AMERICAN INTERNATIONAL UNIVERSITY-BANGLADESH (AIUB)

Report on

Asthma Detection Using IOT System

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Abstract

The paper explores the transformative impact of the Internet of Things (IoT) on interconnected devices through networking technologies. It introduces an innovative IoT application for remote sensing, specifically focusing on oxygen saturation, Heartbeat rate body temperature and seizure. The goal is to utilize wireless sensors for real-time data transmission, enabling web-based monitoring of a patient's health status. The collected data is integrated into a centralized database, forming the basis for proactive health management by alerting individuals to unforeseen issues and allowing for timely interventions. Experimental results highlight the proposed system's user-friendliness, reliability, and cost-effectiveness. The broader implications of IoT include advanced connectivity for embedded devices, surpassing traditional machine-to-machine interactions and fostering automation across various fields. In the context of busy modern lifestyles, technology, particularly smart and medical sensors, emerges as a valuable asset, analyzing continuous patient activity and predicting health issues before symptoms manifest.

***Keywords*—** Remote Patient Monitoring (RPM), IoT, Wireless Sensor, Cloud, Machine Learning

1 Introduction

The Internet of Things (IoT) is a growing trend involving the connectivity of embedded devices through networking technologies, with the potential to impact networking, business, and communication. In the healthcare sector, technological advancements, such as smart and medical sensors, play a crucial role in continuously monitoring individual patient activity and predicting health issues[4]. The shift from traditional to passive sensors allows for remote monitoring of vital signs, facilitating data sharing with healthcare professionals.The focus in Human Health monitoring has evolved from basic wearable sensor readings to advanced data processing, addressing common illnesses and preventable attacks[5]. Challenges in healthcare, such as changes in diagnostic frameworks and shortages in health and social care, drive the need for innovative solutions. The fundamental signs incorporate,

- Heart Beat
- Body Temperature

Elderly individuals, who often require regular health checkups, benefit from the development of a low-power, reliable, and non-intrusive vital signs monitor. Remote Patient Monitoring (RPM) technology enhances accessibility to healthcare for those not in proximity to regular medical settings, thereby reducing healthcare costs[4].

In developing countries, where healthcare access is limited (8% of the population with access to only 20% of medical resources), coupled with increasing cardiovascular diseases, a proposed solution involves a remote monitoring system for human body parameters, specifically focusing on pulse and temperature[6]. The collected data continuously updates a database, enabling the early detection of subtle health issues for potential diagnosis.

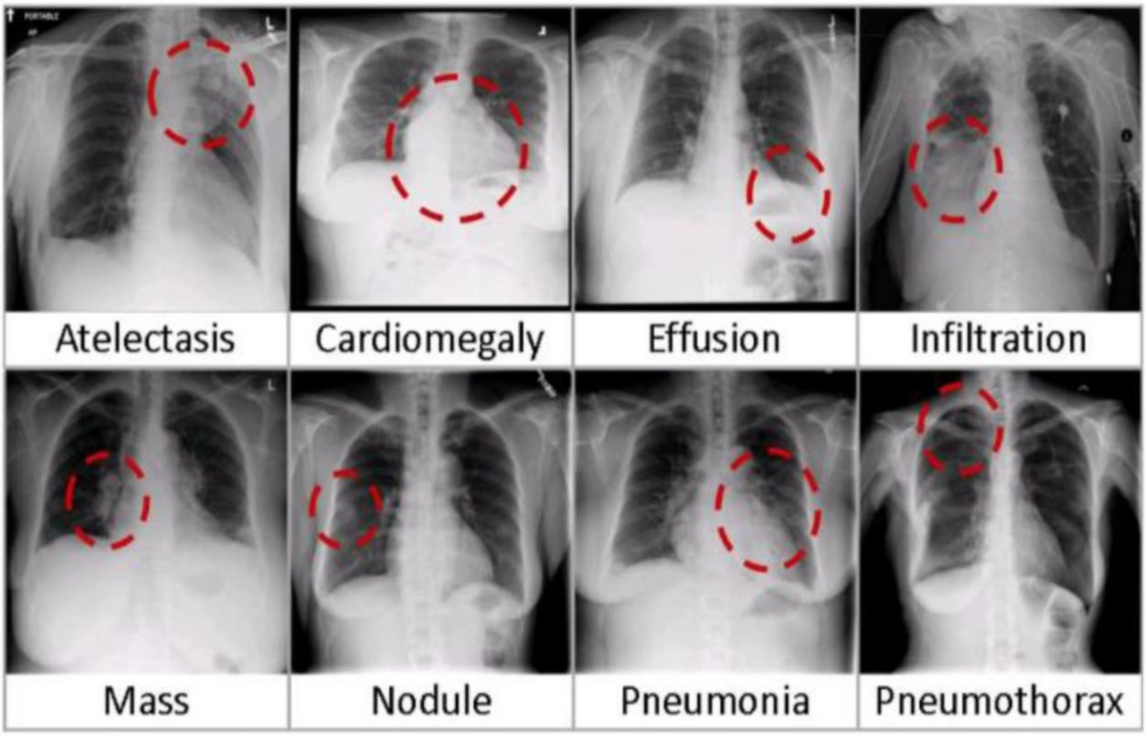


Figure 1: Images showcasing instances of lung diseases.[1]

Atelectasis is a lung condition that results in the collapse of lung bronchioles, manifesting symptoms such as difficulty breathing, increased heart rate, and chest pain. Treatment typically involves deep breathing exercises and physiotherapy. Cardiomegaly, a heart condition leading to an enlarged heart, can be caused by factors like high blood pressure, coronary artery disease, and cardiomyopathy. Effective diagnosis and treatment strategies are essential for managing this condition. Effusion, characterized by fluid accumulation, may cause pain, swelling, and difficulty breathing, with diagnosis involving imaging and fluid analysis. Infiltration during medical procedures may result in swelling and discomfort, but preventive measures like strategic site selection and regular monitoring can mitigate risks. Mass in medicine refers to abnormal tissue accumulation, categorized as benign or malignant, and diagnosis involves imaging, biopsy, blood tests, with treatment strategies varying. Nodules, compact solid masses in tissues, are assessed through ultrasound, biopsies, and laboratory tests. Pneumonia, a lung infection causing inflammation, is diagnosed with antibiotics, treated with supportive care, and prevented through vaccinations and hygiene practices. Severe cases may lead to respiratory failure. Pneumothorax, causing lung collapse due to air infiltration, presents symptoms such as chest pain, breathlessness, and cyanosis. Treatment options include observation, chest tube insertion, needle aspiration, or surgery.

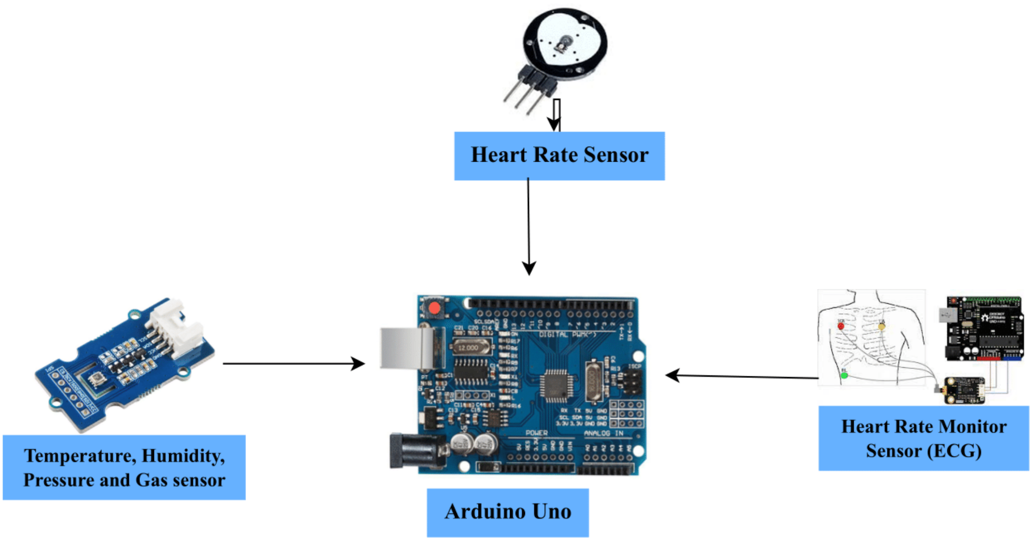


Figure 2: Our Proposed Idea

IoT technologies can enhance these diseases management and prevention, requiring collaboration with healthcare professionals to ensure privacy, security, and a holistic approach to patient care.

2 Methodology

2.1 System Architecture Design

To create an IoT-based asthma detection system, key methods include integrating sensors (oxygen saturation, pulse rate body temperature and seizure), real-time data collection, preprocessing for noise reduction, feature extraction for relevant indicators, implementing machine learning algorithms, setting personalized thresholds, continuous real-time monitoring, secure communication protocols, cloud integration for data storage and analysis, user-friendly interfaces, alert systems for potential asthma attacks, user feedback for system improvement, robust privacy and security measures, and integration with healthcare systems for professional access. Collaboration with healthcare experts and compliance with regulations are crucial for system effectiveness and safety.

