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An IoT-based Asthma Intensity Prediction using Classification Models

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***Abstract*—Asthma is a chronic disease of breathing that increases a patient's risk of an attack. So, taking care of the patients and supervising their health condition is essential to decrease the risk. This article centers on IoT, the ThingSpeak cloud platform, and machine learning methods employed for the prediction of asthma intensity. These sensors include the KY-038 audio sensor, SEN-11574 pulse sensor, and ESP-32 microcontroller, which collect live health data. Data transfer to ThingSpeak is secure. With data protocols, the devices transmit end-to-end data for storage and sharing. The combined use of these IoT sensors enables continuous health tracking for asthma. This data is visualized through a user-friendly mobile app built on platforms like MIT App Inventor. The app facilitates data exchange and even QR code generation, promoting high user engagement. The obtained data is then processed using machine learning algorithms, including Decision Tree Classifiers, Random Forest Classifiers, K Nearest Neighbors, and Logistic Regression. These commonly used algorithms help identify patterns within the data. By analyzing this data, the ML models can predict when an asthma attack is likely to occur and its potential intensity. This enables optimal clinical decision-making, allowing for proactive measures and efficacious asthma management for early intervention, such as using an inhaler or seeking medical attention.**

***Index Terms*—Keywords: Asthma, Internet of Things (IoT), Sensors, Symptoms, Cloud Storage, Risk Prediction, Data Analysis, Machine Learning, Patient.**

I. Introduction

Asthma, a long-term lung disease that causes airways to inflame, is a sad reality for hundreds of thousands across the world, which imposes constant monitoring for effective management. Routine asthma diagnosis approaches often do not have instant data and may miss the beginning and severity of clinical symptoms. The estimated number of people affected by asthma in 2022 is approximately 339 million worldwide. The inhaler medication will help many people with asthma become normal and active. Most asthma-related deaths occur in low- and lower-middle countries where the under-diagnosis and treatment of asthma remain. During the last couple of years, the emerging technologies of IoT, cloud computing, and machine learning have opened the doors to innovative routes for distant supervision and disease management.

This research study introduces a new approach for detecting asthma. It has become IoT (Internet of Things) sensors, the ThingSpeak cloud platform, and machine learning algorithms. The application relies on KY-038 and a pulse sensor to obtain a person's pulse rate or environmental sound levels. This information makes it possible to evaluate the [18] user's lung function and atmospheric condition at the same time. The ESP32 device safely sends the gathered data to Thing-Speak, a powerful cloud platform that handles IoT data. A mobile application made utilizing MIT App Inventor possesses a user-friendly interface and QR codes that allow easy access to health data. It facilitates users' engagement and data fluidity. The data is gathered and processed using decision tree classifiers, random forest classifiers, and KNN algorithms. The algorithms go through data patterns to correctly identify symptoms of asthma. This helps us intervene early and actively in management.

The field testing done in this research work confirms the proposed system's ability to detect an asthma attack timely. It is a hopeful way of monitoring the health of remote people and managing disease in an individualized format. IoT, cloud computing, and machine learning integration have an excellent scope for changing asthma management. It enables patients and healthcare providers to make informed decisions based on this information. Providing a thorough overview of the existing literature, one can also see the clear advantages of this field.

Researchers continue to develop and implement cutting-edge techniques, such as wearable devices and internet-connected systems, for monitoring and managing asthma. Himani B.M. et al. proposed a non-invasive wearable system that integrates different sensors, such as self-reported symptoms, sound, humidity, and pulse, with machine learning models for asthma patients' support. Gautam S. Bhat and his team looked at applying IoT and a smartphone app for asthma risk prediction. They concluded that the traditional neural networks were efficient in forecasting asthma attacks. On top of that, Jason Alanya, Villanueva et al. built an IoT system with ESP32 that detects asthma in kids. It combines several sensors to refine asthma recognition and improve treatment. In addition, these studies indicate the transitional capability of applying IoT and machine learning in asthma treatment and offering new ways of personalized care and preventive measures.

