Smart Healthcare Framework for Asthma Attack Prediction and Prevention

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***Abstract*— Smart healthcare is one of the most exciting applications introduced to provide better disease diagnosis and prediction tools. Recent studies introduced various disease prediction models that employ machine learning techniques by utilizing different features that cause the disease. Asthma exacerbates due to various triggers, including personal and environmental variables. A few works had introduced a complete smart healthcare framework that combines the prediction model with a trigger visualization system. These studies generally use a limited number of triggers in the prediction and visualization process, and traditional machine learning techniques. This paper proposes a smart healthcare framework that provides patients with a sophisticated tool to visualize the asthma trigger and notify them about any predictable attack. The asthma attack prediction is based on utilizing a comprehensive set of patient data and different environmental triggers. It is based on deploying deep learning instead of the traditional machine learning techniques. The prevention model includes a dynamic visualization map of air pollution concentration, which alerts users with high-risk areas. Moreover, a context-aware safe-route recommendation system is proposed to keep users away from any asthma triggers.**

Keywords*— *Prediction, Triggers, Personal data, Air Pollution, Weather, Safe Route.

I. Introduction

Smart Healthcare (SHC) is one of the most exciting smart system applications introduced to improve traditional healthcare and provides better disease diagnostic and prediction tools [1]. SHC systems' features include machine intelligence, context-awareness, knowledge discovery, decision making, reasoning mechanisms, and disease prediction [2].

Disease predictions can range from hospital readmission rates to therapy's responses. It is useful to take appropriate mitigating actions and pre-inform healthcare providers to manage demand and minimize the risks. Health prediction requires reliable data and proper analytical tools to predict specific health conditions or situations. Examples include determining the likelihood of disease, predicting infections, helping a physician diagnose, and even predict future health [3]. Many studies introduced SHC systems for different chronic disease prediction and control [4]–[7]. This research will focus on the prediction models introduced to predict asthma attacks.

Asthma affects more than 300 million individuals globally, and this number is rising sharply over the years [8], [9]. Its symptoms are irritated by many triggers, such as lung functions, high and low temperature, and air pollution. The rate of asthma patients is rising over the years due to the phenomenal increase in air pollution levels caused by the industrial acceleration in our lives [10]. Those patients need a system that can help them control their disease and avoid asthma triggers, which can irritate an asthma attack.

Researchers established different studies to introduce asthma attack prediction models and asthma triggers visualization systems. Currently, there is a limited SHC system that provides asthma prediction with the triggers visualization and considers the user contextual and spatial information (e.g., health condition, user location, and environmental data location). By examining these systems, we found that most of them focused on using personal triggers and neglected other essential triggers. At the same time, asthma attack prediction requires various triggers, including personal and environmental variables. However, most state-of-art solutions focused on introducing a prediction model only rather than developing a complete SHC system. Subsequently, there is a need to consider all asthma triggers to deliver a useful model. Moreover, it is required to provide patients with a recommendation system that alarms them by identifying the nearby triggers. A dynamic visualization map for air quality is necessary to enable policy-makers and citizens to avoid polluted sites and seek direct action.

This paper is providing a complete SHC framework that predicts asthma attacks by using contextual and spatial data. The proposed framework includes a recommendation system that analyzes user location to extract any asthma trigger and provides the patient with a safe route with minimum asthma triggers. It also provides them with a dynamic map for the air pollution concentration that can irritate the asthma attack.

The rest of this paper is organized as the following; Section II introduces a background for asthma and its triggers. Section III discusses the existing asthma attack prediction models and asthma triggers visualization systems. Section IV introduces the proposed framework. Section V introduces a discussion to explain the need for such a smart framework. Finally, section VI concludes.

II. Background

Asthma is a respiratory disease that causes difficulty in breathing as it affects the lungs and causes the airways to get inflamed and narrow [11]. Asthma affects people of all ages and often starts during childhood.

Many triggers can lead to an asthma attack; these triggers irritate the airways and set off the asthma symptoms. They are specified in two categories, personal and environmental (see Fig.1).

The personal variables are commonly taken by physician observation and recorded in the patient's medical record. The environmental variables include weather, air pollution, and pollen [12]. Air pollution was reported as the main asthma trigger. In urban areas, road traffic, burned factory fossil fuels, and specific industrial processes are the main sources of air pollutions. Certain pollutants mostly exist in urban areas: CO, NO2, O3, SO2, and PM10. Their concentrations differ and increased according to the traffic and the industrial activity. An asthma attack is aggravated by air pollution and weather changes, ranging from humidity to cold air and rain. [13]. High temperature causes increasing in ozone level, which raises the pollution concentration leads to asthma symptoms. The more severe asthma patients, the more likely the weather and air pollution will affect them as their airways are already inflamed. Humidity causes shortness of breath and makes it difficult due to the existence of moist air. When humidity exists, high temperature also exits, which leads to an increase in body temperature and sweat. Humidity and rain are causing an increase in dust mites, stir-up mold spores, and ground-level ozone, affecting asthma patients.

