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Research Article

Asthma Wellness Care With Personalized And Predictive Support Platform Using Artificial Intelligence And Machine Learning

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ABSTRACT

The world-wide population with asthma experiences ongoing medical issues because urgent emergency conditions often result in necessary hospital admissions which impacts their general health quality.The Asthma Wellness Care Platform resolves asthma care difficulties by integrating technology for predicting physician records and individualized treatment and continuous data monitoring systems. The application processes real- time data by merging real time data submitted by users through multiple machine learning models including KNN, Random Forest and XGBoost and Logistic Regression to forecast asthma attacks. Using this platform lets users access breath exercise tools while also providing them with an asthma journal record system to enhance asthma management. The chatbot responds immediately to user needs at the same time emergency alerts contact both emergency responders and healthcare providers in critical situations. The platform provides allows users to enhance asthma management while decreasing hospital visits and boosting medical care efficiency through its novel features.

Keywords: Asthma Prediction,Machine Learning,Smart healthcare,Real-Time Monitoring,Artificial Intelligence,Personalized Management

INTRODUCTION

Asthma leads to a lasting chronic respiratory disease that causes airway narrowing along with inflammation which interferes with standard breathing.For asthma management patients require preventive solutions coupled with event- responsive treatments together with improved behaviors for environmental tracking and self-monitoring of their physical state. Traditional asthma healthcare methods that rely on medicine protocols and repeated medical checks provide no information about personal asthma triggers. Patients experience insecurity about deteriorating medical conditions due to present-day passive healthcare system which may lead to emergency hospital admissions and diminished lung function and reduced lifestyle quality. The existing asthma management system needs a crucial change to introduce continuous monitoring services with personalized advice offerings and speed-up therapeutic approaches.The Asthma Wellness Care Platform operates through artificial intelligence systems to deliver predictive analytics with real-time tracking and personalized care for asthma management enhancement. The platform brings better asthma care through its exclusive machine learning solutions along with AI-powered breathing exercise features and super- vised AI chatbot service. The platform generates user-specific recommendations through its prediction capabilities which are made possible by organizational Air Quality Index and sleep quality and stress factor inputs.The platform triggers emergency alerts that notify neighborhood members together with healthcare providers about asthma trigger conditions. A secure authentication system enables healthcare providers to sustain user privacy during assessments of consented personal data. The Asthma Wellness Care Platform uses its integrated system to improve asthma management features to minimize attack occurrences plus enhance patient health status.

The research investigates the asthma care system as it combines various integrated components for development with assessment mechanisms for health technologies and chronic disease management architectures.

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LITERATURE SURVEY

The implementation of artificial intelligence together with machine learning technologies has greatly transformed asthma care procedures. Multiple research investigations analyze how predictive analytics operates with digital health tools to enhance asthma care methodologies. However, many existing systems still face limitations in personalization, real-time monitoring, and holistic user engagement.The Artificial Intelligence Asthma Guard system represents a wearable-based invention which combines physiological parameters with environmental sensors and machine learning models including Support Vector Machines and Random Forest that evaluate asthma attack probabilities according to Almuhanna et al. [1]. The system integrates sensor data yet omits essential characteristics which include mental health reporting and non-stop life pattern surveys and immediate visual alerts. The current research improves the framework by merging stress and sleep trigger investigation with artificial intelligence-operated chat support functions and extended reality breathing visualization. Villa proved that artificial intelligence dynamic systems help control severe uncontrolled asthma [2] in high-risk patients through tracing predictive data methods in population health operational sequences. The system succeeded in identifying periodic risks through clinical coordination but it failed to establish continuous monitoring as well as patient interface tools. The proposed work delivers a system which enables constant environmental and phys- iological tracking alongside mental health evaluation along with augmented reality-assisted breathing assistance for active asthma management.The work of Oyebode et al. and his research associates [3] re- viewed 87 studies on how machine learning supports adaptive and personalized health solutions. The study brings valuable insights yet remains theoretical and does not supply practi- cal solutions for managing asthma as well as other chronic diseases. A real-world asthma care system merges real-time devices with intelligent user communications to meet this requirement.The study by Vatsal et al. introduced an ensemble learning model based on decision trees and Random Forest and Gradient Boosting technology which achieved 90% accuracy for asthma exacerbation prediction [4]. Their prediction system built with clinical data elements failed to include important lifestyle components along with environmental information. The platform builds upon this foundation through integration of air quality index data while adding stress levels and sleep data analysis as well as artificial intelligence-based manage- ment operations.Iqbal et al. [5] developed an asthmatic detection system which combined Deep Q-Networks with voice signals to recognize asthma symptoms. As an innovation this method restricts its diagnostic capabilities to audio signals while excluding broader lifestyle and environmental elements. Our platform receives multiple kinds of input from sleep triggers and stress levels combined with air quality measurements and automated breathing exercises and virtual assistance through bots.Using telemonitoring data Finkelstein and Jeong [6] trained machine learning algorithms which led to high accuracy pre- dictions. The use of self-reported data restricts the system from adapting quickly in real-time and stops it from recognizing external signals. The solution utilizes time-sensitive trigger alert systems supported by stress logs and sleep records alongside artificial intelligence enabled care tools for complete healthcare solutions.Tsang et al. [7] analyzed machine learning deployments within mobile health platforms for asthma where they described symptom prediction systems along with wear- able technology applications. The research suffered from two main drawbacks including small sample sizes and a deficiency in external confirmation procedures. The project enhances previous approaches by employing diverse authentic input data together with validated predictive models for a scalable universal implementation.Bhat et al. [8] designed an asthma risk prediction system through convolutional neural networks based on Internet of Things data including particulate matter measurements within buildings and meteorological variables for peak expiratory flow rate risk zone determination. Peak expiratory flow rate prediction proved effective through the model but the system did not provide comprehensive health assessments. The system executes air quality analysis jointly with stress evaluation and sleep patterns analysis to provide asthma prediction scores and tailor-fit recommendations.Internet of Medical Things together with machine learning enables Al Hamad et al. [9] to monitor elderly patients who have chronic asthma by detecting incidents early and providing emergency backup. The method restricts its application to elderly patient groups while it does not perform multi-trigger analysis or integrate mental health assistance. The present system implements real-time feedback procedures for all user age ranges while offering personalized services.Baker and Berlinski [10] examined pediatric asthma digital health tools which include smart inhalers and wearable de- vices. Monitoring represented a central aspect of their research analysis although predictive modeling

