Machine Learning–Driven Prediction of Asthma Exacerbations: A Step Forward Toward Personalized Care — A Narrative Review

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Abstract

Asthma exacerbations present a major difficulty in asthma management, necessitating the development of effective strategies for timely intervention and prevention. This study examined recent advances and knowledge regarding using machine learning (ML) methods to predict asthma exacerbation in different populations. Through a thorough analysis of existing literature, the study investigates various ML methods, including specific risk factors and biomarkers, and their potential impact on clinical practice. Recent studies have shown that ML can effectively predict exacerbation by utilizing patient demographics, clinical characteristics, environmental factors, and biomarkers. Innovative approaches for extracting distinctive features, ensemble learning techniques, and personalized, predictive models have emerged as potential options for early prognosis and customized treatments. Environmental factors significantly influence exacerbation prediction, emphasizing the importance of incorporating diverse datasets and environmental exposures. While challenges exist in acquiring data, interpreting models, and validating results, ML methods offer valuable tools to improve asthma treatment and enhance patient outcomes. Future advancements in the field will focus on integrating various data types, developing personalized predictive models, and improving model interpretability to integrate them into the clinical workflow seamlessly. By employing proactive, personalized, and data-driven management techniques that cater to each patient's unique needs and align with population health goals, ML has the potential to revolutionize asthma care.

Keywords: *Asthma exacerbation, Asthma Management, Healthcare Systems, Machine learning, Personalized, Prediction models.*

1. Introduction

Asthma exacerbation, characterized by sudden symptom deterioration, presents significant challenges to asthma management, impacting individuals across all age groups and contributing to substantial global morbidity and mortality [1]. These acute episodes, often triggered by allergens, viral infections, and environmental pollutants, can lead to severe respiratory distress requiring immediate medical intervention [2]. Despite advancements in asthma treatments, predicting exacerbations remains complex due to their unpredictable nature and occurrence, even in well-controlled asthma cases [3]. Therefore, to avoid catastrophic outcomes, proactive strategies are desperately needed to identify high-risk patients and carry out prompt interventions [4].

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Machine learning (ML) approaches have drawn interest recently due to their potential for predictive analytics in the treatment of asthma. ML methods offer a promising approach to utilizing the extensive data available in healthcare systems, including patient demographics, clinical characteristics, environmental factors, and biomarkers, to develop robust prediction models [5]. By leveraging modern algorithms and computational techniques, these models can identify patterns and correlations within the data, enabling accurate prediction of asthma exacerbation before it occurs [6], [7]. This proactive strategy has the potential to revolutionize asthma care by facilitating early interventions, optimizing treatment plans, and improving patient outcomes [8].

This study explored recent insights and advancements in using ML approaches to predict asthma exacerbation across diverse populations. The research focuses on integrating findings from existing studies to highlight the potential of ML in enhancing asthma outcomes and promoting personalized treatment strategies. By examining various ML algorithms, incorporating individual risk factors and biomarkers, and assessing the clinical implications, this study provides valuable insights into the role of predictive modeling in addressing the challenge of asthma exacerbation. Ultimately, by harnessing ML capabilities, the research equipped healthcare providers with the tools and knowledge necessary for proactive asthma management, thereby improving the quality of life for individuals with this chronic respiratory condition.

The rest of the paper is organized as follows: Section II summarizes prior research. Section III highlights the outcomes of recent studies. Section IV examines the findings. Section V concludes the paper by summarizing the key insights and suggesting directions for future research.

2. Related Works

Asthma exacerbation signifies a sudden worsening of asthma symptoms, resulting in reduced lung function and greater difficulty in breathing [9]. They are defined by symptoms such as difficulty breathing, wheezing, tightness in the chest, and shortness of breath, which may vary from benign to serious and dangerous [10]. Exacerbation often results from the relationship between a person's genes and external variables, airborne pollutants, respiratory illnesses, weather changes, exercise, and particular drugs [11]. These factors may contribute to inflammation of the airway walls, bronchoconstriction, and increased mucus production, eventually causing airways to shrink and making breathing more difficult [12], [13].

The impact of asthma exacerbation on individuals can be severe, reducing their quality of life, everyday activities, and productivity [14]. Severe exacerbation may demand emergency medical attention, hospitalization, or even admission to the critical care unit [15]. Asthmatic individuals may experience lost school or workdays, social disruption, psychological discomfort, financial strain from healthcare bills, and loss of income [16]. Recurrent exacerbation can cause progressive lung function loss, higher future exacerbation risk, and potentially life-threatening outcomes like respiratory failure or death [17]. Asthma exacerbation places a significant burden on healthcare resources, costs, and facilities [18], leading to increased emergency visits, hospital admissions, and healthcare contacts, further straining healthcare workers [19].