II. LITERATURE REVIEW

There has been tremendous progress in health monitoring, i.e., IoT applications. Countless research studies have been done to understand how the Internet of Things (IoT) and Machine Learning (ML) systems are used to monitor and predict asthma. The following literature review highlights the crucial part of engineering sensors and ML models.

[1] Himani B.M et al.: Researchers designed a slim, non-intruding, wearable device for asthma monitoring that went an additional step in merging the data of pulse, body sound, and humidity with the self-reported symptoms. Being patient-centric, it used technologies such as web and body networks that highlight the role of the patients in informed decision-making.

[2] Gautam S Bhat, et al.: The research focuses on digital buckets using IOT, traditional neural networks for expressing the probability level of asthma. They substituted matrix-type input to classic CNN and reported its promising benefit.

[3] Jason Alanya Villanueva et al.: For them, it is a smart asthma detection system in the backyard Internet of Things. These CO and humidity sensors are MySQL for data gathering.

[4] Dokyeong Kim and S. Cho: The method they applied was based on a deep learning technique that improved asthma risk prediction by combining PEFR data, indoor particulate matter concentration, and a 10-fold multinomial logistic regression model. Experimental research must always be designed and built up for a real solution.

[5] Dilini M. Kotthawala and C. Murray: The research findings demonstrate that [17] ML provides high accuracy and portability for childhood asthma detection compared to the classical methods. The life of science is played by algorithms and analysis driven by Big Data, allowing more complex astronomy research and sophisticated quality healthcare decisions.

[6] Olivier Zhang, Leandro L. Minku: The previous research on machine learning centers for severe asthma exacerbation surpasses the paper-based procedure. The logistic regression method was created to disclose those early individuals who have a higher likelihood of relapse.

[7] Safayat Reza Anan, Md. Azizul Hossain: They formulate an IoT-based remote health system specializing in asthmatic patients, making it easy to operate and cost-effective.

[8] R. Shalini, Sanjana Cholaraju and R. AshaM: Despite technologies like IoT wearables and AI algorithms for asthma management, the disease can be best controlled through patient engagement and self-monitoring.

[9] Aroudi A. and Blasi H.: The authors use data mining and deep learning to study the chemical effects of air particles' toxicity on asthma, taking advantage of the system of sensors that observe air pollution.

[10] M. Lovrić and I. Banić: Aiming to understand better factors leading to [16] childhood asthma treatment success, they identify LOAC as the most accurate. They highlight the need for asthma symptom observation, which is the most important factor for success. Through machine learning, it enables us to discern asthma severity causes.

TABLE I
RESEARCH FINDINGS

Author	Advantages	Limitations
Himani et al (2023)	Utilizes CNN and outperform DNN	Doesn't use cloud for storing the data
Bhat et al (2021)	Utilizes CNN and outperform DNN	It is not affordable.
Jason et al (2021)	Receive instant notification whenever asthma is detected	Did not add the pulse sensor readings for better prediction
Dohyeong Kim (2020)	Performance using LSTM is better compared to Multinomial logistic regression	Difficulty in processing and predicting outcomes in vast dataset
Dilini M. Kothalawala (2020)	Produces good generalisability using ml algorithms	Required more data as data used for prediction is less
Olivier Zhang (2020)	It is efficient compared to traditional paper-based action plans	Data collected through paper diaries may be inaccurate
Safayat Reza Anan (2021)	It is cost efficient and user friendly	Need financial support for large-scale implementation
R. Shalini (2020)	Built with low cost sensors	Did not use ml algorithm for prediction
Rawabi A. Aroud (2020)	Used data mining for obtaining acute asthma result	Comparison of result with other ml algorithms is not performed
M. Lovrić (2020)	Used to find outcomes of various treatment i.e FEV1, FENO, MEF50 and LOAC	Considered small dataset for obtaining results

A. Research Gap

This project has worked on cloud storage where some of the work does not integrate cloud storage to data deposits, appearing as a lack of accessibility and a chance to collaborate. Eliminating pulse sensor information adversely affects prediction accuracy, especially if it is included to obtain accuracy. It is indeed challenging to process huge data sets, hence affecting the relevance of the evaluation, but this project can easily go through huge data sets. Large-scale implementation needs lots of money, while financial backing goes for it, and this project does not cost much.

