# A Study for Applying Machine Learning Algorithms in Advance Asthma Inhaler

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262 million people are affected by asthma globally. Symptoms and disease burden are frequently influenced by the time of day, the season, and one's life. Although many people with asthma have their symptoms under control most of the time, some continue to have poor control, and all are at risk of attacks, which are at best uncomfortable and at worst may necessitate hospitalisation or even end in death.

1. Introduction

Since there is currently no cure for asthma, management efforts are concentrated on symptom control and lowering the risk of episodes. Since there are many different phenotypes of asthma, it is crucial to customise management regimens. One of the cornerstones of management is monitoring, which enables patients to accurately assess their health and take the necessary measures. The use of mobile technologies in medical care is known as "mobile health," or "mHealth." This can include using wearable technology, home monitoring systems, healthcare telephone helplines, and text reminders for medical appointments.3 Machine learning is the best method for processing the numerous streams of data that make up mHealth, many of which are produced at a rate that is faster than a human being can process them.

Without explicit human programming, machine learning involves utilising computers and algorithms to process and detect patterns in massive volumes of data (many observations and many variables). Data from primary, secondary, and tertiary care electronic health records, genomes, pictures, sound recordings, and vital signs have all benefited from its insights into a very broad range of applications. Using data to learn how to complete a task is what is referred to as machine learning. The algorithms typically fall into two categories: supervised learning and unsupervised learning. For activities with a clear objective, supervised learning identifies a mathematical function to connect the data with known labels. On the other hand, unsupervised learning describes patterns and structures in the data without adhering to human-defined labels or categories. The Supplementary Material: Machine Learning contains more information on machine learning algorithms.
Currently, the majority of mHealth interventions that have been deployed in healthcare have been messages and reminders. Monitoring, personalising care, educating, identifying demographic patterns to better focus care, and anticipating asthma attacks using a variety of data sources are all aspects of asthma management that machine learning and mHealth can support. The three main categories of the currently conducted study are: 1) technology development, 2) attack prediction, and 3) patient clustering.
This clinical review will give a critical

overview of recent work that has used machine learning in the context of mobile health to manage asthma remotely, as well as discuss its drawbacks, difficulties, preparedness for deployment, and suggestions for future study.

## 2. Method for Research

For conducting this research we have perused PubMed database search and got the articles we will use and extend further in this research.

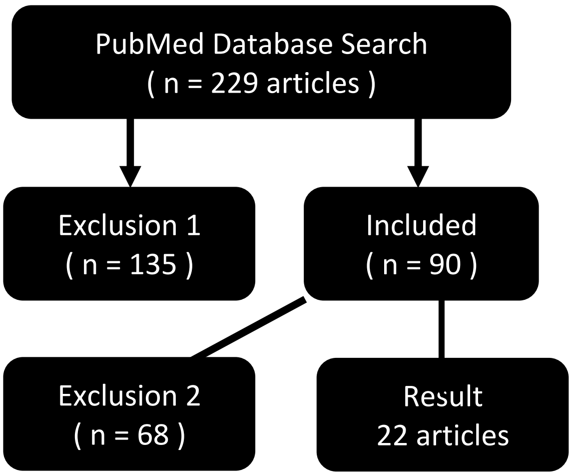


Fig: 1 Article

Exclusion 1: Published in Last 7 Years
Exclusion 2: Not Related to ML

| Algorithms | Validation |
|---|---|
| Predict, ML, AI, Bayesian Machine, Regression, Moran's Index, Getis-Ord Gi* index | ROC, AOC, Accuracy, Validation, sensitivity, Specificity |

Table 1: Work Strategy

## 3. Technology Development

11 of the research that were included have the development of monitoring tools as an objective. These include active and passive cough and wheeze detection, activity detection using smartwatches, home breathing monitoring, and identifying sleeping positions from wearable respiration sensor data. The raw signals obtained from sensors were processed using digital signal processing (DSP), which is a crucial step before using machine learning, in many of the research on technological development that were found.
However, none of the 11 research creating monitoring tools had particularly looked at data from a senior population. Two out of 11 studies included data from children, and five out of 11 studies included data from adults. Only healthy adults who could mimic a variety of breathing patterns were used in several of the adult tests.