III. RELATED WORK

Numerous studies introduced asthma attack prediction models and recommendation systems. Most of these models were built utilizing personal triggers only. Some of them [14], [15] deployed general personal triggers such as respiratory infections, the presence of cold, physical activity, sleep disturbances, and Peak Expiratory Flow Rate (PEFR). Others had used both special and general personal triggers [16], [17] such as asthma severity, blood eosinophil count, and history of asthma attacks, smoking status, obesity, comorbidity, and medication usage.

According to these studies, using both special and general personal triggers plays an important role in improving model performance.

Finkelstein and Jeong [14], [15] used only general triggers and trained the model by using different machine learning methods, including Naïve Bayesian, adaptive Bayesian network, and support vector machine. The model's accuracy in the best case reached 80 percent. On the other hand, Do et al. [17] used both special and general triggers, and the model accuracy was 97 percent. A summary of these models' used triggers is introduced in table 1.

Table 1. SUMMARY OF PREDICTIVE MODELS DEVELOPED BASED ON THE PERSONAL TRIGGERS

Ref#	Personal triggers		Total triggers
	General	Specific	
[14], [15]	Presence of cold, sleep disturbances, and physical activity.	PEFR, medication, respiratory symptoms	6
[16]	Obesity, smoking status, and comorbidity	PEFR, asthma severity, history of asthma attacks, medication, and blood eosinophil count	8
[17]	Night waking, and activities.	FEV1, lung functions used medication. and symptoms	6

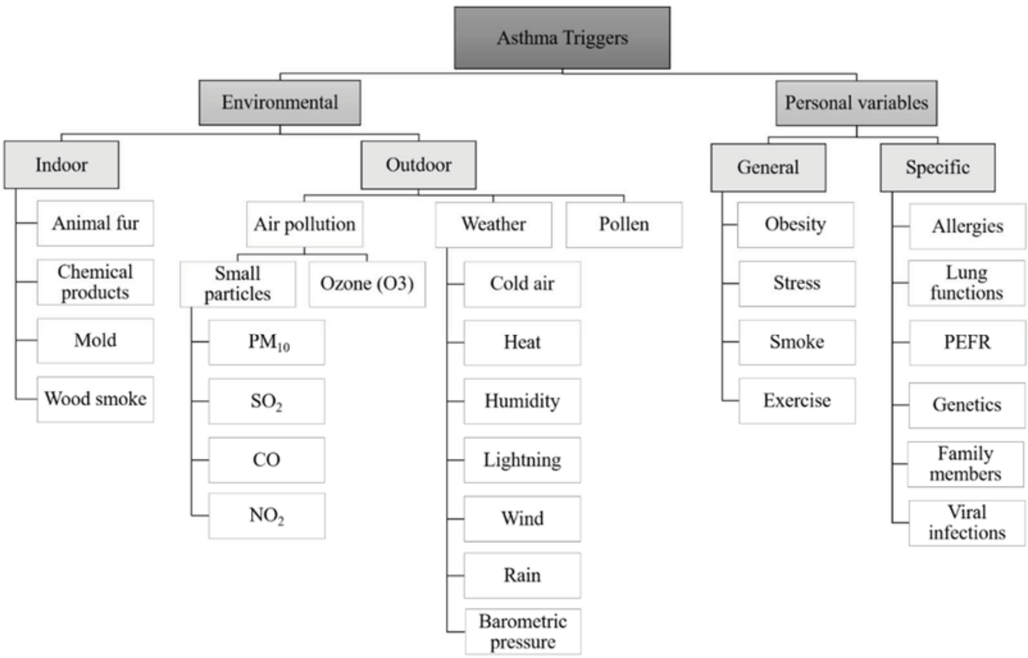

Fig. 1. Categories of Asthma Triggers

Different studies built their models based on the environmental triggers only and ignored the personal triggers. These studies' target was to predict asthma's emergency department visits (ED) regarding the changes in weather and air pollution concentration. The authors in [18] used a regression model to determine the relationship between the number of asthma patients and different environmental variables. They found a positive relationship between asthma ED visits and CO, NO2, and PM2.5 with a coefficient correlation of 0.79, 0.79, and 0.93, respectively, whereas O3 had no relationship. Another variable was considered by Mireku et al. [19], which is Barometric pressure (BP). The model shows that BP has no impact on the number of asthma patients. Ram et al. [20] developed another model and used machine learning instead of regression. The model was trained by using a Decision Tree (DT) and Artificial Neural Network (ANN). ANN outperforms DT with an accuracy of 0.70. A summary of the used weather and air pollution variables for these models is introduced in table 2 with the total number of these triggers.

