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The role of artificial intelligence and machine learning in asthma and chronic obstructive pulmonary disease management

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Abstract: The purpose of this review is to establish the role that AI and ML play in managing asthma and Chronic Obstructive Pulmonary Disease (COPD), with particular emphasis on disease management across various stages, diagnosis, and treatment personalization through monitoring. Data extraction was performed from articles published between December 2018 and October 2024, accessed using Scopus, PubMed, and Google Scholar databases. Articles focusing on the use of AI/ML in the management of respiratory diseases in clinical settings and real-life contexts were included in this study. Theoretical models or reviews of non-respiratory applications of AI/ML were excluded. AI and ML-based technology advancements provide the possibility to extend asthma and COPD management with many improvements. Such technologies can enable early and accurate detection by using advanced imaging and data analysis techniques. AI-driven models, such as MLMP-COPD, far outweigh the usual approaches made for predicting death and exacerbations. Big data analytics and telemedicine help in the integration of diverse data sources. AI and ML have an entirely new dimension and could perform more effectively for the management of both asthma and COPD. Practical implications include integrating AI-driven tools in clinical settings to improve diagnostic accuracy, enhance treatment, and assist in remote patient monitoring.
Keywords: *Artificial Intelligence, Machine learning, Asthma, Chronic Obstructive Lung Disease, Management.*

1. Introduction

1.1. Background of Asthma and COPD

Respiratory diseases (RD) are among the most common diseases in the world, with high morbidity in both acute and chronic forms. The cases are increasing globally due to sharply increased air pollution levels, altered and sedentary lifestyles, unhealthy dietary habits, and repeated outbreaks of microbial infections [1]. Chronic RD (CRD) is a set of diseases involving acute/chronic respiratory infections, asthma, chronic obstructive pulmonary disease, lung cancer, cystic fibrosis, and tuberculosis. Thus, it is necessary to evolve an effective diagnostic method that can diagnose and differentiate at an early stage [2]. RD are classified as acute and chronic conditions in that CRD is the common non-communicable disease with asthma and COPD being spread globally. COPD is the leading cause of disability and mortality, with rates of prevalence ranging from 3.7% to 37% globally. This depends on regions [3, 4]. Factors like smoking rates, occupational exposure and environmental pollution influenced this variation. Asthma also affects millions of people, and its prevalence differs across geographical regions. Asthma is a chronic inflammatory condition in the airways characterized by recurrent wheezing, breathlessness, chest tightness, and coughing. These symptoms are mainly triggered by allergens, air pollution, or respiratory infections [5]. COPD, which includes chronic bronchitis and emphysema, is a progressive disease. This leads to irreversible limitations in airflow. The primary causes of COPD are smoking and more prolonged exposure to pollutants [6].

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Chronic obstructive pulmonary disease (COPD) is a progressive, preventable, and treatable form of chronic respiratory disorder which usually arises in susceptible patients. COPD and asthma occur irrespective of age, race, and sex worldwide [7]. The most important environmental exposures responsible for the disease in any given patient are tobacco smoking and air pollution, but many other agents make important contributions [8]. Patients with chronic airway diseases are also exposed to exacerbation, meaning they are very prone to being hospitalized and even being killed; it primarily affects their quality of life. COPD burden is extended beyond the individual patients as they affect their families, caregivers and health care systems because of increased medical expenses. Early-life events, including those damaging lung development, contribute to susceptibility to COPD and pathogenesis [9]. This disorder affects around 328 million people in the whole world and is considered among the second most common cause of hospital admission through emergency. It is estimated that COPD is going to be one of the leading causes of death globally by 2030 [10].

The global burden of asthma and COPD was increasing because of environmental and lifestyle factors. Air pollution, from delicate particulate matter such as PM 2.5 and PM10, was related to the increased asthma risk and COPD-related hospital admissions [11]. Urban regions with high levels of vehicular emission and industrial pollutants have reported a high prevalence of respiratory conditions. Rapid urbanization leads to sedentary lifestyles that limit the physical activity needed for the function of the lungs [12]. Frequent respiratory infections are caused by environmental pollution that leads to increasing asthma and COPD prevalence [13]. The decline in the prevalence and mortality of age-standardized asthma remains significant and needs continuous public health interventions (14). Asthma and COPD have some similar clinical symptoms, making it challenging to make accurate diagnosis. The variability in disease progression makes it more challenging [13]. Conventional diagnostic approaches like spirometry, imaging and clinical history may not always be sufficient. High variability in inter-observers has limited accessibility, and late-stage diagnosis leads to the suboptimal disease management [14]. So, there is a need for improved diagnostic strategies essential to improving early detection and treatment effectiveness.