The management of exacerbation needs immediate intervention with bronchodilators, corticosteroids, oxygen therapy, and sometimes mechanical ventilation, coupled with patient education and follow-up care to prevent recurrence [17]. Preventive interventions, such as consistent use of controller drugs, allergy avoidance, and individualized asthma action plans, are critical for minimizing the frequency and severity of exacerbations and optimizing long-term asthma management [20], [21]. Successful asthma exacerbation management requires a multidisciplinary approach, involving healthcare providers, patients, caregivers, public health, and community resources to minimize impact. ML and prediction models are vital for proactive management, as they identify exacerbation risks early and provide personalized interventions.

Asthma prediction models are necessary to lower the burden of exacerbation through the identification of patients with a high rate of asthma attacks and provide prophylactic therapy. These models utilize various data sources, including clinical parameters, environmental factors, genetic data, and biomarkers, to forecast the probability of asthma exacerbation [22], [23]. Recent ML approach breakthroughs have drastically increased the prediction model's accuracy and reliability. Many ML algorithms, such as Ensemble ML, Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (TR), Random Forest (RF), Artificial Neural Networks (ANN), and gradient-boosting machines (GBM), Affinity Graph Enhanced Classifier (AGEC), Naïve Bayes (NB), adaptive Bayesian network (ABN), Transfer Learning (TR), Deep Learning (DL), K-nearest Neighbors (KNN), Feedforward Deep Neural Network (FDNN), XGBoost, Recurrent Neural Network (RNN), Long Short-Term Memory model (LSTM) and Proximal Policy Optimization (PPO) have successfully uncovered complex patterns in asthma-related data and correctly predicted exacerbation events [20], [24], [25], [26], [27]. Additionally, personalized predictive models tailored to individual patient characteristics, including genetic predisposition, comorbidities, and environmental exposures, have emerged as promising approaches to enhance prediction accuracy and optimize asthma management strategies [28]. By incorporating real-time monitoring data, such as sensor measurements and electronic health records, these models can offer prompt alerts and tailored recommendations to patients and healthcare providers [29]. This enables early intervention and preventive measures to lower the frequency and intensity of asthma exacerbations [30].

3. Methodology

This review was conducted to synthesize the rapidly evolving landscape of ML applications for asthma exacerbation prediction. A systematic approach was adopted to ensure a comprehensive and unbiased analysis of the literature, despite the review being narrative in nature. The methodology comprised four distinct stages, as illustrated in Figure 1, designed to identify, evaluate, and synthesize relevant knowledge. The process began with a preliminary study to define the scope and research questions, followed by a screening process to apply inclusion and exclusion criteria. The subsequent eligibility and quality assessment phase refined the selection, culminating in the data extraction and compilation stage, where core findings on ML models, data sources, and challenges were synthesized to address the review's objectives.

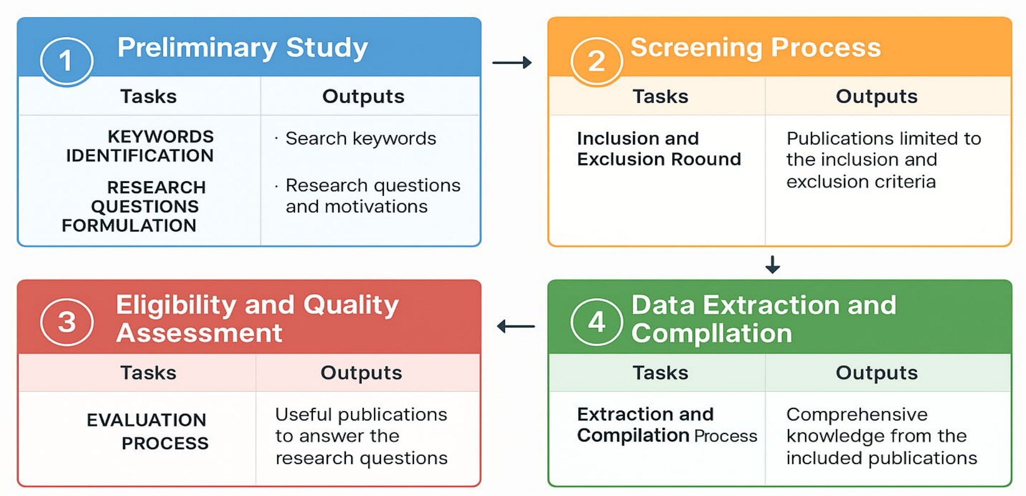

Figure 1. Workflow of the narrative review process

4. Results and Discussion

Recent research on ML methods for predicting asthma exacerbation offers valuable insights into enhancing asthma management and care, encompassing various approaches and datasets. A study [31] developed machine learning models to predict exacerbations within six months post-discontinuation. In a cohort of 3057 individuals, the gradient boosting machine had the highest predictive accuracy with an AUC of 0.76 in development and 0.74 in validation. A study in [32] proposed an RL-based approach for asthma exacerbation prediction. Another study [33] introduced the Weighted Feature Averaging Technique (WFAT) for feature extraction, producing an ensemble ML model with good classification accuracy for early asthma prognosis.