### 3.A. Sleeping Position

Asthma patient's posture, such as whether they are standing or lying down, might affect how they breathe. However, there is conflicting information about the impact of sleeping position on respiratory function. When examining posture-related instabilities, it can be helpful to know the posture at the time the breathing measurement was collected.
Four postures (two standing and three sleeping) were accurately recognised using two wearable sensors placed at the chest and abdomen. However, knowing whose individual the data belonged to was necessary in order to accurately identify postures from sensor data. Using this data, the classifier's performance increased from 21.9% accuracy to 99.5% accuracy; hence, further study or the inclusion of a calibration stage will be

necessary to adapt this approach for the management of asthma.

### 3.B. Activity Monitoring

Elite athletes, healthy people, and members of the general public all use smartwatches to monitor their health. As a result, technology has advanced, making sensors more dependable, inexpensive, and cross-brand compatible. Activity detection utilised motion data (triaxial accelerometery and gyroscopic data, widely acquired in smartwatches), which could enhance passive monitoring capabilities and possibly eliminate the need for queries about activity. DSP was used to analyse the raw signals, and supervised learning (gradient boosted tree classification) on two datasets was used to accurately identify different activities like standing, sitting, and walking from the wrist-worn device signals. In a study of the effectiveness of algorithms trained on two datasets, one of adults and one of children, it was discovered that activity detection worked better in adults, albeit this was complicated by the fact that adults made motions that were strictly prescribed while children recorded movements that were more spontaneous.

### 3.C. Breath Monitoring

Monitoring your breathing and looking for breathing problems could help you possibly spot asthma attacks early. Portable sleep diagnostic devices for tracking breathing during sleep and radar for tracking chest movement have both been suggested as tools for home monitoring. The respiratory waveforms were accurately predicted using deep learning and pulse oximeter characteristics.25 Similar to this, using supervised learning (XGBoost) to identify various breathing patterns using characteristics extracted from chest movement captured by the radar showed promising accuracy.

### 3.D. Cough Monitoring

Wheeze and cough are frequently recorded as indicators of asthma management and are incorporated into validated asthma questionnaires, similar to sleep monitoring. There are projects integrating mHealth and machine learning to create new tools for actively and passively monitoring cough and wheeze, though. People with various respiratory disorders could have their voluntary coughs and respiratory noises recorded and analysed to help with diagnosis. The ability to distinguish between wet (cough with phlegm) and dry coughs was successful, however using recordings alone to diagnose patients had different degrees of success. One study accurately predicted persons who were either healthy, had asthma, had chronic obstructive pulmonary disease (COPD), or had both asthma and COPD with a 93.3% accuracy rate using voluntary cough recordings. With an AUC of 67.8%, another study that used cough type to separate healthy patients from those with respiratory disease performed substantially worse. Wheeze and cough recognition from digital stethoscope recordings has showed promise thanks to the development of novel DSP techniques, a necessary step for being able to extract pertinent information from raw sound signals.

### 3.E. Inhalers Inhale Monitoring

In the field of research on asthma, medication adherence is frequently examined. Another use of mHealth and machine learning is to monitor how inhalers were used and check for proper technique, in addition to monitoring when patients took their medications. Regression models were found to accurately estimate the inhaler inhalation flow profile with 91% accuracy using adult audio recordings from the Inhaler Compliance Assessment (INCA) device that had undergone DSP processing. This unbiased evaluation of inhaler technique may encourage people to take their medications more effectively.

