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AI Asthma Guard: Predictive Wearable Technology for Asthma Management in Vulnerable Populations

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Abstract: This paper presents AI Asthma Guard, a novel wearable device designed to predict and alert users of impending asthma attacks using artificial intelligence. The system integrates physiological and environmental sensors to monitor health metrics such as the heart rate, oxygen saturation, and exposure to specific air pollutants, which are crucial in managing asthma in children and individuals with mental disabilities. Utilizing machine learning models, including support vector machines and random forest, AI Asthma Guard classifies the risk levels of asthma attacks and provides timely notifications. This study details the device's design, implementation, and preliminary testing results, underscoring its potential to improve health outcomes by enabling proactive asthma management. The implications of this technology reflect its alignment with the Sustainable Development Goals by enhancing individual health and well-being. The integration of a companion app leveraging large language models like ChatGPT facilitates user interaction, providing personalized advice and educational content about asthma management.

Keywords: wearable technology; artificial intelligence; asthma management; predictive healthcare; environmental sensing; machine learning; sustainable health solutions

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1. Introduction

Asthma remains a pervasive chronic respiratory condition globally, affecting millions and manifesting through symptoms like wheezing, breathlessness, chest tightness, and coughing. A significant challenge within this realm is the absence of early warning systems for asthma attacks, particularly affecting vulnerable groups such as children under 12 and individuals with mental disabilities like Down's syndrome or autism. These groups often struggle to effectively communicate their symptoms, leading to delays in necessary treatment and increased risks of severe episodes [1]. Asthma attacks are not only life-threatening but also a predominant cause of hospitalization among children and individuals with mental disabilities, underscoring the need for innovative approaches to manage this condition. The unpredictability of asthma exacerbation, coupled with challenges in early detection, further complicates the health risks for these sensitive populations. The proposed smartwatch aims to facilitate timely intervention that could reduce emergency visits, enhance disease management, and ultimately improve the quality of life of asthmatics. This aligns with the third UN Sustainable Development Goal, which focuses on ensuring healthy living and promoting well-being at all ages, and SDG 17's emphasis on leveraging partnerships to advance healthcare innovation through technology [2].

The global incidence of asthma is increasing, with significant impacts particularly observed in children from low- and middle-income countries. Recent studies report that nearly 339 million people worldwide suffer from this condition, experiencing substantial impairments in daily activities, school attendance, and overall quality of life [3]. Monitoring systems and predictive technologies are thus pivotal in managing asthma more effectively.

Initiatives like those described in [4] have demonstrated the feasibility of using sensor-based wearable devices connected to IoT systems for the real-time monitoring of environmental triggers such as NO_2 and aldehyde levels, significantly aiding in early detection and management [4].

Artificial intelligence (AI) has emerged as a transformative tool in the healthcare sector, offering significant advancements in the diagnosis, treatment, and management of asthma. AI technologies enable the development of systems that can predict asthma exacerbations, optimize treatment plans, and monitor disease progression in real time. AI-driven diagnostic tools leverage machine learning algorithms to analyze complex datasets, including patient symptoms, environmental conditions, and physiological parameters. These systems can identify patterns and correlations that may not be evident to human clinicians, thus improving the accuracy of asthma diagnoses. For instance, convolutional neural networks (CNNs) have been applied to interpret spirometry data and chest X-rays, aiding in the early detection of respiratory anomalies that could indicate asthma [5]. In treatment settings, AI models assist in personalizing therapy regimens based on individual patient data, thus enhancing the efficacy of asthma management. Predictive analytics can forecast patient responses to various medications, allowing healthcare providers to tailor treatments that minimize side effects and maximize benefits. Furthermore, AI-driven decision support systems provide clinicians with real-time recommendations during patient consultations, ensuring that the most current guidelines and treatment protocols are applied [6]. For ongoing management, AI systems are integrated with wearable devices and home monitoring equipment to track patient health metrics continuously. These systems analyze data trends to predict potential asthma attacks, enabling preemptive medical interventions. Mobile health applications powered by AI enhance patient engagement and compliance by sending reminders for medication, providing health tips, and facilitating virtual consultations with healthcare providers. This level of ongoing, personalized monitoring significantly improves the quality of life of asthma patients and reduces the frequency and severity of asthma episodes [7].