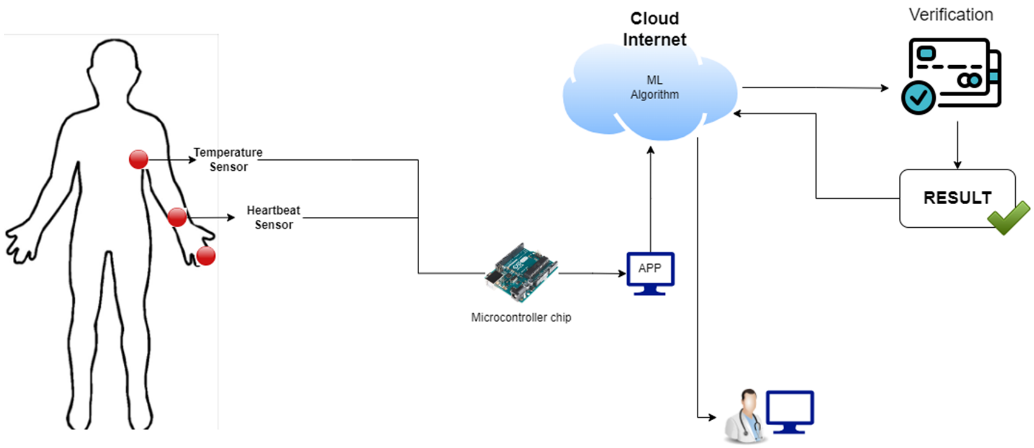


Figure 3: Hypothetical Diagram

In this procedure of Fig. 3, we will collect a comprehensive range of patient data, including vital health metrics like oxygen saturation, body temperature, heart rate, and instances of seizures. This dataset will then be transmitted to a connected mobile application, which acts as a conduit for relaying the information to a cloud-based web application. Operating within the cloud infrastructure, this web application utilizes a sophisticated machine learning algorithm to systematically process the incoming data. The algorithm plays a crucial role in scrutinizing the dataset, determining whether the observed parameters suggest signs of asthma or not. Following this analysis, the findings are relayed back to the mobile app, offering a conclusive evaluation of whether the patient is displaying indications of asthma. This integrated system ensures a real-time, data-driven approach to asthma diagnosis, utilizing cloud-based computation and machine learning algorithms for heightened precision and efficiency.

Heartbeat Sensor: In the domain of Asthma Detection through an IoT System, a heartbeat sensor, also known as a heart rate monitor, plays a pivotal role in monitoring essential signs. Employing light-based technology like photoplethysmography (PPG), this sensor is strategically positioned on easily detectable areas such as the fingertip, earlobe, or chest. Emitting light into the skin, the sensor captures the light absorbed or reflected by blood vessels. The variations in light, associated with changes in blood flow during heart contractions, are then transformed into electrical signals by photodetectors. After undergoing signal processing to extract the pulsatile component and eliminate any noise, the calculated heart rate is presented on a screen, transmitted to connected IoT devices, or recorded for thorough .

Figure 4: Heartbeat Sensor[2]

Temperature Sensor: In the realm of Asthma Detection utilizing an IoT System, the functionality of body temperature sensors becomes pivotal as they identify changes in the body's thermal characteristics. Unlike contact-based thermometers, which gauge heat transfer between the sensor and the body, non-contact infrared thermometers and thermal imaging cameras designed for asthma monitoring detect the infrared radiation emitted by the body's surface. Wearable temperature sensors, an integral component of this system, provide continuous monitoring without necessitating active user participation[7]. The selection of an appropriate temperature sensor is contingent upon several factors, including the intended application, accuracy requirements, and user preferences, thereby enhancing the IoT system's ability to comprehensively monitor and manage asthma-related parameters.

Figure 5: Body Temperature Sensor[3]

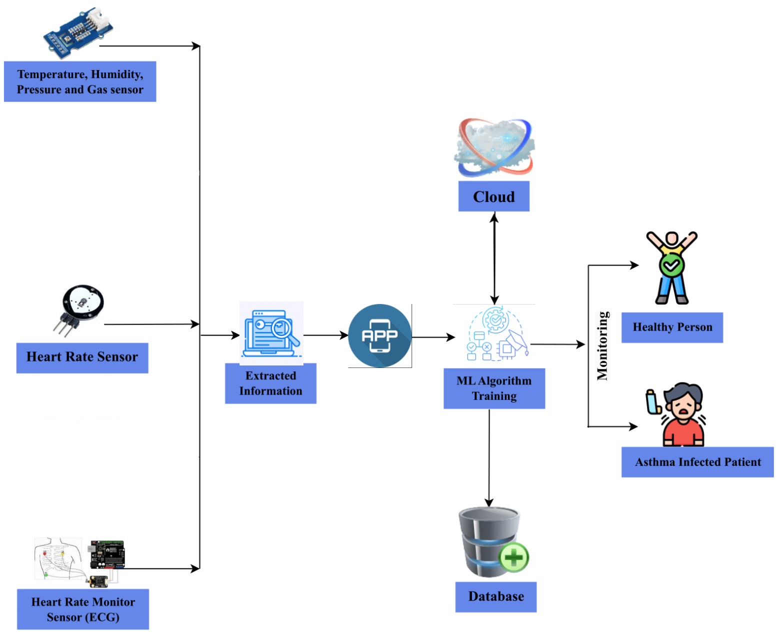


Figure 6: Architecture Diagram of Asthma Detection

2.2 Flow Diagram

The flow diagram for the IoT-based asthma detection system depicts a sequential process beginning with sensor data acquisition, followed by the microcontroller's real-time analysis. The flow then branches into wireless transmission for remote monitoring and alerts, as well as user interface display for accessibility. Simultaneously, data is logged and securely stored, with a connection to cloud services for centralized management. The diagram highlights the continuous loop of information, showcasing the seamless integration of components for effective asthma detection, user feedback, and adherence to regulatory standards. The flow diagram provides a clear visualization of the interconnected stages in the system's operation, ensuring a comprehensive and streamlined approach to asthma management.

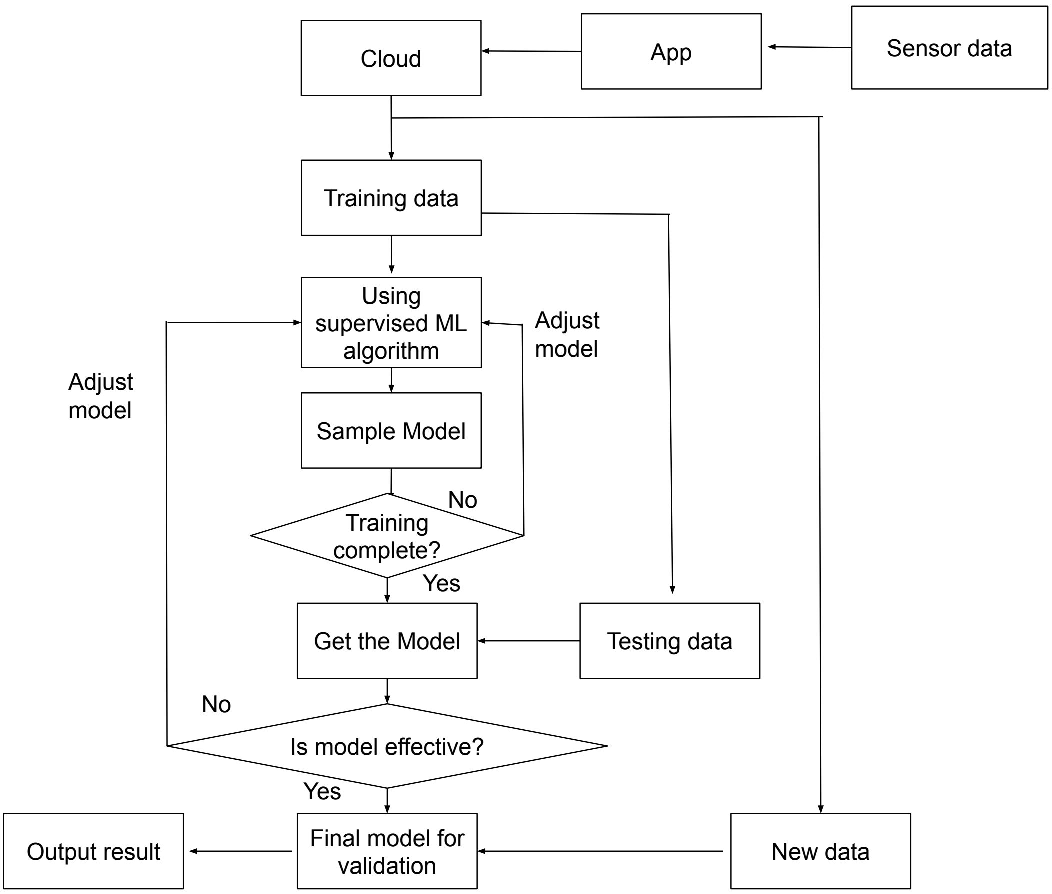


Figure 7: Flow Diagram of the System

2.3 Tree Diagram

The tree diagram for the IoT-based asthma detection system illustrates a hierarchical structure, starting with the central node representing the main system. Branches extend to key components such as sensors, microcontroller, wireless connectivity, power management, and security. Further branches detail specific functionalities like real-time data analysis, alert systems, user interface, and data storage. The structure emphasizes the interconnectedness of these components, showcasing the seamless flow of information from sensors to user interfaces and cloud services. The tree diagram visually encapsulates the comprehensive design, enabling efficient monitoring and management of asthma while adhering to regulatory standards.