Table 2. SUMMARY OF THE PREDICTIVE MODELS DEVELOPED BASED ON THE ENVIRONMENTAL TRIGGERS

Ref#	Environmental triggers		Total triggers
	Air pollution	Weather	
[18]	CO, O3, PM10, PM2.5, NO2.	Humidity and temperature	7
[19]	×	Humidity, temperature, and barometric pressure	3
[21]	Vegetation density and NO2	Temperature and humidity	4
[20]	PM2.5, O3, CO, and NO2.	×	4

The previous studies lack using either personal or environmental triggers, limiting the model's ability to predict individuals' asthma attacks. Different studies [22]–[25] used both of trigger's categories, and the performance of their models shows the ability to predict asthma attacks with more than 0.87 accuracy.

Other studies introduced a visualization system for asthma triggers with the prediction model [24], [25]. These studies provided a self-management tool through the developed visualization system that displays a map of the air pollution concentration in the selected sites. Such tools help asthma patients by informing them about the possibly dangerous areas and places that include asthma triggers. These systems utilize limited personal triggers, and they would generate better prediction and recommendation results if more triggers were used.

Two studies had proposed asthma attack prediction frameworks [26], [27]. However, these frameworks are based on utilizing minimal personal and environmental triggers, which is not sophisticated for predicting asthma attacks. A summary of these models' triggers is introduced in table 3, with the total number of these triggers.

By reviewing all the previous models and systems, we found that they focused on using some triggers and neglected others. The visualization map also displays the air pollution and weather changes only without considering road traffics, crowded areas, and construction sites, which irritate asthma symptoms and leads to asthma attacks.

Table 3. SUMMARY OF PREDICTIVE MODELS DEVELOPED BASED ON THE PERSONAL AND ENVIRONMENTAL TRIGGERS

Ref#	Personal triggers	Environmental triggers		Location	Total triggers
	Specific	Air pollution	Weather		
[22]	PEFR, nose symptom, eye symptom, skin symptom, night symptom, day symptom, fever, dermatitis, rhinitis, medicine, conjunctivitis	CO, SO2, O3, NO2, PH PM10, HydraCarbon, HydraCarbon2	Temperature, and humidity	×	21
[23]	PEFR and FEV 1	O3, PM2.5, PM10, CO, NO2, and SO2.	Temperature, humidity, pressure, wind speed, visibility, and precipitation intensity	×	15
[24]	PEFR	O3, SO2, NO2, CO, PM10	Humidity, temperatures, pressure, rainfall, and wind.	✓	11
[25]	PEFR and medical history.	CO, O3, NO2, SO2, PM10	Temperature, barometric pressure, and humidity.	✓	10
[26]	Medication plan, and asthma symptoms	CO, NO, dust and smoke	×	✓	6
[27]	Food allergen	Pollen	Humidity	×	3

IV. FRAMEWORK FOR ASTHMA ATTACK PREDICTION AND PREVENTION

We have addressed different limitations by reviewing the existing predictive models and asthma trigger visualization systems. In this paper, we introduce a research plan to overcome these limitations through the following:

1) *Improving Prediction Model Performance*: Two main components contribute to increasing the model performance, the use of large datasets and exhaustive variable sets with superior machine learning methods.

2) *Using multiple asthma triggers to predict the attack:* Most existing asthma attack prediction models were introduced using a few triggers. Large numbers of literature were based on utilizing only personal data and ignoring the environmental factors. Some literature combined both categories but used minimal attributes. This proposal's first contribution is to build an asthma prediction model that utilizes a comprehensive set of triggers to provide a more efficient prediction model.

3) *Using Advanced Machine Learning Techniques:* As shown in the review section, most of the predictive models had used traditional data mining, machine learning, and feature extraction algorithms. We plan to improve the model's performance by comparing different machine learning techniques, studying the feasibility of combining two methods to get better results, and modifying the feature selection algorithm to improve the prediction models' accuracy without affecting the computation time.

4) *Introducing Personalized Recommendation System:* An asthma patient needs to keep tracking all the asthma symptoms and triggers to avoid having any attack. To help save asthma patients' lives, a predictive model should notify the user of a predictable situation as soon as a trigger threatens the patient's life without any delay that could worsen the health condition. So far, very few studies have introduced a visualization system that provides the patients with a map for polluted areas. They were based on visualizing the air quality index and show the changes in temperature or humidity. However, many other triggers can cause an asthma attack, which is not considered in these systems.