The trends in scholarly publications on asthma and machine learning were determined through a comparative analysis of Scopus-indexed conference and journal publications, as shown in Figure 1. The data were generated by entering the keywords "asthma" and "machine learning" in the Scopus search engine, which provided the number of publications per year. The base layer of the graph represents the total number of publications on the topic of asthma. This visualization highlights the growth and research interest in both fields, with a particular emphasis on the intersection of machine learning technologies and asthma studies.

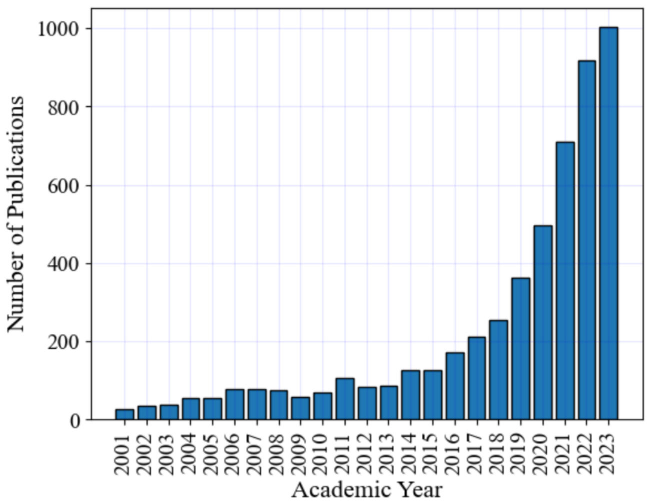

Figure 1. Comparative analysis of scholarly publications on asthma and machine learning. The graph shows the total number of publications on asthma and machine learning in research, illustrating the trends and research interest over time (Source: Science Direct).

In reviewing recent advancements in asthma monitoring, two key studies stand out for their innovative use of machine learning to enhance the predictive capabilities and patient management. The first study, "Home monitoring with connected mobile devices for asthma attack prediction with machine learning" (AAMOS-00) [8], conducted between April 2021 and June 2022, involved 22 UK participants who used an interconnected system of smart devices, including a peak flow meter, inhaler, and smartwatch. These devices collected data on the expiratory flow, inhaler usage, activity, and heart rate, alongside environmental factors like the weather and air quality. Utilizing random forest classifiers, the study achieved high metrics in predicting unscheduled doctor visits, demonstrating the potential of machine learning in forecasting asthma attacks. However, its reliance on active user engagement and its narrow participant criteria during the COVID-19 pandemic may limit its generalizability [8].

In contrast, the study "A Predictive Machine Learning Tool for Asthma Exacerbations", by Lugogo et al. (2022) [9], employed a gradient-boosting trees model to predict asthma exacerbations from data captured by an electronic multi-dose dry powder inhaler with integrated sensors, involving 360 adults over 12 weeks. The model, which incorporated inhalation patterns and patient demographics, showed significant predictive power with a high ROC AUC score, emphasizing the role of integrated sensor technology in managing chronic asthma [9].

Building upon these studies, our project, Asthma Guard, seeks to expand the inclusion criteria and integrate more passive monitoring technologies to improve user adherence and data accuracy. By also conducting our research outside the unusual conditions of a global pandemic, we hope to achieve broader applicability. Asthma Guard incorporates advanced machine learning techniques, including LLMs and regression analysis, to offer a more nuanced and effective approach to asthma management.

In this work, a novel solution is proposed and described: a smartwatch equipped with artificial intelligence capabilities designed to predict and alert users of impending asthma attacks by analyzing both physiological and environmental data. The necessity for the AI-driven Asthma Guard smartwatch arises from the identified gaps in the current asthma management strategies. The device employs advanced technology to monitor vital physiological indicators such as the heart rate and oxygen levels, providing critical data that can preemptively alert both the patient and healthcare providers of potential asthma exacerbations. This capability addresses the immediate needs in asthma crisis prevention and contributes to a broader understanding of asthma management through continuous data analysis.