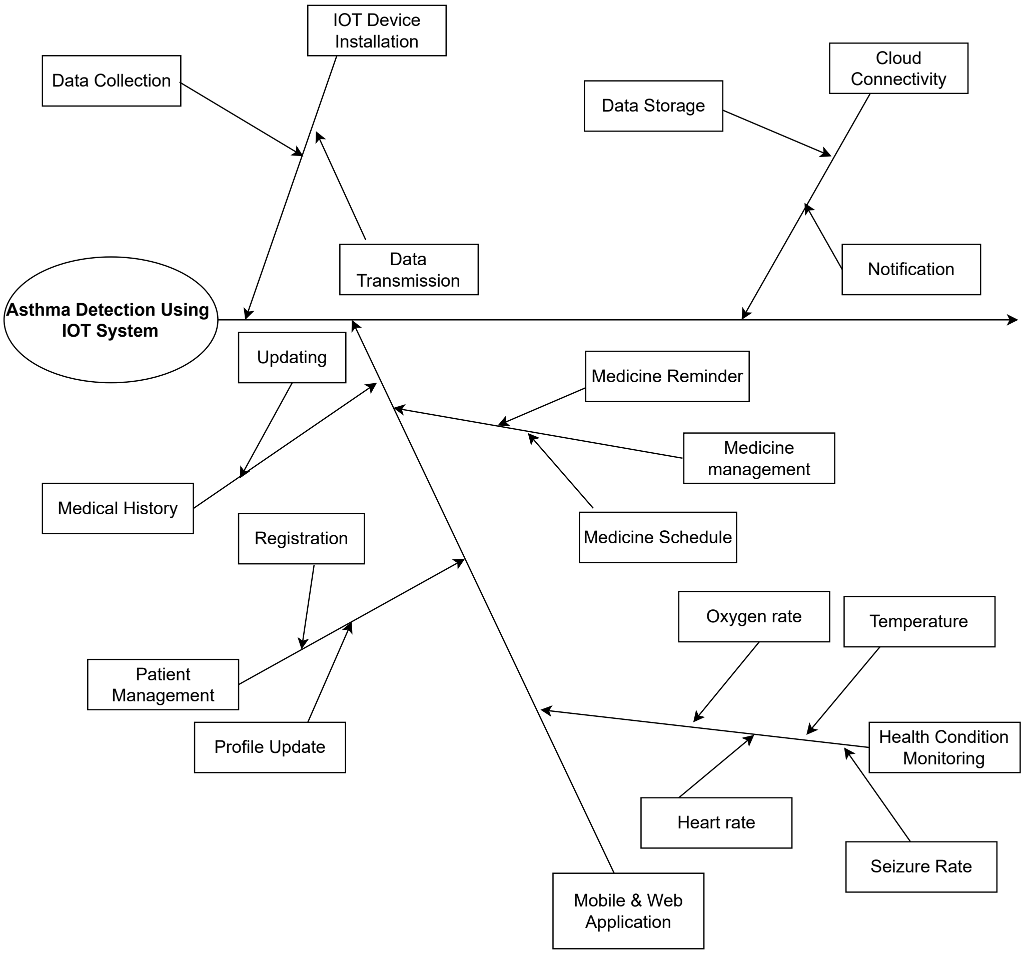


Figure 8: Tree Diagram

2.4 Use Case Diagram

The use case diagram for the IoT-based asthma detection system outlines key interactions between actors and the system. Primary actors include the User, who interacts with the device through the User Interface, and the Healthcare Professional, who accesses historical data through the Cloud Service. Use cases encompass functionalities such as Sensor Data Acquisition, Real-time Analysis, Wireless Transmission, Alert Generation, and Data Storage. The diagram illustrates the seamless flow of information from the User's monitoring to the Cloud Service, emphasizing the system's user-centric design and its utility for healthcare professionals in leveraging historical data for analysis and intervention. The use case diagram provides a concise overview of the system's functionality from the perspective of various stakeholders.

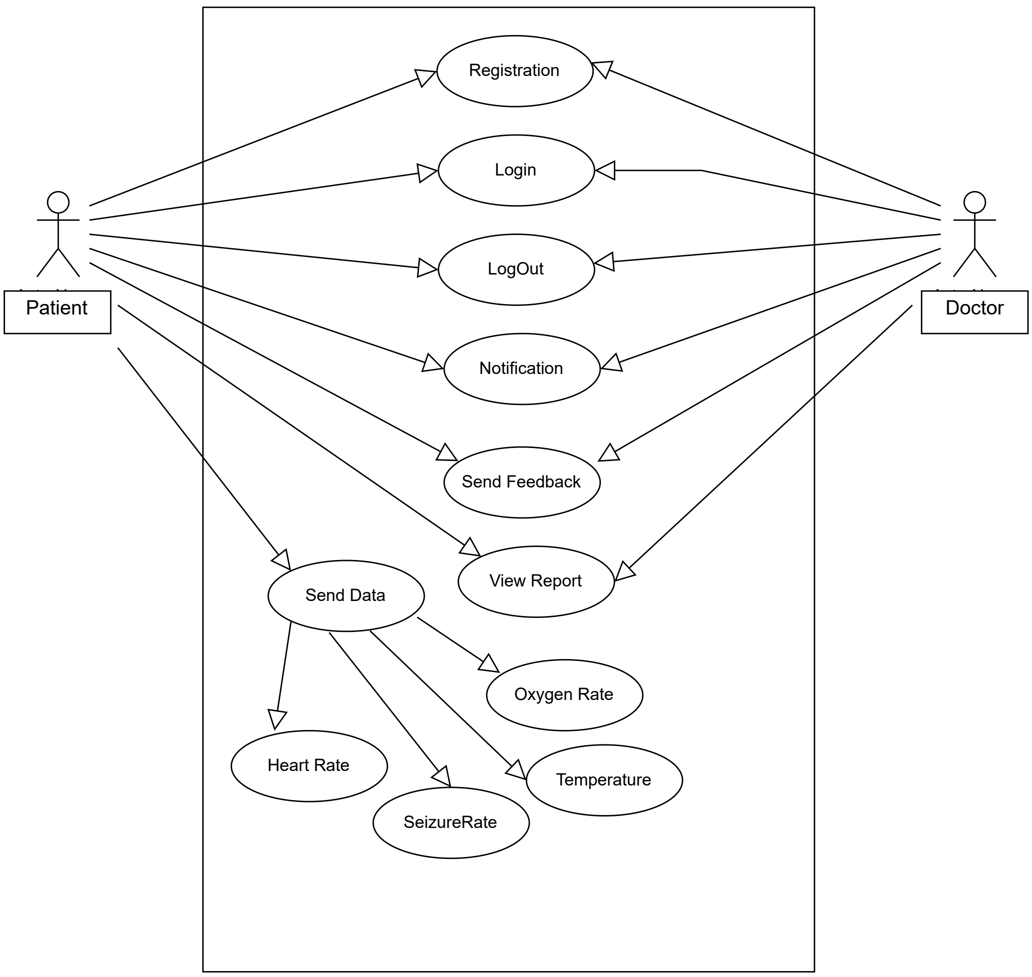


Figure 9: Use Case Diagram

2.5 Prisma Diagram

In Fig. 10, we can see a flow chart that guides how studies are chosen for a systematic review and meta-analysis. It follows the ***Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)*** guidelines. It starts by finding new studies from databases and registers. In this case, 260 studies were found from databases, and none from registers. Then, 35 duplicate records marked as not suitable by automated tools were removed, leaving 225 records. During screening, 195 records were excluded for various reasons like not meeting criteria, not being in English, or not being relevant. This left 30 records for eligibility assessment. After assessment, 10 more records were excluded for reasons like not being a primary study or lacking necessary data. In the end, 20 new studies were included in the review. The flow chart also shows that all the reports for these studies were available to the reviewers. Overall, the flow chart gives a simple and clear overview of how studies are chosen for a systematic review and meta-analysis [8].

