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Asthma Detection and Management using Artificial Intelligence: A Review

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***Abstract*— Asthma is one of the respiratory diseases that is chronic and has millions of patients across the globe. Diagnosis and management are still not easy with its natural variations, and the restriction of the conventional clinical instruments. The review covers the current and future uses of AI in asthma management with special reference to the possibility of improving patient outcomes.**

The analysis identifies the role of AI in assisting the diagnosis, forecasting, and customization of treatment under the assistance of various types of data. These data sources are electronic health records (EHRs), data of wearable devices, environmental factors, and respiratory sounds. Furthermore, the paper will address key technical, ethical, and practical challenges that are not allowing AI to be widely used.

Among these issues, there are problems and challenges to data privacy, algorithm bias, and poor and universally-applicable models. The promising solutions to be mentioned along with the Federated Learning and Explainable AI (XAI) are named as the main items of the further research. Lastly, the paper proposes a vision of patient centered, and proactive, asthma management with the use of AI capabilities.

***Index Terms*— Asthma, Artificial Intelligence, Machine learning, Deep Learning, Federated Learning, Explainable AI, Health- care Analytics.**

I. Introduction

A. The Global Burden of Asthma

Asthma is seen as a global epidemic, and this brings much suffering and pain to the patients, and also to their families and the society. An estimated 300 million individuals across the world are affected by asthma with about 30 million infants and young adults (under 45 years old) being affected by the disease in Europe. In America, the prevalence of asthma is about 8 percent of the population that leads to a chain of healthcare challenges, high healthcare expenses and even death as a result of severe attacks. Asthma is still a thorn in the flesh since it does not require effective management and there is a tendency of low compliance with the procedures, even though research is conducted constantly, and certain guidelines are available. This problem underlines the necessity of new and effective instruments to enable the diagnosis, monitoring, and treatment of asthma [1].

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B. Limitations of Traditional Diagnosis

The traditional means of asthma identification are complex and time consuming indeed. It is the combination of going through medical history of the patient, physical examination and carrying out various tests of pulmonary functions. There isn't a single definitive test considered the "gold standard" for asthma diagnosis. Doctors often resort to spirometry, which is a test that indicates the airflow capacity and the speed of the airflow of the lungs. Another frequently used test, peak expiratory flow (PEF), assesses the maximum speed at which one can exhale. Bronchodilator responsiveness tests are a combination of lung function measurement before and after administering a fast-acting bronchodilator for the purpose of determining if there is reversible airflow obstruction or not. Nevertheless, these procedures come with drawbacks, thus making the diagnosis process difficult. as one example, if a patient suffering from undiagnosed asthma is tested and spirometry results are normal, he/she might be given a diagnosis of asthma as the latter is a variable condition, and normal spirometry or PEF upshot does not exclude the diagnosis Furthermore, these tests demand patient cooperation and a skilled operator using properly maintained equipment, which can be difficult to co-ordinate, especially with very young children. Challenge tests, also known as bronchial provocation tests, such as the ones that utilize methacholine, can assess the degree of sensitivity of the airways and are very important for the correct diagnosis in some cases. On the other hand, their usage is restricted because it requires a significant amount of time, as well as resources, and it may not be applicable to patients taking specific drugs. This presents a basic problem; there is not one universal, reliable biomarker or an easy test for asthma. But, this complexity is the very place where AI models come in handy. In contrast to deterministic diagnostic strategies, machine learning models are able to identify subtle, non-linear patterns in high-dimensional, noisy, and evolving data. This clinical drawback will be converted into a computational strength, which makes AI ideally placed to prove its abilities Challenge tests, or bronchial provocation tests.

C. The Promise of AI

AI and especially ML is an apt fit to the problems of asthma. The ability to process and analyze large and complex data across different sources can help physicians to diagnose more effectively, predict asthma attacks and provide more specific treatment to patients. This paper reviews the existing AI-driven asthma management applications, elaborates on the primary issues to be solved, and provides recommendations on the next research steps.

