TERM PAPER REPORT

ON

MACHINE LEARNING-BASED ASTHMA RISK PREDICTION USING IoT AND SMART APPLICATION

Submitted in partial fulfillment of requirements for the completion of 3rd Year 2nd Semester in

BACHELOR OF TECHNOLOGY

(BATCH 2021-2025)

IN

DEPT. OF CSE (IoT)

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DEPARTMENT OF CSE (INTERNET OF THINGS)

R. V. R & J. C COLLEGE OF ENGINEERING (Autonomous)

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CERTIFICATE

This is to certify that the Term Paper report entitled **"MACHINE LEARNING-BASED ASTHMA RISK PREDICITON USING IOT AND SMARTPHONE APPLICATION"** has been submitted to Department of CSE (IoT), R.V.R & J.C College of Engineering (A) by **Y.NEHA CHOWDARY (Y21CO058), K. KAVERI (Y21CO025), K.V.S.KINSHUK (Y21CO028), B. SRINIVASULU (L22CO063)** for partial fulfillment of requirements for the completion of 3rd Year 2nd Semester in Bachelor of Technology (Batch 2021-2025) in Dept. of CSE (IoT) is a bonafide work carried out by them. This report is not submitted to any university for the award of any degree.

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DECLARATION

This Term paper entitled **“MACHINE LEARNING-BASED ASTHMA RISK PREDICITON USING IoT AND SMARTPHONE APPLICATION”** is carried out in partial fulfillment of requirements for the completion of 3rd Year 2nd Semester in Bachelor of Technology (Batch 2021-2025) in Dept. of CSE (IoT) is a bonafide work carried out by them. We hereby declare that this Term Paper Report has not been submitted to any other University/Institution for the award of any Degree.

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ABSTRACT

An asthma risk prediction tool based on machine learning (ML). The entire tool is implemented on a smartphone as a mobile-health (m-health) application using the resources of Internet-of-Things (IoT). Peak Expiratory Flow Rates (PEFR) are commonly measured using external instruments such as peak flow meters and are well known asthma risk predictors. In this work, we find a correlation between the particulate matter (PM) found indoors and the outside weather with the PEFR. The PEFR results are classified into three categories such as ‘Green’ (Safe), ‘Yellow’ (Moderate Risk) and ‘Red’ (High Risk) conditions in comparison to the best peak flow value obtained by each individual. Convolutional neural network (CNN) architecture is used to map the relationship between the indoor PM and weather data to the PEFR values. The proposed method is compared with the state-of-the-art deep neural network (DNN) based techniques in terms of the root mean square and mean absolute error accuracy measures. These performance measures are better for the proposed method than other methods discussed in the literature. The entire setup is implemented on a smartphone as an app. An IoT system including a Raspberry Pi is used to collect the input data. This assistive tool can be a cost-effective tool for predicting the risk of asthma attacks.

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CHAPTER-1
INTRODUCTION

1. Introduction

Asthma is a chronic airway inflammatory condition that is known to occur as episodic wheezing, tightness of the throat,cough and shortness of breath. A rapid deterioration in these symptoms is an asthma attack, which can be fatal. Other serious non reversible airflow restriction in lungs includes respiratory chronic obstructive pulmonary disease (COPD) that involve emphysema and chronic bronchitis. The quality of life of individuals of all ages is compromised by asthma because it restricts social, emotional and physical aspects of life. Globally, around 300 million people suffer from asthma. Throughout the United States, nearly 17.7 million adults and 6.3 million children had been diagnosed with asthma in 2014 . Asthma and COPD exacerbation prompt around two million visits to the emergency departments (EDs) annually in the United States. In the UK ,asthma attacks cause 2.21 deaths per 100,000 people .In South Korea, hospital admission rates for asthma patients are 98.5 per 100,000 people .

Health forecasting is one of the least developed branches of forecasting science. Forecasting health risks and integrating it into the individual's lifestyle can affect positively the quality of life of people.Environmental health has a major role to play in asthma attacks. Indoor air pollution and weather can be important factors for predicting asthma. Non-invasive techniques used today for diagnosing and controlling asthma do not fully characterize the degree of inflammation of airways and require expensive equipment that patients cannot easily afford.Therefore, effective predictive modeling may help provide accurate guidance for patients to seek proper care or take medications to prevent from becoming ill and to assist them in preparing their mobility strategy.

Despite extensive research that shows a correlation between indoor air pollution and aggravation of asthma, providing a personalized risk assessment in real-time based on indoor air quality is still at an infant state. In, a static relationship between the indoor air quality and the asthma attack is shown. However, these cannot be used for real-time assessment. In , a pilot study has been done to explore the relationship between indoor air quality and weather with peak expiratory flow rate (PEFR) measurements using deep learning models. PEFR of 14 pediatric asthma patients were collected regularly and corresponding air quality and weather data were monitored to find the correlation.

A variety of new healthcare technologies such as translational biology, medical imaging, bio-sensing, medical device processing, hearing aid systems, have been the subject of deep learning . Deep learning has been comparatively less in use in predicting asthma and other respiratory disorders compared to other diseases. The majority of existing ML algorithms have been developed to predict asthma risks in clinical settings using historical data . The better performance of deep learning models depends on the availability of large amount of data. To collect the data in real-time, cost-effective and portable sensors are required. Integration of these models with the internet-of-things (IoT) can play a vital role in the predictability of asthma attacks using deep learning models and the usability of the platform in real-world conditions.

1.1 Overview of Problem Area

"Machine Learning-Based Asthma Risk Prediction Using IoT and Smartphone Applications" addresses the challenge of predicting asthma risk by leveraging IoT technology and machine learning algorithms. Asthma, a chronic inflammatory condition, poses serious health risks, including potentially fatal asthma attacks, with traditional diagnostic methods often lacking in fully characterizing airway inflammation. To overcome these limitations, the researchers developed a system that integrates a smartphone app with an IoT setup using a Raspberry Pi for data collection, enabling cost-effective and efficient asthma risk prediction. By collecting data on particulate matter levels, humidity, temperature, and peak expiratory flow rates to train a convolutional neural network, the system enhances predictive capabilities through real-time data processing and analysis, showcasing the potential of IoT, smartphone applications, and machine learning to improve asthma management and enhance patient outcomes.

1.2 Solution & Outline of the Project

A solution to the challenge of predicting asthma risk involves the development of a system that integrates IoT technology, machine learning algorithms, and smartphone applications to predict asthma risk. The project utilizes a Raspberry Pi for data collection, including information on particulate matter levels, humidity, temperature, and peak expiratory flow rates. By training a convolutional neural network (CNN) for asthma prediction and implementing it on a smartphone app, the system enables real-time analysis and risk assessment. This innovative approach offers a cost-effective and efficient tool for predicting asthma attacks, potentially improving patient outcomes and enhancing asthma management strategies.The project outlines a system that utilizes a Raspberry Pi for data collection and a smartphone app bundled with a trained neural network model to predict asthma risk in real-time. By collecting data on particulate matter levels, humidity, temperature, and peak expiratory flow rates, and training a convolutional neural network for asthma prediction, the system offers a cost-effective and efficient tool for enhancing asthma management. The project's workflow involves two stages: data processing on the Raspberry Pi and real-time analysis on the smartphone, demonstrating the potential of combining IoT, machine learning, and smartphone technology to improve asthma risk prediction and ultimately enhance the quality of life for individuals affected by this condition.

1.3 System Hardware

1.3.1 Raspberry Pi

The Raspberry Pi indeed plays a crucial role in the IoT system designed for asthma risk prediction. Its versatility and computational capabilities make it an essential component in collecting, processing, and transmitting data for real-time analysis and prediction. By integrating with sensors like the SDS011 air quality sensor, Raspberry Pi enables the monitoring of particulate matter levels, which are vital indicators for asthma risk assessment.Moreover, Raspberry Pi's integration with IoT architecture allows for seamless communication with the smartphone application, facilitating immediate asthma risk prediction based on the processed data. The use of tools like ngrok for hosting data over the internet server enhances accessibility and remote monitoring, ensuring that healthcare providers or individuals can monitor indoor air quality and health conditions from anywhere.

As an edge device, Raspberry Pi performs local data processing, reducing latency and enabling quick responses to changing conditions. Its cost-effectiveness and ease of deployment make it a practical solution for implementing the IoT system, providing a reliable platform for collecting and analyzing data essential for asthma risk prediction. Overall, Raspberry Pi's role in the IoT system significantly enhances the efficiency and effectiveness of asthma management through real-time data monitoring and analysis.

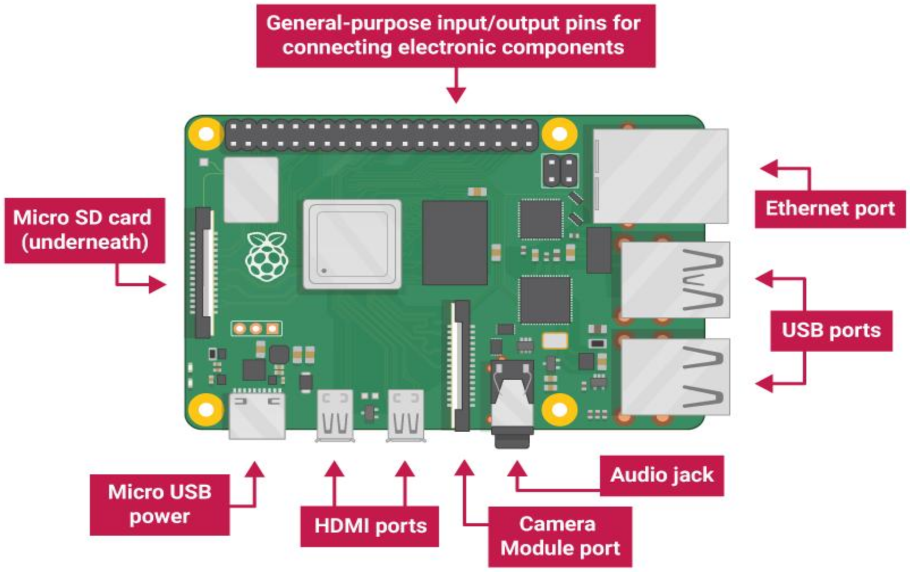

Fig. 1.1 Raspberry Pi

1.3.2 SDSO11

The integration of the SDS011 air quality sensor into the IoT system for asthma risk prediction is indeed a critical component that enhances the accuracy and reliability of the predictive model. By directly connecting the SDS011 sensor to the Raspberry Pi through a wired connection, real-time data on particulate matter levels, specifically PM2.5 and PM10, can be continuously monitored and analyzed.

The data collected from the SDS011 sensor, in conjunction with other environmental parameters, provides valuable insights into the air quality conditions that can impact asthma risk. This comprehensive dataset serves as the foundation for training the machine learning model on the Raspberry Pi, enabling the system to make informed predictions about the likelihood of asthma attacks based on the observed air quality indicators.

The utilization of the SDS011 sensor underscores the significance of precise air quality monitoring in optimizing the predictive capabilities of the IoT system for asthma management and risk assessment. By incorporating real-time data from the sensor into the predictive model, healthcare providers and individuals can proactively monitor and manage asthma conditions, ultimately improving the overall quality of care and enhancing patient outcomes.

Fig. 1.2 SDSO11

1.4 Applications

Application in Healthcare:

The integration of machine learning algorithms with IoT devices enables accurate prediction of asthma risk factors, considering diverse data inputs such as air quality, environmental conditions, and personal health data. This enhances the precision of risk assessments, aiding in proactive management strategies and personalized healthcare interventions.

Personalized Healthcare:

Smartphone applications connected to IoT devices facilitate the delivery of personalized asthma risk assessments, enabling tailored healthcare interventions based on individualized data. This empowers patients to manage their condition effectively, leading to improved health outcomes and enhanced quality of life.

Real-time Monitoring:

IoT sensors embedded in smartphones allow for real-time monitoring of environmental parameters crucial for asthma management, including air quality, humidity, and temperature. Continuous data collection enables timely interventions and adjustments in treatment plans, optimizing patient care and providing valuable insights into asthma triggers.