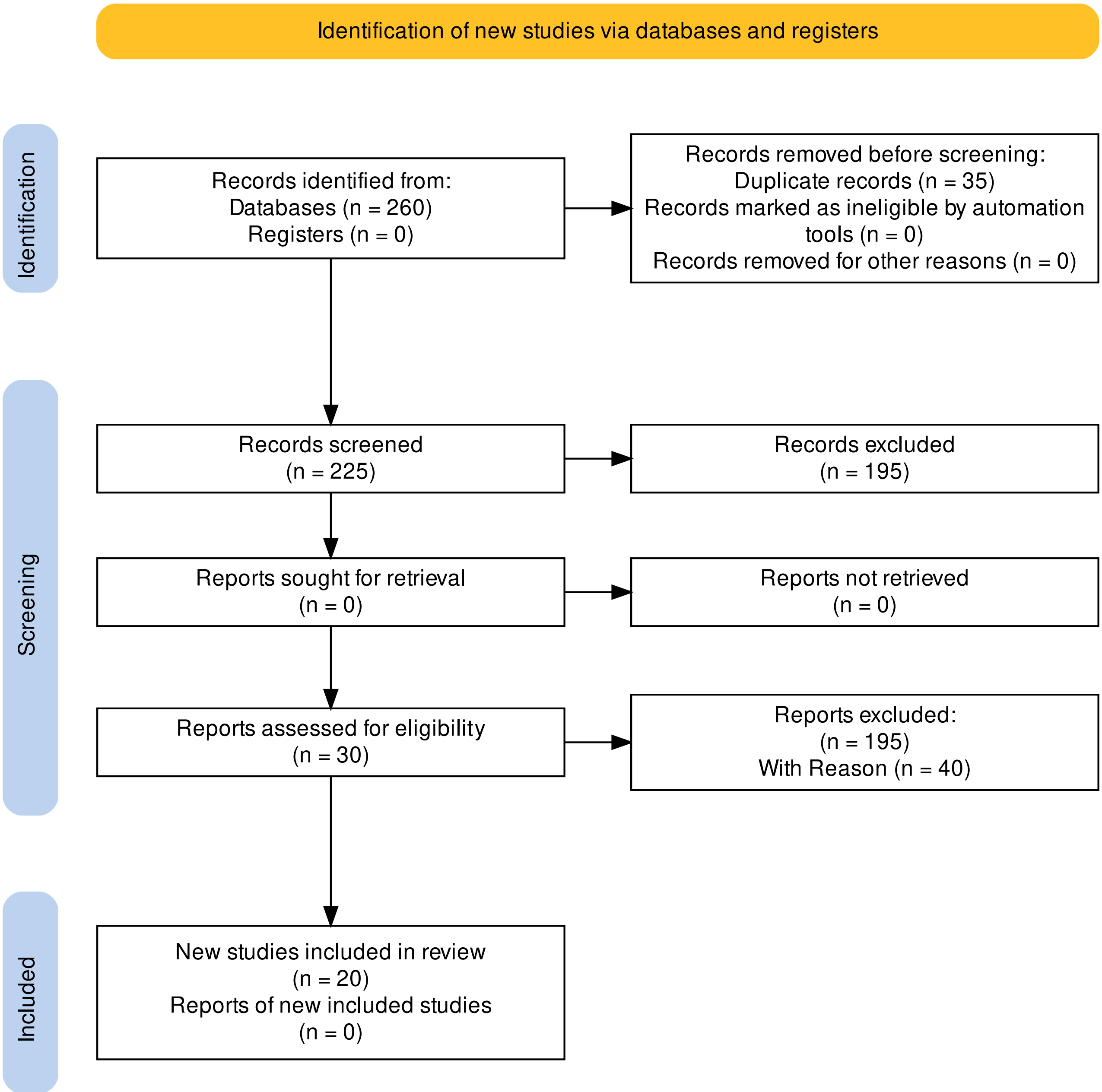


Figure 10: Prisma Diagram

3 Analysis and Discussion

Table 1: Values from the MMLIB+ dataset

Aspect	Heart Rate Sensor	Oxygen Sensor
Objective	Monitors heart rate	Measures oxygen saturation (SpO2)
Data Collection	Continuous heart rate data	SpO2 levels measured continuously
Asthma Detection	Indirect indicator, may signal asthma attack	Direct indicator of respiratory distress during asthma attack
User Comfort	Generally comfortable and non-invasive	Non-invasive and well-tolerated
Data Accuracy	Accurate heart rate data	Highly accurate SpO2 measurement
Real-time Monitoring	Provides real-time data, interpretation may require context	Provides real-time data with alarm triggers for severe drops
Cost & Accessibility	Affordable & widely accessible	Slightly more expensive but widely available
Integration with IoT	Can be integrated into IoT systems	Can be integrated into IoT systems
Data Interpretation	Requires context for asthma detection	Directly reflects respiratory distress, but can be combined with heart rate data
Conclusion	Useful but not asthma-specific	Highly specific for asthma detection, often used in conjunction with heart rate sensor

Overview: Heart rate sensors and oxygen sensors play pivotal roles in an asthma detection system based on the Internet of Things (IoT). These non-invasive tools excel in different aspects, providing crucial insights for comprehensive health monitoring. A heart rate sensor continuously tracks the user's heartbeat in real-time, supplying data on exercise intensity, stress levels, and overall fitness. While it may offer early indications of potential asthma flare-ups, it doesn't directly signal respiratory distress. On the other hand, the oxygen sensor focuses on measuring blood oxygen saturation, a key metric in detecting and managing asthma attacks. It delivers real-time data with alarms for dangerously low readings. Although oxygen sensors may incur slightly higher costs, both sensors are easily integratable into IoT-enabled devices for continuous monitoring. In this asthma detection system, the heart rate sensor functions as a fitness coach, providing a broader perspective on overall well-being, while the oxygen sensor acts as a respiratory guard, directly monitoring for breathing difficulties. The synergy of these sensors within an IoT framework offers a comprehensive and proactive approach to asthma management, contributing to a healthier and more informed lifestyle.

Table 2: Studies of datasets by evaluating Model Accuracy by Accuracy Measurement.

Ref.	Datasets	Accuracy	Assessing Model Precision
[4]	Derivation SIVE II	N/A	Assessing the average performance by classification method class
[5]	Training Validation	25-27%: Cluster 1 57-84%: Cluster 2	Comparing the model's predictions to the actual outcomes
[6]	Used the implemented circuit's sensor's measured values	0.952: Dataset 1 0.817: Dataset 2 0.803: Dataset 3	Used the number of values for true positive (TP), true negative (TN), false negative (FN), and false positive (FP) to measure the accuracy by Accuracy equation
[9]	The initial phase of the study involved testing the system with simulated patients.	N/A	• Crucial for precision. • Requires continuous improvement. • Ensures accuracy at every stage.
[10]	• Combines indoor air quality sensor data. • Combines weather report temperature and humidity.	• 70 • RMSE: 2.42, MAE: 2.12. • Proposed method improved 61.1, 54.3	• Key metric. • Ongoing assessment and refinement crucial. • Optimizes performance in real-world scenarios.
[11]	Data of 5 patient	74.38%	N/A
[12]	• Collected 355 asthma patients. • Collected 1,480 without known respiratory conditions. • Affiliated with Nanjing Medical University.	94.15% 92.20%	N/A
[13]	Kindai University Hospital OPD patients data	SVM 82% DNN 94%	• Logistic regression analysis. • Data analysis. • Comparative analysis.
[14]	Tehran's Imam Khomeini and MasseehDaneshvari Hospitals Dataset	KNN – 1 SVM – 0.9870 RF - 0.9652	Organizing input data, Pre – processing, Data sampling, Adjusting the algorithm, Executing the algorithm, Evaluating the output
[15, 16]	PubMed	Cough Monitoring – 93.3%, Inhaler Technique Monitoring – 91%, Sleep Monitoring – 87.4%, Lung Function Monitoring – 100% [15] Does not mention accuracy[16]	Combining search terms with OR within and AND across columns.[15] Aligns system measurements with traditional methods. Uses sphygmomanometer for accuracy.[16]

[17]	N/A	N/A	• Encapsulates precision and fidelity in system measurements. • Used in blood pressure monitoring and stroke rehabilitation.
[18]	Asthma Hospitalizations and Deaths in New York City from 1982-1986	• 0.5% mortality in US patients. • 99.9% confidence interval: 0.4–0.6.	• Statistical analyses. • Comparison of observed vs predicted outcomes. • Use of specific metrics.
[19]	Does not provide specific information about the datasets	Does not specifically discuss the accuracy of any datasets	Does not mentioned specifically
[20]	132 patients data with each patient record describes 22 different values.	82 97	Compared Asthma with COPD
[21]	The development and validation cohorts consisted of 165 and 101 asthma patients respectively	88 81	Compared XGBoost and Logistic regression

Overview: Table 2 provides a summary of the papers we reviewed and the datasets we collected, such as PubMed, Derivation, SIVE II, Training Validation, among others. Each dataset is associated with its corresponding accuracy. The study also explores the evaluation of the model's accuracy, specifically in the context of an IoT-based asthma patient monitoring system. This evaluation includes assessing true positives, true negatives, false negatives, and false positives. The research emphasizes the significance of continuous monitoring and improvements to ensure accuracy and reliability in producing measurements or predictions, particularly in healthcare areas like blood pressure monitoring and stroke rehabilitation.

Table 3: Studies with different Algorithm and their importance that advancing IOT technology.

Ref.	Algorithms	Description	Analysis	Benefit of use
[4]	Ensemble Algorithms, Supervised Learning Algorithm	Esemble algorithms aim to boost predictive accuracy by merging predictions from diverse models.	• Synergizes predictive capabilities. • Leverages labeled training data. • Improves accuracy in primary care.	Ensemble Algorithms enhance accuracy by combining diverse models in predicting asthma attacks. Supervised Learning Enhances Machine Learning Prediction Model- • Holly Tibble, Athanasios Tsanas' team. • Labeled training data.
[5]	Deep Learning Algorithm, Machine Learning Algorithm, Adam Algorithm	A machine learning algorithm is how an AI system performs tasks, predicting output from input data.	• Contributes to efficient pattern recognition. • Enhances model effectiveness. • Facilitates optimization in training process.	• Recognizes indoor PM concentration patterns. • Adam Algorithm enhances training efficiency.
[6]	Classifying Algorithm	A classifying algorithm assigns predefined labels to input data based on learned patterns, commonly used for tasks like image classification and sentiment analysis.	• Recognizes patterns in data. • Enhances system functionality. • Provides timely asthma patient alerts.	• Timely alerts. • Improved trigger identification. • Optimized early warnings.
[22]	Machine learning-based clustering algorithms	• Groups similar data points based on features. • Identifies patterns and structures without explicit labels.	Machine learning clustering algorithms are vital for revealing patterns in data.	• Discover patterns • Understand data structures • Inform decisions • Widely applicable across industries

[9]	Data Transmission Algorithm, Machine Learning Algorithms	**Data Transmission Algorithm:** • Ensures efficient, reliable data transfer. • Regulates device/system transfer. **Machine Learning Algorithms:** • Enables pattern learning. • Facilitates prediction or decision-making. • Doesn't require explicit programming.	**Data Transmission Algorithm:** Efficiency, Speed, Robustness, Adaptability **Machine Learning Algorithms:** Accuracy and Precision, Generalization, Scalability	**Data Transmission Algorithm:** Efficient Data Transfer, Error Detection and Correction, Bandwidth Optimization, Protocol Standardization, Secure Communication **Machine Learning Algorithms:** Pattern Recognition, Predictive Analytics, Automation of Tasks, Personalization, Classification and Segmentation
[10]	Convolutional Neural Network (CNN), Evaluation Metrics	• Deep learning model for visual data. • Used for image classification and object detection.	• Powerful for visual data analysis. • Comprehensive evaluation metrics for classification/regression tasks.	**Convolutional Neural Networks (CNN):**• Excel in classification and segmentation. • Recognize intricate patterns. • Crucial for facial recognition. **Evaluation Metrics:** • Precision, recall, F1 score, accuracy. • ROC curve area guide model improvement. • Guides deployment decisions.
[11, 20]	Naive Bayes, LIBSVM	Libsvm excels in SVM classification and regression tasks, featuring automated model selection for C-SVM classification.	• Supervised machine learning algorithm. • Primarily used for text classification.	• Requires less training data. • Supports continuous and discrete data types. • Exhibits high scalability. • Operates swiftly.