III. METHODOLOGY

The IoT system integrates two vital sensors, the pulse, and the sound sensors, in the proper location to help us gather multiple data sets the instant they occur. The sound sensor is a component that can learn about noises in the immediate environment, but the pulse sensor digitally shows the user's heart rate. This information is sent directly to the ThingSpeak cloud server, which stores such IoT-acquired data. The absolution of any health information and data leakage is only ensured through the ThingSpeak APIs that secure and correct data transmission. In this context, the complex health data system becomes a powerful tool, allowing us to provide the correct information at the right time.

The internet provides easy access to the data, with a user-friendly interface, making the process more intuitive and hence more simple for the users. Moreover, this portal offers programmatic access via APIs to make integrated use of other applications or services beyond obstacles. This interoperability increases the capability and comprehensiveness of the IoT functional system, allowing for broader use and access of the health data.

The development of the mobile app through MIT App Inventor focuses on the user interface with ease of use and engagement, making the application more approachable to students. The intuitive UI design and feature capabilities like QR code generation are a blissful way for users to access healthcare resources. This user-centric approach favors open data and accessibility, which help everybody monitor and track their health status.

Human beings are constantly being scrutinized by the Internet of Things (IoT) through the monitoring of [14], [15] wheezing sounds and heartbeats, and the data acquisition process already takes place right from the onset. The gathered data are stored in ThingSpeak, complying with security requirements securely, allowing the platform to have enough capacity to handle different representations of data, such as CSV format. Such concordance in turn, allows for meaningful data analysis, with special emphasis on the role of machine learning.

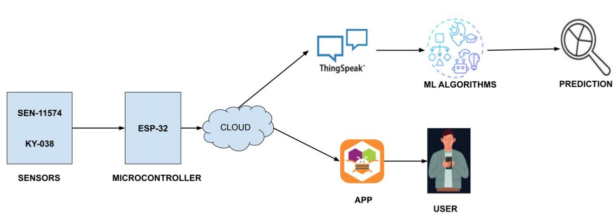

Fig. 1. Asthma Prediction System

The data acquired from IoT sensors is an essential part of the machine learning models reserved for use. Using this massive dataset, machines can be configured to identify specific patterns. These patterns can further be employed to better understand the user's health condition. Due to this iterative selection, predictive models may experience increasing accuracy and perfect functioning through the health monitoring systems.

IV. Process of Asthma Prediction System

Data collection is the first step of the process and requires sensors such as KY-038 and SEN-11574. These values are next transferred to an ESP-32 microcontroller. Here, it goes straight to the cloud for storage using ThingSpeak. The data is shared in a CSV format for further processing by ThingSpeak. Subsequently, the dataset is prepared and analyzed, and eventually, a model based on it is trained. The trained model is tested on efficacy.

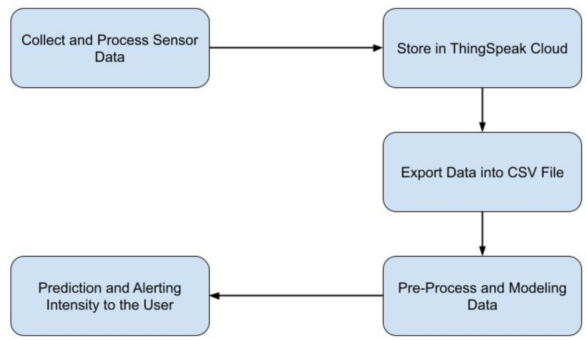

Fig. 2. Flow Process of Prediction System

After validation, the model is employed for the forecast. These predictions are then communicated to the user in graphical form and other forms, and further insights from the dataset accompany the results. This leads to creating a data pipeline system where data passes through different stages, such as data collection, cleaning, analysis, and insights generation.

V. Hardware Implementation

A. Reading From Sensors

The KY-038 Sound sensor and SEN-11574 Pulse sensor are the key links of real-time patient monitoring. These sensors are physically interfaced with an ESP32 board using connection cables, allowing for real-time data transmission and processing. The KY-038 and SEN-11574 are compact, lightweight, and subtly designed microcontrollers that measure breath sound, pulse rate, and SpO2 values.

