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RISK PREDICTION OF ASTHMA BASED ON ML USING IoT &SMARTPHONE APP

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ABSTRACT

Despite a wealth of research on the link between indoor air pollution and the prevalence of allergic diseases, real-time big data and model predictability limitations prevent public health and environmental policies from developing predictive evidence for developing a preventive guideline for patients or vulnerable populations. Although the initiative is still in its early stages, the recent rise in popularity of IoT and machine learning techniques may offer supporting technologies for real-time big data collection and analysis for more precise prediction of allergy disease risks for evidence-based intervention. In this study, we provide a machine learning-based algorithm for predicting asthma risk. Using Internet-of-Things resources, the technology is totally deployed on a smartphone as a mobile health application. Peak Expiratory Flow Rates (PEFR), which are well-known asthma risk factors, are typically monitored using external tools such as peak flow meters. In this study, we use PEFR to identify a relationship between indoor particulate matter and the weather outside. The results of the PEFR are then divided into three risk categories, such as "Green" (Safe), "Yellow" (Moderate Risk), and "Red" (High Risk), and contrasted with the best peak flow number that was reached by everyone. The link between indoor PM levels and meteorological data and PEFR values is mapped using a convolutional neural network (CNN) architecture. The root mean square and mean absolute error accuracy measures of the suggested method are compared to those of deep neural network-based methods. In comparison to other methods addressed in the literature survey, the proposed method performs better according to these performance measures. On the smartphone, the entire configuration is implemented as an app. The input data is gathered using a Raspberry Pi-based IoT device. The cost-effectiveness of this aid in predicting the likelihood of asthma attacks can be demonstrated.

INTRODUCTION

Episodes of wheezing, throat tightness, coughing, and shortness of breath are characteristics of asthma, a chronic condition characterized by inflammation of the airways. A sudden exacerbation of these symptoms, which can be fatal, is known as an asthma attack. Health is one of the predictive science fields with the least amount of study. People's quality of life can be enhanced by anticipating health hazards and incorporating them into lifestyle choices. Environmental health plays a key role in asthma attacks. Health is one of the predictive science fields with the least amount of study. People's quality of life can be enhanced by anticipating health hazards and incorporating them into lifestyle choices. Environmental health plays a key role in asthma attacks. Hence, reliable counsel for patients to seek appropriate care or take drugs to prevent being sick and to help them prepare their mobility strategy may be provided by excellent predictive modeling. In this experiment, the risk of asthma is predicted using a new neural network design. Here, a smartphone has been used to implement the asthma risk prediction model (edge device).

EXISTING SYSTEM

A proposed model that has been utilized in the past to forecast the danger of chemicals existing in the area and determine whether they offer a high, medium, or low risk for asthma patients is the Intelligent Risk Alarm for Asthma Patients using Artificial Neural Network. The information is then split into two groups, the first of which is the training set, which contains 70% of the information needed to train the classifier to forecast the outcome. The second collection, known as the testing data set, contains 30% of the data used to test the classifier. The input layer, hidden layer, and output layer are the three layers of the proposed ANN. All of the chemical gasses used in the study, together with temperature and humidity is present in this input layer. The output layer, on the other hand, is the one with three values, each of which denotes a different type of risk. In other words, the values are centered on the different risk classifications, such as high, medium, or low risk. Each node in the input layer is connected to every other node in the hidden layer using the weight matrix to connect the inputs from the input layer to the hidden layer of the ANN. Random selection is used to choose weight values between -1 and -1. Here, a watch with a MQ5 sensor that scans the atmosphere for pollutants is created. It will inform the worried patient that they have been exposed to excessive pollution levels when the danger becomes more imminent.

PROPOSED SYSTEM

The suggested convolutional neural network (CNN) architecture consists of four hidden layers, including two convolutional layers and two fully linked layers. In order to give superior learning of the input features, the first and second convolutional layers employ 64 feature maps. Each convolution layer's kernel is 11 bytes in size. In a single step, the first and second convolution layers are both convolutionized. The fully interconnected layers consist of 128 neurons. One neuron, all ReLU activation functions, and a linear activation function are present in the output layer. The final network has over 1.5 million learnable parameters. The CNN loss function, or mean squared error, was decreased using the Adam Optimizing Algorithm. We use an IoT to predict the danger of asthma in real time. We use a smartphone, sensors, and an IoT platform to predict the risk of developing asthma in real time. Using a Raspberry Pi, data from an air quality monitor is collected. The weather data is sourced from an online open-source data provider. The data collected by the Raspberry Pi and the meteorological data are both stored on a secure server. After that, the smartphone makes use of this data. The smartphone app that is included with the trained neural network model receives the model's input data from the server and predicts the likelihood of developing asthma.