Another significant study by [34] established the AGEC, which improves predictive accuracy by identifying correlations between samples in a clinical dataset. Additionally, [35] applied ANN to predict temporal risk zones of respiratory disorders, revealing that environmental and infrastructural factors significantly impact respiratory attacks. In the field of chronic obstructive pulmonary disease (COPD), [36] created effective ML models for predicting first-time acute exacerbation of COPD (AECOPD) using GBM and SVM. Personalized healthcare therapies are further advanced by [37], who developed an improved Adam-based FDNN model for personalized asthma predictions.

Moreover, [38] also developed an XGBoost model for asthma diagnosis, stressing the need for accurate operational definitions of asthma in clinical settings. Another study by [39]. A variety of ML approaches were used to investigate the connection between peak expiratory flow rate and exposure to indoor air quality. These studies highlight the substantial impact of ML methods in managing asthma through enhanced prediction and risk assessment, even though they face limitations like small sample sizes, biases in datasets, and the requirement for external validation. Table 1 summarizes these results, illustrating the encouraging outcomes of recent research using ML algorithms to forecast asthma exacerbation. Multiple studies have improved prediction precision, considered environmental influences, and created customized prediction models, aiding in better asthma care management and early intervention strategies.

Table 1. Summary of studies on predictive models for asthma exacerbation

Studies	Algorithms employed	Key predictors	Dataset	Main contribution	Key limitation
[40]	ML classifiers	Comorbidities; prior exacerbations	EHR + national registers (n=29396)	Predict flare-ups from routine clinical data	No environment / wearables; weaker short-term
[31]	Elastic-net; RF; GBM	Demographics ; clinical; regional	OptumLabs (n=3057)	Predict exacerbations after biologic stop	Moderate accuracy; limited biomarkers; no external
[41]	LR; Naive Bayes	Inhaler use; symptoms; adherence	AMHS mHealth dataset	Early warning for control loss	No peak flow; mHealth-only; generalizability
[42]	LR; DT; NB; Perceptron	Daily PEFR; symptom scores	SAKURA daily records (n=728535)	Early severe exacerbation detection	Single cohort; selection bias; no external
[43]	NR	NR	UWM adult asthma records	Assessed model generalizability for hospital visits	Algorithms NR; single site; no external
[44]	NB; ABN; SVM	Daily self-logs	Home monitoring (n=7001 records)	Personalized exacerbation prediction from telemonitoring	Adult cohort; no external validation
[45]	DT; LR; RF	Severity; weather; flu patterns	2 urban pediatric EDs (age 2–18)	Hospitalization prediction; weather adds value	Retrospective; confounding; limited generalizability
[46]	LSTM	PEFR; indoor PM	Pediatric PEFR + PM dataset	LSTM outperforms multinomial LR	Small sample; region-specific; no external
[37]	FDNN	NR	NR	Improved Adam-FDNN for personalized prediction	Dataset NR; asthma-only scope
[39]	TL + imbalance handling	Indoor air quality; PEFR	NR	Improved IAQ–PEFR prediction under imbalance	Limited variables; prediction-only
[47]	Various ML	Asthma attack factors	OPCRD primary care (2016–2018)	Prognostic tool concept; compare ML vs LR	Detail limited Algorithm: cohort constraints
[48]	GLMM	Sleep efficiency; wake counts; FEV1	43 working-aged women	Predict daily outcomes using wearables	Small sample; women-only; no external
[49]	DREAM-POLL model	Thunderstorm conditions; pollen/SPP	S. Australia seasons (2010, 2016)	Forecast thunderstorm asthma outbreaks	Region-years limited; no external

4.1 Diverse ML Approaches for Predicting Asthma Exacerbation

The studies utilized various ML algorithms to predict asthma exacerbation and enhance asthma management. Some of the algorithms deployed include:

a. Ensemble ML: Ensemble ML techniques have become a cornerstone in predictive modeling, offering substantial improvements in accuracy and robustness compared to individual models. These techniques leverage the strengths of multiple learning algorithms to produce a superior predictive performance. Combining the predictions of many base estimators to lower variance (bagging), bias (boosting), or enhance predictions by training a meta-model (stacking) is the fundamental concept underpinning ensemble methods. Combining the predictions of many base estimators to lower variance (bagging), bias (boosting), or enhance predictions by training a meta-model (stacking) is the fundamental concept underpinning ensemble methods [50].
b. AGEC: AGEC can be highly effective in asthma exacerbation prediction models by leveraging affinity graphs to encode relationships between patient data points. In these models, affinity graphs represent instances (patient records) as nodes, with edges indicating the similarity or affinity between them based on factors like demographic information, medical history, environmental factors, and recent symptoms. AGEC improves the classification process by incorporating contextual information derived from the connections among data points, enhancing prediction accuracy [51].
c. ANNs: In the area of asthma exacerbation prediction models, ANNs have demonstrated a great deal of potential. To enable prompt intervention and asthma care, these models attempt to forecast the probability of an asthma attack [52]. The input layer, hidden layer, and outcome are the usual components of the architecture of ANN models employed in asthma exacerbation prediction. The input layer receives various features relevant to asthma prediction, including patient demographics, medical history, environmental factors (like air quality and weather conditions), medication usage, and physiological data (such as lung function measurements and symptom scores) [53].
d. GBM and SVM: GBM and SVM are two prominent supervised learning methods extensively used in ML for regression and classification tasks. Both methods have distinct mechanisms for learning from data and have shown considerable success across various domains, including asthma exacerbation prediction models. This section explores the principles, mechanisms, and applications of GBM and SVM in the context of predicting asthma exacerbation [54].
e. FDNN: FDNN represents a foundational architecture in the realm of ANNs, characterized by the unidirectional flow of information from input to output layers. This architecture can be effectively applied to asthma exacerbation prediction models, offering the potential for improved accuracy and robustness in predicting exacerbation events [37].
f. XGBoost: XGBoost, or eXtreme Gradient Boosting, represents a significant advancement in the implementation of gradient boosting techniques, specifically optimized for computational efficiency and predictive performance. This powerful tool can be effectively applied to asthma exacerbation prediction models, offering enhanced accuracy and efficiency in predicting exacerbation events [38].
g. TL with imbalanced sampling: TL with imbalanced sampling is a pivotal method in ML where knowledge acquired from one task is utilized to enhance performance on a related, often more complex task. This method is particularly advantageous for predicting asthma exacerbation, where datasets are often imbalanced with a minority of exacerbation events. Integrating imbalanced

sampling techniques further optimizes this approach, making it highly effective for healthcare applications [39].

h. LSTM: LSTM models are a specialized type of RNN designed to capture long-term dependencies in sequential data. They are particularly suited for predicting asthma exacerbation because they can handle time-series data and retain long-term information [45].
i. RF: RF is an ensemble learning method combining multiple DTs to improve predictive models' accuracy, robustness, and generalization ability. This literature review elaborates on the principles, mechanisms, advantages, and applications of RFs, emphasizing their contributions to asthma exacerbation prediction [55].
j. LR: LR is a fundamental statistical model used for binary classification tasks, predicting the probability of a binary outcome based on one or more predictor variables. This literature review explores the principles, applications, advantages, and contributions of LR, with a focus on studies highlighted by [40] and [42]

ML algorithms such as LR, employed notably in studies [40] and [42], serve as foundational tools in predicting asthma exacerbation and related outcomes. These algorithms vary in complexity and applicability but share a common objective: leveraging data patterns to make reliable predictions crucial for asthma management. The research draws insights from diverse data sources including clinical databases, electronic health records, environmental monitoring data, and patient-reported information, among others, to construct predictive models. While navigating these challenges, the studies underscore the potential of integrating multiple data sources to predict asthma exacerbation effectively. Continued research and development in this field hold promise for advancing patient outcomes through more accurate and personalized asthma management strategies.

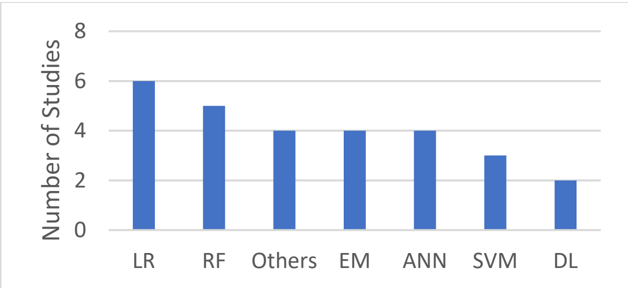

Figure 2. Diverse ML techniques for predicting asthma exacerbation

The presented chart in Figure 2 illustrates the distribution of ML algorithms utilized in asthma exacerbation prediction studies, reflecting a comprehensive analysis of methodological approaches in the field. LR emerges as the most frequently employed algorithm, underscoring its established utility in binary classification tasks inherent to asthma risk assessment. RF and SVM algorithms also feature prominently, highlighting their effectiveness in handling complex datasets and diverse biomarkers. The inclusion of ensemble methods and advanced techniques such as ANNs and DL, including LSTM models, reflects ongoing efforts to enhance predictive accuracy and model robustness in asthma management. This visual representation not only identifies common methodologies, but it also highlights the breadth and sophistication of approaches used to leverage clinical and epidemiological data for better patient outcomes.