The comprehensive solution includes sensors and the necessary drivers to properly interface with the ESP-32 microcontroller. This integration helps achieve optimal operation and accurate data collection, which, in turn, allows the hospital to monitor patients reliably.

The attached image illustrates the physical link between the sensor and the ESP-32 board; thus, the setup process is evident and seems effortless. Moreover, such a clear visualization helps in understanding hardware configuration, and most importantly, it makes the replication and deployment of such settings in various healthcare settings easy.

Furthermore, the sensors' real-time values are the subject of Figure 4, a visual demo and proof of their ability to capture and transmit essential health data. The visualization shows

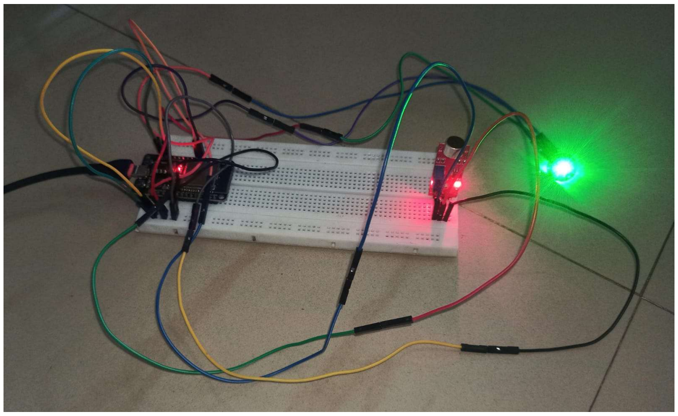

Fig. 3. Sensors connected to ESP-32 microcontroller

the sensors' ability to provide real-time monitoring and health assessment. This will reiterate the role of the sensors.

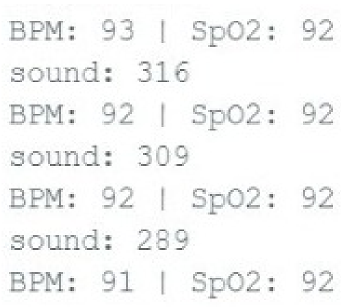

Fig. 4. Data from Sensors

Thus, combining KY-038 and SEN-11574 with an ESP-32 board offers an advanced real-time patient monitoring system. These sensors have a user-friendly structure and accurate data acquisition ability. They are smoothly compatible with the ESP-32, and they contribute to the quality of healthcare provision and improvements in patient care delivery.

B. Storing Data

A signal flow begins after all the sensors are connected and data is transferred to the cloud for centralized storage. These cloud-based storage systems can provide users with data anytime from anywhere, giving unlimited conveniences and flexibility. Cloud technology enables streamlining data management and a user-friendly data viewing interface layer that provides effortless data interpretation and analysis.

On the cloud, the [12] ThingSpeak technology provides the platform for additional accessibility and usability. With real-time feedback and shared data collaborative capabilities, users can be current and active participants in the learning process. This cooperative space reinforces a sense of community and allows working together while monitoring and managing health results.

Cloud technology is characterized by the scalability and reliability of its operations, which are among its key benefits. The scalability of the cloud platform is what allows it to smoothly scale up to cope with increasing amounts of data and rising user requests. Furthermore, the resilience feature in cloud-based infrastructure guarantees 24/7 availability of essential health data, prevents inconvenience, and enhances user experience.

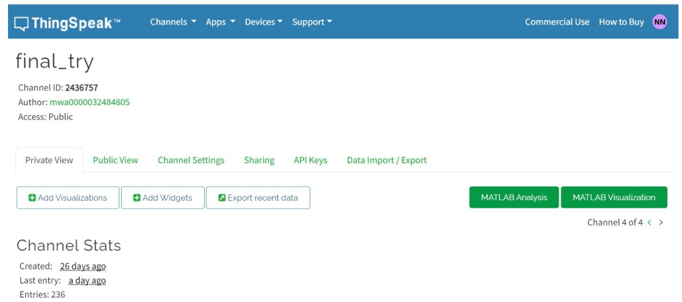

Fig. 5. Data Storing in Thing-Speak

Through the utilization of the cloud, users can track their health metrics and, when needed, intervene accordingly. The real-time availability of data contributes to early detection and timeous intervention, enabling proactive management of health care, which prevents potential problems. Overall, the confluence of cloud technology and sensor systems unlocks the stream of information, develops partnerships, and bolsters users' ability to make rational choices on their health and condition.