## 4. Existing System

CareTRx:
The whole system, known as CareTRx, was introduced in 2014 and consists of a compact cap that fits over the canister of the majority of metered-dose inhalers and is fitted with sensors and on-board memory. The on-board memory saves the information when a user presses down to administer a dose. The cap then automatically connects and syncs to the cloud and the product's app when the user is close to the mobile device. When it is time for a dose, lights around the cap glow. The app has a number of functions, including a logbook that keeps tabs on potential triggers, peak flow, symptoms, and missed doses.

Enhancements/changes to the current system:
1. Count sensor: to record how frequently the medication is inhaled.
2. Air quality sensor: to assess the air quality around the patient.
3. Using the cloud-based data, doctors can advise patients on which medications to take.
4. Doctors can also let the patient know if their asthma symptoms have changed following taking the medicine.

## 5. Objectives

1.To keep track of the full history of medications prescribed to asthma patients, a database needs to be built.
2. Track populations in one location and identify patients with poor control.
3. Examine the patterns of compliance, utilisation of rescue measures, peak flow, triggers, and symptoms.
4. Use aggregated data to access fresh perspectives.
5. Lowers medical facility costs.
6. Examine the air quality in the area where we live.

## 6. Methodology

Two user interfaces are present on the Smart Asthma Inhaler. The patient's user interface is built as an Android-based application.

Doctor:
1. A doctor can prescribe medication by accessing the data sent by the inhaler.
2. Monitors and examines data in support of clinical research
3. Looks into past incidents' medical histories in the database.

1. The inhaler must be used to communicate information, and a mobile application must be used to send location information.
2. Use your inhaler wisely to avoid overdosing.
3. Obtains prompt medical care from a doctor in the event of an emergency.

## 7. Algorithms Used

Moran's index:
One technique for examining the spatial autocorrelation of spatial data is Moran's index. The Moran's I in a dataset ranges from -1 to +1. The spatial autocorrelation

is positive if the Moran's I index value is more than zero, negative if it is lower than zero, and absent if it is close to zero. This equation is used to calculate the Moran's I index.

$$I = \left( \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \right) * \left( \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - x)(x_j - x)}{\sum_{i=1}^{N}(x_i - x)^2} \right)$$

where x is the average number of asthma cases, N is the total number of asthma cases, wij is the spatial weight between polygons i and j, and xi and xj are the numbers of asthma cases in polygons i and j, respectively. This analysis examines the relationship between points and neighbours in the local Moran's I index, where four scenarios are possible:

High-High (H-H): When a value's neighbours and the spatial autocorrelation of that value are both positive.
When one is positive and the other is negative, it is said to be high-low (H-L).
Low-High (L-H): the condition in which the former is negative and the latter is positive.
When the former and later are both negative, the expression is Low-Low (L-L).

Getis-Ord Gi* index:
This index, which combines signs of hot spots (high-risk locations) and cold spots (low-risk areas), is used to look at the accumulation of extremely big or very tiny amounts of the occurrence of an event. Hot spots are indicated by positive Z-score values, whereas cold spots are indicated by negative Z-score values. Getis-Ord Gi* index is derived from the equation

$$G = \left( \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}x_i x_j}{\sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j} \right)$$

Bayesian Machine
With the prior distribution, p()p(), and likelihood, p(x|)p(x|), Bayesian ML aims to estimate the posterior distribution, p(|x)p(|x). From the training set of data, one may calculate the likelihood.
In fact, when we train a standard machine learning model, we do just that. In order to increase the likelihood of seeing the training data xx after having already seen the model parameters, we are undertaking Maximum Likelihood Estimation, an iterative procedure that adjusts the model's parameters.
What makes the Bayesian paradigm different, then? The situation is reversed in that we really aim to maximise the posterior distribution in this case, which treats the training data as constant and calculates the likelihood of any parameter setting given that data. This procedure is known as Maximum a Posteriori (MAP). However, it is simpler to consider it in terms of the likelihood function. Bayes' Theorem allows us to express the posterior as

p(θ|x)∝p(x|θ)p(θ)

