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Wearable asthma prediction device

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ABSTRACT

The paper presents the design for a wearable device to predict asthma attacks for all age groups. The design is developed based on environmental conditions and patient attack history. The wearable device uses temperature/humidity, dust sensors that monitor the surrounding atmospheric conditions and incorporates a machine learning algorithm (decision trees) for prediction of an attack in advance. Concepts of the Internet of Things are used for cloud storage and wireless connectivity with a handheld device, such as a smartphone.

***Keywords**— Wearable, Machine learning, Decision trees, Internet of Things, Cloud storage*

1. INTRODUCTION

There is no cure for asthma. Symptoms can be prevented by avoiding triggers, such as environmental factors and allergens. The conventional method requires chest strap and handheld spirometer which can be bulky. Furthermore, different patients will have different thresholds which have to be taken into account. Personalized medicine is a model that supports medical devices that are customized to suit individual patients on the basis of their predicted response or risk of disease. In the case of asthma, different patients may be affected by varying environmental conditions in different ways. The objective of the proposed device is to provide such a personalized solution to predict and prevent asthma attacks. The machine learning algorithm used will train the device to adapt to its user. A decision tree is trained to the conditions that trigger attacks for the particular user, such as allergic cough and wheeze. The ensemble of decision trees is used to classify the asthma symptoms (cough or wheeze), using a random forest classifier. The environmental conditions measured during a pre-empted attack are transferred to feeds created in Adafruit IO, which is a cloud service. This data, along with the decisions made by the device under these conditions can be retrieved by the patient whenever it is required.

2. SYSTEM OVERVIEW

The proposed system is a low-cost prototype that uses a Raspberry Pi microprocessor. Temperature, humidity and dust sensors are integrated with Raspberry Pi. The sensors receive data from the surroundings, which is used for further processing. The DHT11 sensor is used for measuring temperature and humidity, while the SDS011 sensor is used to measure particulate matter. A machine learning algorithm is incorporated, that uses previous attack history and environmental factors. The concept of decision trees is used for this purpose. The ensemble of decision trees is fed to the Raspberry Pi to predict an impending attack. The wearable is integrated with an LCD to display alert messages. The real-time data is made accessible from a smartphone.

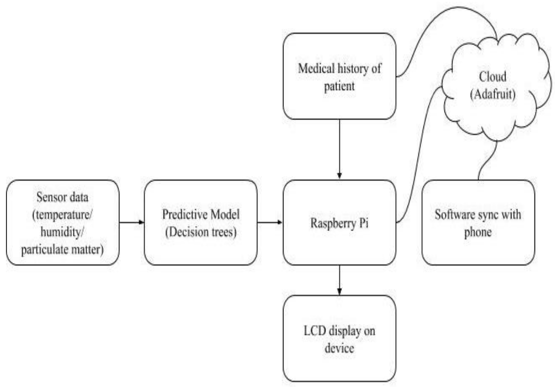

Fig. 1: Block Diagram of Wearable Asthma Prediction system

3. HARDWARE IMPLEMENTATION

The hardware set-up of the proposed system constitutes of the Raspberry Pi 3B, DHT11 Temperature/Humidity sensor, SDS011 Nova PM Sensor, and a 16x2 LCD.

3.1 Raspberry Pi 3B

The Raspberry Pi 3B is a single-board computer that consists of the Broadcom BCM2835 System-on-Chip. It has a RAM size of 1 GB, which is sufficient for the onboard processing required by the predictive model. The board takes a fixed 5V input and provides a polarity protection diode, a voltage clamp, and a self-resetting semiconductor fuse. The Raspberry Pi 3B consists of a 40-pin GPIO header, which can be designated as input or output.

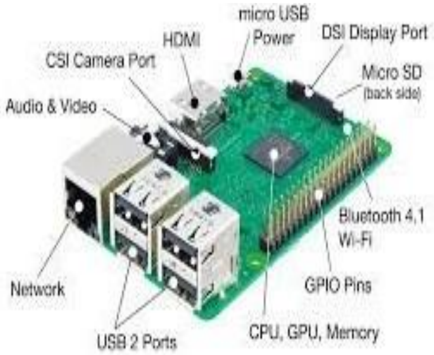

Fig. 2: Raspberry Pi 3B

3.2 DHT11 Temperature/Humidity sensor

The DHT11 Sensor includes a temperature and humidity sensor complex with a calibrated digital signal output. It features a resistive type humidity measurement component and a negative temperature coefficient (NTC) component for temperature measurement. It is integrated with a high-performance 8-bit microcontroller to offer fast response. It can be operated in a temperature range of 0°-50°C with an accuracy of ±2°C, and a humidity range of 20%- 90% relative humidity, with an accuracy of ±4% relative humidity. The DHT11 is calibrated in the laboratory to provide accurate measurements. The sensor has 3 pins, which are the power pin (Vcc), Output (Signal) and ground pin (GND). The output pin of the DHT11 is connected to one of the GPIO pins of the Raspberry Pi.