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and environmental con- nections were not included. The system integrates digital health applications with intelligent predictive analytics features together with environment quality assessment and breathing assistance services for proactive healthcare.The review conducted by Ekpo et al. [11] evaluated artificial neural networks and support vector machines as machine learning models used for predicting pediatric asthma outcomes. The research models delivered insufficient practical benefits while being unable to connect to electronic health care systems. The solution resolves this challenge by integrating trigger-based personalization techniques and real-time monitoring with clinical decision support systems which improve patient health outcomes.Rahat Ullah et al. [12] used Raman spectroscopy along with machine learning classifiers for asthma detection through serum analysis. The support vector machines presented high accuracy figures but face limitations as an invasive system which cannot adapt to different situations. This solution provides a non-physically invasive method which delivers continuous monitoring by utilizing environmental and behavioral information for widespread applicability.A review by Shiqiu Xiong et al. [13] assessed 23 machine learning methods for asthma exacerbation pre- diction where boosting approaches demonstrated the highest effectiveness. The developed models experienced limitations in user-tailored features and real-time operational capability. The system uses real-time air quality indicator data and lifestyle trigger information together with a chatbot platform with asthma score display functionality to enhance user connection. Chen MengHan et al. designed a voice- based asthma risk prediction model that applied convolutional neural networks[14] and long short-term memory networks to produce 88% prediction accuracy. Although the solution demonstrates narrow prediction capabilities it does not adapt well to various real-world situations. Our platform accepts various modes of user input in order to deliver a solution that is wider in scope and focused on human needs.When Eleni A. Chatzimichail et al. developed persistent asthma prediction[15] using multi- layer perceptron-based artificial neural networks they achieved 100% accuracy. The model displayed irregularities because it overfitted while presenting inadequate proof from outside sources. Our platform provides validated predictive models along with real-time information processing capabilities together with customizable support resources for individualized asthma healthcare.

PROPOSED METHODOLOGY

System Architecture

The system architecture of the Asthma Wellness Care with Personalized and Pre- dictive Support Platform as shown in Fig.1 is designed to seamlessly integrate various components, ensuring that data flows efficiently between modules. At the core of the sys- tem is the asthma prediction engine, which analyzes user data (including environmental, physiological, and behavioral) to predict asthma events. This data is continuously fed into the asthma trigger prediction system, which integrates real-time AQI data, wearable device inputs, and allergy tracking to predict potential asthma triggers. The asthma assessment system then processes this data to score the user's asthma condition, offering a comprehensive evaluation of their health.The chatbot interface serves as the user-facing feature, offering real-time assistance and personalized recommendations based on data from the asthma prediction and assessment systems. These components communicate with each other through Application Program Interface's, ensuring seamless data exchange. The system is also designed with an emergency support layer that alerts users and healthcare professionals if critical asthma events are predicted. All data is securely stored and accessible only with user consent, and privacy management ensures that users maintain control over their data. This ar- chitecture enables the system to offer holistic asthma management, empowering users to monitor, predict, and respond to asthma-related events in real time.

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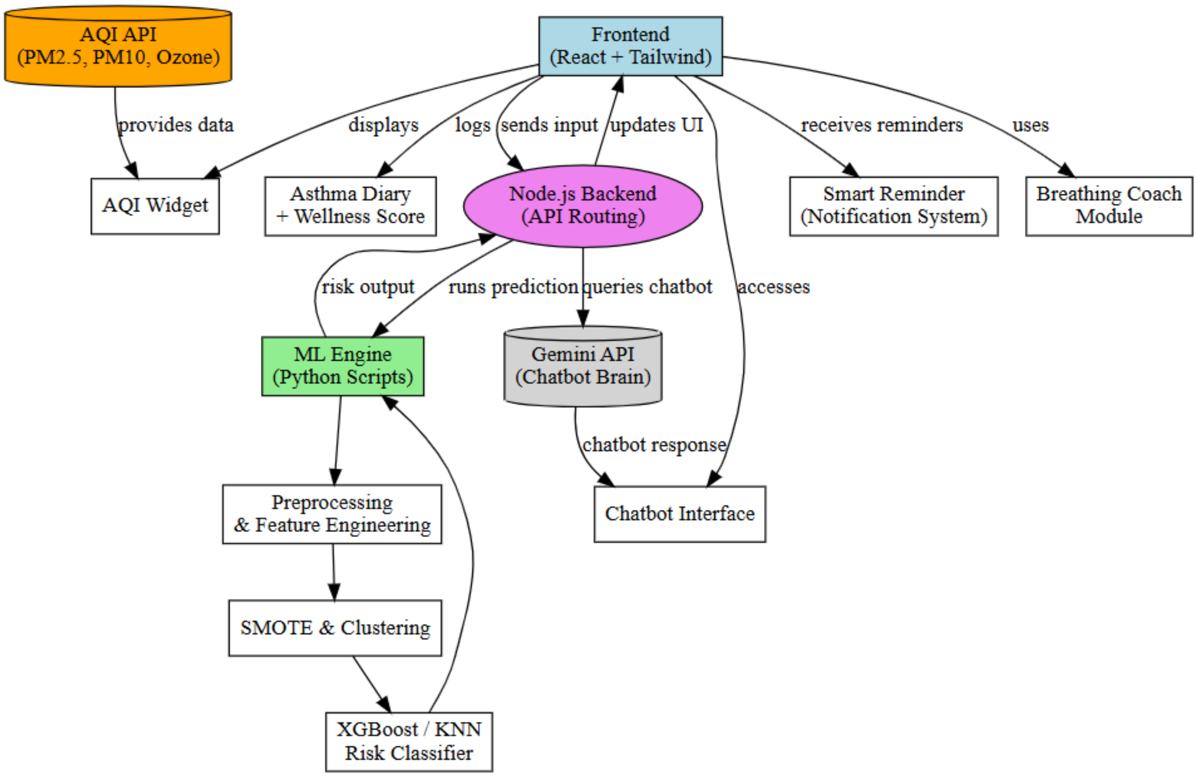