In this research, in addition to the prediction model, we plan to contribute by developing a recommendation system that includes two main parts. The first part analyzes the patient location from source to destination, finds all the asthma triggers (such as crowded areas, construction sites, industrial factories), and recommends a safe route free from any trigger or has the minimum triggers. The second part is to visualize the air pollution concentrations with climate changes and show safe and unsafe zones.

A design of an integrated SHC framework is proposed to utilize contextual and spatial data to predict asthma exacerbations and attacks. Besides, the proposed framework provides many services, including a prevention system that provides a safe-route and a dynamic map for the environmental risk factors that affect people's health. The proposed SHC framework consisting of 4 layers is presented in Fig. 2.

1) ***Data curation layer:*** The first layer is the data curation layer, which loads data from *different* sources, including stream and batch data. The stream data is collected by various environmental sensors, user wearable sensors, and the users' geographical location. In contrast, the batch data is the data loaded from the Electronic Health Record (EHR) from different hospitals and care centers.

2) ***Data pre-processing layer:*** The second layer is the data pre-processing layer, which handles the miss-values and outliers. The Air Quality Index (AQI) and Peak Expiratory Flow Rate (PEFR) will also be calculated in this layer.

3) ***Data mining layer***: The third layer is the data mining layer, which deploys deep learning technique to train the model. Then, it uses a feature selection algorithm to find out the best features that can be used to train the model and minimize the computation time. The trained model is used to predict whether the patient will get an attack based on the calculated AQI, PEFR, and triggers. According to the prediction result, the risk level estimator will use a decision tree to determine the level of risk that faces the patient. The object tracker function will analyze the patient's location to find any trigger that could irritate an asthma attack. These triggers could include gas stations, construction sites, factory sites, or groups of restaurants. This layer also provides a route mining function used to evaluate all possible routes from source to destination and give each route a score according to the existing triggers.

4) ***visualization layer:*** The fourth layer is the visualization layer, where the ArcGIS server will be used. ArcGIS Server includes three main parts: desktop content author, which is used to load the dataset and the model to the server, catalog administrator, which is used to create the dynamic map; and manager administrator used to manage and share the map with users. The visualization model includes a personalized map that provides the user with the safe-route map, where the route with the minimum triggers is visualized. Besides, the regional AQI map is used to provide the user with air pollution concentration in his/her region. Such a visualization model will enable citizens and policy-makers to avoid polluted localities and reduce air pollution.

The following example is a scenario that illustrates the necessity for a personalized asthma attack SHC system according to the user context. Ahmad lives in Makkah and has severe asthma, sensitive to different smells. Therefore, he always needs to stay away from any crowded area, traffic jams, construction sites, factories, or even restaurants. He used to drive to his work through the nearest way generated by traditional map navigation, route A in Fig.3. This route usually includes traffic jams, petrol stations, and restaurants. Using the proposed SHC system, Ahmed is predicted to have an asthma attack according to his health condition and the map analyzer's knowledge. Route B will be generated through the recommendation system to offer a safe-route free from any asthma trigger. Therefore, Ahmed needs to take route B to avoid any asthma attack. Traditional navigation maps do not recognize the user context when suggesting alternative routes. Accordingly, developing a context-aware system is a requirement to enable asthma patients to avoid high-risk areas.

A comparison is introduced in table 4 to show the proposed framework's contributions regarding the existing frameworks. The comparison shows that the proposed framework overcomes the current studies' limitations and provides the users with multiple services and a more accurate method for the prediction process.

V. Discussion

We have addressed different limitations by reviewing the existing predictive models and asthma trigger visualization systems. These models have different limitations, including using limited triggers in the prediction process that leads to decreasing the models' accuracy. Also, most of these models predict the attack without considering what should be done after this prediction. Our proposed framework is introduced to overcome these limitations, and it has many advantages, which include:

1) Using exhaustive asthma triggers to predict the attack: Most existing asthma attack prediction models were introduced using a few triggers. Some literature combined both trigger categories but used minimal attributes. This proposal's first contribution is to build an asthma prediction model that utilizes a comprehensive set of triggers to provide a more efficient prediction model.

2) Using deep learning for model training: As reviewed in this paper, most of the predictive models had used traditional data mining and machine learning techniques, and the prediction accuracies were below 0.87. Using advanced machine learning techniques can increase these models' performance, such as deep learning, which has many advantages over the traditional machine learning techniques. In the proposed framework, deep learning techniques and feature extraction algorithms are deployed, giving a better result than traditional machine learning techniques.