II. Foundational Principles: A Primer on AI/ML in Healthcare

A. Defining Key Concepts

Artificial Intelligence (AI) is a broad area that includes creating machines that can perform tasks requiring human- like intellect. Machine Learning (ML) is an area within AI that stresses a statistical reasoning approach. With the help of algorithms, ML scrutinizes the data, acquires knowledge, and generates educated decisions or forecasts based on that analysis. Deep Learning (DL), a specialized ML area, uses multi-layered neural networks that mimic the human brain to deal with complex, disorderly data like pictures or words.

ML algorithms are split into different categories based on the way they learn. One of the most common types of supervised learning, which is often used for the diagnosis of diseases, relies on having an existing, labeled dataset to predict the following results. Unsupervised learning is opposite to that and is used when there is no labeled training data, and the model has to find the hidden patterns by itself. Reinforcement learning, another type, gives feedback on model performance and helps the model learn the best way to perform a task.

B. Overview of Foundational Algorithms

The algorithmic good old days are the times when all the major ML algorithms found their way into healthcare data through various ways. For instance, Logistic Regression (LR) which is one such algorithm is a probabilistic model that assists in making decisions by providing probabilities for different classes like predicting a yes or no outcome for a patient's flare- up. Another widely used method of decision making in both classification and regression is Support Vector Machine (SVM) which points out the most favorable boundary to discriminate between various groups of data [2]. Besides these, K-Nearest Neighbor (KNN) algorithm is also very common one that classifies a point based on that of its nearest neighbors and Naive Bayes (NB), is a type of probabilistic classifier that operates according to Bayes' Theorem and assumes all input variables are uncorrelated, are also among the most popular methods. Deep learning approaches, especially those based on Convolutional Neural Networks (CNNs), have the potential to completely transform the collecting and the analyzing process of the medical images (X-rays, CT scans) and audio signals. Notably, traditional ML models require manual intervention to select features from the data, whereas, CNNs automatically feature extraction on cough sounds, for instance, patterns in a cough sound etc. processing millions of data points per second. This feature of non-reliance on human experts in the entire process of high-dimensional data handling makes deep learning a great diagnosing tool for complex cases.

C. The Machine Learning Lifecycle

The creation of a supervised ML model for clinical purposes is a meticulous process where the various stages are involved. The initial step is model training where the system receives massive portions of past data which has been correctly labeled.

These labels are very critical because they tend to be made by human experts, either by a physician or a nurse, and he/she closely analyzes the medical reports or photographs to provide a diagnosis or make a future forecast. The involvement of human factor in the process points to the fact that there is a strong connection between AI and human expertise: it is not a substitute of the latter; in fact, it is a device the functioning of which depends heavily on the quality of the former. As an example, a machine can be taught to recognize a disease correctly, but when the training set is contaminated with other patterns like scar treatment patterns, then the machine will be taught to recognize the scar patterns. This error will render the model useless in the procedure of enhancing the initial diagnostic assessments. This shows that model development is not exclusively a technical affair; it is also intimately linked to the care and quality of clinical input. The next stage is validation, which consists of testing the model that has been trained already in a real medical setting. The human experts compare the results of the model with the actual outcomes given by the specialists and thus confirm that the model's performance is at the same level as that of the training stage.