4.2 Diverse Data Sources for ML Models in Predicting Asthma Exacerbation

The studies utilized diverse data sources to create and verify their ML models for predicting asthma exacerbation. Some of the data sources employed include:

a. Clinical datasets: Studies such as [34], [36] utilized clinical datasets containing patient information acquired from hospitals, clinics, or electronic health records (EHRs). These datasets typically comprise demographic information, medical history, symptoms, laboratory test results, and other clinical characteristics important to asthma exacerbation prediction. However, the study did not provide detailed information about the diversity and size of these datasets. This lack of information raises concerns about the potential for bias if the datasets are not sufficiently representative of different populations. For example, if the clinical datasets are predominantly from a single geographical region or demographic group, the models trained on these datasets may not perform well when applied to more diverse populations. This limitation can affect the generalizability and robustness of the models across various demographic groups and geographical regions. Future work should aim to use more diverse and comprehensive datasets to enhance the models' applicability and ensure they are representative of a broader spectrum of the population.

b. Primary care databases: A study by [56] utilized primary care databases, such as the OPCRD. These databases contain longitudinal patient data collected from primary care practices, including information on diagnosis, prescriptions, consultations, and health outcomes. While primary care databases offer a rich source of real-world data, the study did not provide detailed information about the diversity and representativeness of the datasets used. If the primary care data is skewed towards certain demographic groups or regions, it could lead to biased models that do not generalize well to other populations. Future research should use primary care databases encompassing a wide range of demographic groups and geographical regions to develop more robust and generalizable models.

c. Environmental and geographical datasets: Studies like [35] and [55] focused on specific regions such as Tehran, Iran, and incorporated environmental factors into their models. While these studies provide valuable insights into region-specific factors influencing asthma, they are limited in their geographical scope. The reliance on data from a single location may not account for environmental variations in other regions, thus limiting the generalizability of the findings. Expanding the geographical scope of datasets in future research can help build more universally applicable models.

d. Retrospective and specialized datasets: Several studies, including [36], [37], [38] and [45], used retrospective datasets from specialized sources, such as hospitals specializing in pulmonary diseases or datasets focused on specific age groups (pediatric patients). While these datasets are useful for understanding specific aspects of asthma in defined populations, they may not capture the full spectrum of asthma presentations in the general population. The limited sample sizes and specialized nature of these datasets can introduce biases, making it challenging to generalize the findings to broader populations. Future research should consider integrating data from multiple sources and include more varied patient populations to improve the generalizability of the results.

e. Mobile health (mHealth) and telemonitoring datasets: Studies like [41] and [44] utilized data from mHealth platforms and telemonitoring systems. These datasets often include self-reported symptoms, medication usage, and daily monitoring records. While these data sources offer the advantage of continuous monitoring and real-time data collection, they may be subject to self-reporting biases and limited to individuals who have access to and are comfortable using mobile technology. To mitigate these biases, future studies should ensure the inclusion of diverse populations with varying levels of technology access and health literacy.
f. Children-specific datasets: Research such as [57] and [45] focused on pediatric populations, providing important insights into asthma management in children. However, the findings from these studies may not be directly applicable to adult populations. Ensuring that future datasets cover a broader age range can help create models that are applicable across different age groups.
g. Wearable device data: The study by [44] exploited data from fitness tracker sleep devices to evaluate sleep patterns and quality in asthma patients. These datasets include information on sleep duration, efficiency, disruptions, and other sleep-related variables that may relate to asthma exacerbation. However, the study did not detail the diversity and size of the datasets, which presents a risk of bias if the data is not representative of different populations. For example, wearable device users may belong to specific demographic groups with higher socioeconomic status, potentially leading to models that do not generalize well to other populations. Future research should include a more diverse range of participants using wearable devices to ensure that the findings are applicable across various demographic groups and can effectively inform asthma management strategies.
h. Spectrum data: Study [58] exploited the spectrum data collected from Raman spectroscopy of blood sera samples from people living with asthma and healthy controls. These datasets contain information on the spectrum variations associated with distinct biological components, which can be utilized to differentiate between asthma patients and healthy persons. However, the study's limited sample size and lack of external validation raise concerns about the representativeness of the findings. Future work should include larger and more diverse sample sizes to improve the generalizability of the models developed using spectrum data.
i. Spatial databases: Study [49] employed spatial databases containing geographical and environmental data to forecast asthma exacerbation triggered by thunderstorm conditions. These databases include information on pollen counts, meteorological conditions, topography, land use, and other spatial characteristics related to asthma risk. While these datasets provide valuable insights into the environmental triggers of asthma, their applicability may be limited to the specific regions studied. Future research should incorporate spatial data from multiple regions with diverse environmental conditions to enhance the generalizability of the models and improve the prediction of asthma exacerbation in different geographical contexts. By addressing these limitations and incorporating diverse and comprehensive datasets, future research can develop more robust and generalizable models for asthma exacerbation prediction. This approach will enhance the applicability of the models across various demographic groups and geographical regions, ultimately improving asthma

management and patient outcomes. Figure 3 illustrates the different data sources utilized for asthma exacerbation prediction models.