Figure 1.System Architecture explaining the workflow

Data Collection

The project draws its data collection from three different data fields including environ- mental data combined with health data and wearer-collected data. The data collection process divides its information into different categories.Environmental data consists mainly of Air Quality Index because it serves as a crucial element of asthma trigger factors. Environmental data from the Air Quality Index dataset originates from official public repositories that include both real-time Application Program Interface’s and meteorological stations and government databases. A variety of contaminants including PM2.5, PM10, NO2, CO, O3 and SO2 are present in the data subset which affects people suffering from asthma. The collection of Air Quality Index values happens on an hourly basis for different regions thus delivering detailed information about present pollution lev- els. The health tracking data measures heart rate variability together with sleep patterns along with self-reported stress evaluations. The recorded data originates from wearable devices consisting of smartwatches together with fitness trackers that monitor these body signals. Measurement of heart rate variability helps identify stress factors as well as asthma risk indicators and sleep quality serves as essential for managing fatigue-related asthma triggers.Apart from physiological and environmental measurements the system processes user- submitted input data. The system maintains three types of data through asthma diary entries in combination with trigger identification systems. This classification contains data points that describe both symptoms encountered daily and medication consumption patterns along with information regarding environmental conditions as well as emotional and psychological states. The system requires this information to develop customized asthma care strategies and make specific recommendations for patients.The asthma management system depends on medical information such as user health records together with details about asthma types and allergies which users present through their profiles. A custom approach to asthma forecast and asthma care becomes possible with this system.

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Data Preprocessing and Splitting

The collected data needs preprocessing before machine learning applications through multiple operations that increase dataset quality and stability. The data requirement targets preparation for model training purposes before examining asthma triggers along with preventive action recommendations.The essential starting procedure within preprocessing operations involves executing data cleaning tasks. The process starts with identifying defective values and duplicates and incorrect data points. To address missing values the solution includes data imputa- tion using statistical replacements or deletion of untrustworthy incomplete records. By performing this process the dataset becomes stronger while preventing model biases stemming from missing or imprecise data.The data then proceeds to normalization and standardization procedures. Standard normalization techniques become essential for the collected data since its variables use different measurement scales including the Air Quality Index values together with Heart rate variability measurements and sleep hours data. The normalization procedure pre- vents any single variable from controlling the model because of its scale dimensions. The machine learning models receive better performance through the application of Min-Max scaling and Z-score standardization which normalize all features into common distribu- tions or ranges. Temporal consistency of environmental data especially Air Quality Index and pollution metrics is achieved through hourly resampling of these measurements ac- cording to the frequency of asthma-related symptoms. The time-series approach serves to process wearable data since it understands the sequential structures found in these data sets. By applying rolling average functions together with sliding window techniques medical professionals can detect long-term changes in heart rate and sleep quality that serve as indicators for asthma triggers.Desire to understand asthma triggers better drives the analysis approach that inte- grates Pollution Index data with weather condition information about temperature and humidity. The collective Heart rate variability and sleep measurements can be engineered to produce measurable features that include daily average Heart rate variability measure- ments and sleep disruption indices that help manage asthma.Natural language processing tools help analyze text diary entries reported by users through the use of language processing techniques. The predictive model's integration depends on emotional analysis capabilities with keyword detection methods to transform qualitative data into numerical components. The machine learning algorithms receive the categorical data through one-hot encoding processing which converts these variables into usable inputs. The processing concludes with a split of the data into training datasets and testing datasets. The training process consumes 70-80% of data from the available dataset while the test portion consists of 20-30%. The model validation technique ensures that the system does not fit excessively by observing past data which enables accurate predictions for new observations. The model employs cross-validation procedures to attain better robustness and prevent data partition bias.

Data Augmentation

Data augmentation approaches generate synthetic asthma information because asthma- related datasets tend to show imbalance between different asthma triggers. The minority class receives additional samples through SMOTE (Synthetic Minority Over-sampling Technique) which assists the model to absorb data from a balanced dataset.

Model Selection and Development

Machine learning algorithms form an essential requirement in developing the Asthma Wellness Care with Personalized and Predictive Support Platform to identify asthma- related triggers and generate individualized suggestions. This section describes the model selection process by explaining the chosen models while explaining their significance in prediction alongside supporting rationale.

Overview of the Machine Learning Models

The project leverages a variety of machine learning algorithms for asthma prediction and trigger prediction. A system of algorithms consisting of K-Nearest Neighbors, Ran- dom Forest, XGBoost and Logistic Regression serves the project. Hence the selection of models occurred due to their proven capacity in addressing asthma-related data patterns and types.

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KNN:K-Nearest Neighbors functions as an instance-based technique for both regres- sion and classification tasks with its simple nature. The algorithm determines data point categories using a spatial relationship test between these points and their nearest neigh- bors. KNN proves useful for asthma prediction since it detects non-linear relationships which exist between asthma triggers and symptoms. KNN effectively identifies equivalent patterns of triggers within the dataset because asthma emerges from multiple environ- mental and physiological factors thus helping forecast asthma flare-ups.

Random Forest:The ensemble learning method Random Forest constructs numerous decision trees which then produce combined outputs to achieve better results.The system utilizes a mechanism to assess the combined effects between Air Quality Index levels and heart rate variation together with sleep patterns on asthma outcomes.

XGBoost:Using Extreme Gradient Boosting brings decision trees to higher perfor- mance levels through its boosting capability. XGBoost functions excellently when dealing with structured data to achieve tasks that need exact prediction accuracy.

Logistic Regression:The binary class prediction process relies on the Statistical model known as Logistic Regression. The model specifies the likelihood that an input belongs to one of its distinct classes. Logistic Regression acts as a simple model to identify linear relationships between features and classes in asthma prediction this model provides strong suitability as a basic approach.

Justification of selection of the Machine Learning Models

The selected combination of models matches their supportive abilities. KNN models do an excellent job at finding similar patterns because they bring a natural capability to detect nonlinear data relations. Random Forest combines ensemble methods to create robust and accurate predictions, which XGBoost extends through improved predictive accuracy for dealing with intricate data relationships. Logistic regression functions as a basis for comparison through its ability to display linear relationships between features and asthma triggers. The selection of the final implementation model relies on accuracy, precision, recall metrics, and robustness in predicting asthma-related events after applying cross-validation techniques for optimization.