Integrating artificial intelligence (AI) and machine learning (ML) in respiratory medicine improves the diagnostics and patient management. These technologies help in the automated recognition of patterns, predictive modelling and real-time monitoring that helps address traditional methods' limitations. AI-driven automated pattern recognition in medical imaging with convolutional neural networks (CNNs) improves the accuracy of accurately diagnosing lung diseases like pneumonia and lung cancer [15]. Predictive modeling using electronic health records (EHRs) helps refine diagnostic precision. For example, LungDiag, an AI system that uses natural language processing, gets an F1 score of 0.711 in the disease classification [16]. Also, the wearable devices combined with ML frameworks help in real-time monitoring of respiratory conditions like COPD. This is predicted based on environmental and physiological data [17]. The main advantages include fast and accurate diagnosis, thus reducing any delays in diagnostics [15]. Personalized treatment plans improve the outcomes of patients through personalized therapies [18]. Additionally, automation helps reduce healthcare professionals' burden [19]. However, limitations such as the quality of data and clinical integration must be addressed [15, 16].

Artificial intelligence (AI) and machine learning (ML)have emerged as a technological solution for managing chronic respiratory diseases in recent years. Traditional tools make capturing, managing, and processing medical data in time difficult because these datasets are complex, primarily updated, and available in diverse formats [7]. Instead, imaging, genomic, proteomic, and EHRs (Electronic health record) data can be mined with the help of AI/ML to discover new knowledge [8]. This development has caused rapid changes in the use of AI/ML in medicine, especially in medical imaging, where techniques are used not only for fast screening of diseases but also to improve diagnosis accuracy and working efficiency [9]. Wearable devices use AI/ML to check respiratory parameters in real time. This enables timely medical intervention and self-management of respiratory conditions. AI-based predictive models can forecast disease progression. They enable earlier intervention, personalized treatments, and lower healthcare costs. AI/ML could help manage respiratory diseases. However, there are challenges. They include data privacy, algorithm bias, and the need for regulation.

This review discusses the use of AI and ML applications in asthma and COPD management, which delves into their roles from diagnosis to disease phenotyping, treatment personalization, and monitoring. This literature review focuses on the benefits, challenges, and future directions of AI-driven approaches and how they may reshape respiratory disease management and improve patient outcomes.

1.2. Objective

The purpose of this literature review paper is to explore the analytical use of Artificial Intelligence (AI) and Machine Learning (ML) technologies in the management of asthma and Chronic Obstructive Pulmonary Disease (COPD). The objectives of this paper are threefold: first, to explore how AI and ML are applied at various stages in managing disease-from diagnosis through identification of cancer phenotype to treatment personalization and monitoring; second, to evaluate the potential benefits of AI-based methods in improving patient outcomes and healthcare efficiency; and third, to identify the challenges and limitations of AI and ML applications to management of respiratory diseases. Conclusions achieved will guide further research and development, culminating in the effective management of chronic respiratory diseases.

2. Methodology

2.1. Search Strategy

The search Methodology used in this literature review sourced information from databases available on Google Scholar, Scopus and PubMed which published articles from December 2018 to October 2024.The literature focused on keywords such as "predictive modelling", "AI in asthma management, "machine learning in COPD", "remote monitoring in chronic respiratory diseases “and "personalized treatment for respiratory diseases,”.

The time frame from December 2018 and October 2024 was selected for obtaining most recent advancements and developments in AI/ML applications in respiratory care. As this period shows some significant technological advances that are essential for understanding asthma and COPD management.