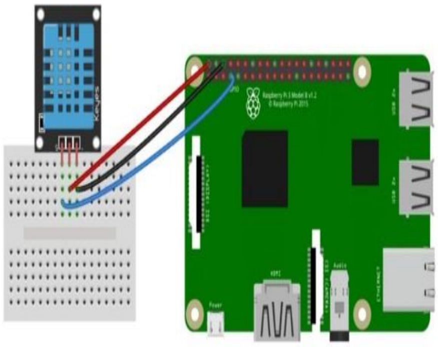

Fig. 3: Hardware integration of DHT11 sensor with Raspberry Pi 3B

3.3 Nova PM sensor SDS011

The SDS011 is a sensor that measures particulate matter (PM) using the principle of laser scattering. It is capable of measuring concentrations from 0.3 to 10µm and has a resolution of 0.3µg/m3. The scattered light is converted into electrical signals and are amplified and processed. The diameter of particles can be obtained from the relationship between the signal waveform and the particulate diameter. The input power requirement ranges from 4.7-5.3V. The SDS011 is connected to the Raspberry Pi 3B through the USB port.

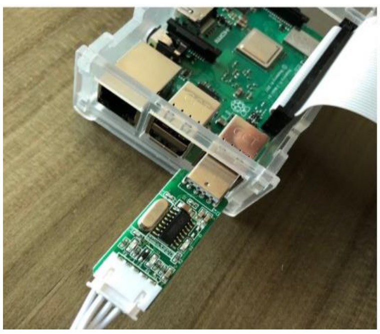

Fig. 4: Hardware integration of Nova PM sensor SDS011 with Raspberry Pi 3B

3.4 16x2 LCD module

A 16x2 LCD has the ability to display two rows of characters, with 16 columns per row. The LCD is used to display alerts such as "COUGH" and "WHEEZE" and environmental conditions including temperature, humidity, and particulate matter. The display has an operating range from 4.7V to 5.3V and current consumption of 1mA. The LCD module is lit with a blue backlight and can work in both 8-bit and 4-bit mode.

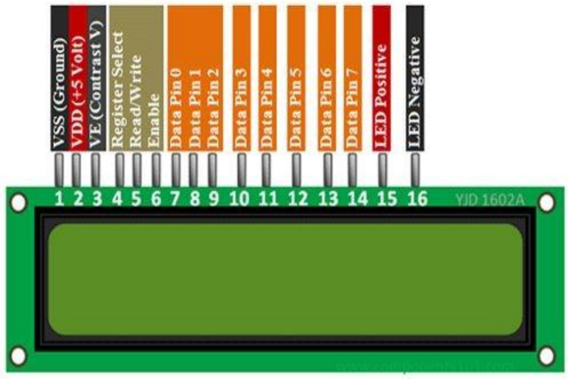

Fig. 5: Pinout configuration of 16x2 LCD display

4. SOFTWARE IMPLEMENTATION

4.1 Predictive model

Predictive modelling is a process that uses data mining and probability to predict outcomes. By analyzing historical events, there is a probability that we might be able to predict what would happen in the future and plan accordingly. But, this data is usually unstructured and complex for humans to analyze in a short period of time.

Predictive modelling collects and processes historical data in huge amounts and uses powerful computers to assess what happened in the past, and then provides an assessment of what will happen in the future. It uses predictors or known features to create predictive models that will be used in obtaining an output. A predictive model is able to learn how different points of data connect with each other. The model may employ a simple linear equation, or it may be a complex neural network, mapped out by a complex software. In our proposed system we have used decision trees as the predictive model.

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is a flowchart-like structure in which each internal node represents a "test" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from the root to leaf represent classification rules. Decision trees are widely used owing to their simplicity and ease of data preparation. Furthermore, the non-linear relationship between the parameters does not affect the performance of the decision tree.