Feature Engineering

Improving machine learning models requires specific processing of data while also creating new features through engineering work. The asthma prediction platform works with a dataset that merges environmental variables with physiological and behavioral indicators that must become suitable characteristics for training purposes.The first feature engineering steps involve data cleaning to manage missing or incon- sistent values, while the second step uses data normalization methods to create equivalent scales across all features. The magnitude of features plays an essential role in prediction because it affects KNN and Logistic Regression models. The predictive model is based on feature selection procedures that determine which variables are most essential for asthma diagnoses. The model considers four essential predictor features which include Air Qual- ity Index ratings together with heart rate variability, sleep duration measurements, and stress levels.The practice of deriving new attributes from existing information through feature engineering requires two methods: it includes daily average calculations based on hourly Air Quality Index values and time-based assessments of stress level changes. Derivative data features generated from original information help detect patterns that appear invisible in basic data. Accurate predictions in asthma systems depend on tracking temporal data patterns which would reveal stress changes and sleep disruptions since these indicators point toward asthma triggers.The process of data preprocessing requires methods for dealing with class imbalance since asthma-related data usually contains this problem. Numerous asthma-related health occurrences show a low frequency when compared to less severe symptoms and events. The model performance benefits from dataset balancing achieved through Synthetic Minority Over-sampling Technique or undersampling because asthma exacerbations occur rarely.

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Feature Engineering

After model training the tools must undergo extensive testing to check whether they achieve suitable performance for operational asthma alerting as well as trigger identification. Multiple performance metrics form part of the evaluation approach to measure model capabilities for untested data analysis as shown in Fig.2.The following performance metrics are necessary for classifying asthma attacks:

Accuracy:This metric allows assessment of the number of accurate predictions the model generates. When working with datasets that have uneven class distribution, accu- racy should not serve as the main criterion.

Precision and Recall:Precision demonstrates the ratio between the number of correct asthma attack predictions among all predic- tions marked as asthma attacks. Recall determines how well a model detects all asthma attacks and stands in contrast to Precision which examines correct asthma attack pre- dictions among all model predictions.High precision prevents model errors that lead to classifying healthy cases as attacks while simultaneously high recall brings accurate detection of asthma events.

F1-Score:The F1-Score computes a single performance measure by combining preci- sion and recall through their harmonic mean. The F1-Score optimization proves essential in asthma applications because it allows for maximum reduction of false positive and false negative errors.

AUC-ROC:AUC-ROC evaluates the ability of a model to differentiate classes irre- spective of class imbalances. The capability of a model to differentiate between asthma attacks and non-attacks increases together with AUC value thus making the detection of asthma triggers more viable in real-world environments.

```
Training K-Nearest Neighbors...
Classification Report for K-Nearest Neighbors:
              precision    recall  f1-score   support

           0       0.98      0.91      0.94       383
           1       0.27      0.62      0.37        21

    accuracy                           0.89       404
   macro avg       0.62      0.76      0.66       404
weighted avg       0.94      0.89      0.91       404


Training Random Forest...
Classification Report for Random Forest:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       383
           1       1.00      1.00      1.00        21

    accuracy                           1.00       404
   macro avg       1.00      1.00      1.00       404
weighted avg       1.00      1.00      1.00       404


Training Logistic Regression...
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       383
           1       1.00      1.00      1.00        21

    accuracy                           1.00       404
   macro avg       1.00      1.00      1.00       404
weighted avg       1.00      1.00      1.00       404


Training XGBoost...
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [06:19:43] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
Classification Report for XGBoost:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       383
           1       1.00      1.00      1.00        21

    accuracy                           1.00       404
   macro avg       1.00      1.00      1.00       404
weighted avg       1.00      1.00      1.00       404
```

Figure.2:Training and Classification Report for Machine Learning Model

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SYSTEM ARCHITECTURE

The proposed system modules are elaborated in detail below. By aligning its structure with modular design principles and AI-powered interactivity, Astreva offers a scalable and user-friendly approach to digital asthma care—prioritizing simplicity, insight, and engagement.

Asthma Trigger Module

The system contains real-time integration of Air Quality Index along with weather in- formation to predict the asthma triggers. This approach would use environmental sensors to track Air Quality Index, pollen index, humidity, and temperature, all known asthma triggers. When combined with data from wearable devices, the system is able to predict potential asthma events based on a user's individual trigger profile.Higher Air Quality Index levels including dominant pollutants with climate analysis and safety measures will be displayed along with visualizations as given in Fig.3. The app also includes monitoring stress and sleep patterns which can trigger asthma attacks as given in Fig.4.Real-time analysis of this data and cross-referencing with historical patterns from the user's asthma diary lead to generation of personalized trigger predictions.This system em- powers users to manage their asthma proactively by offering early warnings, thus allowing them to adjust their environment or medication before a potential trigger escalates into a full-blown attack.

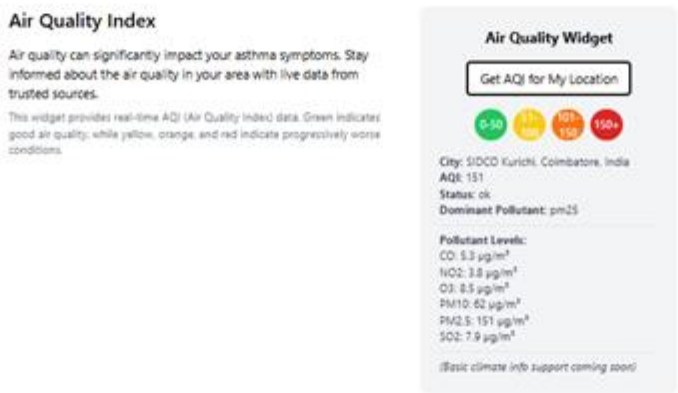

Figure 3.AQI trigger UI interface and working

AI Chatbot Assisstant

An AI-powered chatbot is integrated into the platform to enable personalized asthma management. Utilising powerful tools such as Gemini API, the chatbot will respond to various user queries around asthma symptoms, precipitating factors and management strategies. It will also offer real-time assistance, answering frequently asked questions on everything from asthma medications to lifestyle changes to preventative measures as shown in Fig.5 and Fig.6.

The chatbot will also respond to user input from an asthma diary, advising when to manage symptoms or whether they could have a breathing exercise instead. In case of emergency, the chatbot can provide short-term support by walking the user through the first-aid steps to handle an asthma attack or help them contact healthcare providers. Artificial Intelligence models trained on data specific to asthma therapy will provide the chatbot with intelligent and context-aware responses.This integration enhances user engagement by offering a conversational interface that simplifies asthma management, helping users stay informed and empowered to take control of their condition.