LITERATURE SURVEY

We found better asthma risk (category-wise) prediction when a deep learning model was used to examine the short-term accumulations of the PM records. In this study, the yearlong PEFR data of 14 pediatric asthma patients was matched with the real-time PM 10 and PM 2.5 concentrations. Additionally, we discovered that predicting accuracy may vary based on patient characteristics and accumulation time. However, no attempt has yet been made to predict asthma risk based on a real-time, continuous monitoring of indoor air pollution by using a deep learning framework. Machine learning approaches are being applied now-a-days to identify asthma phenotypes or to predict asthma exacerbations based on the tele-monitored symptoms. This study can be considered as the first of its kind in demonstrating the potential of a deep learning approach as a tool to discover the relationship between indoor air quality and asthma risk and can prove to be useful for estimating the future risks of asthma exacerbations based on the characteristics of a specific patient. We collected PM and PEFR data every ten minutes, which resulted in 352,152 training samples for cluster 1 and 140,860 training samples for cluster 2, even though the sample size was not too large. The sample size which is used in building the neural network would be enough considering that just seven input parameters were employed in this investigation. The presented work is simply a workability study; further model development would be necessary using a larger number of samples and additional covariates, such as ambient air quality and patient-specific characteristics. The interpolation and clustering of PEFR recordings and its matching with the real-time PM monitoring data is, of course, the study's primary weakness.

METHOD FOR PROPOSED ASTHMA PREDICTION

In this section, we discuss the suggested method for forecasting the probability of developing asthma. The data and deep learning network used to train the model are discussed. The suggested system's block diagram is shown in Figure 1. Peak expiratory flow rate (PEFR), which provides the labels for the model's training, indoor air pollution as assessed by PM2.5 and PM10 data, and weather data are the inputs to the deep learning model.

PEAK EXPIRATORY FLOW RATE (PEFR)

A fast test to assess how much air is leaving the lungs is peak flow measurement. Peak expiratory flow rate (PEFR) or peak expiratory flow are other names for the measurement (PEF). Asthmatics are the majority of people who monitor peak flow. Peak flow measurements can reveal how much and how quickly air can be forcefully out from the lungs. Once the entire lung has been inhaled, the measurement should begin. You blow hard through a device's mouthpiece during the test. Most frequently, a peak flow meter (PFM) is employed. This is a little, plastic handheld device. A PFM can be used almost anywhere because it is portable and lightweight. It's crucial to consistently use the same PFM. Different brands and models of meters can produce different readings. The test may occasionally be carried out using a spirometer in a doctor's office or hospital. A handheld mouthpiece for this instrument is corded to a bigger electronic gadget. The following three peak flow zones are identified by color:

Green: It denotes "go." 80% to 100% of your highest peak flow reading, or personal best, is considered the green zone. You should constantly be in this zone. The major airways in your lungs are functioning properly when your measurements are in this range. That implies that you can go about your daily business and fall asleep without incident.

Yellow: This phrase denotes caution or a slowdown. 50% to 80% of your personal best is the yellow zone. This zone's measurements indicate that your big airways are beginning to constrict. Mild symptoms like coughing, exhaustion, breathing difficulties, or tightness in your chest could start to appear. Your regular activities or quality of sleep may be hindered by these symptoms.

Red: It denotes "halt." Less than 50% of your personal best is in the red zone. If your readings fall in this zone, your big airways have severely narrowed. A medical emergency has occurred. Get assistance right immediately. You can be wheezing when breathing in and out, coughing, struggling to breathe, or having retractions (the muscles between the ribs are working hard to help you breathe). You can find it difficult to speak and walk.

INDOOR AIR MONITORING AND WEATHER DATA

During the same time that the PEFR data was collected, low-cost sensors mounted at each patient's home were used to measure the particulate matter PM2.5 and PM10, as well as the temperature and relative humidity, every 10 minutes. The data for weather, PEFR, and indoor particulate matter were then correlated across intervals of 10 minutes.