For our application, the dataset consists of 3 features; temperature, humidity and PM2.5 and 2 labels; wheeze and cough. The decision tree finds the factor (temperature, humidity, or PM2.5) that returns the highest information gain. The information gain is measured as a reduction in entropy of the target class. Mathematically, it is represented as:

$$IG\,(Y\,,X) \;=\; E\,(Y\,) \;-\; E\,(Y\,|X) \qquad (1)$$

Where, *E* (*Y*) represents the entropy of an independent variable

Y, and $E\ (Y\ |X)$ represents the entropy of variable Y given X. The equation of entropy for a given variable X is:

$$E\ (X) = -\sum_{i=1} p_i\, log_2\, (p_i) \quad (2)$$

Where p_i is the frequentist probability of class i in the dataset.

The attribute with the largest information gain is chosen as the decision node. The model was trained on a synthetically generated dataset, created using common thresholds of the three parameters that cause asthma attacks. The decision tree built with the three sensor values as attributes is shown below.

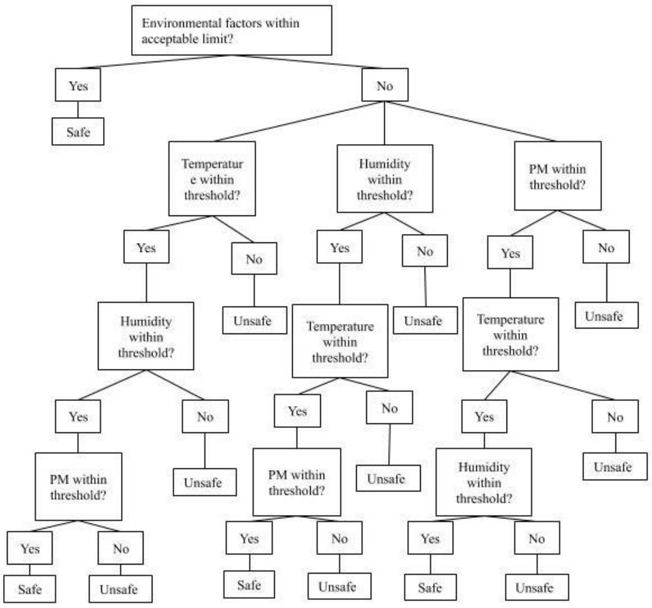

Fig. 6: Decision tree built using the three attributes

However, Decision-tree learners can create over-complex trees that do not generalize the data well. This is called over fitting. Over fitting is one of the most practical difficulties for decision tree models. Hence we go for random forests; a collection of decision trees whose results are aggregated into one final result. Two types of randomness's are built into the trees. First, each tree is built on a random sample from the original data. Second, at each tree node, a subset of features are randomly selected to generate the best split. Feature selection i.e. feature importance contribute majorly to the performance of random forests. This is because firstly, there can be a bias when multi-level categorical features exist in a data set. Secondly, importance scores can be misleading when features are redundant.

4.2 Cloud storage

Adafruit IO is an Internet of Things platform that enables us to control and monitor a connected device through configurable dashboards. The user will be communicating with Adafruit IO over the internet, to monitor the environmental factors measured by the sensors in the hardware set-up. The back-end of the Adafruit IO is where the device sends or receives sensor data, and the front-end is where the user interacts with the web browser. In this system, feeds are created on the Adafruit platform to handle sensor output. The feeds hold metadata about the data that is pushed from a sensor to the cloud. A feed is created for each sensor, and also for each possible output of the predictive model, namely, cough or wheeze. The feeds can be downloaded, edited and shared as required by the user.

5. RESULTS AND DISCUSSIONS

The hardware and software requirements of the system were integrated into a compact portable device. The predictive model was trained on a synthetically generated dataset with 97.2% training accuracy. The sensor data, along with the decisions made by the predictive model were transferred to feeds created in Adafruit IO. The internal circuitry of the prototype is shown below.

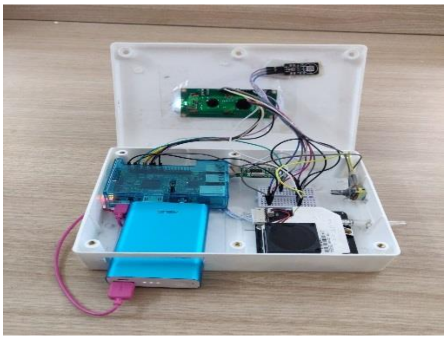

Fig. 7: Internal Circuitry of the System

A 5V power bank was used to power the Raspberry Pi through its USB port. An acrylic casing with an outlet for the DHT11 sensor and the SDS011 PM sensor was used. The external view of the device and the decisions displayed on the LCD module in two different environmental conditions are shown below. A polluted environment was simulated using camphor and dust.