C. App Implementation

Among these algorithms, an offline machine-learning model has been developed to predict asthma. This model has been trained in Google Colab. The model, written in Python with the required libraries imported using sklearn, offers insightful, detailed analysis. Using [11]MIT App Inventor, this app plots voltage and current readings and updates users' phone screens graphically. The graphical user interface (GUI), shown in Figure 6, presents an easy-to-use tool for reading data from the cloud and visualization.

Furthermore, the prediction data is received from the cloud, which quickly trains the model. Users give values in the Google Colab premises used for the prediction. Following that, machine learning algorithms will utilize this data to reach the prediction of the user's asthma status. A taken pm10.5 value is read out by the output result like 'Asthma is not present,' 'Asthma is present and risk is high,' or 'Asthma is not present but there is a moderate risk of getting asthma' which helps users to understand the current asthma risk. This can be seen in the figure 7.

One of the apparent benefits emanates from the fact that users could get these applications via MIT, which fits every pocket and brings cost reduction. Moreover, every tool is free and open source, which can widen the scope for accessibility, user collaboration, and transparency. The fact that this inclusive approach in the asthma prediction model ensures that

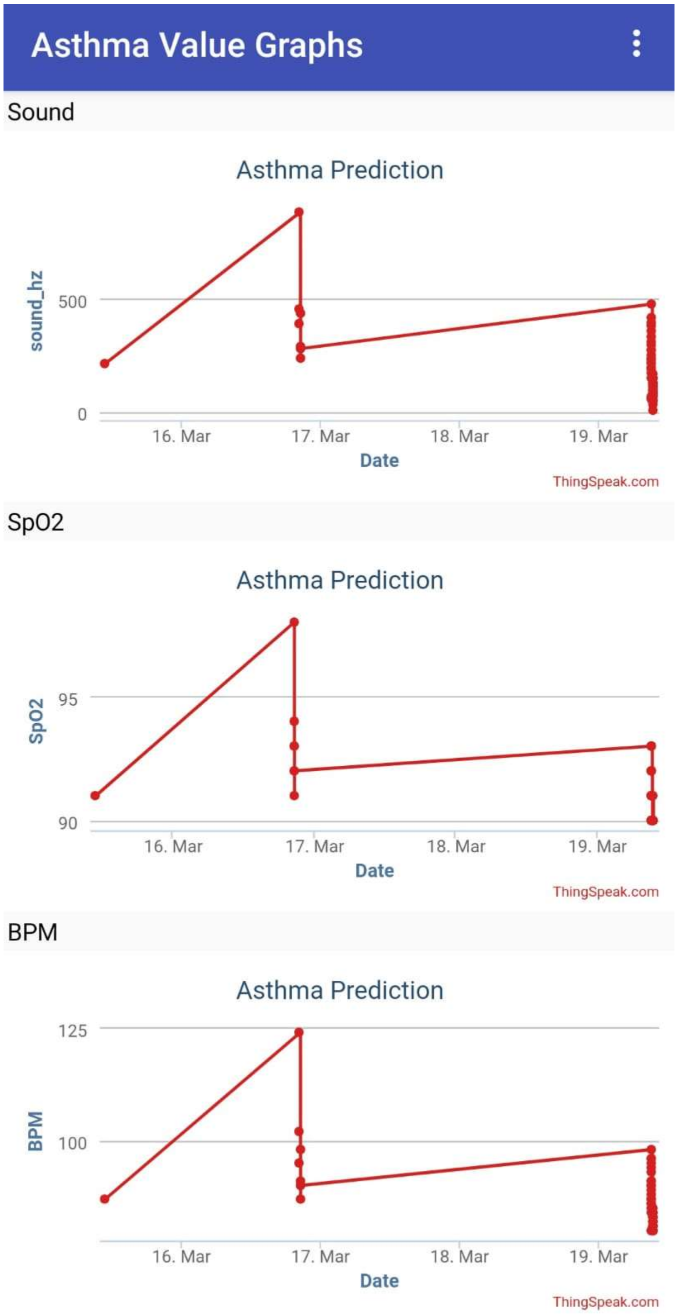

Fig. 6. Graphs displaying Real-Time data

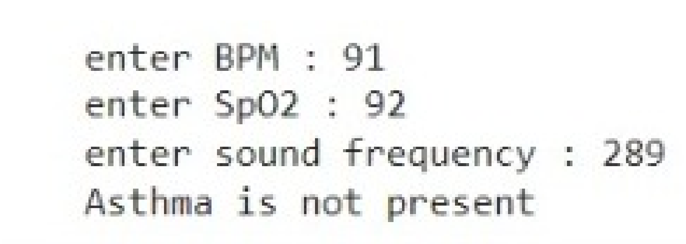

Fig. 7. User entering Values

those with economic limitations can also enjoy the benefits means that the model is welcoming for all.

Through smartphone technology's capability of making things handier, one can avail of these health services, which is a step towards democratizing health care accessibility. This technology represents a significant leap toward developing personalized healthcare treatments, giving people independence to control and manage their health. While the fluid application of machine learning, cloud computing, and smartphone technologies highlights the ability of medical services to be transformed by the latest technology.