2.2. Inclusion and Exclusion Criteria

The inclusion criteria were based on relevance to key aspects of respiratory disease management: diagnosis, monitoring, exacerbation prediction, phenotyping and treatment personalization. “Articles focused on experimental uses of AI/ML in clinic and real-life contexts were preferred, with review articles which provided comprehensive insights into the impact of AI in chronic respiratory care. Theoretical models strictly or reviews of non-respiratory applications of AI/ML were excluded from literature. Thus, it enabled a structured relevant synthesis of existing knowledge that brought forth both potential and challenges in asthma and COPD management through AI/ML.

3. Overview of Artificial Intelligence and Machine Learning in Healthcare

Artificial intelligence (AI)is the technology that presents human intelligence through computer programs. Whereas Machine Learning (ML) is the study of AI technology built on statistics for learning from experience and developing problem-solving skills. Precisely, ML utilizes complex algorithms to analyze huge amounts of data, identify patterns, make predictions independent of specific codes, and improve with sample size to enhance learning [20]. Unlike traditional rule-based AI, ML systems can evolve. They can adapt and improve as they process more data. They are especially valuable in medical research and healthcare systems where; new medical data is always being generated.

Some general machine learning advancements are constantly getting developed for years in the healthcare domain. AI-based application may help in case triage and diagnosis improve on image scanning and segmentation ,assist on decision-making process, predict risk of any disease and even neuroimaging [21]. AI image recognition systems have made significant advancements in the detection of lung nodules. They help radiologists find early-stage lung cancer. AI-powered NLP systems analyze clinical notes and unstructured EHR data. They enable better patient stratification and disease prediction. This transforms patient care and optimizes monitoring for better care of the patients. AI and ML algorithms support clinicians in the identification of the disease much earlier and more accurately with the huge analysis of data in electronic health records, imaging, and data from wearable devices [22]. AI in wearable devices has transformed patient-centric healthcare. Wearables with AI can monitor vital signs and alert users to health issues before they become critical.

A study by Moll, et. al, brought up a mortality prediction model by machine learning, MLMP-COPD for patients with Chronic Obstructive Pulmonary Disease (COPD). The model is based on clinical, spirometric, and imaging features, outperforms existing indexes (BODE, BODE Modifications, and ADO) for predicting cause mortality across two cohorts with COPD. Some of the major predictors include the 6-minute walk distance, Forced Expiratory Volume in One Second (FEV1%) predicted, age, pulmonary artery-to-aorta ratio from imaging. The study invokes the Promise of Machine Learning to enhance mortality prediction for COPD patients, develop an online tool that displays the features and predictions of the model [23]. The online tool not only helps clinicians but also shows them the factors that drive mortality risk which supports shared decision-making with patients.

The most recent advances in AI and ML have shifted the frontier in chronic diseases management, especially regarding diabetes, cardiovascular disease, and respiratory disorders. These technologies form the most crucial basis on which strategies for personalized management of particular patient characteristics are developed such as genetic, lifestyle, and clinical history [24]. Personalized medicine leverages AI/ML to customize treatment regimens for individual patients. This approach considers genetics, comorbidities, and behaviors. It creates more precise, patient-specific treatment plans. In diseases like COPD, AI models predict patients' responses to bronchodilators. This helps tailor their treatment plans.AI and ML-based approaches are thereby introducing innovative monitoring and intervention approaches in chronic respiratory disorders like asthma and COPD. With the most recent development of machine learning models, it can now recognize patterns that predict exacerbations, and patients can get better and prepare with health care providers in advance. Predictive algorithms can analyze environmental factors. These include air quality, pollen counts, and weather changes. They are known triggers for asthma and COPD. AI-powered mHealth (mobile health) apps alert patients in real-time. They encourage patients to adjust their meds or seek care. The ability of AI to support wearable devices and mobile health applications helps in continuously tracking the symptoms, offering tailored feedback so that the patient may take better hold of his or her condition [25]. Tracking symptoms has been linked to better medication adherence and health outcomes for patients with chronic respiratory disorders.