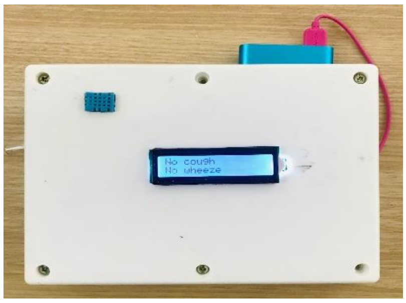

Fig. 8(a): Prediction under safe conditions

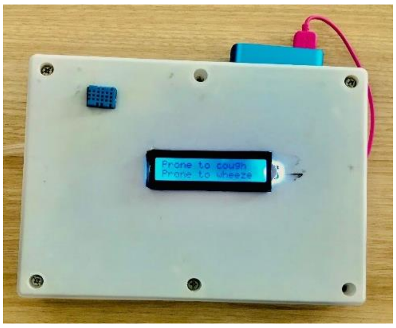

Fig. 8(b): Prediction under polluted conditions

The data transferred to the cloud can be retrieved over the internet using a handheld device such as a smartphone. Snapshots of the feeds received from the sensors accessed by a smartphone are shown below.

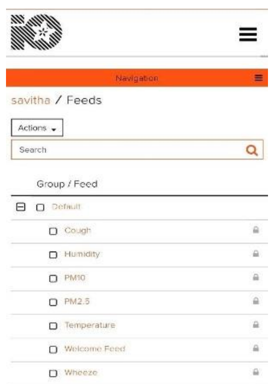

Fig. 9(a): Data Feeds in cloud

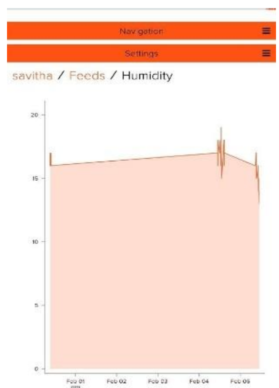

Fig. 9(b): Humidity data

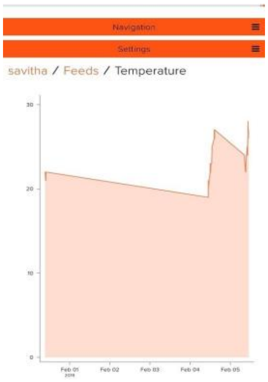

Fig. 9(c): Temperature

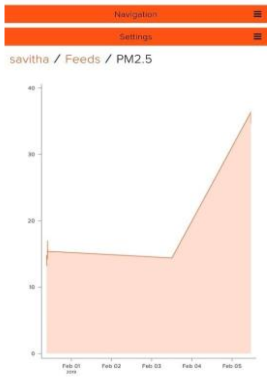

Fig. 9(d): PM2.5 data

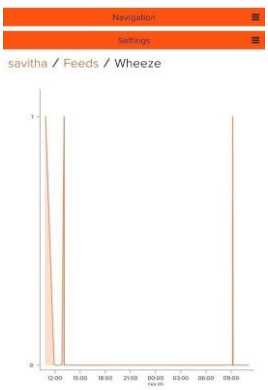

Fig. 9(e): Wheeze Predictions

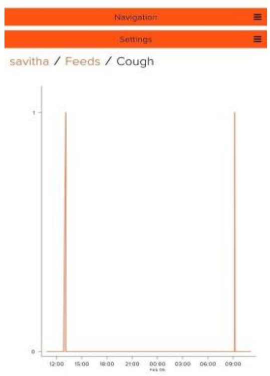

Fig. 9(f): Cough Predictions

6. CONCLUSION

We propose a wearable asthma device in this paper that uses an adaptive strategy and takes into account the unique conditions that trigger asthma for each patient. The device measures the real-time temperature, humidity and particulate matter, which are significant factors that cause breathing difficulty. This data is used by the machine learning model, trained to the user's medical history, to predict the onset of an asthma attack. The current prototype is a compact portable device but uses a few bulky components such as a power bank. The system can be further developed into a wearable by using PCB mountable power supply units and a smaller processor.

7. REFERENCES

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