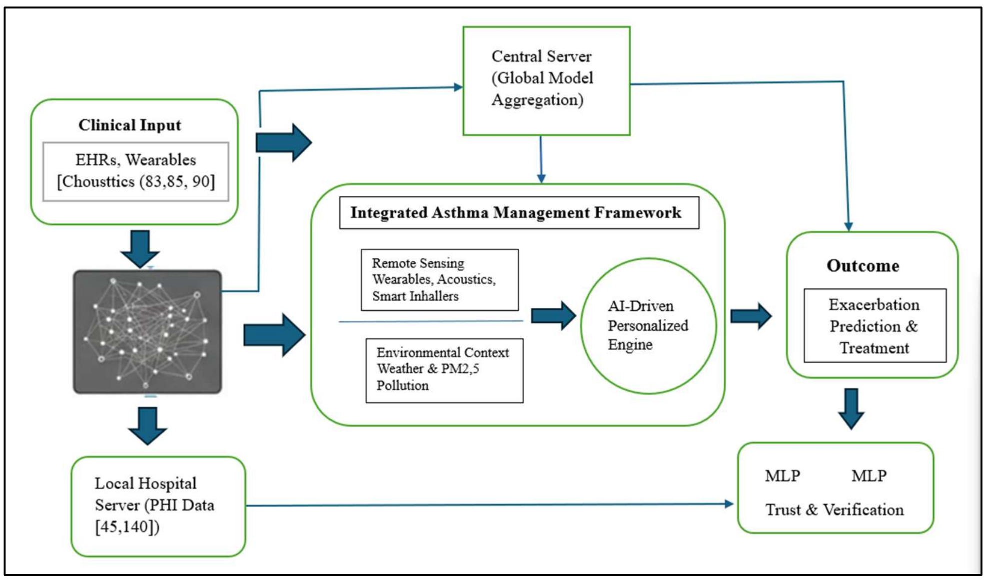

Figure 1: Machine Learning Action Lifecycle for Clinical AI Development

This Figure 1 illustrates the lifecycle involved in developing clinical AI applications, highlighting the phases of inputting clinical data (1), local data storage and privacy (2), model aggregation at a central server (3), AI-driven personalization with remote sensing and environmental data (4), predicting asthma exacerbations (5), and ensuring trustworthy predictions through multipurpose trust layers (6).

III. AI-Powered Applications in Asthma: A Spectrum of Innovation

A. Diagnostic and Triage Augmentation

The traditional clinical diagnostic methods for asthma are being modified by AI. AI can predict the results of very expensive tests with the help of pulmonary function testing. The outcome of methacholine bronchial provocation test (MBPT) has been accurately foreseen by a multilayer perceptron (MLP) model using the data from regular spirometry tests. The AUC for the model is 0.701, its accuracy is 0.758, and its F1-score is 0.853. This method might bring down the use of MBPT and hence, hasten the diagnostics procedures. Moreover, an AI-based program can perform the task of human evaluators by checking the quality of the data collected from the spirometry machines. This can result in more consistency in clinical trials and reduced variability across the raters as human interpretations may sometimes be subjective and lead to differences between raters [3].

Artificial intelligence in non-invasive diagnostics is an area that is getting more attention in research. The reproductive potential of the respiratory system is one of the areas where machines have been used to a considerable extent and has also been explored for coughs, sneezes and wheezes with the help of deep learning algorithms [4].

An AI-based wearable stethoscope capable of monitoring a patient's breath sounds has been created that can differentiate between normal and abnormal breathing in real-time; it can thus detect more than 80 percent of the abnormal events, especially wheezing, with high accuracy. The other side of the coin is that AI can be applied to medical imaging such as X-ray and CT scans which makes spotting the abnormalities much faster and easier. In one research, the collaborative interpretation of pulmonary function tests (PFT) by AI and clinicians resulted in a more accurate diagnosis than each party working separately; the reason was that the diagnoses suggested by AI made clinicians probe the cases more deeply.

B. Predictive Analytics and Proactive Management

AI is not simply used to give patients some static diagnosis as it plays an active role in the management of patients. With the help of different data AI models, it is possible to predict the entitlement of asthma attacks along with their severity. This does not only assist to intervene at the appropriate time but also makes sure that risks are handled more appropriately. One study conducted at the Cleveland Clinic used health record information of more than 60,000 patients and arrived at the conclusion that machine learning was capable of predicting non-severe asthma attacks, hospital visits, and hospitalizations. The study compared a traditional statistical model to two machine learning algorithms, that is, Light Gradient Boosting Machine (LightGBM) and random forest regression. The outcome was always that machine learning models performed more effectively than the conventional ones. The performance of LightGBM was particularly good and had the highest AUC of 0.88 in predicting ER visits and 0.85 in predicting hospitalizations.

In a different study, several machine learning models such as the Logistic Regression, Decision Tree, and Naïve Bayes were used to determine the occurrence of severe attacks of asthma. The strongest model was the logistic regression model with a sensitivity of 90 percent, specificity of 83 percent and accuracy of 100 percent that was identified in a small population in predicting attacks. A study which used an adaptive Bayesian network in telemonitoring model had a sensitivity, specificity, and a 100 percent accuracy. Although these positive results exist, there is a huge challenge.