[12]	Mahalanobis-Taguchi system (MTS), SVM	It serves as a decision-making and pattern recognition system, commonly employed as a multidimensional framework for synthesizing information. The Support Vector Machine (SVM) stands out as a powerful supervised machine learning algorithm adept at tackling both classification and regression tasks.	This system seamlessly combines Mahalanobis distance (MD) and the Taguchi method, forming an advanced synergy of analytical capability and optimization expertise.	SVM's are very good when we have no idea on the data. Works well with even unstructured and semi structured data like text, Images and trees.
[13]	Support Vector Machine (SVM) Learning, Deep Neural Network (DNN)	Deep Neural Networks in Machine Learning- • excel in learning intricate representations. • Enhance performance in image and speech recognition. • Leverage hierarchical features.	SVM analyzes data by finding the optimal hyperplane, maximizing the margin between classes and accommodating non-linear relationships.	Together, SVM and DNN form a powerful toolkit for diverse machine learning challenges.
[14]	K-nearest neighbors, Random forest, and Support vector machine (SVM)	• KNN classifies data based on k-nearest neighbors. • Random Forest uses ensemble learning for robust predictions. • SVM finds optimal hyperplanes for effective classification.	KNN Data Analysis- • Classifies points by k-nearest neighbors. • Determines proximity based on feature similarity.	SVM excels in high-dimensional spaces, offering versatility and effectiveness in complex classification tasks.
[15]	Clinical review and searched PubMed for applications of machine learning to mHealth for asthma	Clinical reviews, conducted by healthcare professionals, comprehensively assess a patient's history, health status, and treatment outcomes.	Healthcare professionals assess intervention efficacy, scrutinize medication responses, and integrate diverse clinical metrics for a comprehensive evaluation.	The meticulous analysis of medical data enhances evidence-based decision-making, fostering continuous improvement in treatment plans.

[18]	Used descriptive and multivariate techniques to examine differences in rates among subgroups and across geographic areas	• Examines variations in hospitalizations and deaths. • Uses statistical and analytical methods. • Explores underlying factors contributing to variations.	N/A	• Descriptive methods simplify data. • Multivariate approaches uncover complex patterns. • Integrating both enhances understanding.
[19]	Does not explicitly mention the specific algorithms	N/A	• Focus on consensus-based criteria. • Avoid traditional algorithms. • Improve control and exacerbation measures.	N/A
[21]	XGBoost and Logistic regression	XgBoost is a gradient boosting algorithm for supervised learning.	XGBoost is a versatile machine learning algorithm that finds applications in a wide range of domains.	• Handles large datasets easily. • Simple estimation procedure. • Easy understanding of linear equations.

Overview: In Table 3, we have reviewed various papers and identified several algorithms, such as Ensemble Algorithm, Supervised Learning Algorithm, Deep Learning Algorithm, Classifying Algorithm, CNN, Naive Bayes, LIBSVM, DNN, and more. We conducted an analysis of these algorithms and discussed the benefits derived from their utilization. Ensemble Algorithms, which encompass Linear Supervised Learning, Deep Learning, Adam Algorithm, and CNNs, contribute to enhanced accuracy in predicting asthma attacks. Deep learning is adept at recognizing patterns in indoor PM concentrations, while the Adam Algorithm optimizes early warning systems. CNNs, inspired by the human visual system, excel in tasks like image classification and segmentation, demonstrating advantages such as reduced training data requirements, high scalability, and real-time prediction capabilities.

Table 4: Comprehensive learning of different algorithms about challenges and significance.

Ref.	Year	Comparison	Challenges	Significance of Applying
[4]	2019	• Assessing model components' contribution. • Predicting asthma attacks in primary care.	• Ensuring model adaptability to new cases. • Balancing accuracy and interpretability. • Handling ethical and privacy issues. • Aligning predictions with clinical significance.	• Enhances robustness. • Mitigates risk of reliance on single algorithm. • Uses labeled data for effective training. • Contributes to precise asthma attack predictions.
[5]	2020	• Considers training speed, interpretability, and overall algorithm performance. • Efficiently develops machine learning-based model.	• Ensuring data quality, • Selecting appropriate algorithms, • Addressing model generalization, • Balancing interpretability, • Handling ethical considerations	• Enhanced adaptability to diverse data. • Efficient training with Adam Algorithm. • Creation of comprehensive model for accurate early warnings in primary care.
[6]	2019	• Identifies strengths and weaknesses. • Enhances asthma care through early warnings.	• Selecting suitable algorithms. • Addressing interoperability issues. • Achieving model generalization. • Handling ethical and privacy concerns. • Gaining user acceptance in healthcare.	Enhanced predictive accuracy, • Efficient utilization of IoT and AI data, • Timely early warnings for asthma patients, • Adaptability to IoT data, • Improved patient care, optimized resource utilization in healthcare settings.
[22]	2019	• Measures exposure to formaldehyde. • Real-life application in pediatric settings.	• Enhancing robustness, scalability, and interpretability. • Broadening applicability to real-world scenarios.	• Reveals meaningful patterns. • Enhances data exploration. • Supports decision-making across diverse industries.
[9]	2023	• Facilitate seamless communication. • Enhance signal quality. • Enable machine learning and prediction. • Ensure sensor data accuracy and reliability.	• Noise, interference. • Computational complexity. • Adaptability in noisy environments.	• Enhances efficiency, accuracy, reliability. • Fundamental for advanced technology development. • Crucial in diverse fields.
[10]	2021	• Essential for selecting, optimizing, understanding model performance. • Crucial in image-related tasks.	• Careful metric selection. • Understanding specific application/task nuances.	• Advance image-related tasks. • Ensure machine learning model reliability and effectiveness.

[23]	2019	Combining Machine Learning and Mechanistic Approaches for Childhood Asthma Understanding	• Long-term effects unknown. • Importance of understanding in clinical practice.	• Enhances understanding. • Provides comprehensive insights.
[11]	2016	• Wireless transmission to central server. • Accessible by healthcare providers. • Useful for remote patient condition monitoring.	• Limited scalability for diverse subjects. • Need for system environment friendliness.	• Formation of adhoc network architecture.
[12]	2020	• Utilizes large dataset of routine blood biomarkers. • Employs robust machine learning for biomarker identification.	Insufficient data, Model bias, Validation in larger and more diverse populations	Simplify Diagnostic Process, Enhance Early Detection, Promote Preventive Measures
[13]	2019	• Logistic analysis, SVM, DNN. • DNN expected for superior performance. • DNN leverages deep learning on comprehensive data.	• Accurately predicting diagnoses based on symptoms and tests. • Enhancing model performance compared to conventional methods.	• Improved model performance. • More precise, effective diagnostic approaches.
[14]	2013	• Demonstrated through comparative analysis. • Achieved notable specificity with five neighbors. • Showcased reliable results in data mining for disease classification.	• Addresses limited physician knowledge. • Addresses disease complexity.	• Achieving precise diagnoses. • Addressing disease complexity. • Improving healthcare classification and differential diagnosis.
[15]	2022	• Provides pragmatic solutions for personalized feedback. • Offers tailored interventions.	• Limited generalizability due to small sample sizes. • Lack of external validation. • Need for representative datasets for wider populations.	• Enhancing patient management. • Predicting attacks. • Clustering patients using diverse data.
[16]	2015	• Enhances inhaler use, adherence, self-management. • Highlights ongoing research.	• History and future evolution. • Potential for personalized self-management.	• Enhances patient experience. • Fosters collaboration between healthcare professionals and engineers. • Emphasizes technological integration in inhaler devices. • Contributes to academic understanding of respiratory medicine.

[17]	2021	• Enhances inhaler use, adherence, self-management. • Highlights ongoing research.	The paper discusses the challenges in healthcare AI applications, including data complexity, automation, ethical dilemmas, regulatory approval, standardization, and clinician education.	• Explores IoT applications. • Provides modeling and simulation insights. • Essential resource for healthcare tech professionals.
[18]	1992	• Descriptive for simplicity. • Multivariates for deeper understanding.	• Emphasize balanced analysis approach.	• Quickly gain insights. • Efficiently summarize data. • Conduct thorough analysis.
[20]	2019	Here naive bayes algorithm performs much better for detecting COPD than Asthma	• User experience and standards issues. • Potential hindrance to expert systems.	• Uses various patient attributes. • Predicts asthma and COPD.
[21]	2022	It compares between XGBoost and Logistic regression in asthma detection.	Study's Low Asthma Incidence- • Difficulty for machine learning models to learn from positive examples.	• Guides future research. • Aims to improve accuracy, interpretability, and clinical utility.

Overview: In Table 4, we have examined various papers and conducted a comparative analysis. Additionally, we have explored the challenges inherent in these papers, particularly those related to predicting asthma using machine learning algorithms. These challenges encompass ensuring adaptability to new cases, striking a balance between accuracy and interpretability, and addressing ethical and privacy concerns. The study also acknowledges hurdles such as noise, computational complexity, and adaptability in noisy environments. Furthermore, it delves into challenges related to user experience and standards, which may impede the integration of expert systems into clinical practice. The research places a spotlight on enhancing asthma prediction accuracy, adaptability, and ethical considerations in healthcare settings. It advocates the utilization of IoT and AI data, along with machine learning-based clustering algorithms for effective data exploration and decision-making. The paper suggests the integration of machine learning and mechanistic approaches to advance the understanding of childhood asthma, streamline diagnostic processes, facilitate early detection, and promote preventive measures.

Table 5: Studies with different methodologies by analysing what problems are solved and the future research.

