Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260071
Published: June 9, 2026

BreatheSmarter: A Low-Cost Smart Device for Early Detection of Asthmatic Attacks

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Abstract

Approximately 262 million people worldwide suffer from asthma, highlighting the critical need for early detection of asthma attacks and the utmost importance of correct inhaler usage. To address this issue, BreatheSmarter was created, which is a highly economical and efficient smart attachment for any standard inhaler that helps patients identify asthma attacks earlier, guides them through the steps of using the inhaler correctly, and sends an alert when the inhaler is used. The attachment was created with a 3D-printed box enclosing an Arduino Nano 33 BLE Sense Rev2, a stethoscope diaphragm, a button, a 0.96" screen, a SIM800L for SMS, and 3 AAA batteries. The device assists users at each stage of inhaler usage, including shaking the inhaler before use; holding their breath after taking a puff; and repeating the steps if a second dose is necessary. The AI model, developed using Edge Impulse, incorporates comparative analysis of 1D vs. 2D convolutional neural networks along with adjustments in learning rates to optimize detection accuracy. By removing noise during training and augmenting the training dataset using Python libraries, the 1D CNN with a learning rate of 0.003 was the most successful, with a training data accuracy of 92.4% and a testing data accuracy of 86.07%. Additionally, a web application was developed that allows users to customize the device by adding their phone number. This innovative device, powered by an optimized AI model, enables early detection of asthma attacks and helps manage symptoms through proper use of inhalers.

Keywords
Smart Inhaler, Asthma, AI, Machine Learning, Wearable Healthcare

1. Introduction

Asthma is a chronic respiratory disease that affects approximately 262 million individuals worldwide (World Health Organization, 2024) and remains a significant public health concern. Despite available effective treatments, poor inhaler technique and delayed recognition of worsening symptoms continue to contribute to preventable asthma hospitalizations (Molimard et al., 2003). These challenges emphasize the importance of developing technologies that promote correct inhaler usage and facilitate timely intervention. Therefore, there is a need for a low-cost, portable system capable of detecting early signs of asthmatic attacks while supporting proper inhaler usage.

Unlike present technologies, BreatheSmarter is an attachment that can be used on any inhaler and is affordable (De, 2026). Not only is BreatheSmarter reducing costs for those in need of smart inhalers, but it also uses machine learning as an early detection system, making the design unique. That being said, a central challenge in the development of this device lies in implementing accurate and efficient machine learning on a low-power embedded platform. Achieving reliable detection requires careful selection and optimization of model architecture and training parameters. Consequently, this work emphasizes the evaluation of convolutional neural network approaches and learning rate configurations to balance detection accuracy with the computational constraints of edge-based processing.

From an industrial engineering and operations management perspective, BreatheSmarter addresses healthcare accessibility, low-cost system design, and emergency response workflow improvement. The device integrates sensing, embedded decision-making, user guidance, and SMS alerting into a compact healthcare support system.

1.1 Objectives
The primary objective of this research is to design and develop BreatheSmarter, a cost-effective device that can be attached to any standard inhaler to transform it into a smart inhaler capable of assisting asthma management. The device aims to detect abnormal breathing sounds associated with asthmatic attacks by integrating an optimized artificial intelligence model designed to operate on a low-power embedded platform, specifically the Arduino Nano BLE 33 Sense Rev2. A key focus of this work is to evaluate neural network architectures and determine the optimal model capable of accurately detecting asthmatic breathing patterns while operating within the constraints of an embedded system. In addition to early detection, the device is designed to assist patients with proper inhaler usage and provide alerts by sending SMS notifications to preconfigured phone numbers, allowing caregivers and family members to respond quickly during potential asthma emergencies. This research also includes the development of a web application that connects to the BreatheSmarter device via Bluetooth, allowing users to configure the device to save their phone number. This study investigates the research question: what neural network architecture provides the most accurate prediction of asthmatic breathing patterns while remaining efficient for deployment on a resource-constrained embedded platform?

1.2 Scientific Background
Proper inhaler usage plays a critical role in effective asthma management. According to the American Lung Association, to ensure optimal delivery of medication, patients are typically advised to begin by taking a deep breath and fully exhaling. The inhaler mouthpiece should then be placed securely in the mouth while the user presses down on the inhaler to release the medication. During this process, the patient should inhale slowly and deeply at the same time to ensure the medication reaches the lungs. After inhaling, the breath should be held for approximately five to ten seconds to allow the medication to deposit in the airways. If a second dose is required, patients are usually instructed to wait approximately thirty seconds before repeating the process (American Lung Association, 2022). However, incorrect inhaler techniques remain common among asthma patients (Sanchis et al., 2016) and can reduce treatment effectiveness, highlighting the importance of devices that assist patients in using inhalers correctly.