CONVOLUTIONAL NEURAL NETWORK BASED PREDICTION

Regression-based analysis is used to evaluate the PEFR readings by the proposed convolutional neural network. A CNN receives a matrix or an image and processes it across the network. CNNs are frequently used for image classification tasks, but they are also being used in a number of studies on disease prediction and voice processing. In these studies, the raw input data is typically presented as a matrix or an array. As a result, CNNs with a matrix input are considered in the suggested technique to forecast the risk of asthma. Regression-based analysis is used to analyze the PEFR readings by the proposed convolutional neural network. A CNN receives a matrix or an image and processes it throughout the network. CNNs are often used for image classification tasks, but they are also being used in a number of studies on disease prediction and voice processing. In these studies, the raw input data is typically presented as a matrix or an array. As a result, CNNs with a matrix input are considered in the suggested technique to forecast the risk of asthma. The weights and biases for all nodes and kernels were included in the training vectors, which were batch-normalized using a normal distribution with a truncated mean and standard deviation of 0.05. The model was trained across ten epochs. The model's performance was evaluated using a 10-fold cross-validation with a single fold leave out.

IoT AND SMARTPHONE IMPLEMENTATION

In this section, we discuss the IoT implementation procedure and tools. We'll discuss real-time data collection, data utilization, and the smartphone app in this part.

OVERALL PROCEDURE

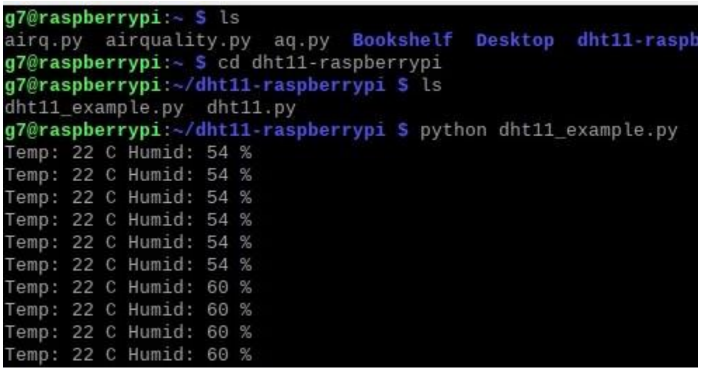
We use a smartphone, sensors, and an IoT platform to predict the risk of developing asthma in real time. A Raspberry Pi is used to collect information from an air quality monitor. The weather data is sourced from an online open-source data provider. The data collected by the Raspberry Pi and the meteorological data are both stored on a secure server.
After that, the smartphone makes use of this data. The smartphone app that is included with the trained neural network model receives the model's input data from the server and predicts the likelihood of developing asthma. The following discussion covers each component of the IoT installation. On the following page, underneath Algorithm 1, the algorithm's pseudocode is shown. The real-time stage on the smartphone and the data processing stage on the Raspberry Pi are used by Algorithm 1 to reflect the tool's overall workflow.

DHT11 SENSOR:

A cheap digital sensor for detecting humidity and temperature is the DHT11. To instantly detect humidity and temperature, this sensor may be simply interfaced with any micro-controller, including Arduino, Raspberry Pi, etc. Both a sensor and a module are available for the DHT11 humidity and temperature sensor. The pull-up resistor and a power-on LED distinguish this sensor from the module. A relative humidity sensor is the DHT11. This sensor employs a capacitive humidity sensor and a thermistor to measure the ambient air. The DHT11 has a temperature range of 0 to 50 degrees Celsius with a 2-degree precision. This sensor has a 20 to 80% humidity range with a 5% accuracy. This sensor's sampling rate is 1Hz. In other words, it provides one reading per second. The DHT11 is a tiny device with a 3-to-5-volt operational range. 2.5mA is the maximum current that can be used for measuring.