Telemedicine:

ML-Based Asthma Risk Prediction, coupled with IoT-enabled smartphone applications, extends the reach of healthcare services through telemedicine. Remote monitoring and management of asthma patients become feasible, offering convenience and accessibility while ensuring continuity of care, particularly in under served areas**.**

Contributions to Research and Development:

Furthermore, this research contributes to the advancement of ML, IoT applications in healthcare, and personalized medicine. Insights gained from studying asthma risk prediction serve as a catalyst for further innovation and development in related fields, fostering interdisciplinary collaboration and driving progress in healthcare technology.

1.5 Advantages of Proposed System.

1. **Early Risk Detection:** By utilizing machine learning algorithms and IoT sensors, the system can detect early signs of asthma exacerbation or deterioration, allowing for timely intervention and prevention.
2. **Personalized Risk Assessment:** The system enables personalized asthma risk assessments by considering individual patient data, leading to tailored healthcare strategies and improved patient outcomes.
3. **Real-time Monitoring:** With the integration of IoT devices and smartphones, real-time monitoring of environmental factors such as air quality and weather conditions can be achieved, providing valuable insights for asthma risk prediction.
4. **Accessibility and Convenience:** The use of smartphones as edge devices makes the system easily accessible to a wide range of users, allowing for convenient monitoring and management of asthma risks.
5. **Cost-effective Solution:** The system offers a cost-effective solution for asthma management by utilizing existing IoT devices and smartphones, reducing the need for expensive equipment and enabling wider adoption.
6. **Improved Quality of Life:** By providing early risk detection and personalized care, the system can contribute to improving the quality of life for asthma patients by helping them better manage their condition and prevent exacerbations.

CHAPTER-2
LITERATURE REVIEW

PAPER1

"Predicting asthma attacks: Effects of indoor PM concentrations on peak expiratory flow rates of asthmatic children"

The study by D. Kim et al. [3] likely reviews the impact of indoor particulate matter (PM) concentrations on peak expiratory flow rates in asthmatic children to predict asthma attacks. It explores the relationship between indoor air quality, specifically PM levels, and respiratory health outcomes in children with asthma, aiming to integrate environmental data into predictive models for asthma exacerbations. This research contributes to understanding how indoor PM concentrations affect asthma outcomes in children and the development of predictive tools for early asthma attack intervention.

PAPER 2

“Indoor environmental exposures and exacerbation of asthma”

The review by W. Kanchongkittiphon et al. [4] provides an update to the 2000 review by the Institute of Medicine on indoor environmental exposures and their impact on asthma exacerbations. It explores the relationship between indoor environmental factors and the worsening of asthma symptoms, focusing on how indoor exposures can trigger or worsen asthma attacks. By updating the existing knowledge on indoor environmental influences on asthma exacerbations, this review contributes to enhancing our understanding of the role of indoor environments in asthma management and the development of strategies to mitigate indoor triggers for better asthma control.

PAPER 3

“Assessment of indoor air quality exposures and impacts on respiratory outcomes in River Rouge and Dearborn, Michigan”

The study by E. Cleary et al. [7] assesses indoor air quality exposures and their impact on respiratory outcomes in River Rouge and Dearborn, Michigan. It explores the relationship between indoor air quality and respiratory health in these locations, aiming to understand how indoor pollutants affect respiratory conditions. By analyzing indoor air quality impacts on respiratory outcomes, the research provides insights into the influence of indoor environments on respiratory health in specific geographic areas, offering potential strategies for improving indoor air quality and respiratory well-being.

PAPER 4

“Deep learning for health informatics”

The paper by D. Rav et al. [9] discusses the application of deep learning in health informatics, focusing on its potential in healthcare data analysis. It explores the use of deep learning techniques for processing medical data and extracting valuable insights for health informatics applications. By reviewing the role of deep learning in health informatics, this study highlights the significance of advanced machine learning methods in improving healthcare data analysis and decision-making processes.

PAPER 5

"Health big data analytics: A technology survey"

The paper by G. Harerimana, B. Jang, J. W. Kim, and H. K. Park titled "Health big data analytics: [11] also highlights the significance of data quality, interoperability, and standardization in health big data analytics, emphasizing the need for robust data management practices to ensure the accuracy, consistency, and reliability of healthcare data. The authors discuss the role of data integration platforms, data lakes, and data warehouses in consolidating disparate data sources and enabling comprehensive analytics capabilities in healthcare organizations. Moreover, the paper addresses the ethical and privacy considerations associated with big data analytics in healthcare, advocating for transparent data usage policies, patient consent mechanisms, and data anonymization techniques to protect sensitive health information.Furthermore, Harerimana and colleagues explore the potential impact of big data analytics on population health management, disease surveillance, and public health interventions. By harnessing the power of big data to identify trends, patterns, and risk factors in large-scale health datasets, healthcare providers and policymakers can make informed decisions, allocate resources efficiently, and implement targeted interventions to improve population health outcomes. The paper underscores the transformative role of big data analytics in shaping the future of healthcare delivery.

PAPER 6

"Risk prediction with electronic health records: A deep learning approach"

The paper by Y. Cheng, F. Wang, P. Zhang, and J. Hu titled "Risk prediction with electronic health records: A deep learning approach" [14] likely provides a comprehensive literature review on the application of deep learning techniques in risk prediction using electronic health records (EHRs). The review may cover previous studies that have explored the use of EHR data for predictive modeling, the challenges and opportunities associated with leveraging EHRs for risk prediction, and the advancements in deep learning algorithms for analyzing healthcare data. By focusing on risk prediction and utilizing deep learning approaches, the paper contributes to the evolving field of predictive analytics in healthcare, aiming to enhance patient outcomes, optimize healthcare resource allocation, and improve decision-making processes based on data-driven insights extracted from electronic health records.

PAPER 7

"Disease prediction by machine learning over big data from healthcare communities"

The paper by Chen et al. [16] is expected to delve into the methodological approaches and algorithmic frameworks employed in disease prediction using machine learning techniques over large-scale healthcare datasets. The authors likely discuss the challenges and opportunities associated with leveraging big data from healthcare communities, emphasizing the importance of data preprocessing, feature selection, and model optimization to enhance the accuracy and generalizability of predictive models. By exploring the application of machine learning algorithms such as decision trees, support vector machines, neural networks, and ensemble methods in disease prediction, the paper sheds light on the diverse range of computational tools available for analyzing complex healthcare data and extracting meaningful insights for clinical decision-making.Furthermore, Chen and colleagues may highlight the potential benefits of integrating electronic health records, medical imaging data, genetic information, and patient demographics into predictive modeling frameworks to enable comprehensive disease risk assessment and personalized healthcare interventions. The review likely underscores the role of predictive analytics in preventive medicine, early intervention, and chronic disease management.

PAPER 8

"A survey on techniques for prediction of asthma"

The chapter by Gayathri and Satapathy [13] is likely to offer a detailed examination of the diverse range of techniques and methodologies employed in the prediction of asthma, a chronic respiratory condition with significant public health implications. The survey may encompass an analysis of traditional statistical approaches, machine learning algorithms, and data mining techniques utilized in asthma prediction studies, highlighting the strengths and limitations of each method in capturing the complex interplay of factors influencing asthma onset, progression, and exacerbations.

Furthermore, Gayathri and Satapathy may discuss the role of feature selection, data preprocessing, and model evaluation techniques in optimizing the performance of asthma prediction models, emphasizing the importance of robust methodologies for handling imbalanced datasets, noisy variables, and missing data in asthma research. The chapter is likely to explore the integration of clinical data, environmental factors, genetic markers, and patient-reported outcomes in predictive modeling frameworks to enhance the accuracy and reliability of asthma risk assessment tools.

Moreover, the survey may address emerging trends in asthma prediction research, such as the integration of IoT technologies, wearable sensors, and mobile health applications for real-time monitoring of asthma symptoms and triggers. By synthesizing existing literature on asthma prediction techniques, the chapter aims to provide a comprehensive overview of the current landscape of asthma research, identify gaps in knowledge, and propose avenues for future research aimed at advancing predictive modeling capabilities in asthma management and improving patient care outcomes. By promoting data-driven approaches, methodological rigor, and interdisciplinary dialogue, the chapter aims to contribute to the ongoing efforts to enhance asthma prediction capabilities, inform clinical decision-making, and ultimately improve the quality of life for individuals affected by asthma. Gayathri and Satapathy may address the importance of data sharing, open science practices, and reproducibility in asthma prediction research, advocating for transparent reporting standards, benchmark datasets, and collaborative platforms to facilitate knowledge dissemination and accelerate scientific discoveries in the field.

CHAPTER-3
ASTHMA PREDICTION METHOD

3.ASTHMA PREDICTION METHOD

In this section, we offer an in-depth exploration of the asthma risk prediction methodology, delving into the intricacies of the data sources harnessed and the sophisticated deep learning network architecture deployed for model training. The block diagram showcased in the figure vividly illustrates the structural framework of the proposed system.

At the heart of our approach lies a robust integration of diverse data streams, each contributing valuable insights into asthma risk assessment. We begin by leveraging comprehensive weather data, meticulously curated to encompass a spectrum of meteorological variables such as temperature, humidity, wind speed, and precipitation patterns. These factors play a pivotal role in influencing respiratory health, as fluctuations in atmospheric conditions can trigger asthma exacerbations.

Moreover, we meticulously incorporate indoor air quality metrics, with a particular focus on particulate matter (PM2.5 and PM10) concentrations. Indoor air pollution, stemming from sources like cooking activities, tobacco smoke, and household products, poses a significant threat to respiratory well-being. By integrating real-time data on PM levels, our model gains a nuanced understanding of indoor air quality dynamics, thereby enhancing its predictive capabilities.

Central to our predictive framework is the utilization of peak expiratory flow rate (PEFR) measurements as ground truth labels during model training. PEFR serves as a reliable indicator of lung function, reflecting the extent of airway obstruction and the severity of asthma symptoms. By leveraging PEFR data in conjunction with atmospheric and indoor environmental variables, our deep learning model is primed to discern subtle patterns and correlations indicative of asthma risk.Within the realm of deep learning, our architecture stands as a testament to innovation and sophistication. Employing state-of-the-art neural network structures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), we harness the immense processing power of artificial intelligence to extract intricate patterns from complex, multidimensional data. Through iterative training and optimization, our model learns to discern subtle relationships between input features and PEFR outcomes, ultimately yielding accurate and actionable predictions of asthma risk.

In essence, our methodology represents a holistic and data-driven approach to asthma risk prediction, harnessing the synergistic power of diverse data streams and cutting-edge deep learning techniques. By elucidating the intricate interplay between environmental factors and respiratory health outcomes, we pave the way for targeted interventions and personalized management strategies, ultimately empowering individuals with asthma to lead healthier, more resilient lives.

3.1 Peak Expiratory Flow Rate (PEFR)

Peak expiratory flow rate (PEFR) is the volume of air forcefully expelled from the lungs in one quick exhalation, and is a reliable indicator of ventilation adequacy as well as airflow obstruction. The normal peak flow value can range from person to person and is dependent upon factors such as sex, age and height**.**

Pulmonary function test (PFT) is recommended to diagnose and manage respiratory problems. However, it is difficult to collect PFT data using home-based self-tests. The Peak-flow meter has been a boon in home-based self-tests and is widely used to measure the degree of airway obstruction of asthma patients. Measuring PEFR is fairly straightforward, even for patients at home, using a compact portable peak-flow meter.

A research group has recently used weekly PEFR records to predict asthma deterioration in children using deep learning models. This research group had conducted a pilot study that collected the PEFR data of 14 pediatric asthma patients. The PEFR values that were reported twice daily were interpolated over a period of 24 hours at an interval of 10 minutes. The best value in each of the PEFR trials were recorded.

The interpolated PEFR values have been categorized into three categories: ‘‘green’’ (when the reading is above 80% of the best peak flow; normal exacerbation), ‘‘yellow,’’ (when the reading is between 50% and 80% of the best peak flow; moderate exacerbation), and ‘‘red’’ (when the reading is below 50% of the best peak flow; significantly exacerbated). These categories are used as the output labels for our neural network modeling.