In the context of respiratory sound analysis, Mel-Frequency Cepstral Coefficients (MFCC) are widely used as a feature extraction technique for processing audio signals. MFCC represents human speech and respiratory sounds in a way that closely reflects human auditory perception (Davis and Mermelstein, 1980). The process begins by splitting the audio signal into short frames and transforming these frames into the frequency domain. The signal is then passed through a Mel-scale filter bank that emphasizes frequencies important to human hearing. Finally, a Discrete Cosine Transform (DCT) is applied to produce a compact set of coefficients that represent the spectral characteristics of the sound. These coefficients are commonly used as input features for machine learning models designed to analyze breathing patterns and detect abnormalities (Huang et al., 2023).

Deep learning techniques are increasingly used to classify respiratory sounds and detect abnormal breathing patterns (Huang et al., 2023). One-dimensional convolutional neural networks (1D CNNs) are commonly applied to sequential data such as audio waveforms, where filters move along the temporal dimension to extract meaningful features. In contrast, two-dimensional convolutional neural networks (2D CNNs) operate on image-like data representations such as spectrograms derived from audio signals. While 2D CNNs can capture more complex spatial patterns in spectrogram images, they typically require greater computational resources compared to 1D CNNs. Therefore, selecting an appropriate neural network architecture is important when deploying machine learning models on resource-constrained embedded platforms.

2. Literature Review
Smart healthcare devices have shown increasing potential to improve asthma management by providing real-time feedback and monitoring (Chan et al., 2017) (Foster et al., 2014). For example, the ProAir Digihaler has built-in sensors that record when the patient inhales and sends the data to a mobile app, generating reports that can be shared with doctors (ProAir Digihaler, n.d.). However, despite these advancements, such solutions often depend on proprietary inhaler designs and are associated with higher costs, limiting accessibility for a broader patient population

(Chan et al., 2017). Additionally, the discontinuation of the ProAir Digihaler device in June 2024 highlights challenges in long-term adoption and sustainability of commercially available smart inhalers.

Furthermore, existing smart inhaler technologies primarily focus on monitoring usage rather than providing early detection of asthma attacks. Current systems lack the ability to analyze physiological signals, such as respiratory sounds, to identify abnormal breathing patterns that may indicate an attack. While recent research has explored the use of deep learning models for respiratory sound classification (Pramono et al., 2017), these approaches have not yet been widely integrated into commercially available inhaler devices. As a result, there remains a significant gap in the development of affordable, non-proprietary solutions that combine real-time inhaler guidance with early detection capabilities based on patient breathing patterns.

3. Methods

3.1 Hardware Development

The development of the BreatheSmarter device began with the integration and testing of the hardware components to ensure proper operation prior to incorporating the artificial intelligence model. The system was programmed using the Arduino language, a variant of C++, and included several functional components: a display screen for presenting text and counters, a gyroscope for detecting shaking motion, and a switch for detecting inhaler actuation when the user presses down on the inhaler. These components were assembled and tested together to verify that the device could monitor inhaler usage and respond appropriately to user actions (Figure 1A). After successful hardware testing, the electrical connections were soldered to improve stability and reliability, and a custom enclosure was designed and fabricated using Tinkercad and 3D printing (Figure 1B). The enclosure was attached to the diaphragm tube of the inhaler to create a compact and functional prototype. To improve signal quality, outside noise was reduced by resealing the device connections and refining the physical assembly; the recordings were further cleaned using Adobe Audition (Figure 2). Once the embedded artificial intelligence model was developed in Edge Impulse, the model was incorporated into the Arduino code to enable abnormal breathing sound detection directly on the Arduino Nano 33 BLE Sense Rev2, leading to the complete creation of the prototype (Figure 1C, 1D). This methodology allowed the device to combine inhaler monitoring, respiratory sound analysis, and embedded processing into a single low-cost smart inhaler attachment.