For children, the Asthma Guard watch serves as a critical layer of security, acting as a vigilant guardian by monitoring environmental and physiological parameters to anticipate and alert users of potential exacerbations. This proactive approach is crucial in minimizing the impact of asthma on children's daily activities and enabling them to lead more active and fulfilling lives.

The solution utilizes a blend of machine learning techniques, including classification with support vector machines and prediction using recurrent neural networks, to enhance the predictive accuracy of the smartwatch. By integrating these technologies, the watch not only predicts asthma attacks but also enhances the overall quality of life through additional features such as GPS navigation, medication tracking, and an integrated large language model like ChatGPT in its companion app. This integration enhances user engagement and provides tailored information management, crucial for effective asthma management.

This article is organized as follows. Section 2 describes the system-level design, detailing the integration of large language models for diagnosis with both machine learning classification and regression models for asthma management. Section 3 presents the findings of the conducted experiments and their implications. Section 4 presents the hardware implementation of the project, showcasing the 3D-printed armband. Section 5 outlines the limitations of the proposed system and potential avenues for further research and exploration. Ethical and privacy considerations are discussed in Section 6, detailing the measures implemented to ensure data security and protect user privacy. Finally, a conclusion is given in Section 7.

2. System-Level Design

The Asthma Guard system features a wearable armband, securely positioned on the patient's arm, as detailed in the block diagram illustrated in Figure 2. The system consists of two ChatGPT-enabled LLMs, which facilitate personalized asthma care. Upon boot-up, the first LLM engages the user or guardian in an interactive sequence, posing questions related to various symptoms and demographic data. This information is then captured and converted into a feature list. The list is processed by a random forest classifier, determining the patient's asthma severity level—mild, moderate, or none.

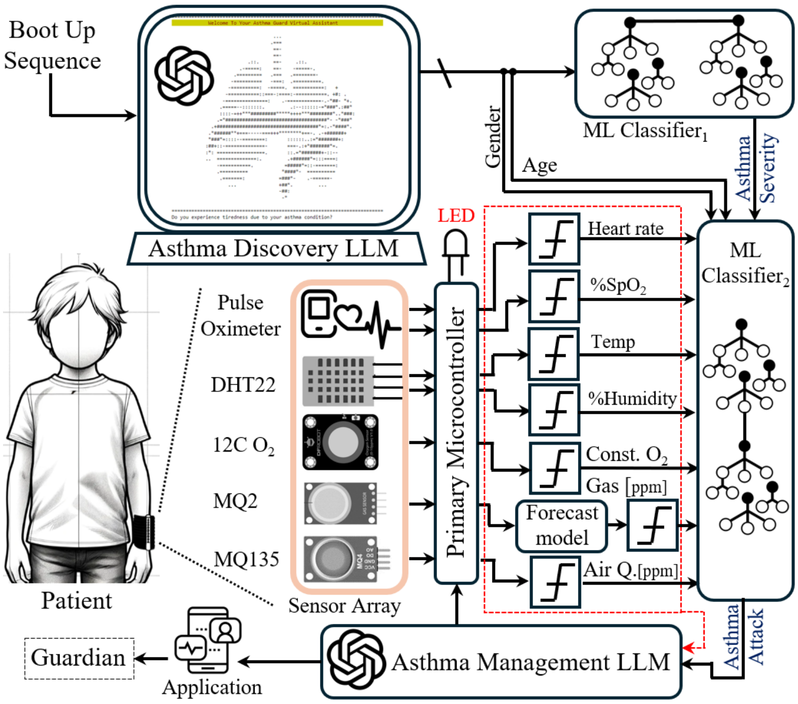

Figure 2. System block diagram of the Asthma Guard management system. The diagram illustrates the flow from user interaction to severity assessment and active management.