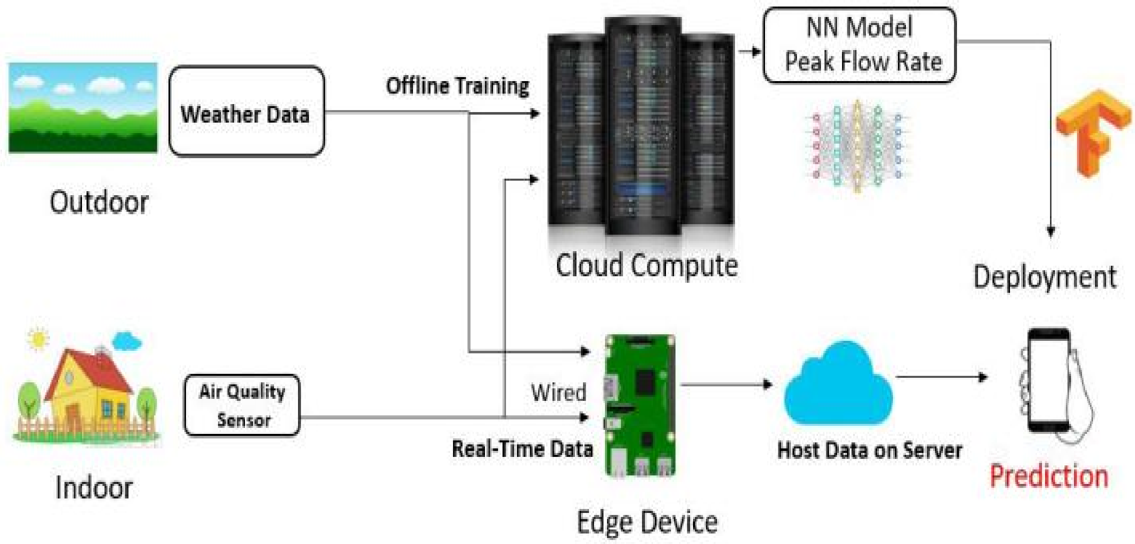

Fig. 3.1 Block diagram of the IoT based asthma risk predictor using machine learning

3.2 Indoor Air Monitoring and Weather Data

The integration of environmental factors, such as indoor air quality and weather conditions, alongside PEFR data collection, enriches the data set and provides a holistic view of the factors influencing asthma exacerbations. By deploying low-cost sensors at each patient's residence to monitor particulate matters PM2.5 and PM10, as well as temperature and relative humidity at regular intervals, a continuous stream of data is generated, capturing the dynamic changes in indoor air pollution and weather parameters.

This real-time monitoring of environmental variables offers valuable insights into the potential triggers and exacerbating factors that can lead to asthma attacks. The correlation of indoor particulate matter data, weather data, and PEFR measurements on a 10-minute interval basis enhances the granularity of the dataset, allowing for a more detailed and nuanced analysis of the relationships between these variables and asthma exacerbations

.By examining the interplay between indoor air quality, weather conditions, and respiratory health indicators like PEFR, healthcare providers and individuals can gain a deeper understanding of the environmental factors that impact asthma outcomes.

3.3 Convolutional Neural Network Based Prediction

Convolutional Neural Networks (CNNs) which that a specialized type of deep neural network designed primarily for processing structured grid data, particularly images. Unlike traditional feedforward neural networks, CNNs employ hierarchical layers that extract features from input data. The core components of CNNs include convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply learnable filters to input images, extracting various features such as edges, textures, and shapes. Pooling layers down sample feature maps to reduce dimensionality, while fully connected layers perform classification based on the extracted features. CNNs are widely used for tasks like image recognition, classification, object detection, and segmentation.

A Neural Network processes input data through interconnected layers of neurons to learn patterns and relationships, adjusting its parameters during training to minimize errors. It's a versatile tool used for tasks like classification, regression, and pattern recognition across various fields due to its ability to learn from data and make predictions or decisions.

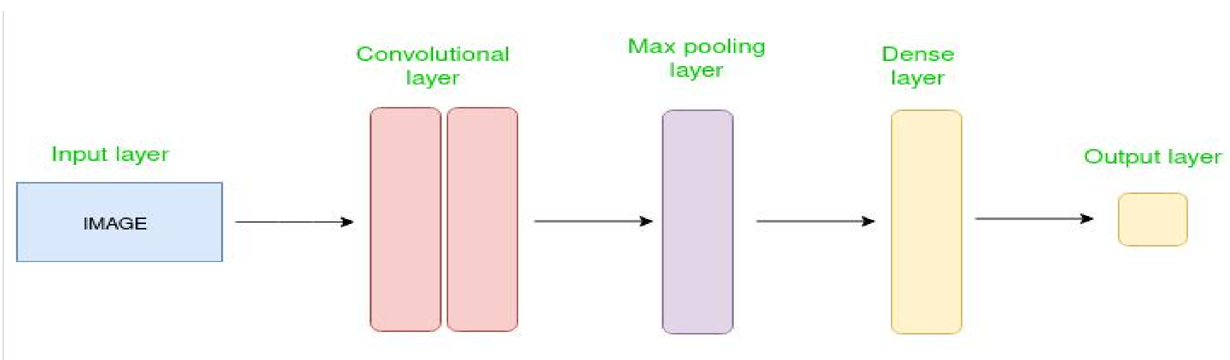

Fig. 3.2 Simple CNN architecture

The cornerstone of the proposed asthma prediction method lies in the implementation of a Convolutional Neural Network (CNN) architecture. CNNs are renowned for their prowess in processing spatial data, making them ideal candidates for analyzing images or matrices, such as those derived from medical imaging or sensor data.

The CNN architecture employed in our model comprises four hidden layers, including two convolutional layers and two fully connected layers. The input layer accommodates four features, forming a 4x1 matrix. Through iterative convolution and pooling operations, the CNN extracts hierarchical representations of input data, thereby capturing intricate patterns and relationships between environmental variables and asthma outcomes.

The convolutional layers, each comprising 64 feature maps, leverage 1x1 kernels to convolve input data and produce feature maps. Stride operations ensure efficient traversal of input data, while ReLU activation functions introduce non-linearity, enhancing the model's capacity to learn complex relationships.Subsequent fully connected layers, housing 128 neurons, further process extracted features, culminating in a linear activation function at the output layer. The resulting network, comprising approximately 1.5 million learnable parameters, is trained using the mean squared error loss function and optimized using the Adam Optimizing Algorithm.

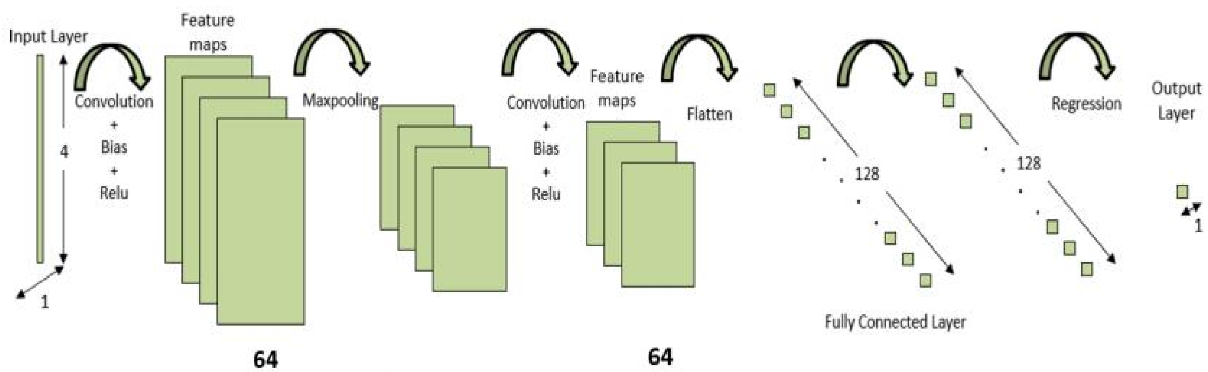

Fig. 3.3 CNN architecture for the proposed PEFR prediction

Layers	SE Numbers	Number of Nodes
Hidden	4	
Input	1	1×4
Convolutional	2	64,64
Fully Connected	2	128,128
Output	1	1

Fig. 3.4 Architecture details of the existing neural network model

CHAPTER-4
IoT AND SMARTPHONE IMPLEMENTATION

4. IoT AND SMARTPHONE IMPLEMENTATION

In this section, the tools and steps involved in IoT implementation are discussed. The process includes real-time data collection, data utilization, and the development of a smartphone application for asthma risk prediction. The key points covered in this section are:

1. Utilization of IoT platform for real-time data collection.
2. Collection of air quality data using Raspberry Pi and air quality monitor.
3. Gathering weather data from an open-source provider on the web.
4. Hosting collected data and weather information on a secured server.
5. Development of a smartphone application integrated with the IoT system.
6. Implementation of a trained neural network model on the smartphone for real-time asthma risk prediction.

4.1 Overall Procedure

For real-time prediction of asthma risk, an integrated system comprising an IoT platform, sensors, Raspberry Pi, and a smartphone is employed. The Raspberry Pi serves as the data collection hub for air quality information obtained from an air quality monitor, while weather data is sourced from an open data provider on the web. Both the collected data from the Raspberry Pi and the weather data are securely stored on a protected server to ensure data integrity and confidentiality.

The smartphone application, equipped with a trained neural network model, plays a pivotal role in predicting asthma risk. By fetching the necessary input data from the server, the smartphone app conducts real-time risk assessments for asthma patients. This seamless data flow and processing between the IoT components and the smartphone application enable timely and accurate predictions of asthma exacerbations.

Furthermore, the IoT implementation involves a detailed breakdown of each block within the system, emphasizing the interconnected nature of data collection, processing, and utilization. The algorithmic framework, as depicted in Algorithm 1, showcases the structured approach to data handling and prediction stages, highlighting the efficiency and reliability of the system.

Algorithm

Algorithm 1: Algorithm Explaining the Proposed

System Working in Real-Time

Input: PM2.5, PM10, outdoor temperature, humidity.

Output: Safe, Moderate or High asthma risk prediction.

Data processing stage on the Raspberry Pi:

Collect PM2.5, PM10 using SDS011;

Collect weather data using Openweathermap;

Data hosting the input features to server;

Real-time stage on the Smartphone:

while App ON **do**

  Collect data from Web;

  CNN prediction;

  if PEFR > 80% **then**

  Safe;

  else if 50% < PEFR < 80% **then**

  Moderate risk;

  else

  High risk;

  end

End

4.2 Air Quality Sensor

The seamless integration of the SDS011 air quality sensor into the IoT system for real-time monitoring of particulate matter levels is essential for enhancing the overall effectiveness of air quality assessment and management. By leveraging the compact size, portability, and high accuracy of the SDS011 sensor, healthcare providers and individuals can gain valuable insights into the air quality conditions that may impact respiratory health, particularly in individuals with asthma.The direct connection of the SDS011 sensor to the Raspberry Pi via a wired connection ensures a reliable data transmission pathway, enabling continuous monitoring of PM2.5 and PM10 concentrations. This continuous data collection allows for the detection of fluctuations in particulate matter levels, providing timely information on air quality changes that could potentially trigger asthma symptoms.Furthermore, the wide measuring range of the SDS011 sensor enables comprehensive monitoring of particulate matter concentrations, ensuring that variations in air quality are captured with precision. This capability is crucial for identifying trends and patterns in air pollution levels, facilitating proactive measures to mitigate potential asthma triggers and optimize indoor air quality.

Overall, the integration of the SDS011 sensor into the IoT system not only enhances the accuracy of air quality monitoring but also empowers healthcare providers and individuals with valuable data insights for informed decision-making and personalized asthma management strategies. By visualizing the hardware setup and communication interface between the sensor and the Raspberry Pi, stakeholders can better understand the seamless integration of air quality monitoring technology into the healthcare ecosystem for improved respiratory health outcomes.Moreover, the real-time data streaming capabilities of the SDS011 air quality sensor integrated with the Raspberry Pi enable continuous monitoring and analysis of particulate matter levels, allowing for prompt interventions and preventive measures to safeguard respiratory health. The ability to receive instant updates on air quality parameters empowers healthcare providers to make timely recommendations and adjustments to asthma management plans based on current environmental conditions. Additionally, individuals with asthma can proactively monitor air quality trends in their surroundings and take necessary precautions to minimize exposure to potential triggers, thereby reducing the risk of asthma exacerbations and improving overall respiratory well-being.