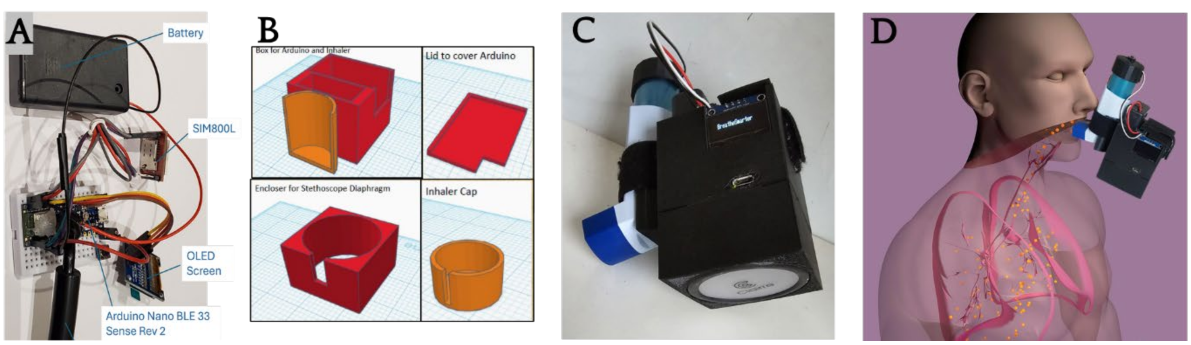

Figure 1. BreatheSmarter Device and Contents (Figure 1D adapted from Science Photo Library)

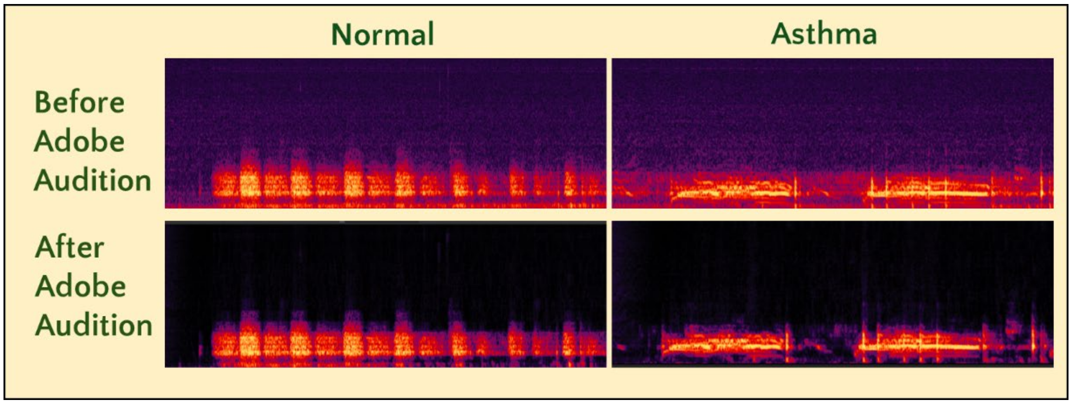

Figure 2. Adobe Audition on Recordings

3.2 Web Application Development

The web application was developed to provide a user interface for configuring the BreatheSmarter device and managing alert settings. The application used HTML for the front end and Python for the back end, with Flask serving as the framework for establishing the web server and handling communication between the user interface and the embedded device. Through the web application, users can enter a phone number into a text field on the HTML page, which is then submitted to the Flask backend for processing. After form submission, the phone number is stored and transmitted to the BreatheSmarter device via Bluetooth communication using the Bleak library. This transmission targets the designated CHARACTERISTIC_UUID associated with the device, allowing the phone number to be saved for later SMS alert functionality. The web application therefore serves as a configuration platform that enables users to personalize the device settings without directly reprogramming the hardware. By integrating wireless communication and a simple browser-based interface, the methodology supports accessibility, usability, and real-time device customization.

3.3 AI Model Development

The artificial intelligence model used in the BreatheSmarter system was developed to detect abnormal breathing patterns associated with asthmatic attacks using respiratory sound analysis. The dataset used for model training was created by recording breathing sounds through the BreatheSmarter device. To simulate breathing sounds for both normal and asthmatic conditions, approximately 100 audio samples were played from Mendeley and Kaggle datasets through the speaker of a stuffed animal placed against a chest area to mimic chest auscultation and were recorded using the device's built-in microphone. These recordings served as the initial dataset for training and testing the machine learning model.

Following data collection, the recorded audio samples were processed to improve signal quality. The audio files were imported into Adobe Audition (Figure 2), where background noise and white noise were removed to enhance the clarity of the breathing sounds. Noise reduction improved the quality of the audio signals and ensured that the model could focus on meaningful acoustic patterns rather than environmental interference (Davis and Mermelstein, 1980).