8. Graphical Analysis

Temperature & Air Quality (User Interface Based)

Environmental Criterial (ML Based)

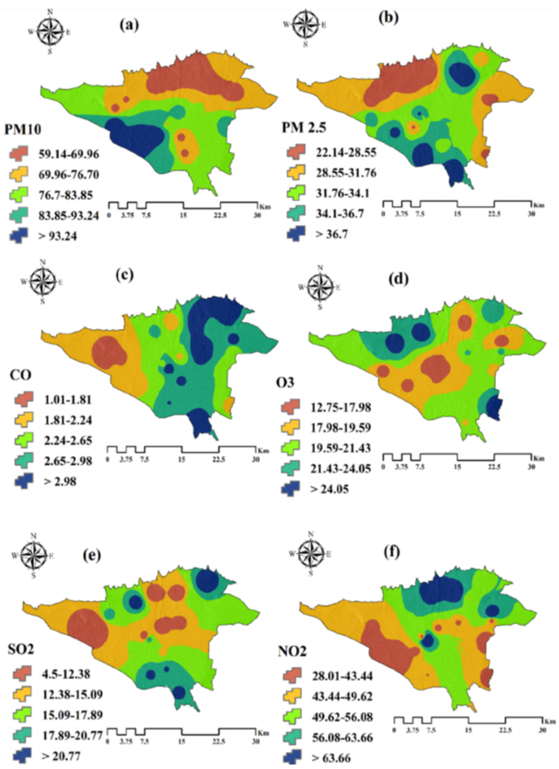


Fig: Environmental criteria affecting asthma ( CA, USA). (a) Particulate matter PM 10, (b) PM 2.5, (c) CO, (d) O3, (e) SO2, (f) NO2

## 9. Results Table (CA, USA)

Spatial autocorrelation indexes

| Index | Moran's I | Getis-Ord Gi* |
|---|---|---|
| Index value | 0.149 | 0.000029 |
| z-score | 6.807 | 2.673205 |
| p-value | 0.00 | 0.007513 |
| distribution | clustered | clustered |

Environmental Criteria Index

| Criterion | Nugget | Range | Partial Sill | SD |
|---|---|---|---|---|
| Rain | 0 | 0.116171 | 0.080033 | 0% |
| O3 | 0.079762 | 0.095789 | 1.17747 | 6.34% |
| CO | 0.11694 | 0.122836 | 0.877 | 11.76% |
| NO2 | 0.028775 | 0.066788 | 1.107712 | 2.53% |
| SO2 | 0.193513 | 0.11833 | 1.36949 | 12.38% |
| PM 10 | 0 | 0.077056 | 0.824453 | 0% |
| PM 2.5 | 0 | 0.075632 | 0.073868 | 0% |

## 10. Attack Prediction

Breath screening

Patients' breath contains volatile organic compounds (VOCs), which originate from indoor pollution and may be used to understand how asthma episodes start, although the research is conflicting.59 The gold standard for VOC measurement is gas chromatography-mass spectrometry (GC-MS), however electronic nose (e-Nose) might be a portable substitute. In mixes of chemical vapours, the e-Nose can find and identify specific chemical components.

Sleep Tracking

Sleep disturbance was frequently utilised as a potential indicator of asthma worsening since it is clinically recognised that increased diurnal variation generating sleep disturbance is an indication of poorly controlled asthma. Many research used questionnaires to record night-time symptoms and sleep quality, but other studies also used devices to get objective sleep data. Two of the four most predictive variables out of 25 total features used to predict asthma attacks using daily (symptom diary-like) questionnaires regarding asthma were those connected to night-time symptoms.