Some of the predictive models are currently speaking, AI is considered to be unreliable and non-standardized due to non-standardized protocols and limited number of patients, and their lack of consistent predictive factors." This variance demonstrates the divide between the performance of a model in a laboratory setting and the performance in actual clinical practice. This "Generalization Gap" is a huge obstacle to the medical use of AI and implies that more challenging, prospective studies and external validation are needed to ensure AI tools are safe and reliable in daily practice. Moreover, the application of AI is very useful in personalized treatment strategies. After the recognition of a high-risk patient or an attack forecasting, AI can be of great help to the doctors by suggesting personalized medication regimens to cope with the foreseen results [5]. This feature is of utmost importance in moving from the old "one-size-fits- all" methodology to the patient-based precision medicine that considers the unique patient "phenol-endotypes."

IV. Data and Methodological Frameworks

A. Clinical Datasets: Electronic Health Records (EHRs)

The development of AI models in asthma research largely relies on Electronic Health Records (EHRs) as a primary data source [6]. These records provide extensive and well-organized data, including information about the patients, their diagnoses at certain times (using ICD-9 codes), medical procedures (with CPT-4 codes), medications, primary complaints, and vital signs. In addition, much of the clinical data is available in unstructured forms, including transcribed consultations, doctors notes, and discharge summaries. The application of Natural Language Processing (NLP) is being used to extract this data, which is a machine learning division. This is because NLP is not only helpful in coordinating care but also in clinical decision-making. Such models as BERT and BioBERT can summarize clinical notes and recognize adverse events, which will reduce the administrative load and hasten the provision of care.

B. Remote Sensing: Wearables, Acoustics, and Environmental Data

Effective AI models against asthma require the use of multi-modal strategy to combine various streams of data in order to create a comprehensive patient profile.

Wearable Technology: The management of asthma is undergoing a paradigm shift with the advent of smart devices capable of delivering real-time data on a continuous basis. In addition to capturing patient compliance and medication taken, smart inhalers also include the monitoring of vital signs such as heart rate, oxygen saturation, and pulmonary function through biometric sensors like smartwatches [7]. A wearable stethoscope patch has a wheezing detector, wheezing being a primary indicator of respiratory failure.

Acoustic Data: Breath sound analysis is an emerging field of investigation. Scientists are developing AI models for the detection of asthma using publicly available limited data sets. The ICBHI data set, which stands for the International Conference on Biomedical and Health Informatics, has 920 labeled sound files of 126 patients, of which respiratory sounds such as crackles and wheezes are included. The Kaggle data set, "Asthma Detection Dataset: Version 2," has a total of 1,211 sound files of different lung problems, of which 288 are specifically of asthma.

Environmental Data: Pollution and weather data are, in this respect, two of the most important external information inputs to a prediction model for asthma triggers. Among the several datasets available, Open Weather provides daily reports on weather such as temperature, humidity, wind speed, and air pressure. Similarly, pollution datasets record parameters such as PM2.5, PM10, CO, and NO2, which not only help in forecasting air quality but also knowing the safe routes for travel purposes.

Public datasets, though advantageous, still reveal a significant lack of data when scrutinized thoroughly. Many of the cited datasets are either synthetically generated (for teaching purposes) or are self-made and kept in small samples under strict control. The use of data that is small-scale, synthetic, or curated is a major limitation in the field, thus hindering the development and application of current models. In fact, the lack of large, varied, and high-quality real-world clinical data is the main reason why AI is not yet ready for extensive clinical deployment and still remains in the laboratory research domain.

Table1 describe the key of AIML Modul and their application in Asthma research. Table2 describe the performance matrix of selected AI module for Asthma prediction. And Table 3 list common data modules and their source for AI in Asthma.

TABLE I: KEY AI/ML MODELS AND THEIR APPLICATIONS IN ASTHMA RESEARCH

Model Name	Model Type (ML/DL)	Application in Asthma
Logistic Regression	ML	Predicting severe asthma exacerbations, forecasting patient outcomes
Random Forest	ML	Diagnosing asthma and COPD, predictive analytics for patient
Convolutional Neural Network (CNN)	DL	Analyzing respiratory sounds from audio, chest X-rays, and CT scans
Multilayer Perceptron (MLP)	DL	Predicting methacholine bronchial provocation test (MBPT) results using spirometry data
Adaptive Bayesian Network	ML	Predicting asthma exacerbations using telemonitoring data
Support Vector Machine (SVM)	ML	Early diagnosis, patient classification, and general respiratory disease diagnosis
K-Nearest Neighbor (KNN)	ML	Classifying respiratory diseases and grouping similar patients for personalized treatment