To expand the size of the dataset and improve model generalization, data augmentation techniques were applied using a Python library. The pitch of the audio recordings was modified to create additional variations of the breathing sounds while preserving their underlying characteristics. Through this process, the dataset was increased from 100 samples to approximately 200 samples, providing more training data for the machine learning model.

Feature extraction was performed using Mel-Frequency Cepstral Coefficients (MFCC), a widely used technique for representing audio signals (Davis and Mermelstein, 1980) in machine learning applications. MFCC features capture important spectral characteristics of sound that correspond closely to human auditory perception. These features were used as the input data for the neural network models. The AI model was developed and trained using the Edge Impulse platform, which supports machine learning deployment on embedded devices. Two convolutional neural network architectures were explored: a one-dimensional convolutional neural network (1D CNN) and a two-dimensional convolutional neural network (2D CNN) (Figure 3).

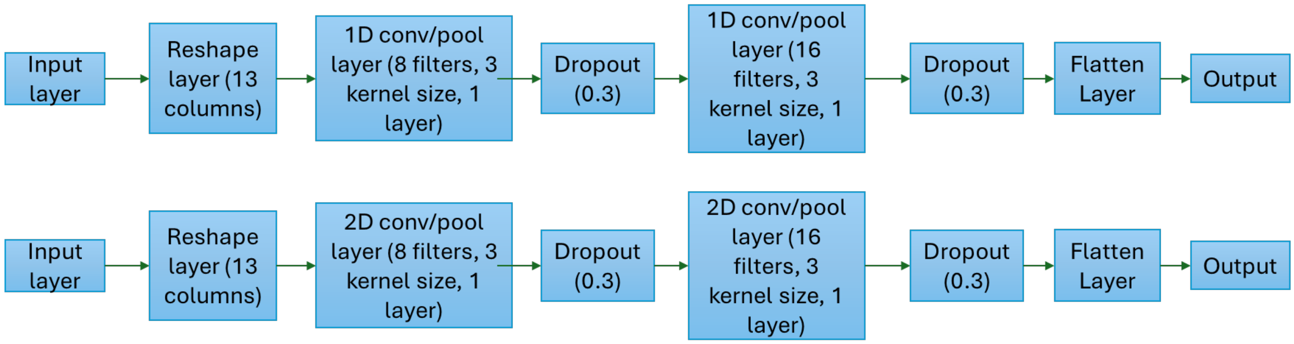

Figure 3. AI Model Pipeline

The 1D CNN processes sequential audio feature data, while the 2D CNN processes image-like representations of the audio features such as spectrograms (Huang et al., 2023). Each architecture included convolution and pooling layers for feature extraction, dropout layers with a rate of 0.3 to reduce overfitting, and a final flattening layer connected to the output classification layer. These architectures were evaluated to determine which model provided the best balance between prediction accuracy and computational efficiency for deployment on the Arduino Nano 33 BLE Sense Rev2. The final trained model was exported from Edge Impulse and integrated into the embedded system code running on the device, enabling real-time detection of abnormal breathing patterns directly on the hardware platform.

4. Data Collection

The dataset used in this study was created by recording respiratory sounds using the BreatheSmarter prototype device. A total of 100 audio samples were collected to represent both normal breathing patterns and breathing associated with asthmatic conditions. To simulate respiratory sounds during data collection, audio recordings of breathing were played through a speaker placed inside a stuffed animal positioned against the chest area to mimic chest auscultation. The BreatheSmarter device recorded these sounds using its built-in microphone. This setup allowed the device to capture breathing audio in a controlled and repeatable manner. The collected recordings included examples of both normal breathing and asthma-related breathing patterns. These recordings served as the initial dataset used for preprocessing, augmentation, and training of the machine learning models used for respiratory sound classification.

Because the respiratory sounds were replayed through a speaker inside a stuffed animal and re-recorded by the device, this dataset represents a controlled simulation rather than real patient respiratory data. Therefore, the reported model accuracy should be interpreted only within this simulated setup and not as clinical asthma detection accuracy.

5. Results and Discussion

5.1 Results

All the parts of the device were soldered together, including the Arduino Nano, an OLED screen for displaying text and counters and a switch for detecting a press on the inhaler, and a SIM800L enabling text messaging (Figure 1A). The diaphragm of a stethoscope tube was cut such that it could be stuck on the microphone of the Arduino Nano, allowing the device to record clear audio. A 3D printed case was created using Tinkercad (Figure 1B), and the device was programmed with Arduino, a variant of C++. A complete prototype was built and used for collecting data (Figure 1C, 1D).