Ref.	Methodology	Problems that are solved	Future Research
[4]	Naïve Bayes, Support Vector Machines (SVM) Random Forests	• Ensures data quality. • Selects appropriate algorithms. • Generalizes to diverse patient profiles. • Interprets results. • Integrates model seamlessly.	• Integration into workflows. • Continuous refinement. • Focus on patient feedback and engagement enhancements.
[5]	Peak Expiratory Flow Rate (PEFR) data and patient clustering, Indoor PM monitoring data	• Predicting asthma attacks. • Validating PM model. • Quantifying peak expiratory flow rates. • Identifying preventive measures. • Contributing to pediatric asthma research.	• Conducting extensive, longitudinal studies. • Validating predictive model. • Exploring PM concentrations. • Investigating intervention strategies. • Incorporating behavioral factors.
[6]	• Utilizes amperometric and gas sensors. • Utilizes PIC18F87K22 microcontroller.	• Importance of early identification. • Efficient IoT data use. • AI integration. • Proactive patient management. • Adaptability to dynamic health conditions. • Privacy and ethical considerations.	• Real-Time Patient Awareness • Identifies nearest medical facilities. • Alerts relevant authorities.
[22]	Wearable IoT Sensor Development, Wearable Device Design, Cloud-Based Informatics System, Data Visualization and Analysis	• Monitors ambient aldehyde levels. • Provides personalized asthma management.	• Address experimentation challenges. • Enhance capabilities in environmental monitoring and health-related applications.
[9]	Sensor Technology, Microcontroller and Sensor Integration, Data Transmission, Testing and Validation.	• Enhances IoT-based remote health monitoring. • Provides comprehensive, effective, and universal asthma care solution.	• Cross-platform compatibility • Increased sensors

[10]	INDOOR AIR MONITORING AND WEATHER DATA, CONVOLUTIONAL NEURAL NETWORK BASED PREDICTION	• Utilizes convolutional neural network. • Utilizes PM and weather data. • Implements IoT platform for individual patient risk prediction.	• Validation and long-term monitoring. • EHR integration. • Improved data collection. • Personalized intervention strategies. • Cost-effectiveness studies. • Ethical considerations.
[23]	The integration of machine learning and mechanistic studies methods	Identifying childhood asthma endotypes, Discovering biomarkers and risk factors	Developing more accurate and generalizable ML models,
[11]	• Utilized LM35 temperature sensors. • Monitored patient's respiratory rate.	• Provides continuous, remote respiratory rate monitoring. • Indicates asthma severity.	• Exploring wearable devices or remote monitoring systems. • Providing continuous monitoring and real-time alerts.
[12]	• MTS compared with SVM. • SVM is a support vector machine.	• Non-invasive, cost-effective. • Potentially more accurate.	• Development of mobile applications. • Patient engagement tools. • Investigation of asthma subtypes and severity.
[13]	Logistic regression analysis, Data Analysis	• Compared to logistic analysis and SVM.	SVM Outperforms Deep Learning in Classification Accuracy
[14]	• Organizing input data. • Pre-processing. • Data sampling.	• Uses k-nearest algorithm with Relief-F strategy. • Utilizes Cross Fold data sampling. • Provides differential diagnosis.	• Refining machine learning algorithms for improved asthma diagnosis. • Exploring innovative pre-processing methods. • Collaborating with medical professionals for larger dataset insights.
[15]	• Systematic literature review.	• Shift from monitoring to personalized algorithms. • Leverage machine learning for feedback.	• Integrates machine learning and mHealth. • Blends active/passive monitoring. • Facilitates seamless data collection.
[16]	PubMed	• Leverages modern technology. • Improves efficiency and patient control.	• Focus on physiological, psychological, environmental, lifestyle indicators.

[17]	• Oscillometric • Capacitance-coupled sensing. • Palpatory (PPT) method. • Pulse transit time (PTT) method. • Cryptography.	• Addressing remote monitoring challenges. • Integrating ECG and PPG. • Implementing smart wearables for stroke rehabilitation.	• Improve blood pressure measurement accuracy. • Enhance stroke rehabilitation technology. • Ensure user-friendly design and accessibility.
[18]	Employed descriptive and multivariate techniques	• Identifies disparities within minority and low-income groups.	N/A
[19]	N/A	• Enhances communication. • Ensures research uniformity. • Improves clinical asthma management, especially in severe cases.	• Reduce the burden of severe asthma in children. • Zero tolerance for asthma deaths.
[20]	• Decision Trees • Neural Networks • Logistic Regression • SVMs • K-Nearest Neighbour • Random Forest	• Developed accurate, efficient method. • Focuses on asthma and chronic obstructive pulmonary disease.	• Utilizes non-invasive data sources. • Predicts diseases based on demographic, socioeconomic, and air-pollution data.
[21]	XGBoost and Logistic regression	• Provides perspective on machine learning.	• Larger, diverse datasets. • Electronic health records, home monitoring, wearable device data.

Overview: In Table 5, we have reviewed several papers and identified various methodologies, including Naive Bayes, SVM, Peak Expiratory Flow Rate (PEFR), Wearable IoT Sensor Development, CNN, and PubMed. The discussion encompasses the problems addressed by these methodologies, as well as considerations for future research. The study concentrates on the prediction of asthma attacks in primary care, employing convolutional neural networks and wearable IoT sensors. It leverages indoor particulate matter (PM) concentrations to comprehend asthmatic children and identify preventive measures. This approach presents a non-invasive, cost-effective, and potentially more accurate alternative to traditional monitoring devices for asthma treatment. The predictive model for pediatric asthma triggers is currently undergoing refinement and integration into clinical workflows, with continuous improvements informed by patient feedback and engagement. The paper proposes avenues for future research in the realm of asthma risk prediction tools. These include aspects such as validation, long-term monitoring, integration with Electronic Health Records (EHR), enhancements in data collection, personalized intervention strategies, considerations of cost-effectiveness, and ethical implications.

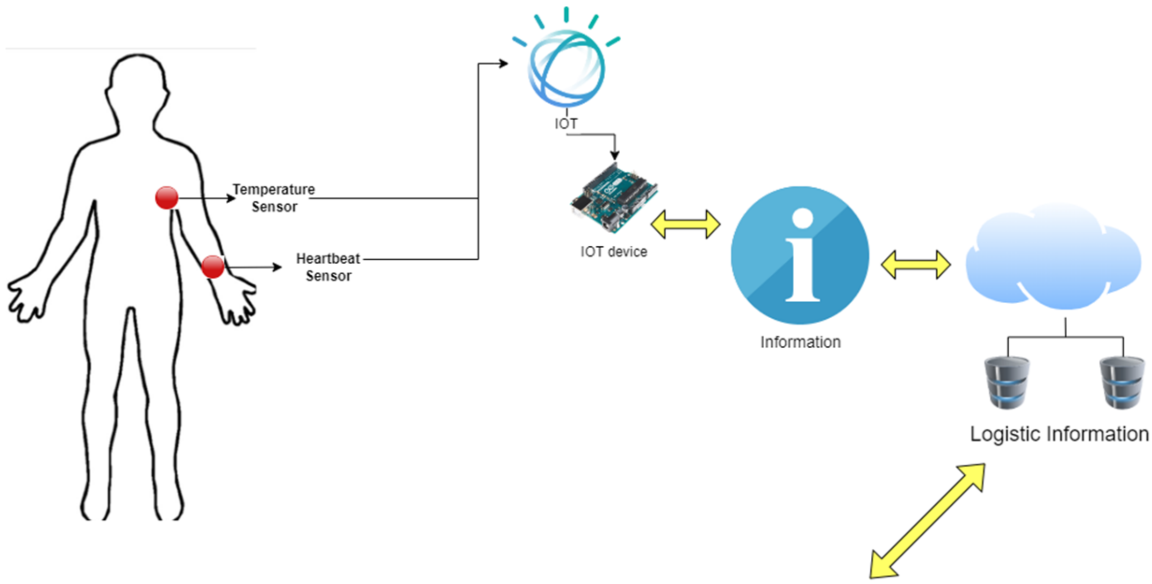
Table 5: Investigations on diverse algorithms.

REF.	Ensemble	Supervised Learning	Deep learning AI	Adam	Classifying	Machine learning	Data Transmissio	CNN	Evaluation Metrics	Naïve Bayes	LIBSVM	MTS	SVM	DNN	kNN	Random Forest	Pubmed	XGBoost	Logistic Regression
[2]	•	•																	
[3]			•	•		•													
[4]					•														
[10]						•													
[11]						•	•												
[12]								•	•										
[14]										•	•								
[23]										•	•								
[15]												•	•						
[16]													•	•					
[17]													•		•				
[18]																	•		
[24]																		•	•

4 Result

4.1 Diagrams

The implementation of the IoT-based asthma detection system yields a comprehensive and user-friendly solution for effective asthma management. Users benefit from real-time monitoring through a seamless interface, receiving timely alerts in the event of potential asthma issues. Healthcare professionals can access historical data stored in the cloud, enabling informed analysis and intervention. The system's integration of sensors, wireless connectivity, and security measures ensures reliable and secure transmission of health data. Overall, the result is an intelligently designed and interconnected system that enhances asthma care by combining real-time monitoring, historical analysis, and user feedback within a regulatory-compliant framework.



Patient	Doctor	Seizure	Temp.	Pulse	O2
Patient1	Doctor1	660/250	96	130/80	102
Patient2	Doctor2	620/230	98	120/80	100
....	....	....	....	....	....

Figure 11: Results of Asthma Attack Prediction

The remote patient monitoring system, derived from the IoT-based asthma detection scenario, provides a sophisticated solution for healthcare. By integrating sensors and wireless connectivity, it enables continuous real-time monitoring of asthma-related parameters. Patients benefit from the convenience of remote data transmission to healthcare professionals, who can access the information through secure cloud services. This system facilitates proactive healthcare interventions, as alerts and historical data analysis contribute to more informed decision-making. The result is an efficient and patient-centric remote monitoring solution that improves the overall quality of asthma care while ensuring data security and compliance with healthcare regulations.