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```
Enter Sleep Data
Hours of sleep (e.g., 7.5): 8
Number of wake-ups: 4
Sleep quality (1-10): 2

Enter Stress Data
Heart Rate Variability (ms): 35
Typing speed (words per minute): 40
Self-reported stress level (1-10): 8

Results:
Sleep Score: 80.00/100
Stress Score: 3.33/100
Predicted Asthma Trigger Risk: Low Risk
```

Figure 4.Sleep and Stress Pattern for trigger monitoring

Figure 5.AI Chatbot Interface

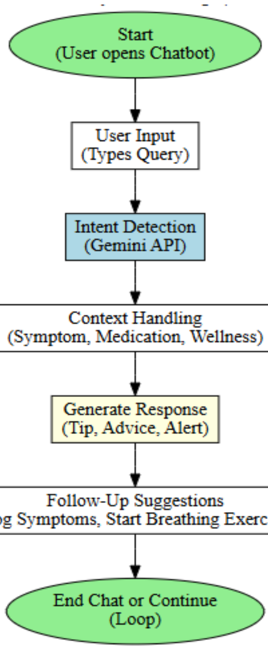

Figure 6.AI Chatbot Workflow

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Breathing Coach Module

The breathing coach was implemented using React and Tailwind CSS with animated inhale–hold–exhale cycles. The timing and visuals were configured to support different lung capacity levels. This module promotes calmness and better lung control during high-risk phases as shown in Fig.7.

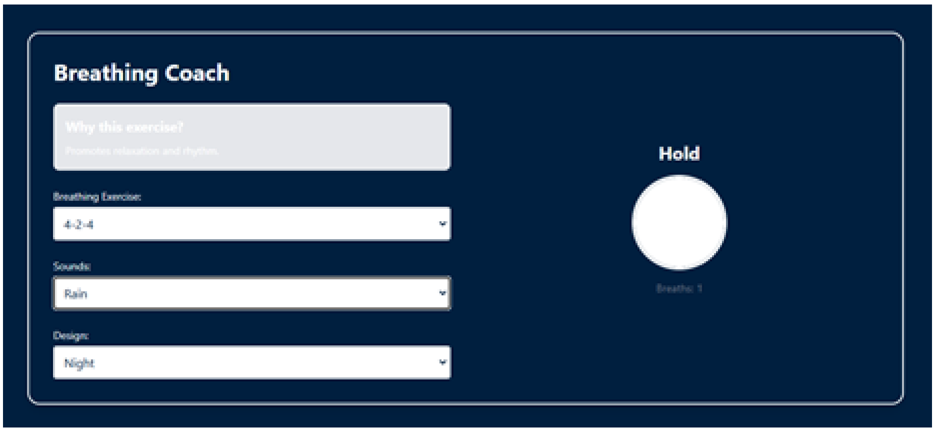

Figure 7: Breathing coach Working UI

Asthma Prediction

The asthma risk prediction module was implemented using Python, incorporating machine learning models such as KNN and XGBoost in Fig.7. The input features—including FEV1/FVC ratio, symptom indicators and exposure data are preprocessed and passed to the trained model. The model outputs a risk category: low, moderate, or high. Integration into the frontend is achieved using Node.js to execute the Python script from a React-based UI.The workflow is shown in Fig.9

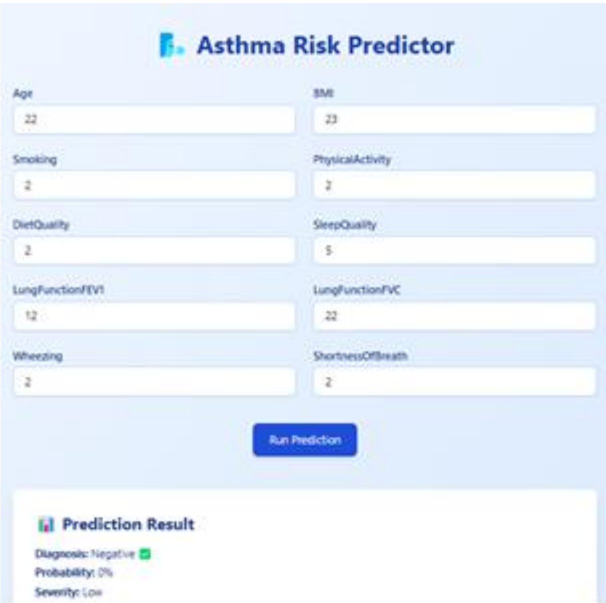

Figure 8: Asthma Prediction Likelihood Working UI

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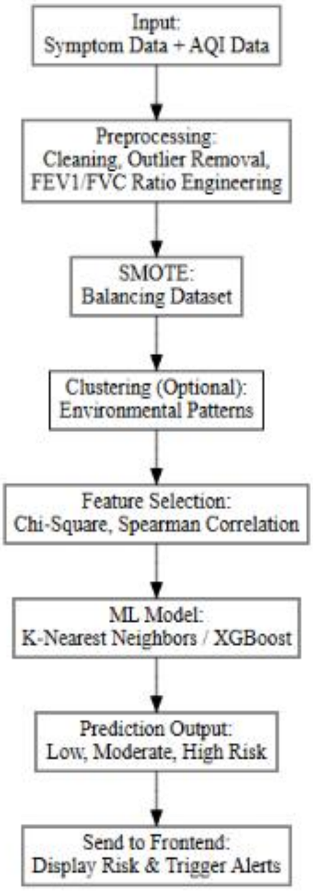

Figure.9: Prediction Flow Workflow using Machine Learning

Smart Reminder System

Browser-based reminders were developed using JavaScript's Notification API. These include medication alerts, symptom check-in prompts, and breathing session nudges. The system ensures that reminders are non-intrusive yet consistent enough to encourage daily routine building as in Fig.10.

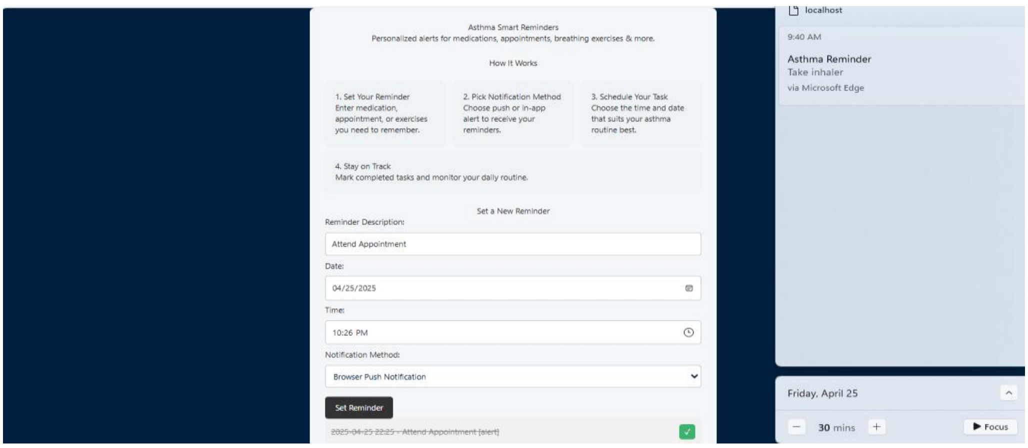

Figure.10: Smart Reminders Working Interface

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Asthma Diary and Score Assessments

One of the key features of the platform is the Asthma Diary as shown in Fig.8 which will also display daily trends based on certain parameters such as stress level,quality of life impact,inhaler use and nightime awakenings and also weekly visualizations to compare asthma symptoms and factors over each day and Score Assessment System where users can log their daily asthma-related symptoms, triggers, and medications as given in Fig.11 and Fig.12. Through a diary, the system can maintain an extensive record of asthma events and monitor the user's health through time. Each entry notes the severity of symptoms, possible triggers, and adherence to medications.The system scores each entry based on the impact of the symptoms, the effectiveness of the interventions, the severity