TABLE II: SUMMARY OF SELECT AI MODELS AND STUDIES FOR ASTHMA PREDICTION

Study / Source	Model	Application	Dataset Size / Type	Key Metrics (AUC)	Context / Limitations
Cleveland Clinic Study	LightGBM	Predicting non-severe exacerbations, ED visits, and hospitalizations	60,302 patients (EHR data)	0.71 (OGB), 0.88 (ED visit), 0.85 (Hospitalization)	Large retrospective EHR study; strong use of real-world data.
Finkelstein & Jeong	Adaptive Bayesian Network	Early prediction of asthma exacerbation	Telemonitoring data	100% Accuracy, Sensitivity, Specificity	Small controlled dataset; limited generalizability.
ProAir Digihaler Study	Logistic Regression	Predicting severe asthma exacerbations	Clinical & demographic data	0.85 AUC, 90% Sensitivity, 83% Specificity	Predictors inconsistent; not yet fully reliable for clinical deployment
Spathis & Vlamos	Random Forest	Asthma diagnosis	Not specified	80.3% Precision	Identifies FEV1, smoking, age, and wheezing as key features.

TABLE III: COMMON DATA MODALITIES AND THEIR SOURCES FOR AI IN ASTHMA

Data Modality	Specific Examples	Data Sources
Clinical	Diagnoses (ICD-9), procedures (CPT-4), medications, vital signs, pulmonary function tests (PFTs), symptoms (wheezing, coughing, chest tightness)	Electronic Health Records (EHRs), patient symptom diaries, clinical trials
Acoustic	Wheezing sounds, cough sounds, lung sound recordings	Digital stethoscopes, wearable devices, public datasets (ICBHI, Respiratory Sound Database)
Environmental	Temperature, humidity, pollen count, pollution metrics (PM2.5, PM10)	Public weather and pollution APIs (e.g., OpenWeather), environmental sensors
Wearable Remote	Medication adherence, peak expiratory flow (PEF) readings, heart rate, oxygen saturation levels	Smart inhalers, wearable stethoscopes, smartwatches, peak flow meters

V. THE CRITICAL PATH FORWARD: ADDRESSING CHALLENGES AND ETHICAL CONCERNS

A. Data Privacy, Security, and Algorithmic Bias

The integration of AI into the healthcare sector brings along not only the technical challenges but also the ethical and regulatory difficulties that are the major issues [8]. AI systems that require large amounts of sensitive patient information are a serious concern for privacy. Among these is Protected Health Information (PHI), which in the US is closely regulated by HIPAA, for instance. The sharing of information with cloud service providers and third parties for the application of AI has become commonplace, and as a result, the risk of breaches and unauthorized uses has become even more significant. Studies have suggested that even the most seemingly anonymous information may not necessarily be secured as well as expected, since the most sophisticated algorithms of AI have the potential to identify as much as 85.6 percent of adults in such seemingly secured information sets by disclosing hidden attributes. In 2018, a survey revealed that no more than 11 percent of the American adult population was willing to contribute information to tech firms.

Bias in algorithms was another topic which is frequently mentioned in conversations about AI in the healthcare sector. AI systems will reflect the degree of bias present in the data used during training. This can result in biased data affecting healthcare inequality, dictating unequal healthcare outcomes for underprivileged groups. These factors could be:

Data Bias: This type of bias arises if the available dataset on which the algorithm is trained is imbalanced in the sense that it may be dominated by one particular ethnic group. Development

Bias: This bias arises due to inappropriate feature selection or a lack of modeling from the algorithm development phase.

Interaction Bias: This type of bias may arise due to variability in the manner in which healthcare practitioners retrieve or provide information in different settings. If left unaddressed, the bias in AI systems can selectively benefit or mischaracterize certain groups of patients.

