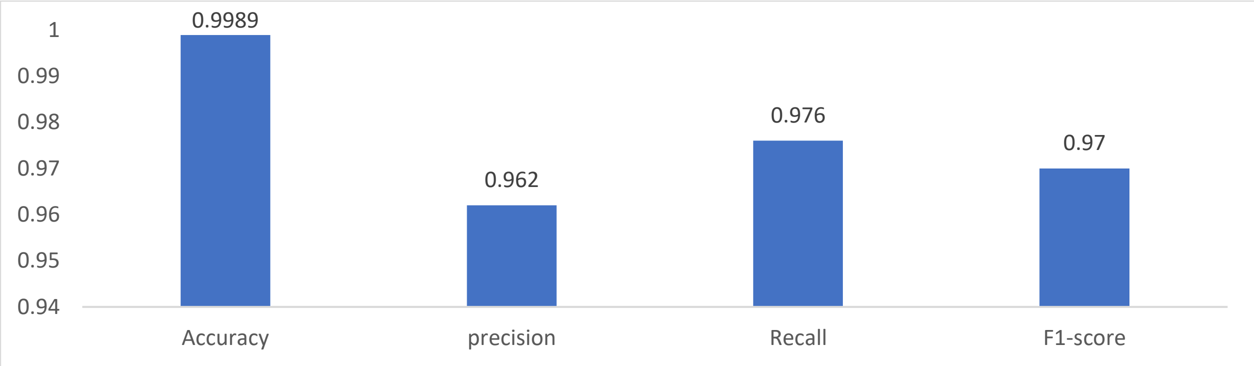


Figure 4. 1: Performance evaluation of ensemble model on City_day data

Figure 4. 8 shows the performance metrics of an ensemble-voting classifier on the 'cityhour' dataset. Metrics include a Precision of 0.972, Recall of 0.996, F1 score of 0.981 and Accuracy of 0.998. The model demonstrates strong overall performance, with scores indicating effective prediction capabilities and a balanced approach to true positives and negatives.

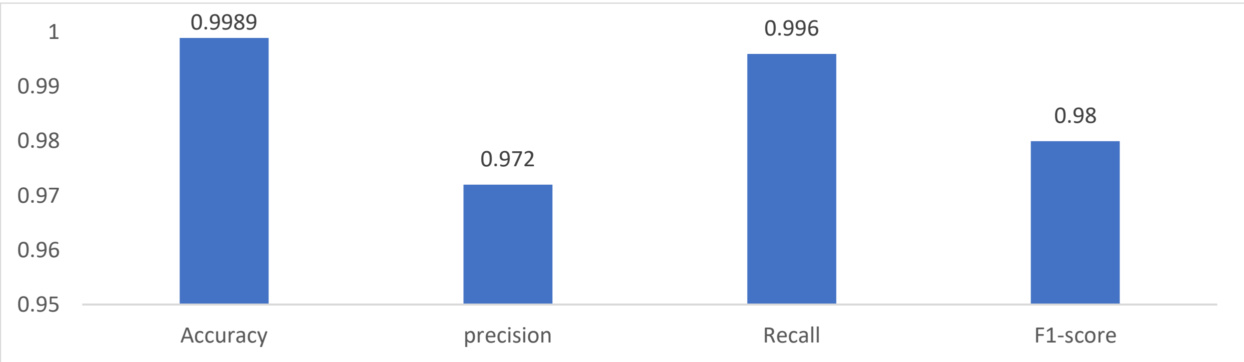


Figure 4. 2: Performance evaluation of ensemble model on City_Hour data

Figure 4. 9 illustrates the performance metrics of an ensemble model on a patient dataset. Metrics include Precision of 1.0, Recall of 1.0, F1 score of 1.0 and Accuracy of 1.0. The model achieved perfect scores across all metrics, indicating highly effective performance, though perfect scores could suggest overfitting, particularly if assessed on the training set.

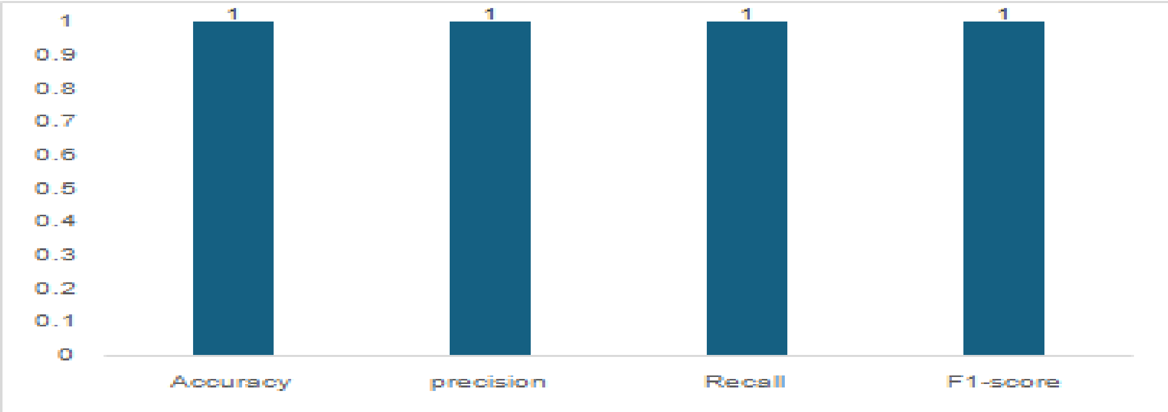


Figure 4. 3: Performance evaluation of Ensemble model on Patient Asthma prediction