3.1. Advantages of Machine Learning over traditional models in healthcare

Traditional models would depend on elaborate preprocessing of data and assumptions about linearity and independence among different variables, whereas ML can efficiently analyze large, diverse datasets and can uncover intricate patterns even in noisy or incomplete data. This lets ML models analyze unstructured data, like physician notes, imaging files, and patient-reported outcomes. Traditional statistical models often exclude this data. As a result, AI models are more adaptable and robust in the face of real-world medical complexity. This capability subsequently leads to better risk prediction and facilitates the integration of diverse types of data-cases, clinical, physiological, imaging, and demographic-towards a holistic approach to disease assessment [26-28]. Federated learning lets AI systems train models across multiple healthcare institutions. It does this without sharing sensitive patient data. This ensures privacy while improving model performance. This approach is becoming essential in multi-centre clinical studies and healthcare collaborations. Therefore, ML promotes the development of personalized screening, diagnostics, and interventions that could improve medical decision-making and catalyse the innovation in healthcare. For example, stroke and heart disease risks can be assessed now a days which enables targeted early interventions. This in turn may reduce hospitalizations and improve survival rates. Machine Learning applications are informed medical decision-making, diagnosis, treatment planning, and promising results in screening early Chronic Obstructive Pulmonary Disease (COPD). A major advance in AI is the creation of CAD systems for radiology. These systems analyze chest X-rays and CT scans. They find anomalies that may indicate COPD, lung cancer, or pneumonia. Radiologists use these insights to prioritize cases and expedite the diagnosis process. ML-based tools deliver personalized diagnostics that can deliver personalized diagnostics which can maximise the patient's outcomes and quality of life [29, 30]. Also, AI-driven "digital twins" of patients are being explored. They create a virtual patient replica to simulate disease progression and treatment response. This lets clinicians test multiple treatment strategies in silico. They can do this before applying them to the real patient. Thus, it personalizes healthcare at an unprecedented level. Figure 1 shows the workflow of AI-ML integration in asthma and COPD management.

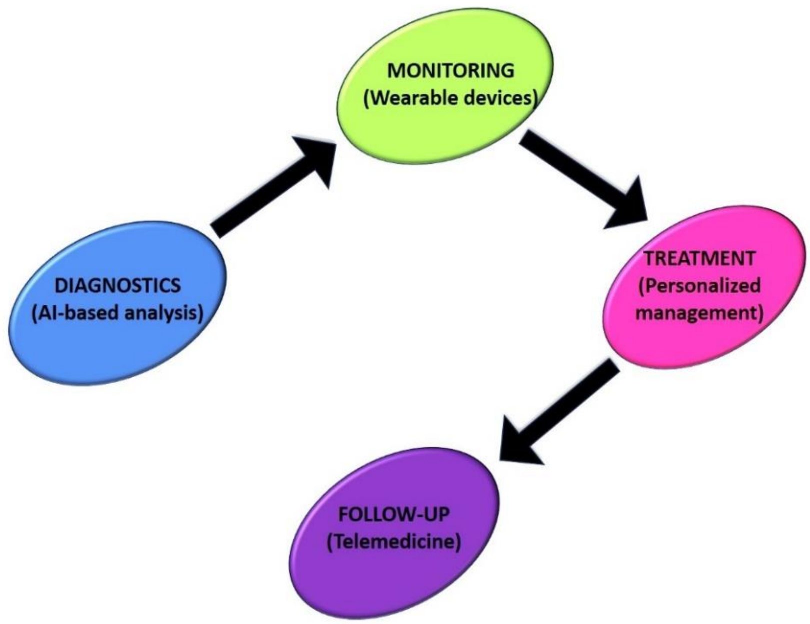

Figure 1.
Workflow for AI-ML integration in asthma and COPD management.

4. Applications of AI and ML (Artificial Intelligence and Machine Learning) in COPD and Asthma Management

Artificial Intelligence (AI) and Machine learning (ML) revolutionise the pathology of asthma and Chronic Obstructive Pulmonary Disease (COPD) through numerous folds in the management of care, starting with diagnostics, to disease monitoring, towards tailored treatment. The technologies are more precise and data-based for the health care provider to intervene better at the right time. Table 1 shows the key applications of AI and ML in COPD and asthma management.