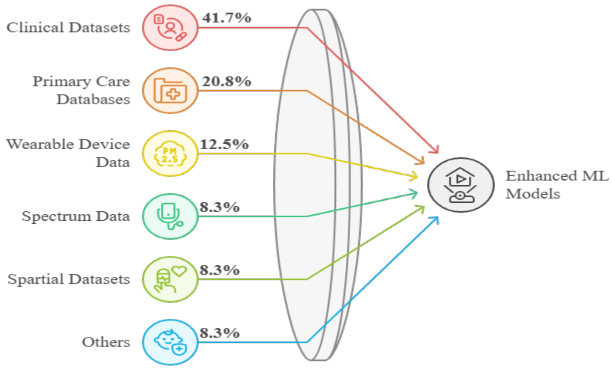

Figure 3. Diverse data sources for ML models in predicting asthma exacerbation

4.3 Key Risk Factors and Biomarkers in Predicting Asthma Exacerbation

The research included several risk factors and biomarkers important to asthma exacerbation prediction. These parameters and biomarkers provide vital insights into asthma exacerbation's underlying mechanisms and triggers. Some of the often-utilized risk factors and biomarkers are:

a. Symptoms: Symptoms such as wheezing, coughing, shortness of breath, chest tightness, and nocturnal awakening are major signs of asthma exacerbation. Studies like [38], [45] included symptom data in their predictive models to discover patterns suggesting exacerbation. By tracking these symptoms, the models can identify early warning signs of asthma attacks and provide timely interventions. However, the study did not provide detailed information about the diversity and size of these symptom datasets, raising concerns about potential biases if the data is not representative of different populations. Future work should incorporate diverse symptom data from various demographic groups to improve model generalizability.

b. Environmental variables: Environmental factors play a crucial role in initiating asthma exacerbation. These include air pollution, allergens (such as pollen, and dust mites), meteorological conditions (such as temperature, humidity, rainfall), and indoor air quality. Studies such as [35], [49] investigated environmental elements in their analysis to determine their impact on asthma exacerbation risk. While these studies provide valuable insights into region-specific environmental triggers, their findings may not be generalizable to other regions with different environmental conditions. Future research should include environmental data from multiple regions and diverse environmental conditions to enhance the robustness and applicability of the models.

c. Clinical and epidemiological aspects: Clinical factors such as comorbidities, past exacerbation, medication adherence, and healthcare utilization history are major predictors of asthma exacerbation. Studies such as [40], [41] included clinical and epidemiological data in their predictive models to examine their predictive value. These datasets typically include detailed patient histories that are crucial for accurate risk prediction. However, the study did not provide detailed information about the diversity and representativeness of these datasets. Ensuring a broad range of clinical data from diverse populations is essential to developing models that are applicable across different demographic groups and healthcare settings [59].

d. Biological indicators: Biological markers, including blood markers, inflammatory markers, and genetic markers, can provide insights into the inflammatory processes and immunological responses driving asthma exacerbation. Studies such as [57], [58] utilized biomarkers such as blood basophil count, immunoglobulin E (IgE) levels, and Raman spectral changes to predict asthma exacerbation and treatment outcomes. These biological indicators are crucial for understanding the underlying mechanisms of asthma and improving prediction accuracy. However, the study's limited sample size and lack of external validation present challenges to generalizing the findings. Future research should incorporate larger and more diverse samples to validate and enhance the predictive power of biological markers.
e. Lung function testing: Lung function tests, such as spirometry and peak expiratory flow rate (PEFR) measures, are routinely used to assess airway blockage and monitor asthma control. Studies such as [42], [58] combined spirometry data and PEFR measurements into their predictive models to assess daily disease control and detect early indicators of exacerbation. These tests provide objective measures of lung function and are integral to asthma management. However, the study did not detail the diversity and size of the lung function test datasets. Future work should include diverse populations to ensure the models are applicable across different age groups, ethnicities, and geographic regions [60].
f. Demographic factors: Demographic factors such as age, sex, race, socioeconomic class, and geographical location may affect asthma exacerbation severity. Studies such as [27], [46] included demographic data in their analysis to identify population-specific risk variables and customize interventions accordingly. Demographic data is crucial for understanding how asthma affects different population groups and for developing targeted interventions [32]. However, the study did not provide detailed information on the representativeness of the demographic data used. Future research should ensure the inclusion of a wide range of demographic variables to create more equitable and effective predictive models. These risk factors and biomarkers give essential information for constructing reliable predicting models of asthma exacerbation and enhancing asthma management techniques. Integrating numerous data sources and incorporating a wide variety of risk factors and biomarkers might boost the predicted accuracy of ML models and facilitate individualized asthma management. Figure 4 illustrates the different risk factors and biomarkers utilized for asthma exacerbation prediction models.