of the disease, and other factors. The users will be able to view their asthma management revealed using this scoring methodology and will help do a trend analysis. Meaning, if someone enters something in the diary, the system uses predictive analysis to suggest things. If, for example, a user frequently logs feeling great pain and elevated stress, the system will recommend techniques to alleviate stress.Over time, the scoring system helps evaluate the effectiveness of treatment plans, providing both the user and healthcare providers with valuable insights into asthma management, ensuring a personalized and data-driven approach to care.

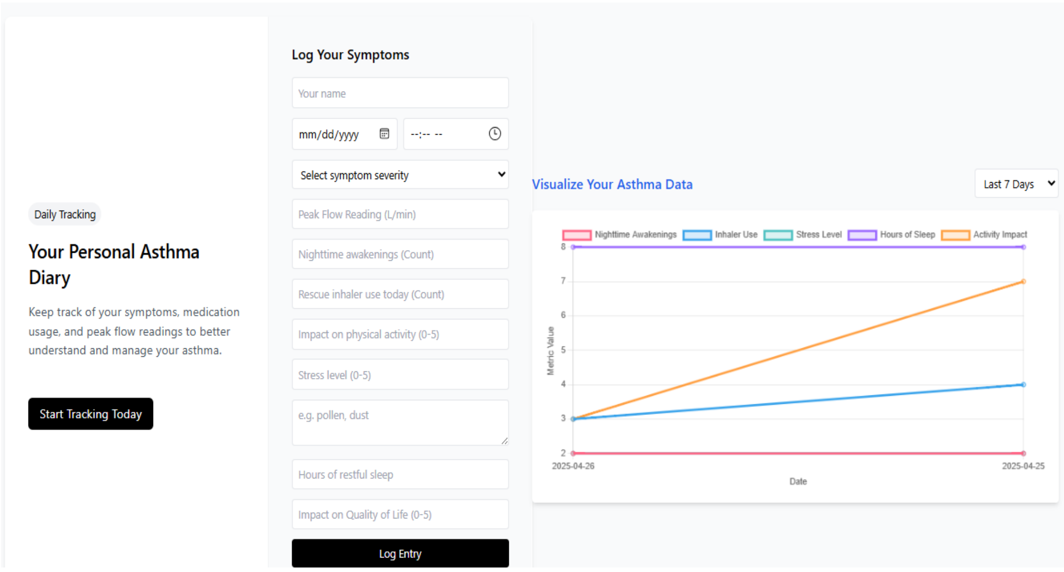

Figure.11. Asthma Diary Interface and Visualizations Interface Working

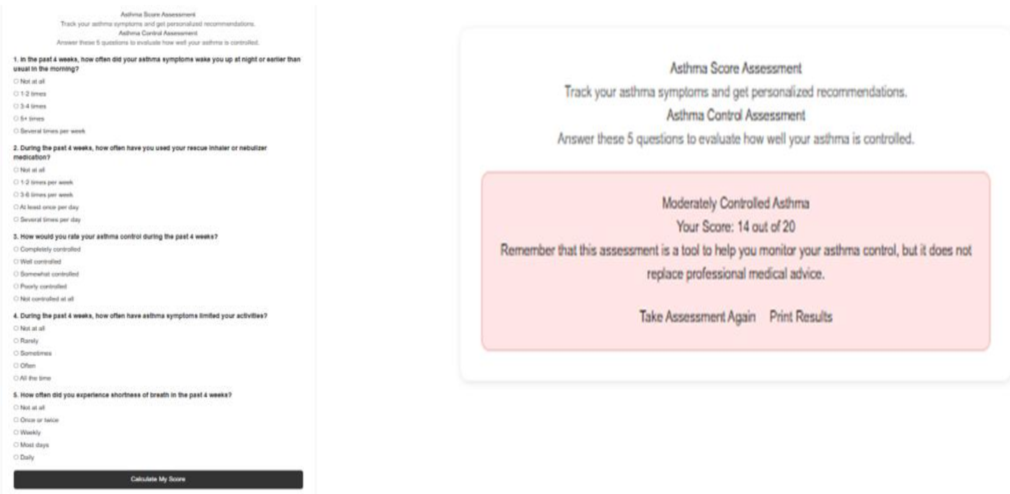

Figure.12.Score Assessments Interface Working

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RESULT AND DISCUSSION

The Asthma Wellness Care with Personalized and Predictive Support Platform brings a major breakthrough to asthma man agement by implementing data-based and cus- tomized interven tions. Users gain complete asthma care through the platform which combines machine learning algorithms with user input data and environmental inputs alongside AI-based help. KNN along with Random Forest and XGBoost and Logistic Regression models enable precise asthma-related event forecasting which gets strengthened through real-time Air Quality Index measurements and continuous output. An AI- powered chatbot brings enhanced user experience through personalized assistance which uses user health data for making recommendations. The healthcare system enables users to take control of their asthma by predicting triggers while performing real time assessments which lowers attack risks for improved daily functionality. The asthma diary together with score assessment reveals new user engagement elements that let people take preventive measures based on their tracking data through breathing exercises. Technical problems involving data integration and model parameters adjustment and real-time data linkages proved solvable by implementing repeated development methods and making use of reliable solutions. Future developments for the platform offer significant opportunity for enhancement. Future development should focus on adding more health conditions to the system together with implementing advanced sensor technology and deep learning model applications for improved prediction accuracy. Personalized asthma management becomes a reality through this platform since it delivers proactive user-friendly capabil ities.

Sample Code:

This section includes key code snippets used in the development of core modules within the Astreva – Asthma Wellness Care With Personalized And Predictive Support Platform Using Machine Learning And Artificial Intelligence. The complete source code is available in the official project repository in Github.

1.asthma_predictor.py