Table 1.
Applications of AI and ML in COPD and asthma management

Application Area	Technology used	Key functions
Electronic Health Records (EHRs)	Natural language processing (NLP)	Extracts clinical information from EHRs, identifies condition patterns, and informs research on disease causes.
Digital health tools	Wearable devices, health apps, smart inhalers	Tracks inhaler use, symptoms, and trigger patterns; enables telehealth communication.
Big data analytics	Machine learning, omics data integration	Identifies disease biomarkers, phenotypes, and personalized treatment strategies.
Telemedicine	Video consultations, remote monitoring	Provides real-time access to specialists, supports remote diagnosis, and facilitates patient-clinician interactions.
Predictive algorithms for COPD exacerbations	ML algorithms, sensor devices, mobile apps	Predicts exacerbations, identifies risk factors, and forecasts disease progression.
Early COPD diagnosis	Deep learning, Image analysis (CT, X-rays)	Identifies structural lung changes from imaging for early diagnosis of COPD.
Pulmonary Function Test (PFT) interpretation	AI-based PFT analysis software	Improves PFT result interpretation, provides accurate diagnostic support.

4.1. Electronic Health Records

Electronic health records have been widely deployed in health care, thus generating massive amounts of real-world data. Techniques of natural language processing represent an AI approach to extract information from clinical narratives in electronic health records. In addition, health records offer the ability to mine for temporal condition patterns that potentially may reveal previous unknown associations between diagnoses and inform research into those potential causes for the future [31, 32]. AI models, trained on vast patient health records, can find early signs of COPD and asthma. Traditional clinical methods may miss these signs. This can lead to earlier and better interventions. Applications of these technologies to the practice of allergy remain in early developmental stages. Electronic health record mining from some studies has reported prevalence of food allergy or drug allergy. An algorithm based on natural language processing was capable of classifying asthma from such records [33, 34].

4.2. Digital Health Tools in Asthma and Allergy Management

Potential applications of wearable devices and personal monitoring tools include asthma and allergies. Asthma apps can collect longitudinal data regarding symptoms and inhaler use to help caregivers track changes over time. It would allow integrating external data - for example, weather, air quality and levels of various allergens, that would provide a broader view about symptom and/or trigger patterns to the patients and their caregivers. This information can be communicated with clinicians through visits at the clinic or telemedicine [35]. Moreover, wearable devices now have advanced AI. They can predict asthma attacks by monitoring real-time physiological changes. This helps in early detection of potential exacerbations.

Further, online health diaries allow patients to record environmental and behavioural variables that may influence asthma and allergy symptoms. For instance, a study in 132 patients and 25,016 diary entries revealed that asthma symptoms were correlated with environmental tobacco smoke exposure, temperature, sleep, and air quality. Adolescents and caregivers expressed interest in using smartphones to track asthma, and app-based spirometers have been validated as providing accurate lung function measurements in the community and may help detect more prompt changes in patients' symptoms [36, 37].

Another application of sensor technology is monitoring how patients use inhalers, by recording timing and frequency patterns. In a pilot study with a 120-patient sensor-activated asthma management platform, the following results were achieved after 30 days: reduced use of short-acting beta-agonist, more symptom-free days, and better asthma control. These inhaler-use tracking systems use AI to find unusual usage patterns. This may indicate worsening symptoms. It enables timely intervention. All these data-driven tools offer a wider picture of symptoms and triggers, thus allowing much easier clinician-patient collaboration and management effectiveness beyond ordinary clinical visits [38, 39].

4.3. Big Data

In allergy and immunology, big data generates large volumes of complex, multidimensional information. One prediction model using big data to assess asthma emergency department visits had good accuracy [40]. Big data can be obtained from genome, transcriptome, epigenome, microbiome, and metabolome studies. Recently, a study protocol for the estimation of the prevalence of severe asthma using big data methods was published. Similarly, there is an increasing need to integrate large cohorts' big data using the approaches of machine learning to identify disease biomarkers and characterize molecular phenotypes/endotypes that define precision medicine approaches. Researchers have analyzed large datasets and developed ML models that can identify new COPD and asthma phenotypes. Traditional methods cannot distinguish these phenotypes. This work opens the door to personalized treatments. Personal health profiles captured by individuals through mHealth technology may add another big data dimension to clinical trials with deeper phenotyping and real-time exposome profiling [41, 42].