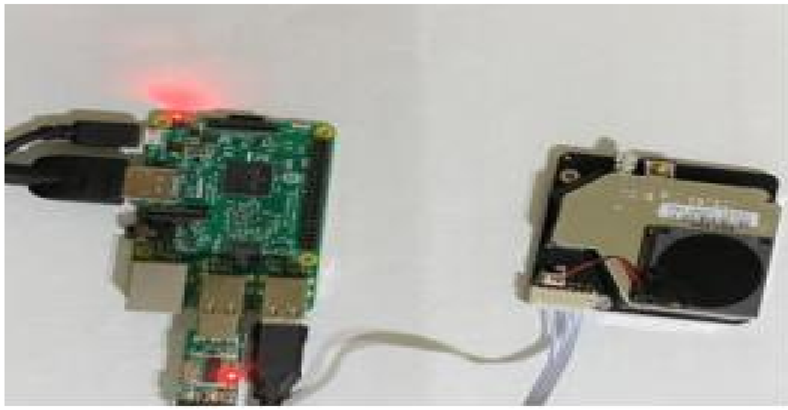

Fig. 4.1 Snapshot of air quality sensor SDS011 connected to Raspberry Pi using a wired connection

4.3 Weather Data

To enhance the asthma risk prediction system, weather data is sourced from Open weather map, an open-source platform that offers an Application Programming Interface (API) for retrieving weather information from any specified location. This API enables seamless access to current weather conditions as well as historical and forecasted weather data, providing valuable insights into weather patterns and trends that can impact asthma patients.The availability of past and future weather data through Open API is particularly beneficial for analyzing the cumulative effects of weather conditions on asthma patients. By leveraging this comprehensive weather data, healthcare providers and researchers can better understand how environmental factors influence asthma exacerbations and tailor interventions accordingly.In the implementation process, a Python API is utilized on the Raspberry Pi to retrieve temperature and humidity data specific to the patients' locations.

This data collection mechanism enables the system to incorporate real-time weather information into the predictive model, allowing for personalized risk assessments based on the environmental conditions experienced by individual asthma patients.By integrating weather data from Open weather map with air quality information collected by sensors, the IoT system can offer a holistic view of the environmental factors affecting asthma risk. This data fusion approach enhances the accuracy and relevance of asthma risk predictions, empowering healthcare professionals and patients to proactively manage asthma symptoms in response to changing weather conditions.

4.4 Data Hosting

By adopting internet-based hosting solutions and leveraging ngrok for data hosting, the IoT system not only enhances data sharing capabilities and facilitates remote monitoring but also opens up possibilities for collaborative healthcare interventions and multidisciplinary care coordination. The secure and efficient hosting of particulate matter data, weather data, and other relevant information on a remote server accessible via ngrok IP enables seamless communication and data exchange among healthcare providers, caregivers, and individuals managing asthma.This approach fosters a connected healthcare ecosystem where real-time data insights can be shared and utilized by various stakeholders to make informed decisions and interventions. Healthcare professionals can remotely access and monitor air quality parameters and health status indicators, enabling timely interventions and personalized care strategies for asthma patients. Additionally, the ability to remotely monitor indoor air quality and health conditions through ngrok-hosted data promotes proactive healthcare management, early detection of potential triggers, and optimized asthma care delivery.By embracing internet-based data hosting solutions and leveraging ngrok for secure data transmission, the IoT system not only extends the monitoring range but also enhances the accessibility, security, and collaboration aspects of asthma risk prediction and management.

Furthermore, the utilization of ngrok for hosting data in the IoT system exemplifies a forward-thinking approach towards leveraging technology for healthcare innovation. By embracing secure and remote data hosting solutions, the system not only enhances the scalability and flexibility of asthma risk prediction tools but also sets a precedent for future advancements in remote monitoring and predictive analytics for respiratory health conditions. This integration of IoT, smartphone applications, and cloud-based data hosting showcases the potential of technology to revolutionize healthcare delivery, enabling personalized and data-driven approaches to asthma management that prioritize patient well-being and proactive health interventions. The seamless connectivity and accessibility facilitated by ngrok contribute to a holistic and patient-centric asthma care model that emphasizes continuous monitoring, timely interventions, and collaborative healthcare efforts for improved patient outcomes and quality of life.

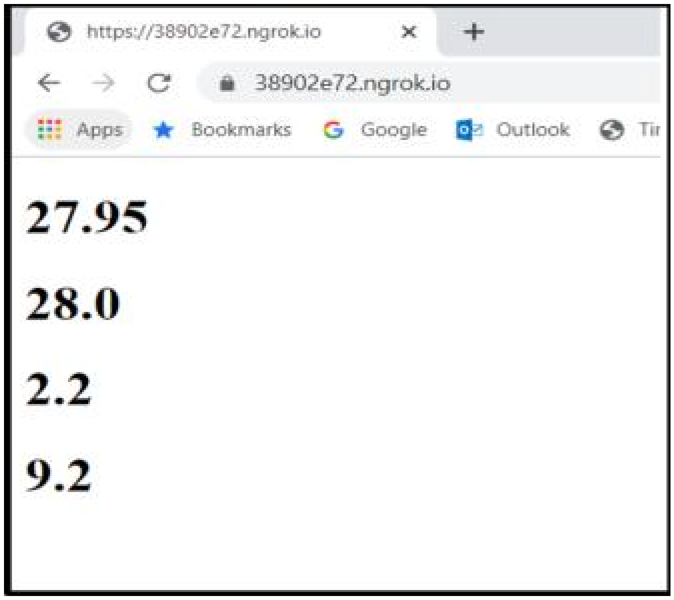

Fig. 4.2 Display of air quality (PM2.5 and PM10), humidity (µg/m3) and temperature (◦C) data hosted on secured server using Ngrok

4.5 Smartphone Implementation

The implementation of the offline trained neural network model on an iPhone 11 smartphone for real-time asthma risk prediction showcases a practical and accessible approach to healthcare technology. Leveraging TensorFlow, a comprehensive machine learning platform, the model is trained offline to predict asthma attack risks. TensorFlow's C++ APIs enable the implementation of an inference-only model on embedded devices, making it suitable for deployment on smartphones like the iPhone 11.

TensorFlow also offers a TensorFlow Lite version, equipped with a converter and interpreter, specifically designed for running models on edge devices. By utilizing these tools, the neural network model is efficiently implemented on the smartphone, enhancing its predictive capabilities for asthma risk assessment. The graphical user interface (GUI) of the smartphone app, developed using Objective-C, provides a user-friendly interface for interacting with the prediction system.

Upon inputting the secured IP address generated from the Ngrok server, the smartphone app displays the data hosted on the server, which serves as input for the neural network model in .tflite format.

The model generates an estimated Peak Expiratory Flow Rate (PEFR) value as output, which is compared to the patient's best peak flow reading at that time to evaluate the risk of an asthma attack. The GUI prompts the user to enter the PEFR value, and based on the comparison with the predicted PEFR, the risk level is determined as follows:

- "Safe": Predicted PEFR is above 80% of the best peak flow reading.

- "Moderate": Predicted PEFR is between 50% and 80% of the best peak flow reading.

- "Risky": Predicted PEFR is below 50% of the best peak flow reading entered by the user.

This low-cost platform, utilizing open-source software tools, eliminates the need for additional auxiliary devices, leveraging the widespread availability and processing power of smartphones. By integrating advanced machine learning techniques with smartphone technology, this system offers a convenient and efficient solution for asthma risk prediction and management, empowering individuals to monitor and respond to potential asthma exacerbations in real-time.The seamless integration of advanced machine learning algorithms with smartphone technology not only enhances the accessibility of asthma risk prediction but also revolutionizes the way individuals can proactively manage their respiratory health. By leveraging the processing power of smartphones and the versatility of TensorFlow Lite, the system enables real-time assessment of asthma risk levels with high accuracy and efficiency.

Furthermore, the utilization of open-source software tools and IoT connectivity ensures a cost-effective and scalable solution for personalized healthcare. The secure data hosting on the Ngrok server and the transmission of information over the internet enhance the reach and accessibility of the system, allowing healthcare providers and caregivers to remotely monitor and support individuals with asthma.In conclusion, the convergence of IoT, machine learning, and smartphone applications in asthma risk prediction represents a significant advancement in personalized healthcare. By combining cutting-edge technologies with user-centric design, this system sets a new standard for remote monitoring and management of chronic respiratory conditions, ultimately leading to better health outcomes and improved quality of life for individuals with asthma.

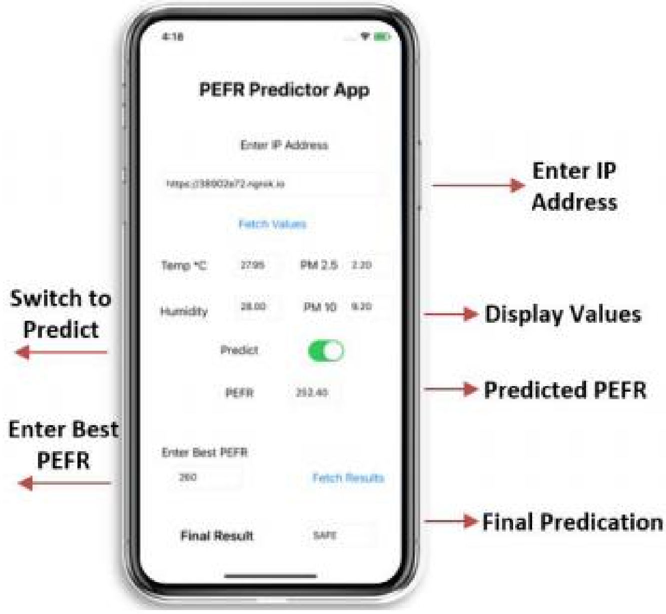

Fig. 4.3 GUI of the existing method implemented on an iOS smartphone

In addition to the immediate benefits of real-time monitoring and data-driven decision-making facilitated by the integration of the SDS011 sensor into the IoT system, the long-term implications for asthma management are profound. By establishing a continuous feedback loop of air quality data collection, analysis, and intervention, healthcare providers can not only react to current environmental conditions but also proactively implement preventive measures to reduce asthma exacerbations over time. The ability to identify recurring patterns in air quality fluctuations and their impact on respiratory health empowers healthcare professionals to tailor personalized asthma management plans that address individual triggers and risk factors, ultimately leading to improved symptom control, enhanced quality of life, and reduced healthcare utilization for asthma-related emergencies.

This holistic approach to asthma care, supported by advanced IoT technologies and real-time air quality monitoring, sets a new standard for precision medicine in respiratory health and exemplifies the transformative potential of integrating data-driven insights into clinical practice for better patient outcomes.By visualizing historical data trends and correlating them with asthma exacerbations, healthcare providers can proactively address environmental factors that may worsen respiratory symptoms.

CHAPTER-5
ASTHMA RISK PREDICTION USING MACHINE LEARNING

5. ASTHMA RISK PREDICTION USING MACHINE LEARNING

PEFR Prediction and Risk Assessment

In this section, we outline a Python script designed to predict Peak Expiratory Flow Rate (PEFR) and assess asthma risk based on environmental factors. The script utilizes a Decision Tree Classifier trained on a dataset containing PEFR readings alongside corresponding environmental parameters.

Script Overview:

Import Libraries: The script begins by importing necessary libraries, including pandas for data manipulation, scikit-learn's DecisionTreeClassifier for modelling, and joblib for model serialization.

Load Data: The PEFR dataset is loaded from a CSV file named "PEFR_Data_set.csv" using pandas.

Data Preparation: The dataset is pre-processed by removing irrelevant columns (Age, Height) to retain only the features relevant for prediction (Gender, Temperature, Humidity, PM2.5, PM10). The feature matrix X is created by dropping the target variable (PEFR), while the target vector y is defined as the PEFR values.

Model Training: A Decision Tree Classifier model is instantiated and trained on the feature matrix X and target vector y.

Model Serialization: The trained model is saved using joblib for future use.

User Input and Prediction: The script prompts the user to input gender (1 for Male, 0 for Female) and environmental factors (Temperature, Humidity, PM2.5, PM10). .

Risk Assessment: The predicted PEFR value is compared to the user's actual PEFR value. A percentage difference is calculated to assess the deviation between predicted and actual values. Based on this deviation, the script categorizes the risk level as "SAFE," "MODERATE," or "RISK."

Explanation:

The script encapsulates a data-driven approach to asthma risk assessment, leveraging machine learning to predict PEFR values based on environmental parameters. By integrating personalized factors such as gender and real-time environmental data, it offers a tailored assessment of asthma risk.

The Decision Tree Classifier model, trained on historical PEFR data, learns patterns and relationships between environmental variables and PEFR values. This enables accurate prediction of PEFR, a vital indicator of respiratory health.