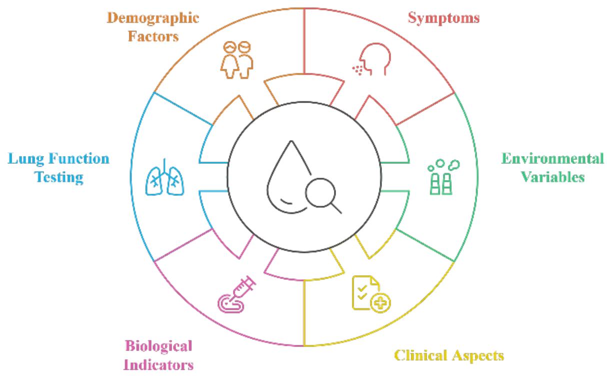

Figure 4. Risk factors and biomarkers for ML models in asthma prediction

4.4 Study Characteristics

The following Figures 5-7 provide useful insights into several aspects of ML algorithms for predicting asthma exacerbation, bringing recent insights into this area of research. As the prevalence of asthma continues to rise globally, accurate prediction models are necessary for successful management and intervention tactics. The figures give insight into essential variables such as regional distribution, publishing trends, journal distribution, and the frequency of personalized methods within the discipline. By reviewing these tables collectively, researchers and practitioners can gain a thorough picture of recent breakthroughs and trends in ML applications for predicting asthma exacerbation.

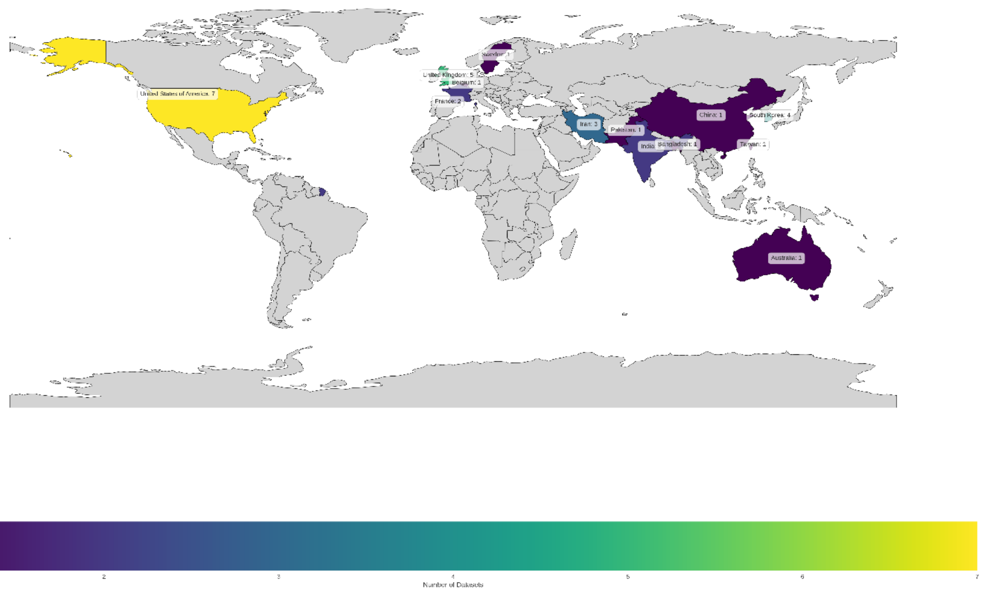

Figure 5. Global distribution in ML approaches for asthma exacerbation prediction: A country-wise overview

Figure 5, exhibiting the geographical distribution of studies linked to optimization strategies for predicting asthma exacerbation, presents a thorough snapshot of the global environment in this research subject. It illustrates the widespread interest and engagement of several countries in harnessing ML technologies to address asthma exacerbations. Countries like the United States, the UK, and South Korea emerged as prominent contributors, indicating their extensive research infrastructures and competence in asthma care and computational approaches. Additionally, nations like India, Iran, and Pakistan emphasize the widening reach of research efforts, demonstrating a growing awareness and interest in resolving asthma exacerbation with advanced computational methodologies.

Moreover, instances of collaboration efforts between countries, as indicated by mentions like "USA and South Korea" and "France and the UK", underline the collaborative and multidisciplinary nature of research in this domain. Such collaborations stimulate knowledge exchange and facilitate the creation of more robust and generalizable predictive models. Overall, the chart gives significant insights into the global distribution of research attempts targeted at predicting asthma exacerbation, stressing the necessity of international collaboration and the collaborative effort towards improving asthma management worldwide.

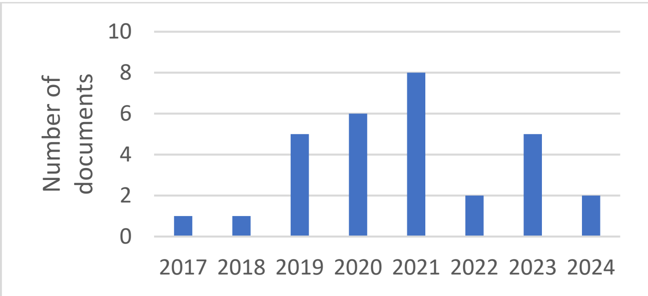

Figure 6. Publication trends in ML approaches for predicting asthma exacerbation (2014-2024)

Figure 6 illustrates the publishing patterns in ML algorithms for predicting asthma exacerbation, delivering useful insights into the temporal distribution of research activity within this discipline. Notably, the years 2020 and 2021 stand out with the highest frequencies of publishing, recording six and eight times, respectively. These peaks in publishing activity reflect substantial periods of heightened interest and research production, possibly indicating notable improvements or greater attention to predictive modeling for asthma exacerbation during those years. Additionally, the persistent presence of papers throughout many years, including 2019 and 2023, suggests a sustained commitment to studying ML techniques for asthma prediction. The table's data underlines the dynamic nature of research in this domain, demonstrating trends and patterns in publication frequency that offer useful insights into the growing landscape of predictive modeling for asthma exacerbation.