Monitoring Lung Function
Peak expiratory flow (PEF) decline is a key sign of asthma attacks. Patients will occasionally utilise peak flow metres at home to acquire accurate measurements and determine whether further therapy is necessary. Peak flow metres and spirometers both assess lung function, but spirometers do so in greater detail. Action plans employ criteria of 80% of a person's best PEF to decide when action is necessary; if a person's PEF drops below 60%, urgent action is required. Asthma action plans frequently employ a decline in PEF and/or a change in symptom score to assess self-management in response to deterioration. Smart peak flow metres, which frequently require a smartphone app to function, let patients measure and monitor their PEF.

Adherence Evaluation
The use of a questionnaire to measure medication adherence and forecast asthma attacks is occasionally utilised. Despite being clinically significant, neither of the two trials included the adherence to controller medication as a key predictor in their analyses. In contrast, and in line with clinical guidelines, two of the four most predictive variables were those based on the usage of short-acting pain relievers.

Monitoring the Environment
Weather changes, and air pollution (such as particulate matter, carbon monoxide (CO), and nitrogen dioxide ($NO_2$)) are some typical environmental asthma triggers that could be monitored to lower the risk of exposure. Additionally, keeping track of asthma triggers, such as viral infections, passive smoking, and pets, may help to better understand an individual's asthma and their symptoms. A plethora of information for analysis can be obtained by linking patient health records with data from meteorological and pollution monitoring stations.

## 11. Discussion

In this review, a variety of machine learning applications for supporting asthma care have been discussed, including those for creating novel technologies, forecasting acute attacks at the individual level, and gaining insight into asthma phenotypes by grouping patients together. Examples of successful machine learning applications include attack prediction from sleep quality, control prediction from exhaled breath, and identifying asthma patients based on medication adherence. Other examples include improving existing methodologies by using fewer resources while still achieving similar or better results, such as smartphone-based passive cough monitoring.

## 12. Future Scope

Machine Learning Based:
Algorithms for machine learning are reliant on data input. The next logical step is to validate the findings in bigger, more representative groups because the majority of current studies rely on relatively small sample sizes and frequently selected populations. Future studies should think about expanding on the models that are already in place, gathering multi-dimensional data simultaneously from a variety of sources and devices to create a more full picture of a person and their surroundings, and evaluating the usefulness of certain technologies. Future research into the development of mHealth devices for asthma should take into account studies like MyAirCoach and Biomedical REAl-

Time Health Evaluation (BREATHE), which mix many sources of data longitudinally. Children, teenagers, and adults with asthma, COPD, and other respiratory disorders, some alone and others in combination, provided the data necessary to train the machine learning models. It is unknown whether the model created for one population can perform similarly with a new or more general population, despite the fact that any variance in the performance of the algorithms trained on data from either age group was probably unlikely to be directly related to age. Another topic for future research is extending the capability of current technologies, enhancing performance, and confirming outcomes against other devices. For instance, different breath sounds could be added to wheeze detection to broaden its application to various respiratory conditions. Similar to the "cocktail party problem" in machine learning, cough detection might be applied to more challenging data, such as a mix of numerous individuals and background noise. Machine learning-based advancements in image identification and video analysis show promise and may be used to improve inhaler method monitoring.

Inhaler Based:
GSM (Global System for Mobile Communications) integration into the inhaler will eliminate the need for cell phones.
The smart device's design can be greatly simplified, making it less clumsy.
An air quality sensor can be adjusted to display precise environmental contamination levels.
To extend the life of the sensors, a built-in power supply can be added to the circuit.

## 13. Conclusion

A wide range of capabilities have been investigated using mHealth devices in recent breakthroughs in the application of machine learning to asthma control. The algorithms have shown promising results, but their evaluation has at best been limited to internal validation. Furthermore, a restricted demographic and short datasets were mostly used to construct the algorithms. As a result, it is unknown how well these algorithms would perform in the broader population in a practical setting. Future studies should focus on merging data from numerous, different sources and include external validation with a high sample size.

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