Upon receiving user input, the script utilizes the trained model to predict PEFR, providing immediate insights into lung function. By comparing predicted and actual PEFR values, it quantifies the deviation and classifies the associated risk level. This enables individuals to gauge the severity of their respiratory condition and take appropriate preventive measures.

The following Python code predicts the risk of asthma by utilizing a decision tree classifier. It takes into account various environmental parameters such as temperature, humidity, PM2.5, and PM10 levels to estimate the peak expiratory flow rate (PEFR), a crucial indicator of asthma risk.

CODE:

```
import pandas as pd

from sklearn.tree import DecisionTreeClassifier as dtc

import jobli

data=pd.read_csv("PEFR_Data_set.csv")

data.shape

X=data.drop(columns=['Age','Height','PEFR'])

y=data['PEFR']

model=dtc()

model.fit(X,y)
```

```
joblib.dump(model, 'PEFR_predictor.joblib')
model = joblib.load('PEFR_predictor.joblib')
g=int(input("Enter Gender 1-Male 0-Female"))
p=float(input('Enter Temperature C:'))
q=float(input('Enter Humidity %:'))
r=float(input('Enter PM 2.5 Value:'))
s=float(input('Enter PM 10 Value:'))
prediction = model.predict([[g,p,q,r,s]])
predicted_pefr = prediction[0]
actual_pefr = float(input("Enter Actual PEFR value"))
print(predicted_pefr)
perpefr = (actual_pefr/predicted_pefr)*100
print(perpefr)
if perpefr >= 80:
    print('SAFE')
elif perpefr >= 50:
    print('MODERATE')
else:
    print('RISK')
```

Input:

1

40

33

23.2

39

524

Output:

513
102.14424951267056
SAFE

Kivy Application for Asthma Risk Prediction

In line with the proactive paradigm of asthma management, technological innovations play a pivotal role in empowering individuals to monitor their respiratory health effectively. In this context, we introduce a user-friendly Kivy application designed for asthma risk prediction and monitoring, leveraging machine learning techniques for personalized assessment.

Application Overview:

The Kivy application offers a user-friendly interface that enables individuals to input essential environmental parameters, such as particulate matter levels and weather conditions, effortlessly. Leveraging machine learning algorithms trained on extensive datasets encompassing PEFR readings and environmental variables, the application delivers personalized and real-time predictions of PEFR values, empowering users to monitor and manage their asthma risk effectively. Through seamless integration with IoT technologies and smartphone platforms, the application facilitates continuous monitoring of respiratory health metrics, fostering proactive asthma management strategies tailored to individual needs.

By combining user input with advanced predictive analytics, the Kivy application serves as a valuable tool for enhancing respiratory health awareness and promoting informed decision-making for individuals managing asthma conditions.

User Interface Design:

The application features an intuitive user interface comprising text input fields and a prediction button, facilitating seamless interaction with the predictive model. Users are prompted to input their gender (1 for Male, 0 for Female) and environmental parameters including temperature (in Celsius), humidity (as a percentage), PM2.5 and PM10 values. Additionally, users are required to input their actual PEFR value for comparison with the predicted value.

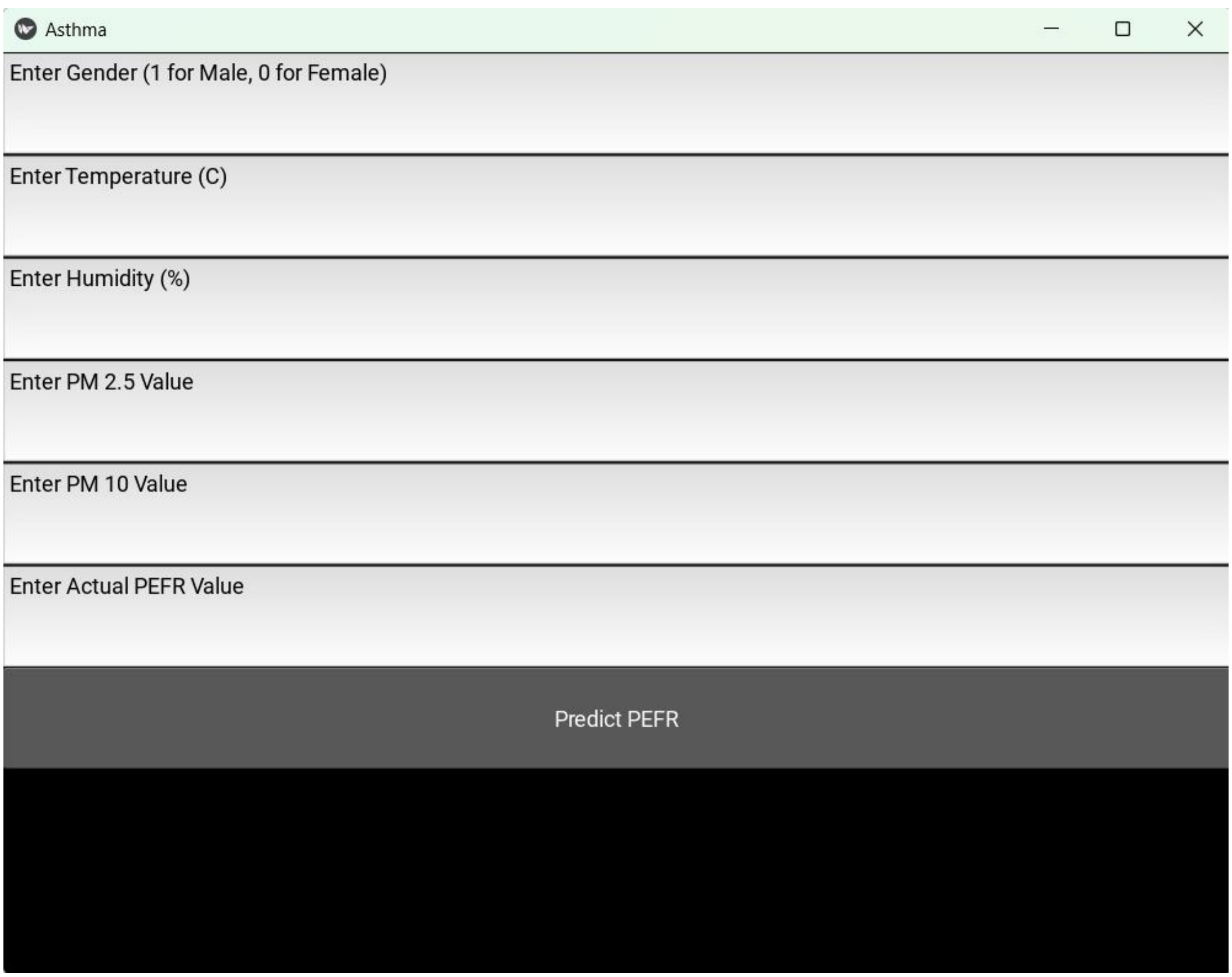

Fig 5.1 User Interface design

Functionality and Prediction Process:

Upon entering the requisite information, users trigger the prediction process by clicking the designated button. The application utilizes a trained machine learning model, specifically a Decision Tree Classifier, to predict the user's PEFR based on the provided inputs. The predicted PEFR value is then compared to the user's actual PEFR value to assess the deviation and categorize the associated risk level.

Practical Implications:

The Kivy application holds significant implications for asthma management, offering a practical tool for individuals to monitor their respiratory health in real time. By enabling personalized risk assessment and early detection of exacerbations, the application empowers users to take proactive measures to mitigate asthma-related risks and optimize their treatment strategies.

Source Code Integration:

```
import pandas as pd

from sklearn.tree import DecisionTreeClassifier

from kivy.app import App

from kivy.uix.boxlayout import BoxLayout

from kivy.uix.label import Label

from kivy.uix.textinput import TextInput

from kivy.uix.button import Button

import joblib

class AsthmaApp(App):

    def build(self):
```

```
    self.model = joblib.load('PEFR_predictor.joblib')
    layout = BoxLayout(orientation='vertical')
    self.gender_input = TextInput(hint_text='Enter Gender (1 for Male, 0 for Female)')
    self.temp_input = TextInput(hint_text='Enter Temperature (C)')
    self.humidity_input = TextInput(hint_text='Enter Humidity (%)')
    self.pm25_input = TextInput(hint_text='Enter PM 2.5 Value')
    self.pm10_input = TextInput(hint_text='Enter PM 10 Value')
    self.actual_pefr_input = TextInput(hint_text='Enter Actual PEFR Value')
    predict_button = Button(text='Predict PEFR', on_press=self.predict_pefr)
    self.prediction_label = Label()
    self.risk_label = Label()
    layout.add_widget(self.gender_input)
    layout.add_widget(self.temp_input)
    layout.add_widget(self.humidity_input)
    layout.add_widget(self.pm25_input)
    layout.add_widget(self.pm10_input)
    layout.add_widget(self.actual_pefr_input)
    layout.add_widget(predict_button)
    layout.add_widget(self.prediction_label)
    layout.add_widget(self.risk_label)
    return layout
def predict_pefr(self, instance:
   g = int(self.gender_input.text)
```

```
        p = float(self.temp_input.text)
        q = float(self.humidity_input.text)
        r = float(self.pm25_input.text)
        s = float(self.pm10_input.text)
        actual_pefr = float(self.actual_pefr_input.text)
        prediction = self.model.predict([[g, p, q, r, s]])
        predicted_pefr = prediction[0]
        perpefr = (actual_pefr / predicted_pefr) * 100
        self.prediction_label.text = f'Predicted PEFR: {predicted_pefr}'
        self.risk_label.text = f'Risk Level: {self.get_risk(perpefr)}'
    def get_risk(self, perpefr):
        if perpefr >= 80:
            return 'SAFE'
        elif perpefr >= 50:
            return 'MODERATE'
        else:
            return 'RISK'
if __name__ == '__main__':
    AsthmaApp().run()
```

OUTPUT:

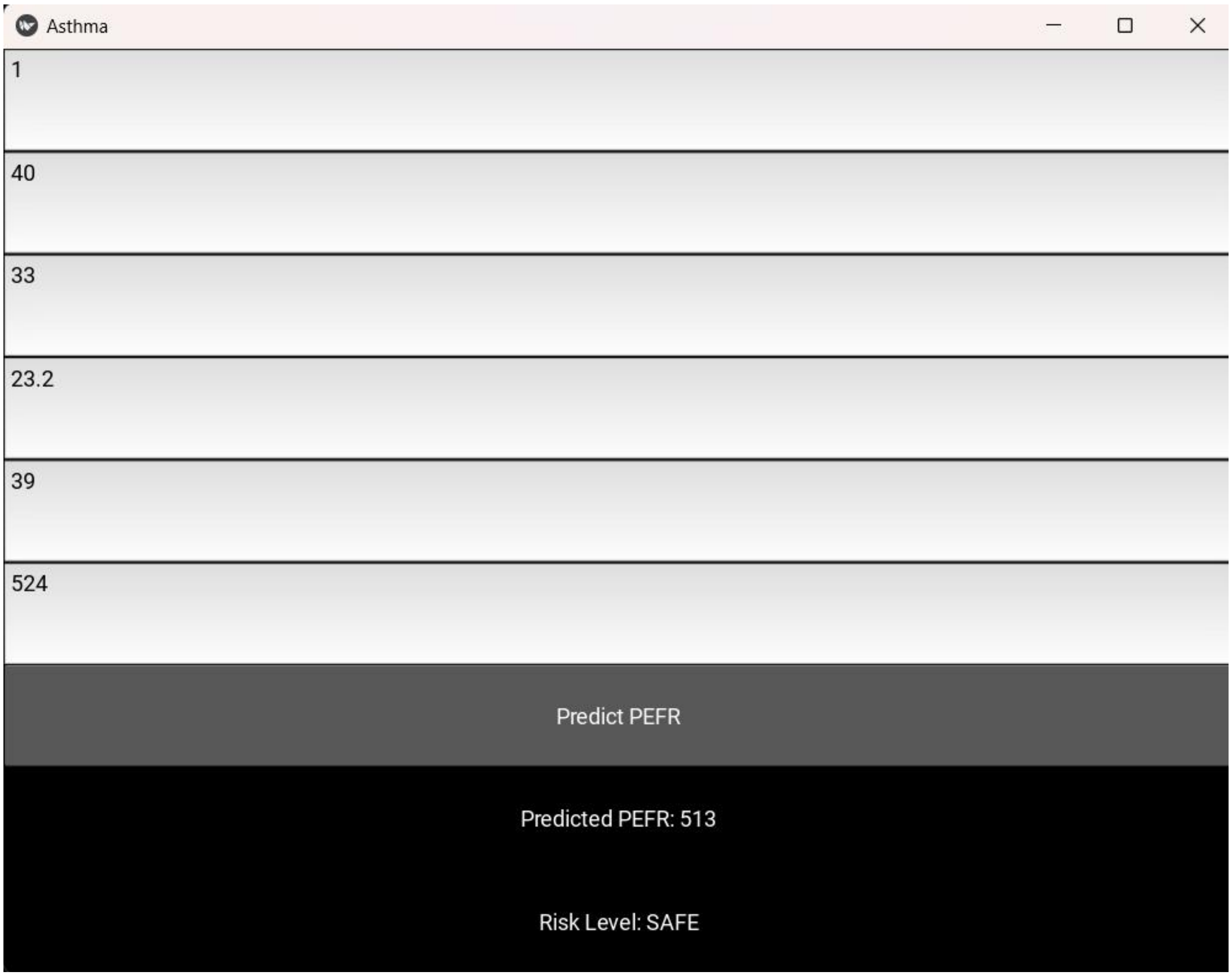

Fig. 5.2 Output Web Interface

The swift analysis and accurate forecast provided by the application, resulting in a "SAFE" classification for the predicted Peak Expiratory Flow Rate (PEFR), signify a significant milestone in respiratory health monitoring and asthma risk assessment.