INTERFACING WITH DHT11 SENSOR:

OUTPUT:



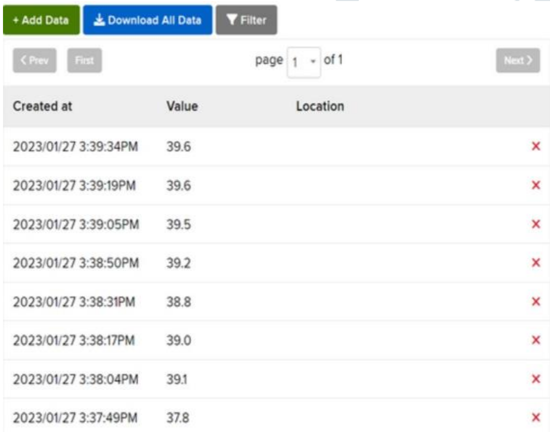
```
g7@raspberrypi:~ $ ls
airq.py  airquality.py  aq.py  Bookshelf  Desktop  dht11-raspb
g7@raspberrypi:~ $ cd dht11-raspberrypi
g7@raspberrypi:~/dht11-raspberrypi $ ls
dht11_example.py  dht11.py
g7@raspberrypi:~/dht11-raspberrypi $ python dht11_example.py
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 54 %
Temp: 22 C Humid: 60 %
Temp: 22 C Humid: 60 %
Temp: 22 C Humid: 60 %
Temp: 22 C Humid: 60 %
```

AIR QUALITY SENSOR:

We continuously track the particle matter using an SDS011 air quality sensor. By a wired connection, the sensor is immediately connected to a Raspberry Pi. A tiny, transportable, and precise sensor, the SDS011 air quality sensor measures PM2.5 and PM10. For the sensor to function effectively with the Raspberry Pi, it is attached to a USB port, and the device's maker has supplied drivers. The sensor can measure between 0.0 and 999.9 g/m3, which is a large range for tracking particle matter.

INTERFACING WITH SDS011 SENSOR:

PM 2.5:

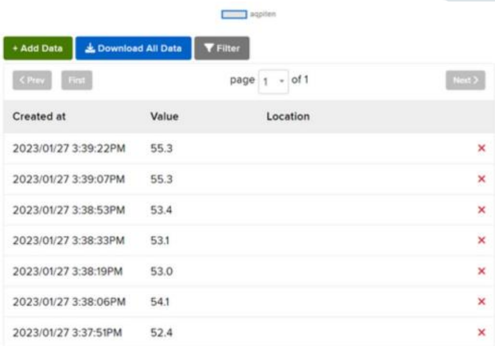


+ Add Data | Download All Data | Filter

‹ Prev | First | page 1 of 1 | Next ›

Created at	Value	Location
2023/01/27 3:39:34PM	39.6	
2023/01/27 3:39:19PM	39.6	
2023/01/27 3:39:05PM	39.5	
2023/01/27 3:38:50PM	39.2	
2023/01/27 3:38:31PM	38.8	
2023/01/27 3:38:17PM	39.0	
2023/01/27 3:38:04PM	39.1	
2023/01/27 3:37:49PM	37.8	

PM 10:



+ Add Data | Download All Data | Filter

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Created at	Value	Location
2023/01/27 3:39:22PM	55.3	
2023/01/27 3:39:07PM	55.3	
2023/01/27 3:38:53PM	53.4	
2023/01/27 3:38:33PM	53.1	
2023/01/27 3:38:19PM	53.0	
2023/01/27 3:38:06PM	54.1	
2023/01/27 3:37:51PM	52.4	

DATA HOSTING:

Once the weather and particulate matter data have been gathered on the raspberry pi, they are hosted on a secure server and made available to the raspberry pi. While a raspberry pi can connect to a smartphone via low latency Bluetooth, the proposed technique uses the internet to establish the connection in order to extend the monitoring range.

ALGORITHM:

Real-time algorithm for describing the proposed system

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

SOFTWARES USED:

ANDROID STUDIO (BACKEND): The IDE that is required for creating Android apps is called Android Studio. Tools from Android Studio are available to increase your productivity when developing Android apps.

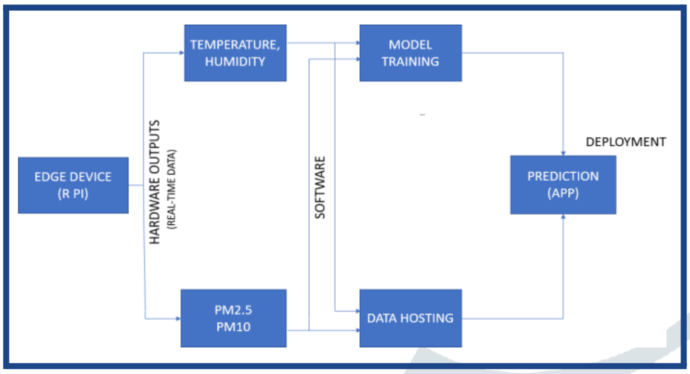
PYTHONANYWHERE: Python programs may be easily written and executed in the cloud thanks to PythonAnywhere. You can use any current web browser to launch a console session or write your programs in a web-based editor.