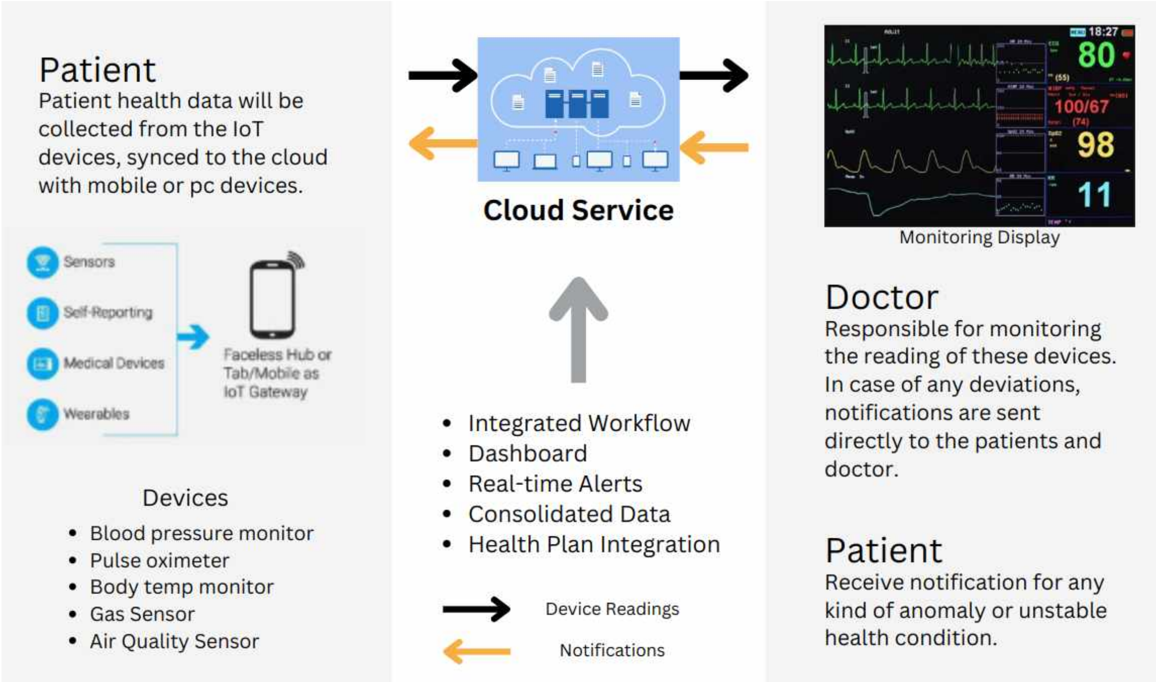


Figure 12: Remote patient monitoring system

4.2 App Development

The application dashboard for the IoT-based asthma detection system provides users with an intuitive interface for monitoring and managing their asthma condition. Displaying real-time data from sensors, the dashboard offers insights into vital parameters such as oxygen saturation, respiratory rate, and temperature. Users receive instant alerts in the event of potential asthma issues, fostering timely intervention. Additionally, the dashboard includes a user-friendly interface for medication reminders and feedback submission, enhancing patient engagement. With clear visualizations and seamless navigation, the dashboard ensures an accessible and comprehensive user experience, empowering individuals to actively participate in their asthma management.