This severity metric, alongside the patient's age and gender, is forwarded to a second random forest classifier. This classifier also receives data from sensors embedded in the Asthma Guard armband, which includes a microcontroller, early warning LED, and Wi-Fi communication module. The sensors integrated are a pulse oximeter [10], an I2C O_2 sensor [11], DHT22 for humidity and temperature sensing [12], MQ2 for smoke detection [13], and MQ135 for air quality monitoring [14].

The details of the various sensors integrated into the armband are listed in Table 1. Data from the aforementioned sensors, except for the MQ2 sensor data (which are first processed through a polynomial regression forecasting model to predict potential smoke hazards), are fed into the decision device before reaching the second classifier. The classifier analyzes these combined data to produce an asthma attack prediction. Upon prediction, the system's microcontroller activates a blinking red LED and establishes communication with a second ChatGPT-enabled LLM. This LLM is responsible for managing the asthma protocol, informing and guiding the guardian through the necessary steps following an asthma alert.

Table 1. Summary of sensors in the Asthma Guard system.

Sensor	Function
Pulse Oximeter	Monitors blood oxygen saturation, crucial for patients with respiratory issues [10].
I2C O_2 Sensor	Measures the oxygen concentration in the environment, providing insights into potential asthma triggers [11].
DHT22	Measures the ambient temperature and humidity, which influence asthma conditions [12].
MQ2	Detects smoke and combustible gases, crucial in preventing asthma exacerbations due to the inhalation of smoke [13].
MQ135	Monitors broader air quality parameters including ammonia, nitrogen oxides, and other harmful gases [14].

To ensure continuous model validation and updates, the AI Asthma Guard system includes several mechanisms designed to maintain and enhance its accuracy and reliability. A crucial component of this system is an ongoing feedback loop that continually refines and updates the machine learning models with real-world data. This feedback loop involves collecting data from users during regular usage, which are then analyzed to identify patterns and improve the model performance. Additionally, rigorous safety protocols are implemented to mitigate risks associated with AI "hallucinations" or erroneous advice. Human oversight plays a critical role in this process, with healthcare professionals regularly reviewing and validating the system's outputs. This combination of continuous data integration and strict safety measures ensures that the AI Asthma Guard system remains effective and trustworthy for asthma management.

The LLM-enabled app communicates with the AI Asthma Guard device via Bluetooth and cloud services, enabling real-time data collection and analysis. It securely collects, processes, and stores user data, utilizing anonymization and aggregation techniques to safeguard their privacy. The app empowers users with data management capabilities, allowing them to view, edit, and delete their records. Featuring a user-friendly interface, the app facilitates seamless interaction with the AI Asthma Guard device, delivering personalized advice, educational content, and real-time notifications based on health data. Examples include daily health summaries and asthma management tips. By integrating ChatGPT, the app offers enhanced functionality with personalized, context-aware responses, predicting asthma attacks, providing tailored treatment recommendations, and improving user education. Moreover, it boosts user engagement through medication reminders, health tips, virtual consultations with healthcare providers, and proactive asthma management strategies.

3. Results and Discussion

3.1. Machine Learning Classifier 1

The first classifier is trained on the data found in [15]. The performance of Classifier 1, aimed at assessing the severity of asthma, exhibited significant challenges and limitations. The precision and recall rates for each class were approximately 0.23, meaning that only about 23% of the predictions for each class were correctly classified. The F1-scores ranged from 0.22 to 0.24, reflecting the model's struggle in balancing the precision and recall effectively. Overall, the accuracy was 23%, only slightly better than random guessing, expected to be about 25% due to the balanced nature of the dataset.

The detailed analysis of the model performance highlighted frequent misclassification and suggested issues with the features used, the model selection, or the dataset's quality and representativeness. Despite repeated attempts to enhance the model performance through feature engineering and hyperparameter tuning, the study did not yield substantial improvements.

The results underscore the need for future work to focus on improving the quality and diversity of the data used for the training of the classifier. A more comprehensive dataset, possibly incorporating more detailed clinical information, environmental factors, and individual patients' history, could provide a richer basis for model training and help in capturing the complex nature of the asthma severity more accurately.