The distribution of publications across multiple journals offers important insights into the dissemination of research findings in the field of ML algorithms for asthma exacerbation prediction. It also gives an overview of the intellectual landscape and the channels used to disseminate new ideas. Notably, a varied array of periodicals is featured in the chart, indicating the interdisciplinary nature of the subject area. Journals such as "PloS One", "BMJ Open", and "IEEE Access" feature several publications, showing their popularity as outlets for research dissemination in this sector. This implies a wide-ranging interest and engagement with the topic from researchers and practitioners across multiple disciplines. Furthermore, the inclusion of specialty journals like "Journal of Translational Medicine", "Environmental

Monitoring and Assessment", and "Journal of Personalized Medicine" highlights the unique focus areas within the field.

These journals focus on specialist subjects linked to translational medicine, environmental monitoring, and personalized healthcare, showcasing the variety of research undertaken in asthma exacerbation prediction. The chart demonstrates the dynamic and diversified character of research in ML techniques for forecasting asthma exacerbation. It highlights the variety of publications utilized to communicate fresh discoveries and stresses the collaborative and multidisciplinary efforts that drive progress in the discipline.

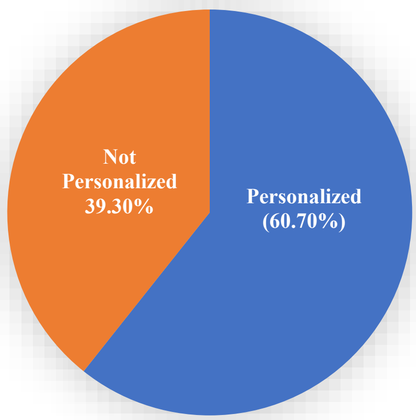

Figure 7 Summary of personalization in asthma exacerbation prediction models

Figure 7 analyses the frequency of tailored techniques within the study. The study demonstrates that 61% of the tactics deployed were individualized, while 39% were not. This discovery recommends a substantial effort to adapt predictive models for asthma exacerbation to specific patient features. The popularity of personalized methods emphasizes the continued inquiry by researchers into tailored therapies and forecasts, underscoring the importance of individualized approaches in boosting the accuracy and effectiveness of asthma management tactics.

4.5 Challenges, Opportunities, and Future Directions in ML-Based Asthma Exacerbation Prediction

Predictive modeling for asthma exacerbation presents both methodological challenges and clinical opportunities. As summarized in Table 1, asthma exacerbation is influenced by diverse and complex risk factors, including clinical indicators, environmental exposures, biomarkers, demographic characteristics, spatial conditions, and temporal patterns. This creates challenges in data integration, feature selection, and multicollinearity management, especially when datasets differ in size, quality, representativeness, and format. In addition, many existing models face limitations related to interpretability, external validation, and generalizability across different patient populations and healthcare settings. These issues are particularly important in clinical contexts where transparent and reliable decision-making is required.

Despite these challenges, ML offers strong potential to improve asthma care through early risk prediction, personalized intervention, real-time monitoring, and better resource allocation. Figure 8 illustrates a machine learning-driven framework for asthma exacerbation prediction, where multi-modal data sources such as demographic, clinical, biomarker, environmental, spatial, and temporal data are processed through data analysis, feature engineering, feature selection, and model development stages to generate predictive outputs. The framework also highlights key future directions, including personalized predictive models, improved integration of heterogeneous data, interpretable and transparent algorithms, rigorous external validation, real-time decision support, and integration into clinical workflows. Therefore, the effective use of ML in asthma exacerbation prediction requires not only high predictive accuracy but also reliable validation, explainability, and practical clinical implementation to support proactive and patient-specific asthma management.

5. Conclusion

This study highlights the growing potential of ML in improving the early prediction and management of asthma exacerbations. By analyzing various ML models, from logistic regression to deep learning, applied across clinical, environmental, and sensor data, it's clear that ML offers powerful tools for identifying patterns linked to asthma attacks. Importantly, the shift toward personalized predictive models that account for individual risk factors and environmental triggers opens new doors for tailored asthma care. Real-time data integration from wearables and health records further supports proactive management through early warning systems. Still, challenges remain in making these models interpretable, clinically validated, and seamlessly integrated into healthcare workflows. Addressing these issues is essential for gaining trust among clinicians and ensuring practical adoption. Ultimately, ML stands to revolutionize asthma care by enabling more precise, timely, and patient-centered interventions that can improve outcomes and reduce the overall burden of the disease.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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