4.4. Telemedicine

Telemedicine is fast emerging as the convenient method of accessing medical services across the world. For example, in 2019 alone, a massive health system in the United States-the Cleveland Clinic-concluded 41,000 virtual visits under all medical specialties. In fact, just six months into 2020, the number of virtual visits reached over 500,000 [43]. There are studies that prove telemedicine is similar to in-person visits for the outpatient management of asthma [34]. A study consisting of 169 children with asthma compared disease control and patients' satisfaction after 6 months of in-person visits or telemedicine care and found them to be the same. AI-powered telemedicine platforms use predictive analytics in which patient-reported data are analyze for patterns. This helps clinicians spot changes in disease status which leads to quicker interventions and better health outcomes. There are also surveys that found out that patients and allergists tend to be as satisfied with telemedicine, or even prefer it to in-person visits [44, 45]. Due to the COVID-19 pandemic, telemedicine has now become an important part of daily practice by allergy and immunology clinics worldwide [46]. Telemedicine could be of much help to deliver proper speciality care for allergic conditions in rural communities, where in-person visits are not feasible due to shortage of resources [47]. Even in the USA, where private practice is the most common, there are still quite a few policy barriers, like a fragmented reimbursement system, which challenge the wider spread. AI-driven remote monitoring tools can be beneficial for this. They provide personalized care and timely interventions which could reduce the burden on healthcare infrastructure. In the near future, when combined with device sensor input, electronic health records and big data Artificial Intelligence(AI), telemedicine will likely make transformational changes in how allergy care is delivered [48].

Several research works have been conducted to determine the severity and to predict future exacerbations in patients with Chronic Obstructive Pulmonary Disease(COPD) using Artificial Intelligence(AI) [49, 50]. This is done by feeding data from patients' health record, self-reported symptoms by patients, monitoring certain parameters using sensor-enabled devices, using mobile applications, or computer software.

In one study, the study was conducted on the patients' breath sounds that were recorded daily for a period of 6 months using telemonitoring through sensor devices. These were analyzed with an ML algorithm. It had an accuracy rate of 78% for detection and was able to forecast acute exacerbation of COPD on average 4.4 days in advance of the onset [51]. Another study used the ML algorithm to predict COPD exacerbations among participants in the TelEPOC program. This is a telemedicine program for patients with COPD. The patients provided the TelEPOC database their heart rate, temperature, oxygen saturation, breathing rate, number of steps taken, and a symptom questionnaire daily. Based on these outcomes, scientists established an alarm system in terms of exacerbation, which has three levels: green, yellow, and red that can predict exacerbation in the next 3 days with a curve of 0.87.

Table 2.
Key outcomes of AI and ML in COPD and asthma management.

Area of focus	AI/ML model used	Dataset	Outcome	Accuracy
Asthma Classification (EHRs)	NLP Algorithm	Clinical Narratives from EHRs	Classified asthma from electronic health records.	Not Reported
Asthma Symptom Tracking (Wearables & Apps)	Mobile App Algorithms	Symptom Logs, Trigger Data, Air Quality	Identified symptom-trigger relationships, tracked inhaler use.	Not Reported
Asthma Management (Inhaler Use Monitoring)	Sensor-Activated Platform	Sensor Data from Smart Inhalers	Reduced short-acting beta-agonist use, improved asthma control.	120-Patient Study
Asthma Emergency Prediction	Big Data Model	Large Cohort Studies, Omics Data	Predicted emergency department visits for asthma patients.	High Accuracy
Asthma Telemedicine Care	Video Consultation Tools	Patient Symptoms, Clinician Feedback	Care comparable to in-person visits for asthma; increased access.	No Significant Difference
COPD Exacerbation Prediction	ML Model (TelEPOC)	Vitals (heart rate, O2 sat, steps, symptoms)	Predicted COPD exacerbations 3 days in advance.	AUC = 0.87
COPD Exacerbation Detection	Sensor Data & ML Model	Breath Sounds Recorded Over 6 Months	Detected COPD exacerbation 4.4 days before onset.	78% Accuracy
Early COPD Detection	Graph Convolutional Network (GCN)	CT Images from Danish Lung Cancer Database	Early COPD detection based on lung structure changes.	AUC = 0.81, Accuracy = 77%
Pulmonary Function Test (PFT) Analysis	AI-based PFT Software	PFT Test Results	100% correct pattern recognition, 82% accurate diagnosis.	100% Pattern, 82% Diagnosis

Artificial Intelligence -Machine learning(AI-ML) has recently been used to predict the early acute respiratory failure, ventilator dependency, and mortality of patients with COPD after hospitalization with excellent predictive performance [52]. Table 2 shows the major outcomes of ML and AI in COPD and asthma management.