Given the current model's limitations, the dataset requires further updates and expansions in data collection to improve the accuracy. However, this does not detract from the merits of the proposed design. The initial classification can be conducted as part of a preliminary screening phase by a physician or guardian to set the level of asthma severity, thus still providing a valuable tool for early asthma management.

The dataset used for the training of Classifier 1 was sourced from an online repository primarily for diagnostic purposes (Ref. [15]). The sub-optimal performance of Classifier 1 highlights the need for a more comprehensive and representative dataset. Future work will focus on collecting our own data, which will include detailed clinical information, environmental factors, and individual patients' history. This approach aims to enhance the model's accuracy and reliability. Additionally, the primary purpose of the diagnostic phase is to determine the severity of the asthma. To address the limitations of the current dataset, we have introduced a feature whereby a medical professional can determine the severity level during a preliminary screening. This adjustment reduces the dependency on the online dataset and ensures that the system remains effective. Future updates will incorporate new data to further improve the model's performance.

3.2. Machine Learning Classifier 2

In contrast, Classifier 2 exhibited remarkable performance, achieved after rigorous hyperparameter tuning using a grid search. From the classification report in Table 2, the overall accuracy stands at an impressive 99%, suggesting that the model accurately predicts both classes—no asthma attack (class 0) and asthma attack (class 1) conditions—with a high degree of reliability. The precision and recall for both classes are also outstanding, with values nearing 99%. This high precision indicates that the model has a low false positive rate, while the high recall suggests a low false negative rate. The F1-scores, which denote the harmonic mean of precision and recall, further affirm the model's balanced and robust ability to classify asthma attacks accurately. These metrics collectively underscore the efficacy of the tuned model in providing reliable predictions, crucial for the real-time monitoring and management of asthma.

Table 2. Classification report of Classifier 2.

Class	Precision	Recall	F1-Score	Support
0	0.98	0.98	0.98	65
1	0.99	0.99	0.99	135
Accuracy		0.99		
Macro Avg	0.99	0.99	0.99	200
Weighted Avg	0.99	0.99	0.99	200

The confusion matrix for Classifier 2, shown in Figure 3, provides a clear indication of its performance on a binary classification task. The matrix reveals that the classifier correctly identified 64 instances as class 1 (true positives) and 134 instances as class 0 (true negatives), demonstrating a high level of accuracy in distinguishing between the two classes. There are very few errors, with just one instance misclassified as class 1 instead of class 0 (false positive) and one instance misclassified as class 0 instead of class 1 (false negative). This suggests that the classifier was both highly sensitive in detecting class 1 and highly specific in confirming instances of class 0, leading to overall effective performance in class separation.

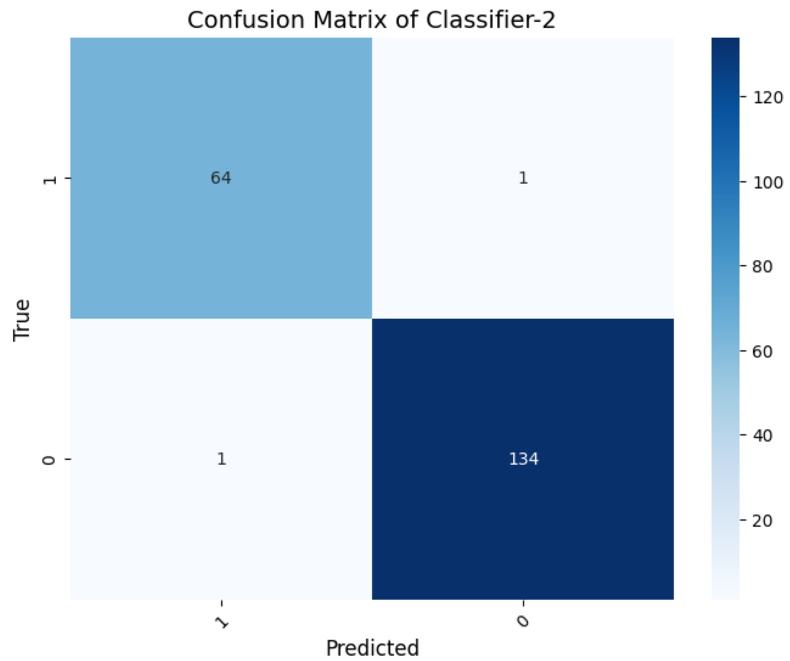

Figure 3. Confusion matrix of Classifier 2.