The accuracies of 1D CNNs and 2D CNNs at different learning rates (0.001, 0.002, 0.003, 0.004, and 0.005) were plotted (Figure 4).

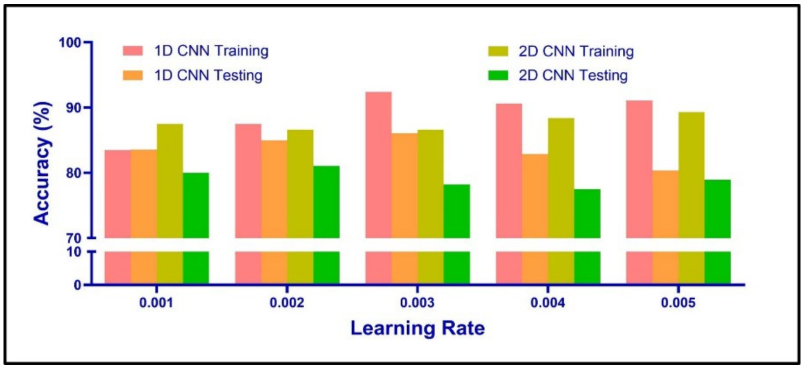

Figure 4. Accuracy vs. Learning Rate

While 1D CNNs outperformed the 2D CNNs in most cases, the 2D CNN did slightly better than the 1D CNN with a learning rate of 0.001. This suggests that the 2D CNN architecture, which processes spectrogram-like representations of the audio data, may benefit from smaller, more gradual weight updates to capture subtle patterns in respiratory sounds. However, as the learning rate increased, the 1D CNN proved to be more stable and accurate. For the 1D CNN models, a learning rate of 0.003 yielded the highest performance across all tested learning rates (86.07%), while for the 2D CNN models, the best results were achieved with a learning rate of 0.005 (78.93%).

For the 1D CNN with a learning rate of 0.003, the training data set had an accuracy of 92.4% with a loss of 0.23. It correctly identified 90.9% of true asthma recordings as asthmatic and 93.9% of normal recordings as normal. On the testing dataset, an accuracy of 86.07% was achieved, with 85% of actual asthma recordings predicted as asthmatic and 87.1% of normal recordings predicted as normal (Figure 5). For the 2D CNN with a learning rate of 0.005, the training data set had an accuracy of 89.3% with a loss of 0.30. It correctly identified 90.9% of true asthma recordings as asthmatic and 87.7% of normal recordings as normal. On the testing dataset, an accuracy of 78.93% was achieved, with 77.9% of actual asthma recordings predicted as asthmatic and 80% of normal recordings predicted as normal (Figure 5).

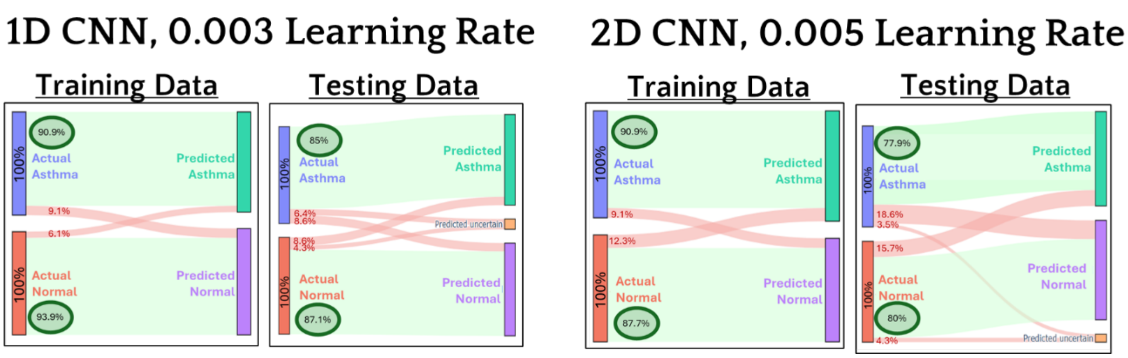

Figure 5. AI model testing and training accuracy

5.2 Discussion

The results of this study show that both 1D and 2D convolutional neural networks are capable of classifying respiratory sounds for asthma detection, but their performance varies significantly depending on the learning rate and data representation. Overall, the 1D CNN model outperformed the 2D CNN across most tested configurations, achieving a higher testing accuracy of 86.07% compared to 78.93% for the best-performing 2D CNN. This suggests that directly processing raw audio waveforms using 1D convolutions may be more effective for this task, particularly in resource-constrained embedded systems.