This all-in-one solution smartly combines modern technology with user-oriented design and gives a user-friendly asthma prediction and maintenance tool. With these, its effectiveness and possibility to be used on a larger scale to provide healthcare solutions that are available to everyone of all classes gain traction.

VI. Results

The evaluation of model performance here relies on two key metrics: root mean square error (RMSE) and mean absolute error (MAE)[13], which are two of the errors frequently used. These parameters are just detection criteria for identifying the best model. The sense of RMSE and MAE computation for the data set is shown, clarifying the accuracy of each model.

TABLE II
Results Obtained from Algorithms

Algorithm	RMSE	MAE	Accuracy
Logistic Regression	0.98	0.59	0.59
Decision Tree Classifier	1.05	0.62	0.44
Random Forest Classifier	1.10	0.77	0.59
k-Nearest Neighbour	1.05	0.66	0.59

Evaluation is done by dividing the data set into code sections of individual patients. Among the data, a proportion of 80% is dedicated to training, with the remaining 20% allocated for the tests. In a clearer way, the model will be fed only with the training data during the training phase, allowing an independent The Figures 8 and 9 show the obtained values of RMSE and MAE.he logistic regression, an RMSE of 0.98, is calculated. With a RMSE of 1.20, a decision tree classifier follows. The RMSE of the random forest classifier is 1.054, and the KNN is 1.054. On the other hand, Logistic Regression, Random Forest, Decision Tree Classifier, and KNN have MAEs of 0.59, 0.66, 0.85, and 0.66. Consequently, the tabled findings utilize a chart for better comparison and understanding. And the figure 8 and 9 shows the obtained values of RMSE and MAE.

Logistic regression, with this range of results, becomes the leading model, surpassing the other algorithms, referring to the measurements of RMSE and MAE. The lower error rate in this particular algorithm implies more accurate predictions than the attained random forest, decision trees, and KNN. This means that Logistic Regression was selected as the best option for how asthma would be predicted in this research.