```
import sys

import json

import pandas as pd

import joblib

from datetime import datetime

FEATURES = [

   'Age', 'BMI', 'Smoking', 'PhysicalActivity', 'DietQuality',

   'SleepQuality', 'PollutionExposure', 'PollenExposure', 'DustExposure',

   'PetAllergy', 'FamilyHistoryAsthma', 'HistoryOfAllergies', 'Eczema',

   'HayFever', 'GastroesophagealReflux', 'Wheezing', 'ShortnessOfBreath',

   'ChestTightness', 'Coughing', 'NighttimeSymptoms', 'ExerciseInduced',

   'LungFunctionFEV1', 'LungFunctionFVC'

]

def load_model_and_scaler():

   model = joblib.load("best_knn_model.pkl")

   scaler = joblib.load("scaler.pkl")
```

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```
    return model, scaler
def classify_severity(prob):
    if prob >= 0.85:
        return "Very High"
    elif prob >= 0.6:
        return "High"
    elif prob >= 0.4:
        return "Moderate"
    else:
        return "Low"
def get_recommendations(data):
    recs = []
    if data["Smoking"] == 1:
        recs.append("Quit smoking to improve lung health.")
    if data["PhysicalActivity"] < 2:
        recs.append("Increase physical activity.")
    if data["PollutionExposure"] > 2:
        recs.append("Avoid polluted environments.")
    if data["DietQuality"] < 2:
        recs.append("Improve your diet.")
    if data["SleepQuality"] < 2:
        recs.append("Ensure better sleep hygiene.")
    if data["Wheezing"] == 1 or data["ShortnessOfBreath"] == 1:
        recs.append("Seek medical advice immediately.")
    return recs
def main():
    try:
        input_data = json.load(sys.stdin)
        missing = [feat for feat in FEATURES if feat not in input_data]
        if missing:
            raise ValueError(f"Missing input fields: {missing}")
```

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```
        model, scaler = load_model_and_scaler()
        df = pd.DataFrame([input_data])[FEATURES]
        scaled = scaler.transform(df)
        pred = model.predict(scaled)[0]
        prob = round(model.predict_proba(scaled)[0][1], 2)
        result = {
            "diagnosis": int(pred),
            "probability": prob,
            "severity": classify_severity(prob),
            "recommendations": get_recommendations(input_data),
            "timestamp": datetime.now().isoformat(),
            "model": "K-Nearest Neighbors v1.0"
        }
        print(json.dumps(result))
    except Exception as e:
        error_response = {
            "error": str(e),
            "timestamp": datetime.now().isoformat()
        }
        print(json.dumps(error_response))
        sys.exit(1)
if __name__ == "__main__":
    main()
```

2.app.py

```
from flask import Flask, request, jsonify
import subprocess
import json
app = Flask(__name__)
@app.route("/predict-asthma", methods=["POST"])
def predict_asthma():
    input_json = json.dumps(request.json)
```

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```
    result = subprocess.run(
        ["python", "asthma_predictor.py"],
        input=input_json.encode(),
        stdout=subprocess.PIPE,
        stderr=subprocess.PIPE
    )
    if result.returncode != 0:
        return jsonify({"error": result.stderr.decode()}), 500
    return jsonify(json.loads(result.stdout.decode()))
if __name__ == "__main__":
    app.run(port=5001, debug=True)
```

3.train_and_save_model.py

```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from imblearn.over_sampling import SMOTE
import joblib
data = pd.read_csv('asthma_disease_data.csv')
FEATURES = [
    'Age', 'BMI', 'Smoking', 'PhysicalActivity', 'DietQuality',
    'SleepQuality', 'PollutionExposure', 'PollenExposure', 'DustExposure',
    'PetAllergy', 'FamilyHistoryAsthma', 'HistoryOfAllergies', 'Eczema',
    'HayFever', 'GastroesophagealReflux', 'Wheezing', 'ShortnessOfBreath',
    'ChestTightness', 'Coughing', 'NighttimeSymptoms', 'ExerciseInduced',
    'LungFunctionFEV1', 'LungFunctionFVC'
]
X = data[FEATURES]
y = data['Diagnosis']
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42, test_size=0.2)
smote = SMOTE(random_state=42)
```

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```
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_resampled)
X_test_scaled = scaler.transform(X_test)
param_grid = {
  'n_neighbors': [3, 5, 7, 9],
  'weights': ['uniform', 'distance'],
  'metric': ['euclidean', 'manhattan']
}
grid = GridSearchCV(KNeighborsClassifier(), param_grid, scoring='f1', cv=5)
grid.fit(X_train_scaled, y_train_resampled)
best_knn = grid.best_estimator_
joblib.dump(best_knn, 'best_knn_model.pkl')
joblib.dump(scaler, 'scaler.pkl')
print("✅ Model and Scaler saved successfully!")
```

4.Prediction.jsx

```
import React, { useState } from 'react';
const Prediction = () => {
 const [input, setInput] = useState({});
 const [result, setResult] = useState(null);
 const [loading, setLoading] = useState(false);
 const handleChange = (e) => {
  setInput({ ...input, [e.target.name]: parseFloat(e.target.value) });
 };
 const handleSubmit = async (e) => {
  e.preventDefault();
  setLoading(true);
  try {
   const res = await fetch('http://localhost:5001/predict-asthma', {
    method: 'POST',
    headers: { 'Content-Type': 'application/json' },
```

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```
      body: JSON.stringify(input),
    });
    const data = await res.json();
    setResult(data);
  } catch (error) {
    console.error('Prediction failed:', error);
  }
  setLoading(false);
};
return (
  <div className="p-6 max-w-4xl mx-auto">
    <h1 className="text-2xl font-bold mb-6">Asthma Prediction</h1>
    <form onSubmit={handleSubmit} className="grid grid-cols-2 gap-4">
      {[
        'Age', 'BMI', 'Smoking', 'PhysicalActivity', 'DietQuality', 'SleepQuality',
        'PollutionExposure', 'PollenExposure', 'DustExposure', 'PetAllergy',
        'FamilyHistoryAsthma', 'HistoryOfAllergies', 'Eczema', 'HayFever',
        'GastroesophagealReflux', 'Wheezing', 'ShortnessOfBreath', 'ChestTightness',
        'Coughing', 'NighttimeSymptoms', 'ExerciseInduced', 'LungFunctionFEV1', 'LungFunctionFVC'
      ].map((feature) => (
        <input
          key={feature}
          type="number"
          name={feature}
          placeholder={feature}
          onChange={handleChange}
          required
          className="border p-2 rounded"
        />
      ))}
      <button
```