The dataset was divided into training (70%), validation (15%), and testing (15%) sets, ensuring that the model was evaluated on unseen data, and its generalizability was assessed. Additionally, 10-fold cross-validation was performed during the training process. This technique involved splitting the training data into 10 subsets, training the model on nine subsets, and validating it on the remaining subset. This process was repeated 10 times, with each subset used as the validation set once, and the average performance across all folds was reported. To prevent overfitting, L2 regularization was applied, which helps to maintain a balance between bias and variance by penalizing large coefficients. Furthermore, learning curves that showed the training and validation performance over time were included, aiding in the diagnosis of overfitting and ensuring that the model's performance stabilized as it learned from the data. By incorporating these methods, a comprehensive validation of Classifier 2's performance was conducted, ensuring its reliability and generalizability.

3.3. MQ2 Sensor Forecasting Model

The MQ sensor forecasting model utilizes a moving window of four past samples to predict future smoke levels. This approach allows the model to capture temporal patterns in the data, making predictions based on recent trends. The predicted smoke levels are then compared to a threshold, which is determined by the first LLM assessing the asthma severity. By comparing the forecast smoke levels against this threshold, the system can predict the likelihood of an asthma attack and alert users accordingly, enabling proactive asthma management.

To assess the model's effectiveness, we compare its predictions with actual observed values, examining the alignment and accuracy of the predictions. The performance metrics, including an R2 value of 0.922, demonstrate the model's reliability in predicting the smoke levels and supporting asthma risk assessment. This high degree of accuracy is crucial in managing asthma symptoms and ensuring timely intervention, particularly in vulnerable populations.

The performance of the regression model is illustrated in Figure 4, showing the observed and predicted smoke levels for the testing data. One observation from the graph is the close alignment between the predicted and observed values, indicating that the random forest regressor has accurately identified the main trends in the data. This visual consistency suggests that the model can predict the smoke levels with a high degree of accuracy.

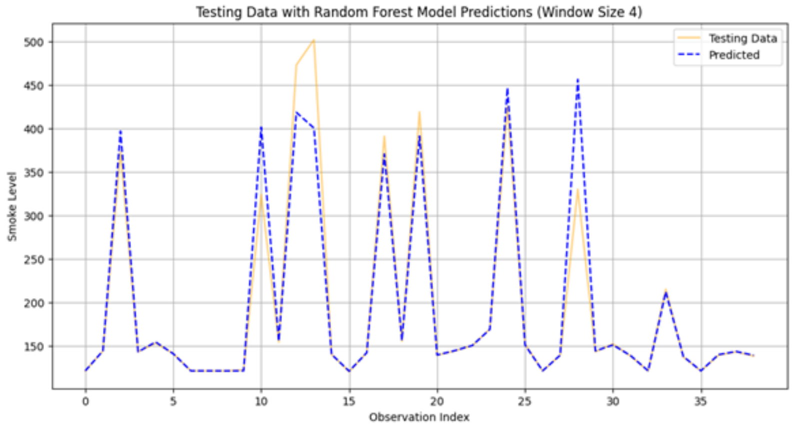

Figure 4. Performance of the regression model, illustrating the observed and predicted smoke levels for the testing data.

4. Hardware Implementation

For the hardware part, a variety of sensors are needed. Starting with the physiological sensors, the heart rate and oxygen saturation readings are taken from the pulse oximeter Sensor. Environmental readings such as the temperature and humidity are captured by the DHT11 sensor. Additionally, the oxygen concentration, CO2, and smoke levels in the surroundings are measured using the I2C oxygen sensor, MQ135, and MQ2, respectively. All of these sensors provide input to the microcontroller, ESP32, which collects the readings and sends them to our application over the internet for model application. Finally, the output is displayed on an OLED 0.96″ screen, and, if the readings are abnormal, a buzzer is activated. The circuit diagram in which all sensors and outputs are connected to the microcontroller is shown in Figure 5.