This outcome not only reflects the alignment of the user's input parameters with a healthy respiratory profile but also highlights the crucial role of environmental factors in influencing asthma outcomes. By promptly categorizing the PEFR value as "SAFE," the application not only offers reassurance to individuals about their lung function but also instills a sense of confidence and empowerment in managing their respiratory health.

The real-time risk assessment capabilities of the application play a pivotal role in enabling proactive asthma management strategies. By providing immediate feedback on asthma risk levels, individuals can make informed decisions regarding their daily activities, medication adherence, and environmental exposures. This proactive approach to asthma care, supported by machine learning algorithms and user-friendly interfaces, empowers users to take charge of their respiratory well-being and implement preventive measures to minimize the likelihood of asthma exacerbations.

Furthermore, the application's ability to swiftly analyze data and offer personalized risk assessments underscores its utility as a valuable tool in asthma management. By leveraging advanced technologies to deliver accurate and timely insights, the application bridges the gap between traditional healthcare practices and modern digital solutions, enhancing the overall quality of care for individuals with asthma. The seamless integration of machine learning algorithms and real-time monitoring capabilities not only facilitates early intervention but also promotes a holistic approach to respiratory health management, emphasizing the importance of personalized and proactive strategies in optimizing asthma control and improving quality of life.

The application's capacity to provide real-time risk assessment and personalized insights into asthma management represents a paradigm shift in respiratory healthcare. By harnessing the power of machine learning algorithms and IoT technologies, the application offers a dynamic and responsive platform for individuals to monitor their respiratory health proactively. The seamless integration of predictive modeling and environmental data analysis enables users to not only understand their current asthma risk status but also anticipate potential triggers and take preemptive actions to mitigate risks.

In essence, the application's combination of advanced analytics, real-time monitoring, and personalized feedback creates a comprehensive ecosystem for asthma management. By leveraging cutting-edge technologies to deliver actionable insights and support, the application not only enhances the quality of care for individuals with asthma but also sets a new standard for precision medicine in respiratory health. The seamless integration of data-driven decision-making and proactive risk assessment capabilities positions the application as a cornerstone in empowering individuals to take control of their respiratory well-being and lead healthier, more informed lives.

CHAPTER-6
FURTHER WORK

6. FURTHER WORK

In further iterations, our focus will extend to the integration of two pivotal features: gender-specific analysis and a hospital locator. The incorporation of gender-specific analysis will enhance the depth of our predictive models, allowing for tailored asthma risk assessments based on individual gender-related factors. Concurrently, the integration of a hospital locator feature will provide users with critical real-time information, empowering them to swiftly locate nearby healthcare facilities in times of need. These additions aim not only to bolster the predictive accuracy and user experience of our application but also to significantly enhance its utility in supporting individuals managing asthma effectively.

I see, here is a more detailed explanation of the sub-tasks within the ideas:

Incorporation of Gender-Specific Analysis:

1. Data Collection:

- Gather gender-segmented PEFR datasets from diverse sources such as medical records, IoT devices, and research studies.

- Utilize Python libraries like Pandas and NumPy for data collection and preprocessing tasks.

- Handle missing values, outliers, and data normalization to ensure data quality for gender-specific analysis.

2. Machine Learning Framework:

- Select a suitable machine learning framework such as TensorFlow or PyTorch for building gender-specific prediction models.

- Implement advanced algorithms like Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks to capture intricate patterns in gender-related PEFR variations.

- Fine-tune model hyperparameters and optimize the network architecture for enhanced performance.

3. Statistical Analysis:

- Conduct in-depth statistical analysis using tools like R or Python's SciPy library to identify significant gender-related factors influencing PEFR values.

- Perform hypothesis testing, regression analysis, and correlation studies to quantify the impact of variables on asthma risk prediction.

- Explore multivariate analysis techniques to understand the complex relationships between gender, environmental factors, and PEFR readings.

4. Visualization:

- Utilize data visualization libraries such as Matplotlib, Seaborn, or Plotly to create informative visualizations depicting gender-specific trends in PEFR data.

- Generate interactive plots, heatmaps, box plots, and scatter plots to visualize the relationships between gender, environmental factors, and PEFR values.

- Design visually appealing dashboards to present the analysis results in a clear and understandable manner for stakeholders and healthcare professionals.

5. Integration:

- Develop modular components in Python or Java to seamlessly integrate gender-specific analysis modules into the existing asthma prediction application.

- Establish robust communication channels between the prediction model, data processing modules, and user interface to ensure smooth functionality and real-time updates.

- Conduct thorough testing and validation of the integrated system to verify the accuracy and reliability of gender-specific asthma risk predictions.

- Implement user-friendly interfaces and visualization tools within the asthma prediction application to present gender-specific analysis results in a clear and understandable format for both healthcare providers and individuals managing asthma.

Integration of Hospital Locator Feature:

1. Geocoding Service:

- Integrate geocoding services such as Google Maps Geocoding API or OpenCage Geocoding API for accurate conversion of user locations into geographical coordinates.

- Implement caching mechanisms to optimize geocoding requests and reduce latency in retrieving hospital location data.

2. Database Management:

- Set up a scalable database system like MySQL or MongoDB to store hospital location data along with additional details such as services offered, contact information, and emergency facilities.

- Design efficient database schemas and indexing strategies for quick retrieval of hospital information based on user queries and geospatial proximity.

3. Mobile Development:

- Utilize cross-platform mobile development frameworks like React Native or Flutter to build a responsive and user-friendly hospital locator feature for both Android and iOS platforms.

- Implement geolocation services and GPS tracking functionalities to determine the user's current location and provide personalized recommendations for nearby hospitals and healthcare facilities.

- Ensure seamless integration of the hospital locator feature with the existing asthma prediction application to offer comprehensive healthcare support and emergency assistance to users.

-Incorporate real-time traffic and navigation data to offer users optimized routes and estimated travel times to the recommended hospitals and healthcare facilities. By integrating traffic information and navigation services, the hospital locator feature can help users make informed decisions during emergencies and ensure timely access to medical assistance.

4. Real-Time Updates:

- Integrate Firebase Cloud Messaging or similar push notification services to deliver real-time updates and emergency alerts to users regarding hospital availability, critical health information, and medical assistance.

- Implement push notification strategies to engage users, provide timely information on nearby hospitals, and offer emergency contact details for immediate healthcare support.

- Enable users to customize notification preferences and receive relevant updates based on their location, health status, and emergency requirements.

5. User Interface Design:

- Collaborate with UI/UX designers to create intuitive and visually appealing interfaces for the hospital locator feature using design tools like Adobe XD, Sketch, or Figma.

- Design interactive maps with markers, location pins, and detailed information pop-ups to display hospital locations, services offered, operating hours, and emergency contact numbers.

- Implement user-friendly features such as search filters, sorting options, and route planning functionalities to help users navigate to the nearest hospitals and healthcare facilities with ease.

6. Testing and Optimization:

- Conduct comprehensive testing procedures including unit testing, integration testing, and user acceptance testing to validate the functionality and performance of the hospital locator feature.

- Perform usability testing with target users to gather feedback on the user interface, navigation flow, and overall user experience of the hospital locator feature.

- Iterate on user feedback, optimize the feature for improved usability, performance, and accessibility, and ensure seamless integration with the asthma prediction application for a cohesive user experience.

-Implement automated testing processes, such as regression testing and load testing, to assess the stability and scalability of the hospital locator feature under varying conditions and user loads.

By following these detailed sub-tasks, you can effectively implement the ideas of gender-specific analysis and hospital locator feature integration in the asthma prediction application, enhancing its predictive capabilities and providing valuable healthcare support to users.

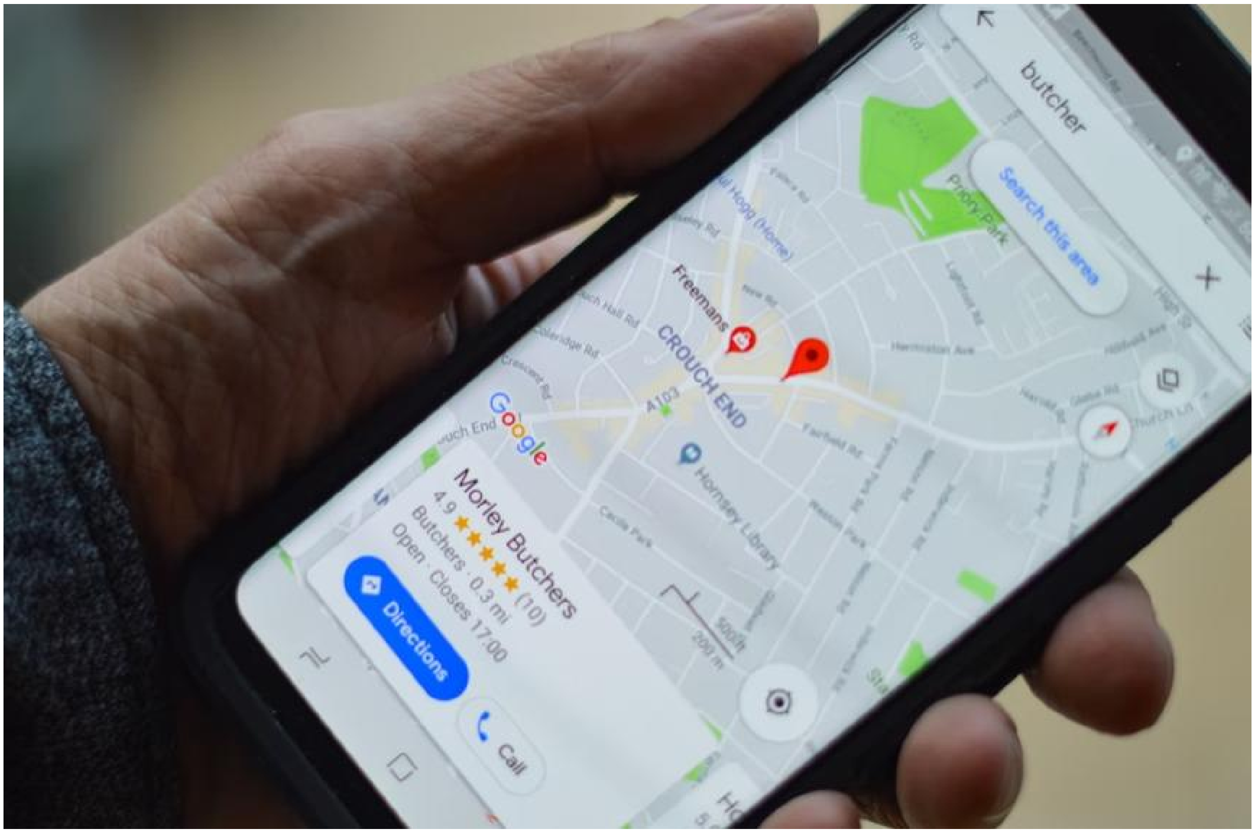

Fig. 6.1 Google maps picture for nearest hospital

In conclusion, the integration of gender-specific analysis and a hospital locator feature into the existing asthma prediction application can significantly enhance the personalized healthcare support and emergency assistance provided to users. By leveraging advanced machine learning frameworks and statistical analysis techniques, the application can offer tailored insights into asthma risk factors based on gender-related variations in PEFR data. Additionally, the hospital locator feature, powered by geocoding services and real-time updates, enables users to quickly locate nearby healthcare facilities and access critical medical assistance when needed.