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```
      type="submit"
      className="col-span-2 mt-4 bg-blue-600 text-white py-2 rounded hover:bg-blue-700"
     >
      {loading ? "Predicting..." : "Predict Asthma Risk"}
     </button>
    </form>
    {result && (
     <div className="mt-8 p-4 border rounded shadow bg-gray-100">
      <h2 className="text-xl font-bold mb-2">Prediction Results</h2>
      <p><strong>Diagnosis:</strong> {result.diagnosis ? 'Asthma Detected' : 'No Asthma'}</p>
      <p><strong>Probability:</strong> {result.probability * 100}%</p>
      <p><strong>Severity:</strong> {result.severity}</p>
      <div className="mt-4">
       <h3 className="font-semibold">Recommendations:</h3>
       <ul className="list-disc ml-6">
        {result.recommendations?.map((rec, idx) => (
         <li key={idx}>{rec}</li>
        ))}
       </ul>
      </div>
     </div>
    )}
   </div>
 );
};
export default Prediction;
```

5.Chatbot.jsx

```
import React, { useState } from 'react';
const Chatbot = () => {
 const [messages, setMessages] = useState([
  { type: 'assistant', text: "🌬️ Hello! I'm Respira, your Asthma Assistant. How can I help you today?" }
```

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```
]);
const [input, setInput] = useState('');
const sendMessage = async () => {
 if (!input.trim()) return;
 const userMessage = { type: 'user', text: input.trim() };
 setMessages(prev => [...prev, userMessage]);
 setInput('');
 try {
  const res = await fetch('http://localhost:5000/api/chat', {
   method: 'POST',
   headers: { 'Content-Type': 'application/json' },
   body: JSON.stringify({ message: userMessage.text })
  });
  const data = await res.json();
  const botMessage = { type: 'assistant', text: data.response || 'No response from Gemini API.' };
  setMessages(prev => [...prev, botMessage]);
 } catch (err) {
  setMessages(prev => [
   ...prev,
   { type: 'assistant', text: 'Oops! Something went wrong. Please try again later.' }
  ]);
 }
};
return (
 <div className="p-4 max-w-2xl mx-auto">
  <div className="h-80 overflow-y-auto border rounded p-4 bg-gray-100 mb-4">
   {messages.map((msg, i) => (
    <div key={i} className={`mb-2 text-${msg.type === 'user' ? 'left' : 'right'}`}>
     <span className="inline-block p-2 rounded bg-white shadow">{msg.text}</span>
    </div>
   ))}
```

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```
      </div>
      <div className="flex">
        <input
          value={input}
          onChange={e => setInput(e.target.value)}
          className="flex-1 border rounded-l p-2"
          placeholder="Ask about asthma..."
        />
        <button onClick={sendMessage} className="bg-blue-600 text-white p-2 rounded-r">Send</button>
      </div>
    </div>
  );
};
export default Chatbot;
```

6.Astreva.jsx

```
import React, { useEffect } from 'react';
import { Link } from 'react-router-dom';
import AOS from 'aos';
import 'aos/dist/aos.css';
const Astreva = () => {
  useEffect(() => {
    AOS.init({ duration: 1000 });
  }, []);
  return (
    <div className="bg-blue-50 min-h-screen text-gray-800 font-sans">
      {/* Navbar */}
      <header className="bg-white shadow-md p-4">
        <div className="max-w-7xl mx-auto flex justify-between items-center">
          <h1 className="font-bold text-2xl">Astreva</h1>
          <nav className="space-x-6">
            <Link to="/" className="hover:text-blue-600">Home</Link>
```

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```
          <a href="#features" className="hover:text-blue-600">Features</a>
        </nav>
      </div>
    </header>
    {/* Hero */}
    <section className="text-center py-24">
      <h2 className="text-4xl font-bold mb-4">Managing Asthma Made Simple</h2>
      <p className="text-gray-600 mb-6">Track symptoms, predict triggers, and breathe better every day.</p>
      <Link to="/chatbot" className="bg-blue-600 text-white py-2 px-6 rounded">Chat with Respira 🌬️ </Link>
    </section>
    {/* Features */}
    <section id="features" className="py-20 bg-white" data-aos="fade-up">
      <div className="grid grid-cols-1 md:grid-cols-3 gap-8 max-w-6xl mx-auto">
        {[
          { title: 'Asthma Diary', to: '/asthma-diary' },
          { title: 'Prediction & Triggers', to: '/prediction' },
          { title: 'AQI Insights', to: '/aqi' },
          { title: 'Score Assessment', to: '/score-assessment' },
          { title: 'Breathing Coach', to: '/breathing' },
          { title: 'Smart Reminders', to: '/reminders' }
        ].map((feature, i) => (
          <Link key={i} to={feature.to} className="p-6 bg-blue-50 rounded shadow hover:shadow-lg text-center">
            <h3 className="font-semibold text-lg">{feature.title}</h3>
          </Link>
        ))}
      </div>
    </section>
  </div>
 );
};
export default Astreva;
```

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CONCLUSION

The Astreva system presents an innovative and user-centric approach to asthma management by combining artificial intelligence, environmental data, and interactive wellness tools into a single, lightweight platform. Unlike traditional asthma care methods that rely on reactive treatment and manual tracking, Astreva offers real-time risk prediction, guided respiratory support, and intelligent decision-making—all without the need for user authentication or data storage.Key modules such as the machine learning-based asthma risk predictor, AQI-triggered environmental alerts, animated breathing coach, AI-powered chatbot, and smart reminders work in unison to empower users to proactively manage their condition. The system was designed to be accessible, responsive, and highly interactive, ensuring ease of use across various devices.Through rigorous machine learning testing, manual module validation, and thoughtful UX design, Astreva has demonstrated its ability to deliver both accuracy and usability. It stands as a scalable solution suitable for educational, healthcare awareness, or personal wellness applications.In conclusion, Astreva bridges the gap between technology and healthcare by offering a proactive, AI-enhanced asthma care experience that prioritizes personalization, simplicity, and real-time support for individuals living with asthma.

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