3) Introducing Personalized Recommendation System: So far, very few studies have introduced a visualization system that provides the patients with a map for polluted areas. They were based on visualizing the air quality index and show the changes in temperature or humidity. However, many other triggers can cause an asthma attack, which is not considered in these systems. In the proposed framework, we provide the patient with three different services. These services are including; alarm system to notify the patient of a predictable attack, a visualization map for air pollution concentration in the selected area, and a safe-route map from source to destination that shows an alternative route with minimum triggers.

The proposed framework includes an asthma attack prediction and attacks prevention via a recommendation system with two main parts. The first part analyzes the patient location from source to destination, finds all the asthma triggers (such as crowded areas, construction sites, industrial factories), and recommends a safe route free from any trigger or has the minimum triggers. The second part is to visualize the air pollution concentrations with climate changes and show safe and unsafe zones.

VI. CONCLUSION AND RECOMMENDATIONS

Constructing an SHC system to predict asthma attacks for asthma patients and visualize the risk of air pollution is critically important. The same air pollution data streams have different effects on different users according to their sensitivity and asthma level. Consequently, map visualization must be customized by the user context. The proposed SHC framework has various services that offer better asthma attack prediction and prevention methods. The suggested risk factors are more diverse and should be collected through different sources. Besides, a recommendation system is proposed based on a reasoning mechanism to alert the user and provide a pollution-safe route that keeps him away from any asthma trigger. Moreover, the visualization services provide users with an air pollution visualization map to monitor the high-risk places of asthma triggers.

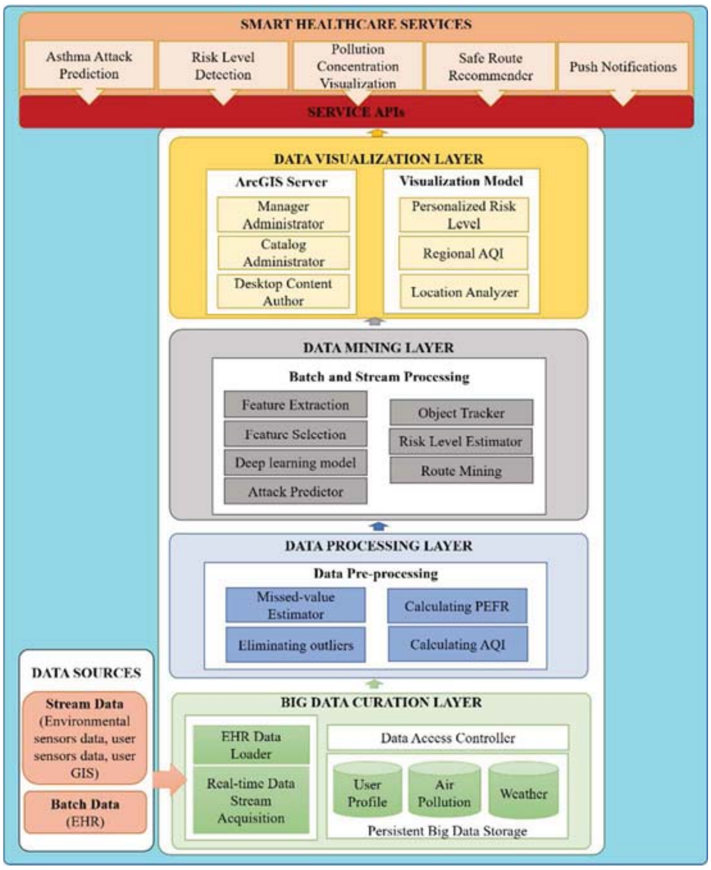

Fig. 2. The proposed framework for asthma attack prediction and prevention .

Table 4. COMPARISON BETWEEN THE EXISTING MODELS AND THE PROPOSED FRAMEWORK

Work	Used risk factors						Personalized risk level	Personalized recommendation system	Air pollution map
	PEFR	Bio-signals	Medical history	Air pollution	Weather	Location			
Proposed framework	✓	✓	✓	✓	✓	✓	✓	✓	✓
[22]	×	✓	✓	✓	✓	×	×	×	×
[23]	✓	×	✓	✓	✓	×	×	×	×
[24]	✓	×	×	✓	✓	✓	×	×	✓
[25]	✓	×	✓	✓	✓	✓	✓	×	✓
[27]	×	×	✓	✓	✓	×	×	×	×
[26]	×	✓	×	✓	✓	×	×	✓	✓

Fig. 3. Example of different routes with high and low concentrations of asthma trigger.

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