B. Transparency and Trust: The Emergence of Explainable AI (XAI)

One of the major barriers that currently prevents the green light to be given to AI in the healthcare system is the “black box” phenomenon whereby the decision-making logic of the complex model cannot be observed by medical doctors. To build an atmosphere of trust and cooperation, the demand for transparency and explainability in AI is increasing. Explainable AI (XAI) is a method that can provide the solution by revealing the reasons of an AI’s specific conclusion. For example, there is a newly developed XAI-based tool for analyzing cough sounds that uses a Convolutional Neural Network (CNN) and “occlusion maps” to locate the regions within cough spectrograms that are of diagnostic significance [9]. This not only allows the AI to give a diagnosis but also to point out which particular spectral characteristics’ patterns within the cough sound were most indicative of a particular disease. For clinicians, it would be the case that the AI’s findings are verifiable, and this could lead to the creation of new medical knowledge that human researchers or conventional methods might have missed previously. Trust and accountability to the clinicians have become the primary motivation behind the need for the development of these new frameworks

C. Facilitating Multi-Site Collaboration: The Promise of Federated Learning

The technical and ethical issues in AI healthcare do not exclude each other; on the contrary, they are the main drivers of the coming era of technical novelties. The need for patient privacy protection and compliance with HIPAA rules has led to the emergence of one central technology: Federated Learning (FL). Federated Learning is a machine learning technique that allows patient data across multiple hospitals or clinical trial sites to remain at their local origin while still enabling the global model to be developed. In this scenario, a central server is not used to collect the data from each site but rather interacts with them to construct the global model, and only the model parameters the local training updates are sent to the central server. This process deals with the problem of data privacy by maintaining private information at the local site and allows for access to large datasets at the same time for model training. This strategy deals with the entire problem of lack of datasets in a wise manner and hence presents an opportunity for model development to be generally applicable and robust without tampering with the privacy of patients [10].

VI. Conclusion and Future Research Directions

A. Recapitulation

The data shown in this report have demonstrated the value of AI in delivering the complexity in diagnosing, as well as managing, asthma, through the power and transformation it offers. AI models have shown success in various tasks, ranging from clinical tasks through improved measurement, through chest images, exacerbation predictions, through to the creation of treatment strategies. There are still significant barriers, however, which have yet to be addressed. These barriers include the lack of large, high-quality, real-world data, as well as the conflicting demands of data privacy.

B. The Path Forward

No future research must be concentrated on different critical domains if AI want to become a widely implemented clinical instrument rather than being just a research topic of interest. Multimodal Data Integration: Merging different data streams is the main AI issue in asthma. The models will have to transform from dependence on single data types into hybrid systems that are strong enough to combine inputs from different sources such as EHRs, wearables, lung sound monitoring, and environmental sensors thus providing a complete patient's view.

Federated Learning and Consortiums: The formation of large, multi-site research collaborations is necessary for overcoming the problems of data scarcity and the protection of privacy. Federated learning can be used by such research groups to create large, high-quality datasets that represent the whole range of patients with asthma worldwide and they can do this without revealing the identities of the patients at any time. That's how the gap known as the "Generalization Gap"-the difference between how good these models are when being tested in actual applications and how good they become in the lab-is to be closed.

Real World Clinical Validation: Real-world clinical validation will require the collaborative effort of the entire community to move from retrospective studies to prospective studies that will thoroughly test AI models in the real world. In addition to the accuracy of the model, the prospective studies will need to gauge the usefulness of the model, the effect of the model on the current state of the clinical processes in place, and the ultimate effect of the model on patient health outcomes. The Rise of Generative AI: The large language models (LLMs) like ChatGPT new roles include their development as assistants to physicians who have the capacity to offer decision support, as well as produce personalized educational materials for patients. Future studies should focus on how they can be integrated in clinical settings in a safe and effective manner, and how they should be viewed not only as tools to reduce administrative burdens, but as tools to improve patient communication.

C. A Vision for AI-Augmented Asthma Care

Finally, the future of artificial intelligence in the treatment of patients with asthma will be all about improving the abilities of the physician using smart solutions that have all the information required for personalized and very effective prophylactic treatment of the patients, as opposed to replacing the physicians. And in conjunction with the current technology that is being seen in artificial intelligence, the advancement of information and technology will play an important role in the promotion of the approach that aims to improve the quality of life of patients all over the world suffering from the burden of asthma.

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