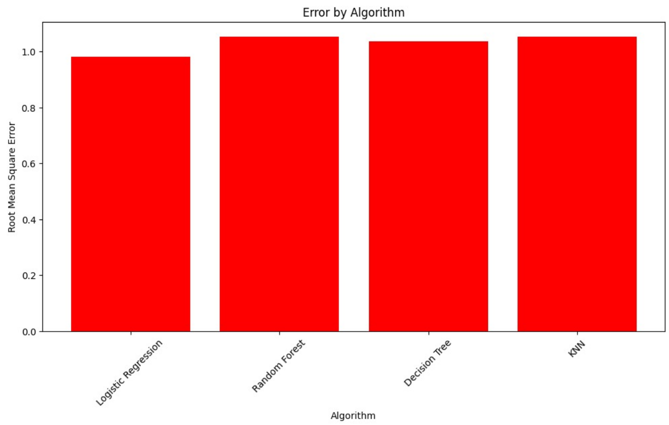

Fig. 8. RMSE for Various Algorithms

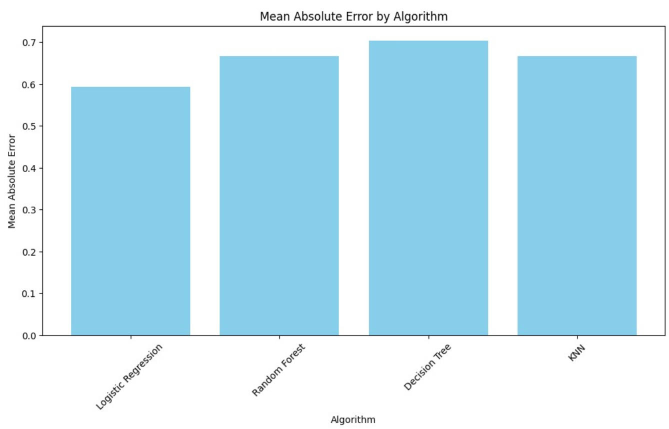

Fig. 9. MAE for Various Algorithms

The above findings prove that a suitable machine learning algorithm greatly matters for predictability. Logistic Regression thus stands out as the modality that can be added to the arsenal of tools for improving asthma care quality while boosting patient treatment outcomes.

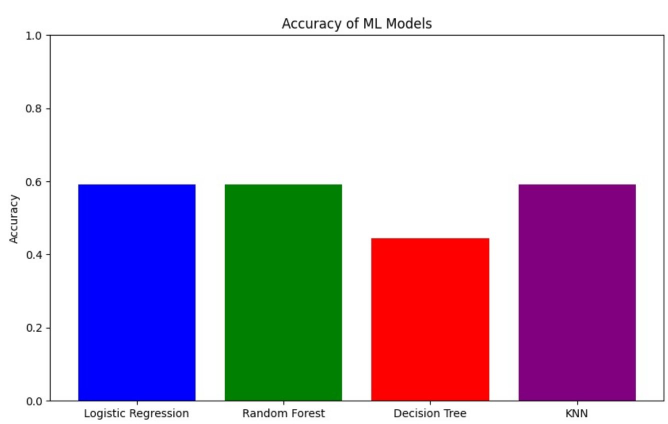

Fig. 10. Accuracy for the Algorithms

After applying machine learning algorithms, which are Logistic Regression, Decision Tree Classifier, Random Forest Classifier, and K Nearest Neighbor to sensor-derived data, the accuracy scores are as follows: Logistic Regression showed 0.592, Decision Tree Classifier resulted in 0.444, Random Forest Classifier has 0.592, and K Nearest Neighbor displayed as 0.592. From this result, the Decision Tree Classifier has the lowest accuracy, and the others have almost identical accuracy values. This implies that Logistic Regression, Random Forest Classifier, and K Nearest Neighbor achieve the same level of accuracy in predicting outcomes based on the sensor data, with Logistic Regression and Random Forest Classifier being more accurate than the Decision Tree Classifier. Figure 10 shows the accuracy of various algorithms.

VII. Conclusion

This research work focuses on an innovative asthmatic prediction method based on machine learning algorithms and the Internet of Things (IoT) devices. The proposed system collects critical data with sensors, which are subject to analysis. A detailed analysis shows that logistic regression performs superior to other algorithms. Integrating an edge device, sensors, and an IoT (Internet of Things) platform helps improve operational efficiency. In addition, the implementation utilizes a smartphone m-health application that extensively uses multiple IoT resources. Through the application of these innovative tools, it provides personalized asthma risk prediction specific to patients. This novel framework points to a new healthcare paradigm characterized by proactive asthma management based on diagnostic analytics and IoT integration. This method, through improving results and reducing healthcare costs, looks promising for revolutionizing asthma management in the future.

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Conflict of Interest

The authors declare that there is no conflict of interest.

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