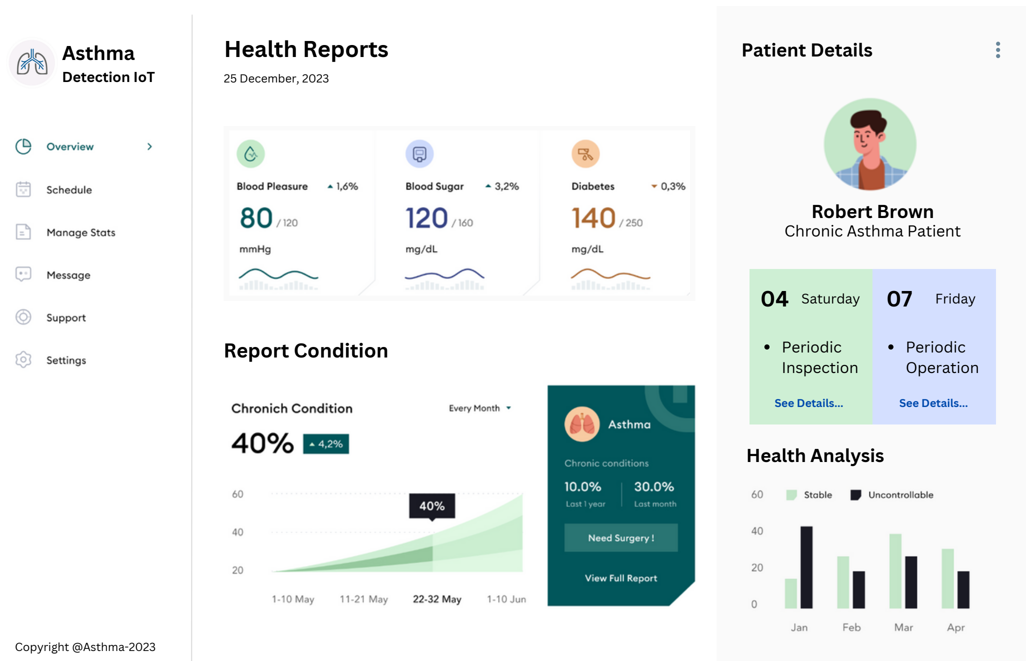


Figure 13: Dashboard of Asthma Detection Application

4.3 Simulation

4.3.1 Temperature Sensor Simulation

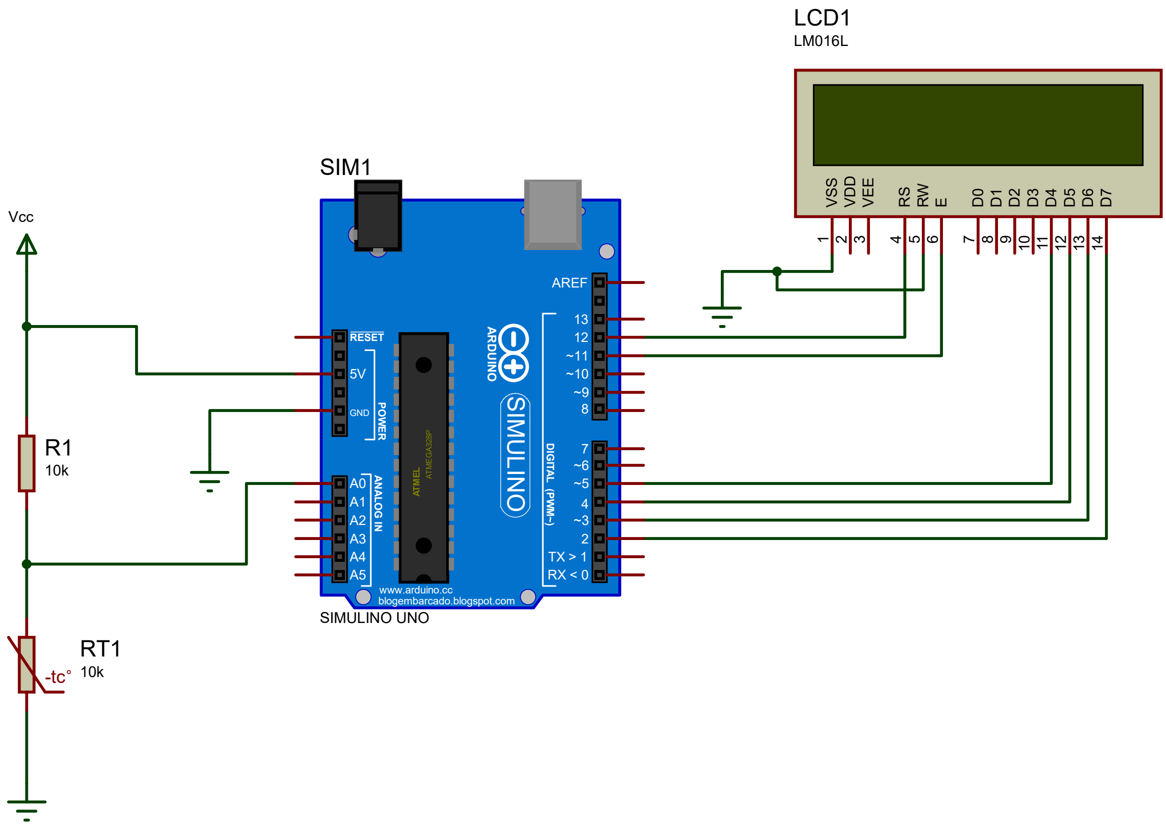


Figure 14: Temperature Monitoring Model

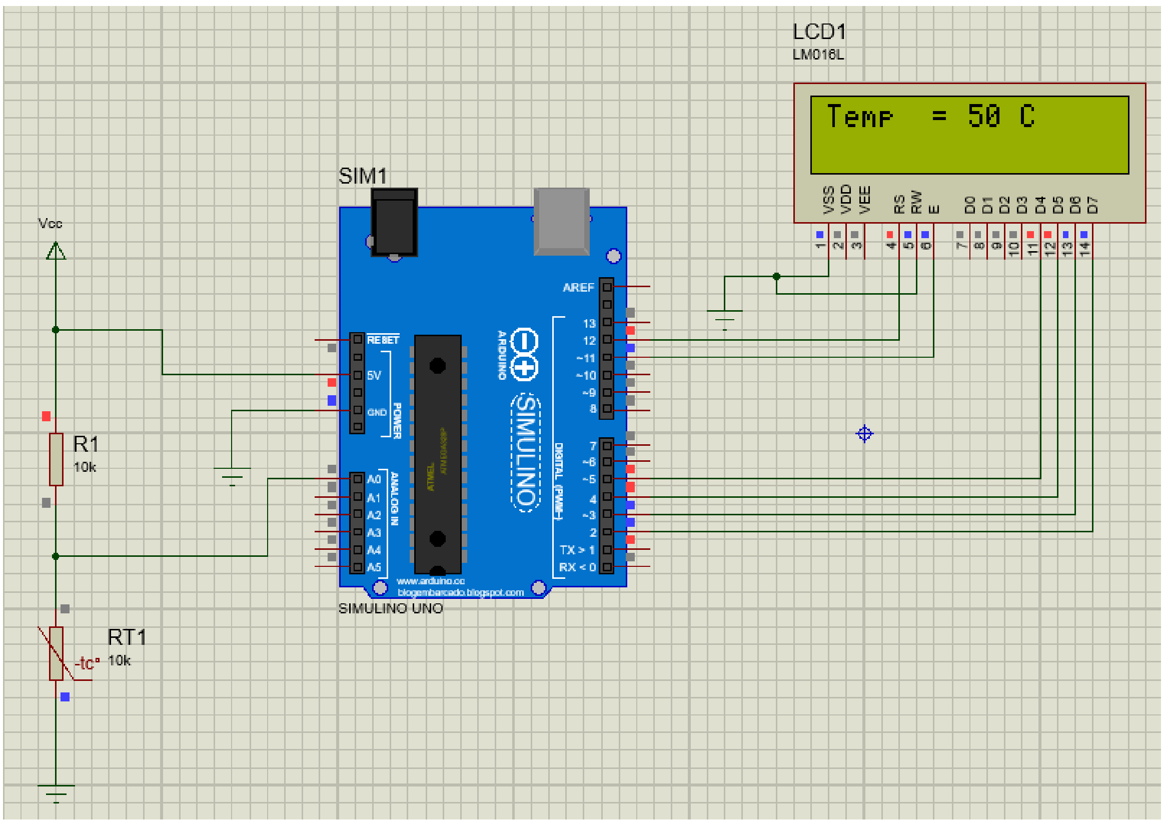


Figure 15: Temperature Monitoring

Arduino code to run the circuit:

```
#include <LiquidCrystal.h>

int THERMISTORPIN = 0,  BCOEFFICIENT = 3380 ;

float THERMISTORNOMINAL = 10000 , TEMPERATURENOMINAL = 25 , SERIESRESISTOR = 10000;

LiquidCrystal lcd(12, 11, 5, 4, 3, 2);

int sample[5];

void setup() {
 Serial.begin(9600);
 lcd.begin(16, 2);
}

void loop() {

  int i;
  float average;

  // take N samples in a row, with a slight delay
  for (i=0; i< 5; i++) {
   sample[i] = analogRead(THERMISTORPIN);
   delay(10);
  }

  // average all the samples out
  average = 0;
  for (i=0; i< 5; i++) {
     average += sample[i];

  }
  average /= 5;
   // convert the value to resistance
  average = 1023 / average - 1;
  average = SERIESRESISTOR / average;

  float steinhart;
  steinhart = average / THERMISTORNOMINAL;     // (R/Ro)
  steinhart = log(steinhart);                  // ln(R/Ro)
  steinhart /= BCOEFFICIENT;                   // 1/B * ln(R/Ro)
  steinhart += 1.0 / (TEMPERATURENOMINAL + 273.15); // + (1/To)
  steinhart = 1.0 / steinhart;                 // Invert
  steinhart -= 273.15;                         // convert to C

  lcd.print("Temp  = ");
  lcd.print((int)steinhart);
  lcd.print(" C");

  delay(500);
  lcd.clear();
}
```

4.3.2 Heart Rate Sensor Simulation

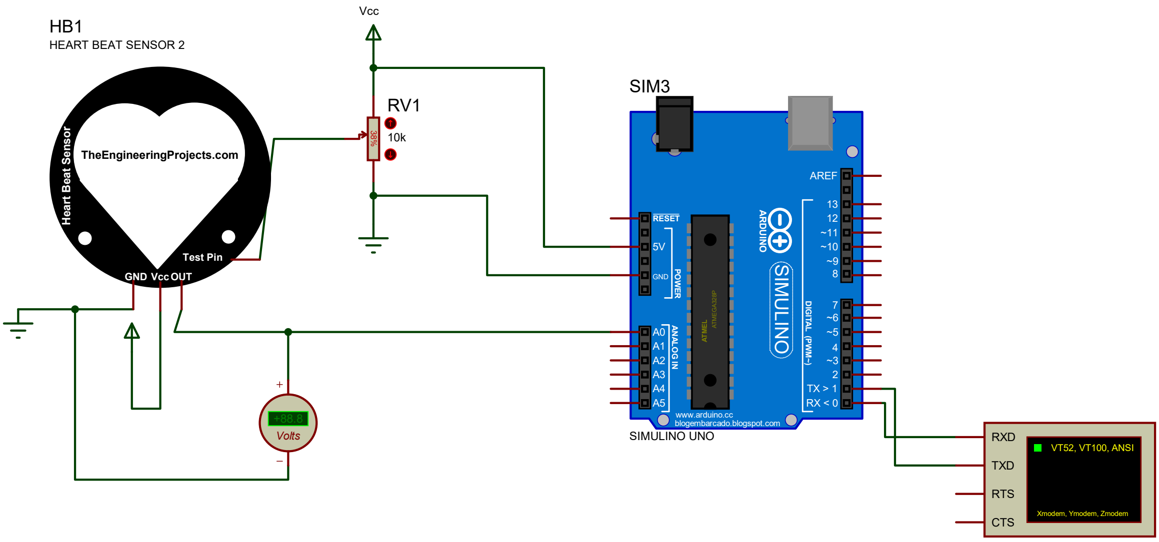


Figure 16: Heart Rate Monitoring Model

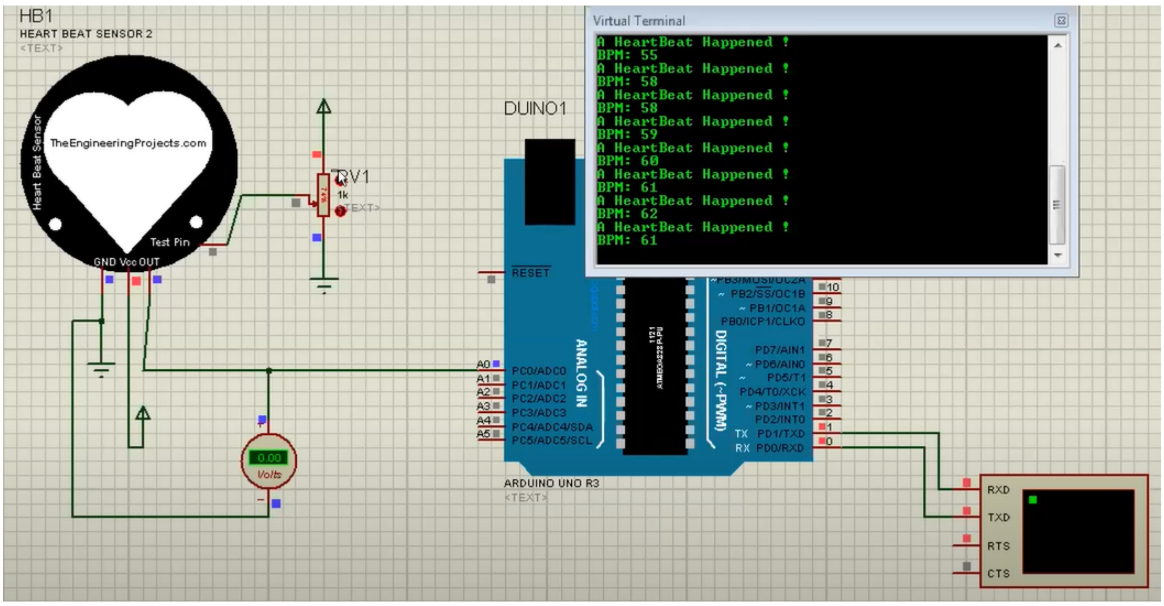


Figure 17: Heart Rate Monitoring

Arduino code to run the circuit:

```
#define USE_ARDUINO_INTERRUPTS true
#include <PulseSensorPlayground.h>

//  Variables
const int PulseWire = 0;
const int LED13 = 13;
int Threshold = 550;

PulseSensorPlayground pulseSensor;


void setup() {

  Serial.begin(9600);

  // Configure the PulseSensor object, by assigning our variables to it.
  pulseSensor.analogInput(PulseWire);
  pulseSensor.blinkOnPulse(LED13);
  pulseSensor.setThreshold(Threshold);

  // Double-check the "pulseSensor" object was created and "began" seeing a signal.
   if (pulseSensor.begin()) {
    Serial.println("We created a pulseSensor Object !");
  }
}

void loop() {

 int myBPM = pulseSensor.getBeatsPerMinute();
if (pulseSensor.sawStartOfBeat()) {
 Serial.println("A HeartBeat Happened ! ");
 Serial.print("BPM: ");
 Serial.println(myBPM);
}

  delay(20);

}
```

5 Conclusions

The integration of IoT technology into asthma monitoring systems offers a promising approach to enhancing patient care and improving disease management. IoT-enabled systems can continuously collect and transmit real-time data on various physiological parameters and environmental factors, providing valuable insights into patient condition and potential triggers. This information can be used to alert caregivers, healthcare providers, and emergency services in case of an impending asthma attack, enabling timely intervention and potentially preventing severe exacerbations. Additionally, IoT-based systems can facilitate personalized treatment plans, medication adherence monitoring, and education about asthma triggers and management strategies. While further research and development are needed to optimize the effectiveness and reliability of these systems, the potential benefits of IoT-based asthma monitoring are significant and could revolutionize the way asthma is managed and controlled.

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