FLASK SERVER: A flask server is a collection of one or more computers that are packed together and solely dedicated to running software applications over the internet. It is server software that can handle HTTP requests on the public internet, private LANs, and private WANs.

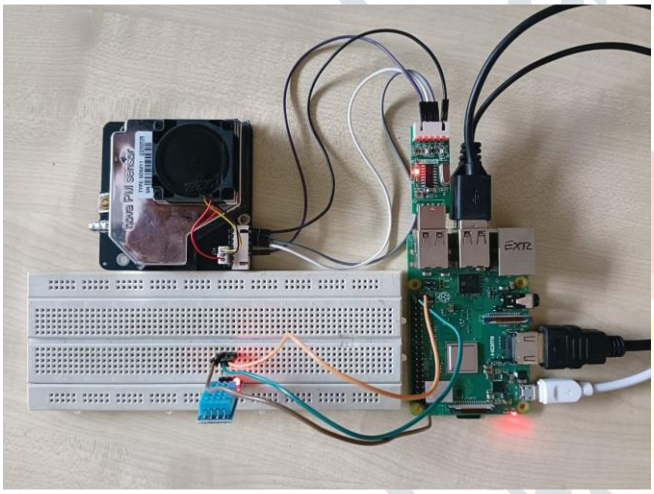
XML (FRONTEND): A markup language and file format for storing, sending, and recreating arbitrary data is called Extensible Markup Language (XML). It outlines a set of guidelines for document encoding in a way that is both machine- and human-readable. The simplicity, generality, and Internet-wide usability of XML are prioritized in its design objectives.

PYTHON for ASTHMA PREDICTION: Python is a popular high-level, general-purpose programming language. Python can be used on a server to create web applications. It is used in machine learning, web development, desktop applications, and many other fields.

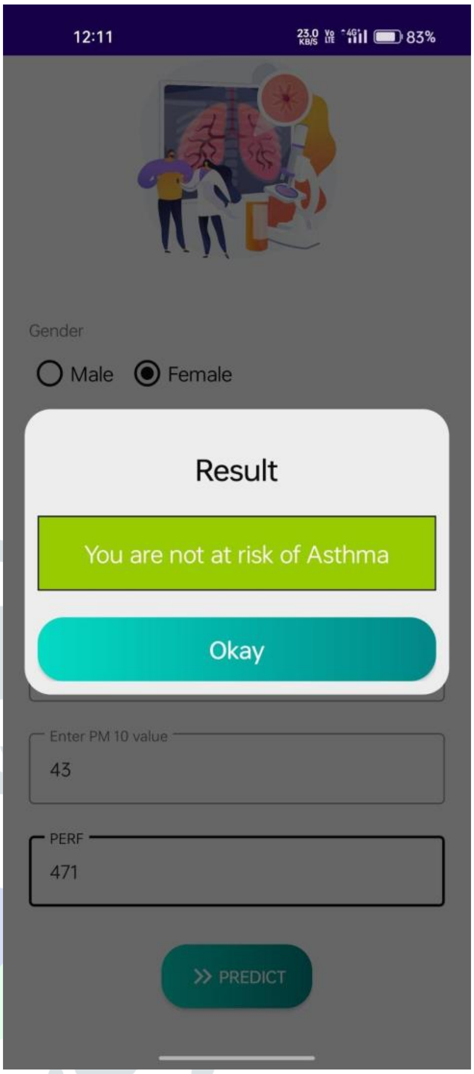
BLOCK DIAGRAM:



HARDWARE IMPLEMENTATION:



SMARTPHONE IMPLEMENTATION:



CONCLUSION:
In this study, we developed a convolutional neuralnetwork-based algorithm for predicting the risk of developing asthma. The PEFR readings are forecast using straightforward PM and weather information. Using unbiased assessments, the proposed method's performance enhancement is seen. This affordable gadget consists of sensors, an IoT platform, and an edge device. Using various IoT resources, the entire tool is implemented on a smartphone as an m-health application. The technique can be used to accurately forecast a patient's risk for getting asthma.

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