4.5. Use of AI (Artificial Intelligence) Technology in Early Diagnosis

AI technology is used to analyze some of the early images of COPD, including the lung CT scans and X-ray images. It can accurately pinpoint the changes in the lung structure through deep learning algorithms, which can assist doctors in the early and precise detection of COPD [53]. The imaging omics process primarily involves importing imaging data, delineation of the region of interest using software tools like ITK-SNAP and 3D Slicer, feature extraction of imaging omics, and establishing machine learning models based on the chosen features of imaging omics, which can be logistic regression (LR) model, the support vector machine (SVM) model, the K-nearest neighbour (KNN) algorithm, etc. AI image analysis further boosts diagnosis and tracks disease progression. It helps adjust treatments in time. The performance of the machine learning model is put to the test at last. Example: Li Z et al /ei presented in 2022 an early diagnostic model for COPD using Graph Convolutional Network. It employed chest computed tomography image data based on the Danish Lung Cancer

Screening Trial which is a publicly available database. The GCN model achieved an accuracy of 0.77 and area under the curve of 0.81 [54].

4.5.1. Pulmonary Function Test for Early Diagnosis Of COPD

Pulmonary function testing is an integral part of overall management of Chronic Obstructive Pulmonary Disease (COPD). It is diagnosed for different purposes assessment in regard to the effectiveness of pharmacological and nonpharmacological therapies instituted, as well as in prediction. This is because low pulmonary function is associated with a greater exacerbation and hospitalization frequency and higher mortality risk [55, 56]. It is standardized and commonly used, PFT lends itself well to the development and use of AI for test result interpretation and diagnosis. Topalovic, et al. [57] reported that AI-based software correctly matched PFT pattern interpretations 100% and made proper diagnoses in 82% of cases, whereas PFT pattern recognition by pulmonologists met guidelines in 74.4% and diagnoses were correct in 44.6% of them [57]. In this connection, advanced AI models are being developed that give real-time feedback on pulmonary function test results which in turn allow for immediate adjustments in the treatment of COPD patients.AI can interpret PFT and make diagnoses with better accuracy than one pulmonologist and even approximate a panel of expert practitioners [58]. Nevertheless, these findings should be treated with caution. Since the probabilities of the different AI-generated diagnoses rely on the prevalence of disease in the training data set, real-life scenarios must be considered in building initial training datasets to reflect accurately the prevalence of disease.

5. Limitations of AI/ML (Artificial Intelligence/Machine Learning) in Respiratory Disease Management

5.1. Dependence of High-Quality Data

The importance of Artificial Intelligence (AI) models in healthcare solely depends on the learning data. For respiratory disease management, such as asthma and Chronic Obstructive Pulmonary Disease (COPD), diverse datasets are needed. The onset of the disease, patient responses and symptoms can differ significantly between different demographics. Insufficient data diversity can exacerbate these issues, as under representation in some AI training data could result in incorrect predictions for underrepresented groups. This limitation takes an important position in a condition such as asthma, whereby even with the smallest alterations in prevalence, triggers, or response to treatment, the figures can vary [59]. Therefore, addressing this gap through better data collection and inclusion of diverse patient cohorts is essential.

5.2. Ethical Concerns of Data Privacy

Patient privacy must be protected since Artificial Intelligence (AI) depends on accessing and analyzing personal health data, like patient medical history, complaints, and other demographic information. Data privacy issues are critical for the maintenance of patient trust and alignment with legal standards. The aspect is particularly important because health data is very sensitive; it must be treated with caution and ensured through advanced encryption methods and transparent data-sharing protocols. The adoption of "privacy-by-design" approaches is crucial, as AI applications in respiratory care might be engaged in ethical and legal battles if not checked [60].