One possible explanation for the superior performance of the 1D CNN is its ability to capture temporal patterns in respiratory sounds without requiring transformation into spectrograms. While 2D CNNs leverage time-frequency representations that can reveal more complex patterns, they may also introduce additional noise or redundant information during preprocessing. This is supported by the observation that the 2D CNN performed best at a lower learning rate (0.001), indicating that smaller weight updates were necessary to stabilize training and extract meaningful features from spectrogram data. In contrast, the 1D CNN remained stable across a wider range of learning rates and achieved optimal performance at 0.003, suggesting greater efficiency.

The difference between training and testing accuracy also provides insight into model generalization. The 1D CNN showed a moderate gap between training accuracy (92.4%) and testing accuracy (86.07%), indicating slight overfitting but still maintaining strong generalization performance. On the other hand, the 2D CNN exhibited both lower training and testing accuracies, suggesting that it struggled to effectively learn discriminative features from the available dataset. This may be due to the increased complexity of 2D models, which typically require larger datasets and greater computational resources to achieve optimal performance.

The most significant limitation of this study is the simulated data collection method. Since respiratory sounds were played through a speaker inside a stuffed animal rather than recorded directly from human patients, the model may have learned features of the playback setup rather than clinically meaningful respiratory patterns. As a result, the reported accuracies of 86.07% for the 1D CNN and 78.93% for the 2D CNN should not be interpreted as real-world asthma detection performance.

Despite these promising results, several limitations should be acknowledged. The dataset used for training and testing may not fully represent the variability of real-world respiratory sounds, including differences in recording environments, patient demographics, and severity of asthma symptoms. Additionally, while noise reduction and data augmentation were applied, further improvements in preprocessing techniques and dataset size could enhance model performance, particularly for the 2D CNN. Future work could explore hybrid models, larger datasets, or real-time validation in clinical settings to further improve detection accuracy and reliability.

6. Conclusion

This study successfully achieved its objectives of designing, developing, and evaluating a low-cost smart inhaler attachment capable of guiding proper inhaler usage and detecting asthma-related respiratory patterns. The BreatheSmarter device integrates embedded artificial intelligence, real-time user feedback, and communication features into a single portable system, demonstrating the feasibility of combining multiple healthcare functions in an accessible design (De, 2026).

The results showed that the 1D CNN model outperformed the 2D CNN, achieving a testing accuracy of 86.07 percent at an optimal learning rate of 0.003. This indicates that 1D CNNs are more effective and stable for processing respiratory audio signals, particularly in resource-constrained embedded environments. The findings also highlight the importance of selecting appropriate model architectures and tuning hyperparameters for optimal performance.

The main contribution of this research is the development of an affordable, non-proprietary solution that not only tracks inhaler usage but also incorporates respiratory sound analysis for early detection of asthma attacks. This addresses a significant gap in existing smart inhaler technologies, which primarily focus on usage monitoring rather than predictive detection. Future work may focus on expanding the dataset, improving model robustness, and validating the system in real-world clinical settings.

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Biography

Shriyadita De is a young innovator, STEM enthusiast, and community leader dedicated to advancing science, technology, and education. She is currently a junior in the STEM Magnet Program at Montgomery Blair High School in Silver Spring, Maryland, where she explores the intersection of biology, data science, engineering, and machine learning. Shriyadita's technical skills in coding languages and machine learning frameworks have been applied to numerous innovative projects. Among her notable works is BreatheSmarter, a smart attachment for inhalers that detects early signs of asthma attacks and helps users follow correct inhaler usage protocols. Her work has earned multiple awards, including top honors at the ScienceMontgomery Fair, recognition as a Thermo Fisher JIC Innovator, and the Lemelson Early Inventor Award. Passionate about applying technology for social good, Shriyadita is the Founder & CEO of BrainBox, a nonprofit organization that creates engaging science kits and books designed to inspire elementary and middle school students. The BrainBox initiative has received national recognition from organizations that support and fund its mission, and Shriyadita has been selected as a speaker to present her project at the national level. Through BrainBox, she aims to make STEM education accessible and engaging for young learners, nurturing curiosity and creativity from an early age. In addition to her technical achievements, she contributes to STEM outreach through ScienceWithShriya, a platform featuring educational videos and science content designed to inspire children's interest in scientific exploration.