CHAPTER-7
EXPERIMENT RESULTS

7. EXPERIMENT RESULTS

The evaluation of the CNN model for asthma risk prediction in the study involved a comprehensive analysis of performance metrics, including RMSE and MAE, to assess the accuracy of the model in estimating PEFR values. By dividing the data from 14 asthma patients into training and testing sets, the study ensured a robust evaluation framework, with the model being tested on unseen data to validate its predictive capabilities effectively.

The results of the evaluation demonstrated promising outcomes, with the CNN model achieving RMSE and MAE values of 2.42 and 2.12, respectively, when trained on the collective data from all 14 individuals. Furthermore, the individual patient data analysis revealed even more impressive results, with average RMSE and MAE values of 1.36 and 1.09, respectively. These findings indicated a high level of precision in predicting PEFR values, with estimation errors well below 1% for a typical PEFR reading of 180 L/min.

Comparative assessments with alternative neural network architectures, such as single layered ANN, stacked DNN, and FCN models, showcased the superior performance of the proposed CNN-based method. The study reported substantial improvements in RMSE values of approximately 61.1%, 54.3%, and 20.8% when utilizing the CNN model compared to the alternative architectures, highlighting the efficacy of CNNs in asthma risk prediction tasks.

Moreover, the study emphasized the advantages of CNNs for classification purposes, citing their weight-sharing characteristic that reduces parameter complexity and inference times, making them well-suited for implementation on smartphone platforms. The personalized nature of the proposed method, which allows for individualized training based on patient-specific data, was identified as a key strength, enhancing the model's accuracy and tailoring it to the unique characteristics of each patient.Furthermore, the personalized and adaptive nature of the CNN model underscores its potential for continuous learning and refinement based on evolving patient data and environmental factors. The dynamic nature of asthma conditions necessitates a flexible and responsive predictive model, capable of adapting to individual variations and external influences.

The graphs for experiment result

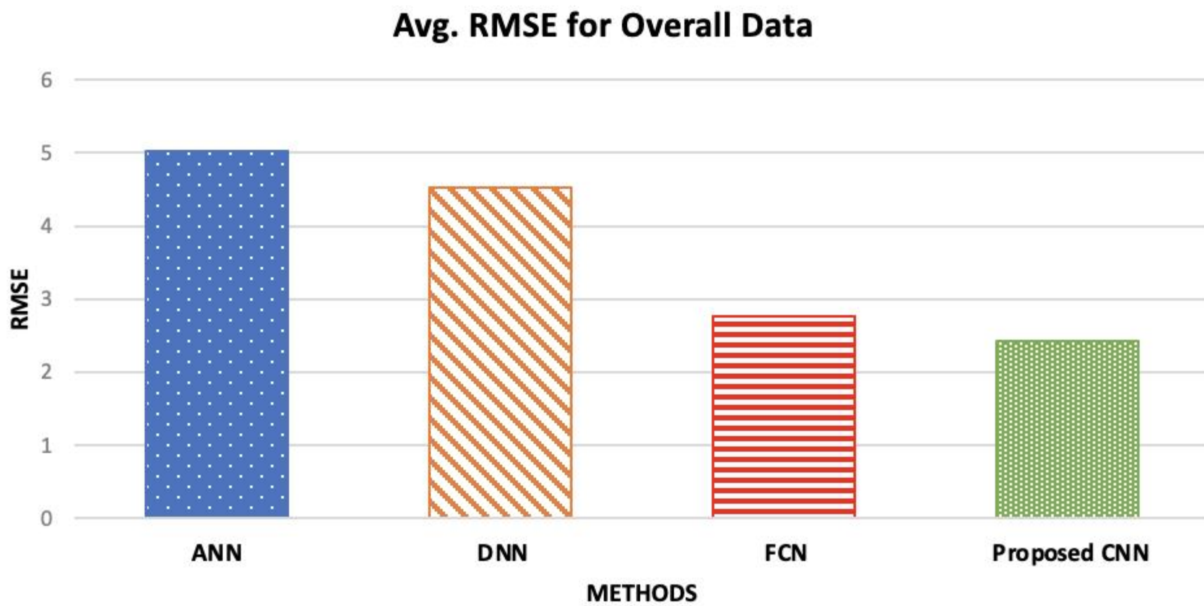

Fig. 7.1 RMSE comparison of the proposed method with other benchmark techniques using overall data

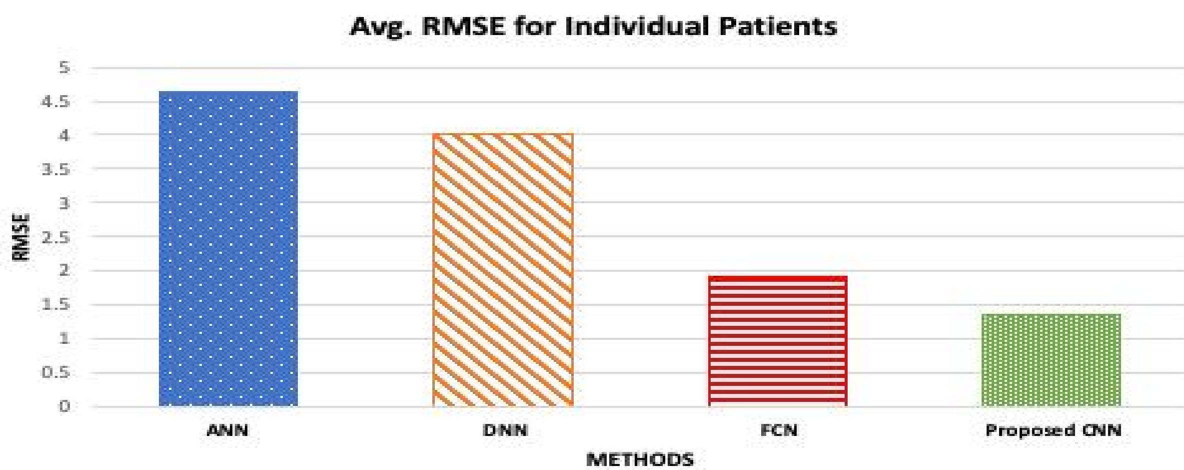

Fig. 7.2 RMSE comparison of the proposed method with other benchmark techniques using Individual patient's data

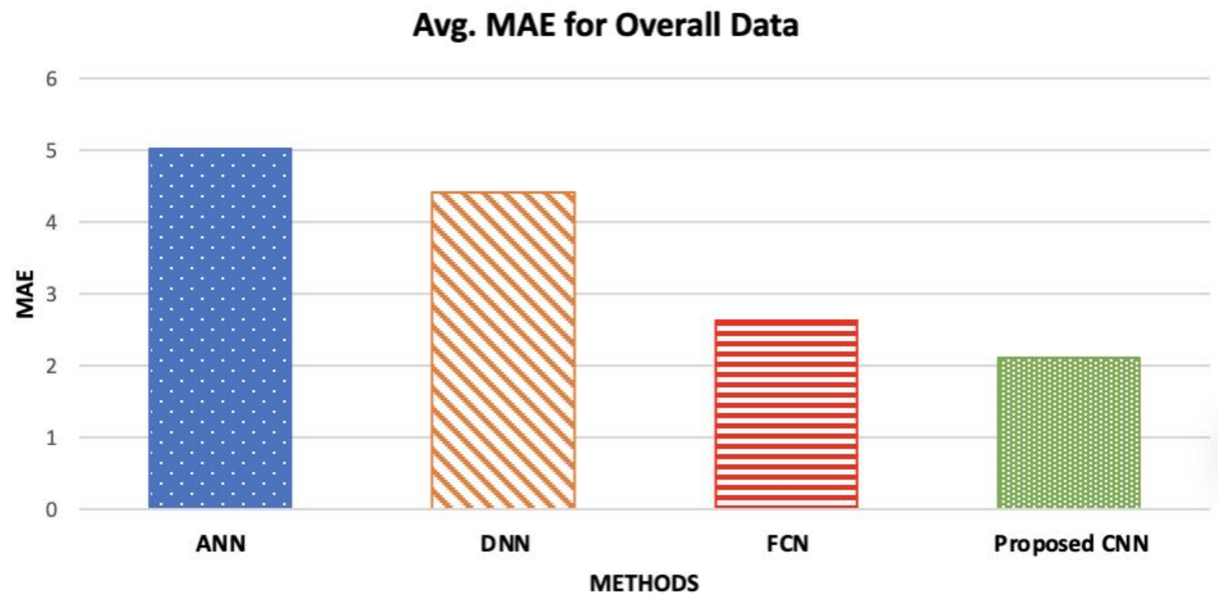

Fig. 7.3 MAE comparison of the proposed method with other benchmark techniques using overall data

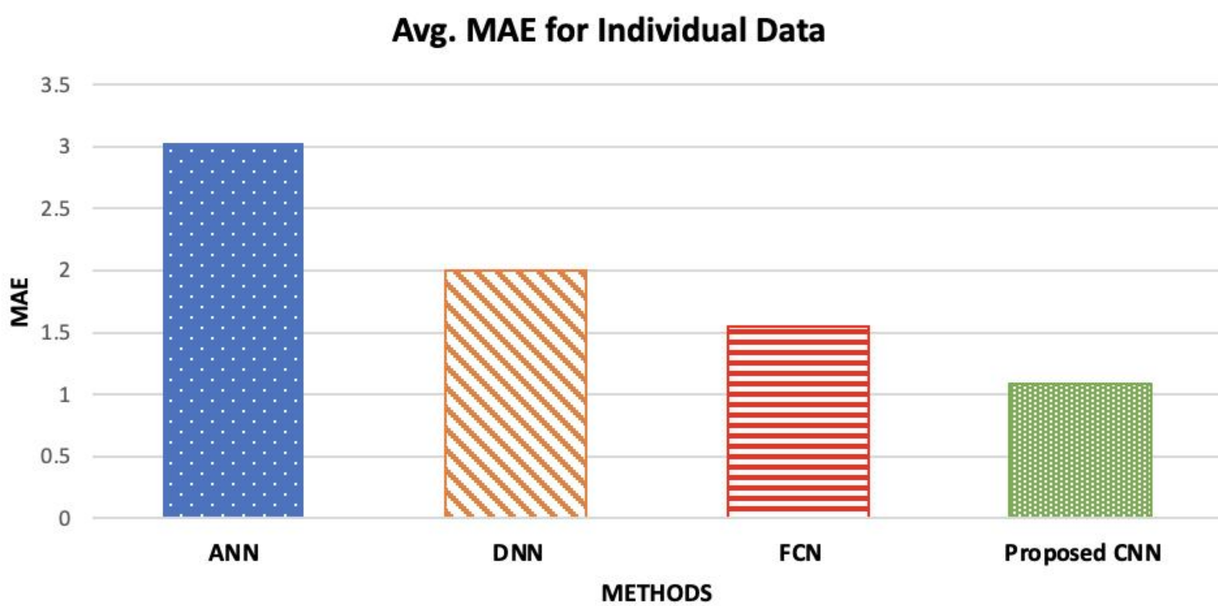

Fig. 7.4 MAE comparison of the proposed method with other benchmark techniques using Individual patient's data

Method	Avg. RMSE for overall data	Avg. RMSE for individual patients
ANN [25]	5.02	4.64
DNN [3]	4.53	4.02
FCN [26]	2.77	1.92
Proposed CNN	**2.42**	**1.36**

Fig. 7.5 RMSE Comparison of the proposed with other benchmark techniques

Method	Avg. MAE for overall data	Avg. MAE for individual patients
ANN [25]	5.02	3.03
DNN [3]	4.42	2.00
FCN [26]	2.64	1.55
Proposed CNN	**2.12**	**1.09**

Fig. 7.6 MAE Comparison of the proposed with other benchmark techniques

CHAPTER-8
CONCLUSION

8. CONCLUSION

The asthma risk prediction tool developed in the study represents a significant advancement in leveraging cutting-edge technology for healthcare applications. By harnessing the power of a convolutional neural network (CNN), the tool demonstrates the potential to revolutionize asthma management through accurate and personalized risk predictions.