5.3. Artificial Intelligence (AI) Tools in Healthcare

Quality and diversity of training data, along with ethical challenges are the major areas of focus for limitations of AI tools in healthcare. Biases and inaccuracies due to inadequate representation of diverse demographics or medical conditions in the datasets can be the reasons which would hamper the applicability of the tool across diverse populations and healthcare systems [49]. For instance, in certain management systems, AI tools might lead to a lower generalizability, further limiting their utility in diverse settings. Ethical concerns range from data privacy, bias in algorithms, and health inequities, in that order. Since bias can affect nearly every stage of the AI development process-from data collection to implementation-it can harm particular social groups while also breaching health equity. This is crucial. Health data is very sensitive. It must be treated with caution. It must use advanced encryption and clear data-sharing protocols. "Privacy-by-design" approaches are vital. AI in respiratory care may face ethical and legal issues if unchecked. Data regulation is becoming necessary to ensure ownership, as well as access and sharing, of data and mitigate risks associated with bias and inequality in healthcare technology.

6. Recommendations and Future Prospectives

Some recommendations for improving AI and ML applications in the management of COPD and asthma are based on this review of AI and ML applications. That is, healthcare institutions must prioritize the combination of AI-driven tools in clinical workflows. This involves infrastructure and training the clinicians to interpret the AI-generated data. Establishing an interdisciplinary team that consists of data scientists, clinicians, and IT specialists can help quickly adopt this technology. Also, there is a need to standardize the protocols for the collection and analysis of data. Future studies must aim to create and use large, diverse, and high-quality datasets that have various demographics and clinical settings. These efforts can help in reducing the bias and improve the generalizability of AI models. Additionally, ethical and regulatory frameworks must be increased to protect patient data privacy and ensure equitable access to AI-driven healthcare. Adopting privacy-by-design approaches and advanced encryption methods will be necessary for the maintenance of patient trust. Regulatory bodies should work collaboratively with technology developers to establish clear guidelines that can address data security, algorithmic bias, and ethical considerations. Furthermore, there is significant potential for increasing telemedicine services combined with AI-powered remote monitoring tools. Investments in telehealth platforms in under-resourced or rural areas can help in bridging the gap in healthcare accessibility. Future research should also focus on evaluating the cost-effectiveness of these technologies in diverse healthcare systems. By addressing these recommendations, stakeholders can increase the integration of AI and ML into respiratory care. This will lead to improved outcomes for patients with asthma and COPD, along with a more efficient, personalized, and equitable healthcare system.

Future research directions for COPD management include the validation of models using large, real-world datasets and continuous monitoring in a clinical setting to overcome the limitations such as single-source populations and lack of external validation. There is also an urgent need to identify phenotype-specific therapeutic strategies since existing phenotype classification is inadequate for tailored therapy. Artificial Intelligence /Machine learning (AI/ML) may help in exploiting the phenotypic heterogeneity by aggregating diverse sources of data. Combining wearable health monitors with AI may improve personalized treatment. These will require balanced efforts to take AI/ML applications in enhancing inhalation therapy compliance, particularly through error detection at an early stage and personal interventions [24]. Further AI/ML research should be dispersed into the low-income settings to enhance the morbidity of high financial burdens and data integrity in the under-resourced health systems. Further, ensuring equitable access to AI/ML-driven healthcare system and training healthcare staff in resource-limited areas can provide better individualized treatment and management for those affected by COPD worldwide.

7. Conclusion

Artificial intelligence and machine learning has an entire new dimension for the management of asthma and Chronic Obstructive Pulmonary Disease (COPD) by applying acutely accurate diagnostics, continuous monitoring, and individualized approaches to treatment. These technologies combine data from multiple sources for comprehensive analysis of wearable devices, electronic health records and imaging data to improve patients' clinical decisions and outcomes. Although much success has been achieved so far, challenges still prevail such as the robust validation of models outside of training data, improving data quality, and adaptation to a wide range of population. Future studies should explore phenotype-specific treatment, better compliance with drugs, and continuation of AI/ML interventions into the regions with limited access. Although AI/ML have many promising applications in transforming respiratory care with novel solutions for a heavy burden on chronic airway diseases worldwide, they come with their limitations.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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