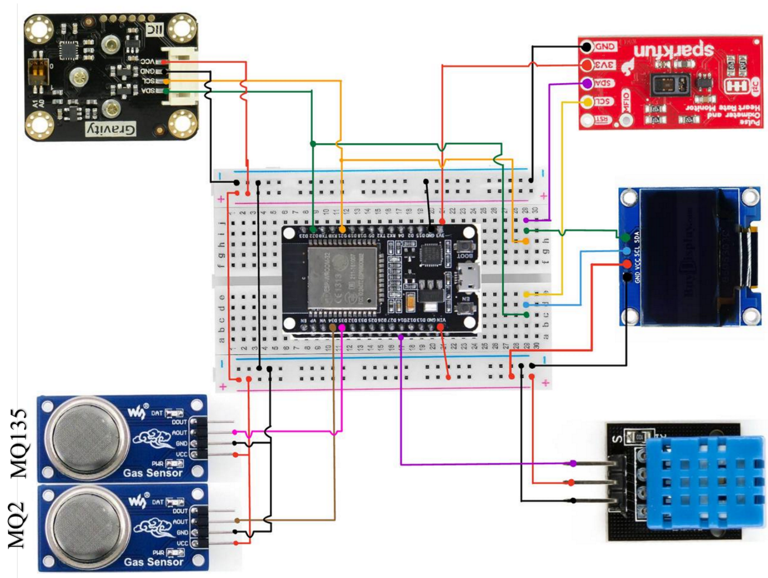

Figure 5. Circuit diagram. All sensors and outputs are connected to the microcontroller ESP32.

Converting this circuit into a wearable device such as a watch or bracelet presented significant challenges due to the relatively large sizes of the components involved. Initially, we fabricated a basic enclosure to house all of the components, except for the sensors, which were externally mounted to effectively detect environmental changes. This design ensures that the device's functionality is not compromised by its form factor. The Asthma Guard bracelet is shown in Figure 6.

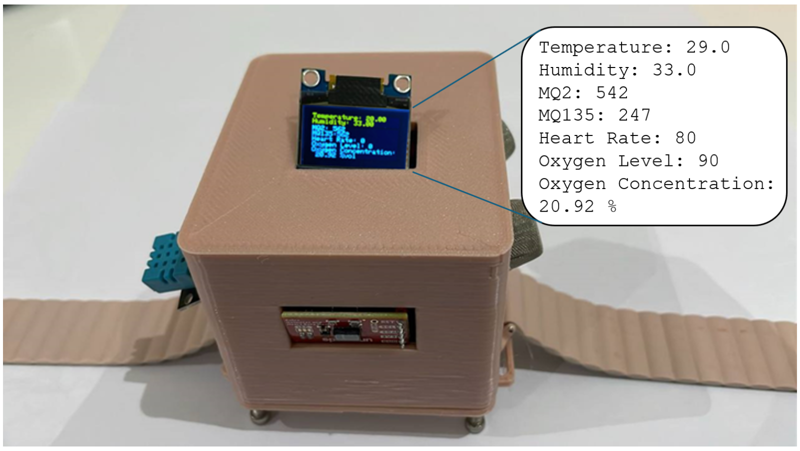

Figure 6. Asthma Guard bracelet. The basic enclosure houses all of the components, with the sensors externally mounted. The debug window shown on the display is rendered in the figure inset.

To address the challenges of miniaturizing the hardware components in the AI Asthma Guard device, a potential roadmap for future improvements has been developed. This plan includes several key strategies to ensure that the device remains functional and compact. Smaller, more efficient sensors will be utilized, and advanced integration techniques such as System-in-Package (SiP) and System-on-Chip (SoC) solutions will be employed. These approaches will allow for a more compact and lightweight design, suitable for wearable technology.