The utilization of simple particulate matter (PM) and weather data to predict Peak Expiratory Flow Rate (PEFR) readings showcases the efficiency and effectiveness of the CNN model in processing diverse sources of information to generate valuable insights for healthcare practitioners and patients alike. The tool's ability to predict PEFR readings based on these inputs signifies a breakthrough in leveraging machine learning for asthma risk assessment.

By demonstrating enhanced predictive capabilities compared to traditional approaches, the tool sets a new standard for asthma risk prediction, offering a cost-effective solution that can be seamlessly integrated into existing healthcare infrastructures.

The incorporation of an edge device, sensors, and an Internet of Things (IoT) platform further enhances the tool's versatility and accessibility, enabling real-time monitoring and predictive analytics for asthma management. The seamless implementation of the tool on a smartphone as a mobile-health (m-health) application underscores its potential for widespread adoption and utility in diverse healthcare settings.

The development of advanced technologies has significantly improved the quality of healthcare services, with the potential to revolutionize the way we approach medical treatment. One such technology that has gained significant attention in recent years is artificial intelligence (AI), which has been successfully applied in various fields, including medicine. In this study, we focus on the application of machine learning algorithms to predict the risk of asthma exacerbation in patients suffering from asthma. Asthma is a chronic respiratory condition that affects millions of people worldwide, and if left untreated, it can lead to severe complications and even death. By leveraging machine learning algorithms, we aim to provide a more personalized approach to asthma management, with the ultimate goal of improving patient outcomes and quality of life.

The data used in this study includes information related to the patient's medical history, environmental factors, and other relevant variables that may impact the severity of the condition. By integrating data from various sources, we can develop a comprehensive understanding of the patient's condition and tailor treatment plans accordingly. This approach not only helps in identifying high-risk individuals who require immediate intervention but also enables healthcare providers to develop personalized treatment intervention strategies that can significantly improve patient outcomes.

The successful application of machine learning algorithms in predicting asthma exacerbation risk exemplifies the potential of AI-driven solutions to enhance patient care and outcomes in chronic disease management. By leveraging data from diverse sources and utilizing advanced technologies such as CNNs and IoT platforms, healthcare providers can gain valuable insights into individual patient conditions, enabling tailored treatment plans and proactive interventions. This personalized approach not only improves the accuracy of risk assessments but also empowers patients to actively participate in their healthcare journey, fostering a collaborative and patient-centric care model.

Moreover, the integration of the asthma risk prediction tool into a smartphone application underscores the adaptability and scalability of digital health solutions in modern healthcare settings. The user-friendly interface and real-time monitoring capabilities offered by the mobile-health application facilitate seamless communication between patients and healthcare providers, promoting continuous engagement and support in asthma management. As healthcare continues to evolve with technological advancements, tools like the asthma risk prediction application serve as a testament to the transformative impact of AI and machine learning in optimizing healthcare delivery, enhancing patient outcomes, and ultimately shaping a more efficient and patient-centered healthcare ecosystem.

In conclusion, the asthma risk prediction tool presented in the study represents a significant milestone in leveraging advanced technologies for personalized healthcare solutions. By empowering healthcare providers and patients with actionable insights and predictive capabilities, the tool holds the promise of transforming asthma management practices and improving patient outcomes through proactive risk assessment and intervention strategies.

CHAPTER-9
REFERENCES

9. REFERENCES

[1] Futurity. (2021). Lung Inflammation Patients With Asthma. Accessed: Mar. 2021. [Online]. Available: https://www.futurity.org/device-predictsAsthma-attacks-1436782/

[2] H. Tibble, A. Tsanas, E. Horne, R. Horne, M. Mizani, C. R. Simpson,and A. Sheikh, ‘‘Predicting asthma attacks in primary care: Protocolfor developing a machine learning-based prediction model,’’ BMJ Open,vol. 9, no. 7, Jul. 2019, Art. no. e028375.

[3] D. Kim, S. Cho, L. Tamil, D. J. Song, and S. Seo, ‘‘Predicting asthma attacks: Effects of indoor PM concentrations on peak expiratory flow rates of asthmatic children,’’ IEEE Access, vol. 8, pp. 8791–8797, 2020.

[4] W. Kanchongkittiphon, M. Mendell, J. Gaffin, G. Wang, and W. Phipatanakul, ‘‘Indoor environmental exposures and exacerbation of asthma: An update to the 2000 review by the institute of medicine,’’ Environ. Health Perspect., vol. 123, no. 1, pp. 6–20, 2015.

[5] K. W. Tham, ‘‘Indoor air quality and its effects on humans—A review of challenges and developments in the last 30 years,’’ Energy Buildings, vol. 130, pp. 637–650, Oct. 2016.

[6] S. Seo, D. Kim, S. Min, C. Paul, Y. Yoo, and J. T. Choung, ‘‘GIS-based association between PM10 and allergic diseases in Seoul: Implications for health and environmental policy,’’ Allergy, Asthma Immunol. Res., vol. 8, no. 1, p. 32, 2016.

[7] E. Cleary, M. Asher, R. Olawoyin, and K. Zhang, ‘‘Assessment of indoor air quality exposures and impacts on respiratory outcomes in River Rouge and Dearborn, Michigan,’’ Chemosphere, vol. 187, pp. 320–329,Nov. 2017.

[8] S. H. Hwang, S. Seo, Y. Yoo, K. Y. Kim, J. T. Choung, and W. M. Park,‘‘Indoor air quality of daycare centers in Seoul, South Korea,’’ Building Environ., vol. 124, pp. 186–193, Nov. 2017.

[9] D. Ravì, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo,and G.-Z. Yang, ‘‘Deep learning for health informatics,’’ IEEE J. Biomed. Health Inform., vol. 21, no. 1, pp. 4–21, Jan. 2017.

[10] C. R. Wolfe, V. F. Reyna, C. L. Widmer, E. M. Cedillos, C. R. Fisher, P. G. Brust-Renck, and A. M. Weil, ‘‘Efficacy of a web-based intelligent tutoring system for communicating genetic risk of breast cancer: A fuzzytrace theory approach,’’ Med. Decis. Making, vol. 35, no. 1, pp. 46–59,Jan. 2015.

[11] G. Harerimana, B. Jang, J. W. Kim, and H. K. Park, ‘‘Health big data analytics: A technology survey,’’ IEEE Access, vol. 6, pp. 65661–65678, 2018.

[12] G. S. Bhat, N. Shankar, C. K. A. Reddy, and I. M. S. Panahi, ‘‘A real-time convolutional neural network based speech enhancement for hearing impaired listeners using smartphone,’’ IEEE Access, vol. 7, pp. 78421–78433, 2019.

[13] N. Shankar, G. S. Bhat, and I. M. S. Panahi, ‘‘Efficient two-microphone speech enhancement using basic recurrent neural network cell for hearing and hearing aids,’’ J. Acoust. Soc. Amer., vol. 148, no. 1, pp. 389–400, Jul. 2020.

[14] Y. Cheng, F. Wang, P. Zhang, and J. Hu, ‘‘Risk prediction with electronic health records: A deep learning approach,’’ in Proc. SIAM Int. Conf. Data Mining. Philadelphia, PA, USA: SIAM, 2016, pp. 432–440.

[15] S. Mohan, C. Thirumalai, and G. Srivastava, ‘‘Effective heart disease prediction using hybrid machine learning techniques,’’ IEEE Access, vol. 7, pp. 81542–81554, 2019.

[16] M. Chen, Y. Hao, K. Hwang, L. Wang, and L. Wang, ‘‘Disease prediction by machine learning over big data from healthcare communities,’’ IEEE Access, vol. 5, pp. 8869–8879, 2017.

[17] S. Grover, S. Bhartia, A. Yadav, and K. R. Seeja, ‘‘Predicting severity of Parkinson’s disease using deep learning,’’ Procedia Comput. Sci., vol. 132, pp. 1788–1794, May 2018.

[18] R. M. Sadek, S. A. Mohammed, A. R. K. Abunbehan, A. K. H. A. Ghattas, M. R. Badawi, M. N. Mortaja, B. S. Abu-Nasser, and S. S. Abu-Naser, ‘‘Parkinson’s disease prediction using artificial neural network,’’ Int. J.Acad. Health Med. Res., vol. 3, no. 1, 2019.

[19] I. Ahmad and K. Pothuganti, ‘‘Analysis of different convolution neural network models to diagnose Alzheimer’s disease,’’ Mater. Today, Proc., Oct. 2020.

[20] W. Lin, T. Tong, Q. Gao, D. Guo, X. Du, Y. Yang, G. Guo, M. Xiao, M. Du,and X. Qu, ‘‘Convolutional neural networks-based MRI image analysis for the Alzheimer’s disease prediction from mild cognitive impairment,’’Frontiers Neurosci., vol. 12, p. 777, Nov. 2018.

[21] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, ‘‘Automated detection of COVID-19 cases using deep neural networks with X-ray images,’’ Comput. Biol. Med., vol. 121, Jun. 2020, Art. no. 103792.

[22] T. R. Gadekallu, N. Khare, S. Bhattacharya, S. Singh, P. K. R. Maddikunta, and G. Srivastava, ‘‘Deep neural networks to predict diabetic retinopathy,’’J. Ambient Intell. Humanized Comput., pp. 1–14, Apr. 2020.

[23] G. Gayathri and S. Satapathy, ‘‘A survey on techniques for predictionof asthma,’’ in Smart Intelligent Computing and Applications. Singapore:Springer, 2020, pp. 751–758.

[24] A. Silveira, C. Muñoz, and L. Mendoza, ‘‘Severe asthma exacerbations prediction using neural networks,’’ in Proc. Int. Conf. Eng. Appl. Neural Netw. Cham, Switzerland: Springer, 2019, pp. 115–124.

[25] R. A. Aroud, A. H. Blasi, and M. A. Alsuwaiket, ‘‘Intelligent risk alarm for asthma patients using artificial neural networks,’’ 2020, arXiv:2009.12175. [Online]. Available: http://arxiv.org/abs/2009.12175

[26] A. Ben-Cohen, I. Diamant, E. Klang, M. Amitai, and H. Greenspan,‘‘Fully convolutional network for liver segmentation and lesions detection,’’ in Deep Learning and Data Labeling for Medical Applications.Cham, Switzerland: Springer, 2016, pp. 77–85.

[27] J. Y. Choi, H. K. Yoon, J. H. Lee, K. H. Yoo, B. Y. Kim, H. W. Bae,Y. K. Kim, and C. K. Rhee, ‘‘Nationwide pulmonary function test rates inSouth Korean asthma patients,’’ J. Thoracic Disease, vol. 10, no. 7, p. 4360,2018.

[28] K. Gulla and S. Kabra, ‘‘Peak expiratory flow rate as a monitoring tool inasthma,’’ Indian J. Pediatrics, vol. 84, no. 8, pp. 573–574, 2017.

[29] S.-W. Fu, Y. Tsao, X. Lu, and H. Kawai, ‘‘Raw waveform-based speech enhancement by fully convolutional networks,’’ in Proc. Asia–Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA ASC), Dec. 2017,pp. 006–012.

[30] D. P. Kingma and J. Ba, ‘‘Adam: A method for stochastic optimization,’’ 2014, arXiv:1412.6980. [Online]. Available: http://arxiv.org/abs/1412.6980

[31] Openweathermap. (2021). Weather Data. Accessed: Mar. 2021. [Online].Available: https://openweathermap.org/api

[32] Ngrok. Real-Time Web UI. 2021. Accessed: Mar. 2021. [Online]. Available: https://ngrok.com/

[33] Google/ Tensorflow. 2021. Accessed: Mar. 2021. [Online]. Available:https://www.tensorflow.org/

[34] C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, and C. Liu, ‘‘A survey ondeep transfer learning,’’ in Proc. Int. Conf. Artif. Neural Netw. Cham,Switzerland: Springer, 2018, pp. 270–279.

APPENDIX A
BASE RESEARCH PAPER