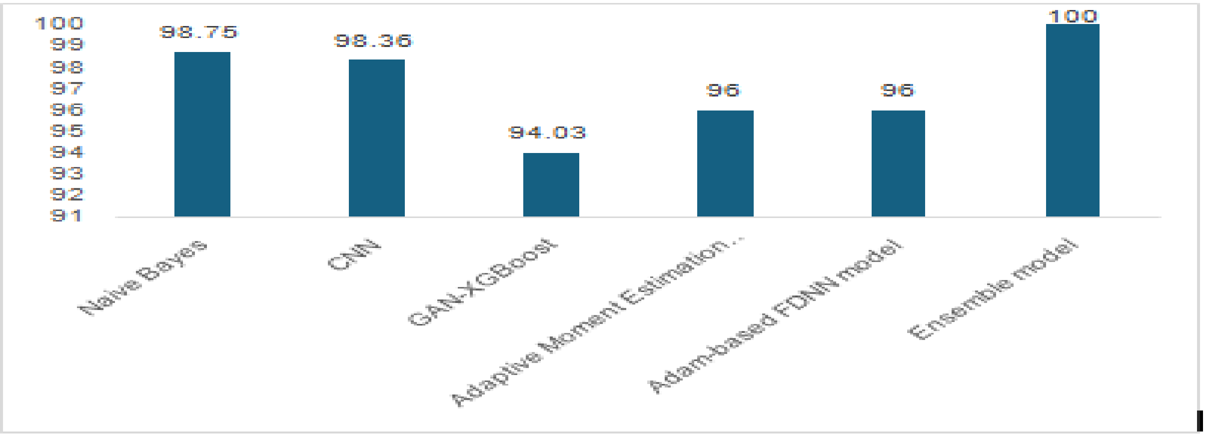
4.6.4 Comparative analysis

Table 4. 10 displays the accuracy scores of several ML methods used for a specific task or dataset. The Ensemble model stands out as the most effective strategy, with an outstanding accuracy of 100%. This is achieved by harnessing the capabilities of both LightGBM and XGBoost frameworks, resulting in exceptional predictive performance. Naive Bayes closely follows, with an impressive accuracy rate of 98.75%. Naive Bayes, despite its simplicity, demonstrates remarkable effectiveness for this job, surpassing more intricate models. CNNs exhibit impressive performance, with an accuracy of 98.36%. This suggests that the dataset likely contains visual or structured information that is highly compatible with CNNs. The Adaptive Moment Estimation (Adam) optimizer and the Adam-based Feedforward Deep Neural Network (FDNN) model both get a 96% accuracy by employing adaptive learning rates and momentum to effectively train neural networks. GAN-XGBoost, a combination of Generative Adversarial Networks and XGBoost, achieves the lowest accuracy of 94.03%, indicating that it could not be as appropriate for this particular job compared to the other approaches. The ensemble model performs the best, followed closely by Naive Bayes and CNN.

Table 4. 10: comparative analysis

Authors	Technique	Accuracy
Akbar et al., (2019)	Naive Bayes	98.75
Priya et al., (2020)	CNN	98.36
Lee et al., (2024)	GAN-XGBoost	94.03
Haque et al., (2022)	Adaptive Moment Estimation (Adam)+CNN	96
Haque et al., (2023)	Adam-based FDNN model	96
Present study (2024)	**Ensemble model**	**100**

Figure 4. 10 below illustrates the accuracy scores of various ML techniques applied to a specific task or dataset. It highlights XGBoost-LightGBM as the top performer with 100% accuracy, followed by Naive Bayes and CNN, while GAN-XGBoost records the lowest accuracy at 94.03%.



CUNCLUSION

Asthma is a chronic respiratory condition affecting more than 300 million people all over the globe. By the year 2025, there are chances that this number may raise to approximately 400 million people. The asthma is inflamed and obstructed due to narrowing in the airways and symptoms like wheezing, shortness of breath, or chest tightness. For asthmatics, the ability to predict and prevent attacks is essential, especially because environmental factors, including allergens, pollutants, and weather variations, play a significant role in triggering these symptoms. Recent years of advancement in AI have been bright promises in controlling diseases; especially through the evolution of expert systems that simulate human knowledge.These systems combine medical knowledge with sophisticated data analysis to provide valuable visions for managing chronic conditions like asthma. This study focuses on designing an expert system to assess the probability of asthma attacks based on real-time environmental parameters, such as air quality, temperature, humidity, and allergens. By analyzing these factors, the system offers timely warnings and recommendations, empowering patients to take necessary precautions.

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