Advanced integration methods, including flexible printed circuit boards (PCBs) and compact sensor modules, are being considered to achieve a more streamlined and portable device. Prototypes of the miniaturized device will be developed and tested, with iterative design improvements to optimize the size and functionality. These prototypes will be evaluated for their performance, user comfort, and durability to ensure that they meet the required standards.

Collaborations with hardware manufacturers and research institutions specializing in wearable technology have been established. These partnerships will provide access to the latest advancements in miniaturization and help to accelerate the development process. By following this potential roadmap, the challenges of miniaturizing the AI Asthma Guard device can be overcome, ensuring its suitability for wearable applications without compromising its functionality.

5. Limitations

Throughout the development of the Asthma Guard wearable armband, our team has faced a series of challenges and limitations that require careful consideration.

One major challenge was related to the precision and consistency of the onboard sensors. These aspects are quite crucial, as they directly influence the device's capability to classify risks and forecast asthma episodes accurately. Additionally, the effectiveness of our machine learning algorithms relies on acquiring extensive and varied datasets, which may underperform in uncontrolled settings. The publicly available datasets did not align with our needs because they primarily consisted of survey-based data, lacking relevance to our project's specific requirements. Although there were a few datasets that might have been useful for our project, legal access to them proved to be unattainable.

The inclusion of the ChatGPT module also raises significant concerns about the protection and confidentiality of critical health information. Another issue is the armband's need for ongoing adjustments and firmware updates to accommodate varying environmental and user-specific factors. Moreover, the difficulty in enlisting participants for trials has hampered our efforts to confirm the device's practicality and effectiveness under normal usage conditions. The challenge of assembling a large and diverse dataset has further strained our capacity to fine-tune and improve the algorithms' predictive power.

6. Ethical and Privacy Considerations

In this work, several critical measures are outlined to ensure data security and privacy for users. Robust data security measures, including end-to-end encryption, secure storage solutions, and strict access controls, are implemented to protect user data, which are anonymized to prevent misuse. A clear and transparent consent process ensures that users or their guardians are fully informed about the data collection, their usage, and their rights. Comprehensive privacy policies detail data management, sharing, protection, retention periods, and user rights regarding access and deletion. Ethical considerations are also addressed, focusing on continuous monitoring and data collection, particularly for vulnerable populations, and include strategies to mitigate risks such as data breaches and unauthorized access.

7. Conclusions and Future Work

This work introduces a smart armband with artificial intelligence, designed to predict and alert users of impending asthma attacks by analyzing physiological and environmental data. This device uses advanced technology to monitor indicators like the heart rate and oxygen levels, offering preemptive alerts and improving asthma management through continuous data monitoring. It also employs machine learning techniques to enhance the predictive accuracy and features like GPS and medication tracking. By integrating technologies like ChatGPT, the watch improves user engagement and provides personalized asthma management, significantly benefiting children by allowing them to lead safer, more active lives.

To align with the Sustainable Development Goals (SDGs) and ensure that the AI Asthma Guard technology benefits vulnerable populations globally, several key strategies have been implemented. Accessibility is enhanced through a user-friendly interface that supports multiple languages and provides training and support materials for users and healthcare providers. Affordability is addressed by exploring various funding models, including partnerships with healthcare providers, government subsidies, and collaborations with non-profit organizations, to reduce the cost burden on end-users. Scalability is ensured through detailed plans for mass production and global distribution, leveraging collaborations with international health organizations and initiatives to deploy the device in low- and middle-income countries. These strategies collectively aim to make the AI Asthma Guard technology accessible, affordable, and scalable, thereby enhancing health and well-being in alignment with the SDGs.

Moving forward, our focus will be on enhancing these elements, broadening the demographic reach of our dataset, and executing thorough real-world trials to improve the system's overall precision and dependability. We also plan to investigate more sophisticated machine learning techniques to achieve finer risk evaluations and predictions. Addressing these issues will be pivotal in leveraging Asthma Guard to transform asthma care and elevate patient outcomes more broadly.

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