IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 25 May 2024, accepted 2 August 2024, date of publication 8 August 2024, date of current version 20 August 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3440502

SURVEY

Optimization Techniques for Asthma Exacerbation Prediction Models: A Systematic Literature Review

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This work was supported in part by Universiti Teknologi PETRONAS (UTP), and in part by the Collaborative Research Fund (Cost Center) under Grant 015ME0-341.

ABSTRACT Asthma exacerbations pose a significant global health concern, necessitating effective predictive models to anticipate and manage these events. This systematic literature review examined the optimization techniques employed in asthma exacerbation prediction models, spanning machine learning algorithms and computational optimization methods. The objective was to synthesize existing evidence, identify trends, and delineate future research directions in predictive modeling for asthma exacerbations to enhance predictive accuracy and clinical utility. A comprehensive search strategy was devised, yielding 27 eligible articles for analysis. The result revealed various optimization techniques, including feature selection, model optimization, and environmental factor integration. The result also revealed that machine learning algorithms' effectiveness in predicting asthma exacerbations varied depending on various factors (such as dataset quality and model complexity), with various optimization techniques (such as feature selection and ensemble learning) used for improving predictive accuracy. Integrating environmental and spatial factors enhanced prediction models, enabling tailored interventions. In addition, personalized asthma management strategies informed by predictive models led to better control and reduced healthcare utilization. The review also highlighted the implications for personalized asthma management, as well as methodological limitations, and proposed future research directions to improve model reliability and advance personalized healthcare understanding, thereby contributing to the United Nations' Sustainable Development Goals related to health, innovation, and sustainability. Thus, progress made in asthma exacerbation prediction and the identification of challenges and areas for improvement were covered, providing valuable insights for researchers, clinicians, and policymakers aiming to enhance asthma care through predictive modeling.

INDEX TERMS Asthma exacerbation, machine learning, optimization, personalized and prediction models.

I. INTRODUCTION

Asthma, a chronic respiratory condition characterized by airway inflammation, bronchial constriction, and variable airflow limitation, represents a notable worldwide health issue affecting a considerable population globally [1], [2]. Despite significant progress in treatment and management strategies, asthma exacerbations continue to impose a substantial burden on healthcare systems worldwide [3]. These exacerbations, marked by sudden worsening of symptoms, lead to increased morbidity, mortality, and healthcare utilization rates, driving the quest for effective predictive models to foresee and manage these events [4], [5]. The significance of asthma exacerbations extends beyond their immediate impact on individual patients' health to encompass broader implications for healthcare systems and society, including

The associate editor coordinating the review of this manuscript and approving it for publication was Sawyer Duane Campbell.

economic costs [6]. Efforts to address asthma align with the United Nations' Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health And Well-Being), by aiming to ensure healthy lives and promote well-being for all, including those affected by chronic respiratory conditions. Additionally, initiatives targeting asthma management and prevention contribute to broader SDGs, such as SDG 11 (Sustainable Cities And Communities) by promoting healthier urban environments and SDG 13 (Climate Action) by mitigating environmental factors contributing to respiratory illnesses. Thus, the SDGs provide a comprehensive framework for addressing the multifaceted challenges posed by asthma, guiding efforts to improve healthcare outcomes, promote sustainability, and enhance the quality of life for affected individuals globally.

Beyond the physical discomfort experienced by patients, exacerbations incur substantial economic costs stemming from hospitalizations, emergency department visits, and medication expenses [7]. Moreover, they engender psychological distress and impair patients' productivity and quality of life [8]. Given the multifaceted nature of asthma exacerbations, effective prediction models promise to transform asthma management by enabling proactive interventions and targeted strategies tailored to individual patients' needs [9]. Predictive models represent a pivotal tool in addressing the challenges posed by asthma exacerbations [9]. By leveraging a diverse array of factors, including clinical parameters, physiological biomarkers, environmental exposures, and behavioral patterns, these models offer insights into the likelihood and severity of future exacerbations [10]. Through the integration of optimization techniques, predictive models seek to enhance their predictive accuracy and clinical utility, thereby empowering healthcare providers with the foresight needed to intervene effectively and mitigate exacerbation risks [11]. Moreover, predictive models facilitate in identifying individuals at high risk and vulnerable populations, allowing for tailored interventions and allocation of resources, leading to enhanced patient healthcare outcomes and more efficient healthcare delivery [12].

This review investigated optimization techniques for improving predictive models for asthma exacerbations. It covered traditional machine learning (ML) methods, advanced algorithms, and computational optimization methods [13]. The effectiveness of some methods, such as support vector machines and neural networks, in revealing complex data patterns was scrutinized to evaluate their efficacy [14], [15], [16]. Furthermore, computational optimization techniques, such as genetic algorithms and simulated annealing, were investigated for their potential role in improving predictive accuracy [17], [18].

The review provided a comprehensive analysis of optimization techniques, risk factors, data sources, model evaluation metrics, and implementation challenges associated with asthma exacerbation prediction models. It aimed to offer valuable insights to researchers, clinicians, and policymakers regarding the progress in predictive modeling for asthma exacerbations. Specifically, the review critically evaluated optimization methodologies, identified areas lacking knowledge, and suggested future research directions. It examined the effectiveness of various optimization techniques, including ML algorithms and computational methods, to improve predictive accuracy and clinical utility. Additionally, the review highlighted underexplored areas and emerging trends, aiming to inform the development of personalized asthma management strategies in the future.

The organization of the review is as follows: Section I introduces the topic and provides the background and significance of the study. Section II delves into the literature review for the topic which includes asthma and its types, metrics for measuring asthma, different ML models for asthma prediction, optimization techniques and its application to asthma. Section III outlines the research methodology applied in this review, detailing the search strategy, inclusion and exclusion criteria, and study selection process. Section IV assesses the efficacy of these optimization techniques through empirical analysis. In section V the empirical findings from the results section are critically analyzed in this section and answer the research questions. Section VI highlights the limitations of the studies. Section VII discuss the challenges and future directions. Section VIII concludes the studies and the references used in the study are displayed at the end of the paper.

II. LITERATURE REVIEW

Asthma is a complex and heterogeneous respiratory condition that affects millions of individuals worldwide [2]. It is characterized by chronic inflammation of the airways, leading to recurrent episodes of wheezing, breathlessness, chest tightness, and coughing [19]. Understanding the various types of asthma and the metrics used to measure its severity and control is crucial for effective diagnosis and management. Furthermore, the advent of ML has opened new avenues for improving asthma care through predictive modeling and personalized treatment plans [20]. In this section we have discuss different types of asthma, metrics for evaluating asthma condition, machine learning models for predicting asthma, optimization techniques, and application of ML to asthma.

A. TYPES OF ASTHMA

The categorization of asthma is crucial for effective diagnosis and management.

1. **Allergic (Extrinsic) Asthma:** This type, also known as atopic asthma, is triggered by external allergens such as pollen, dust mites, pet dander, and mold. Allergic asthma is often associated with other allergic conditions like eczema and allergic rhinitis. Studies have shown that immunoglobulin E (IgE) plays a significant role in the pathophysiology of allergic asthma [21].
2. **Non-Allergic (Intrinsic) Asthma:** Non-allergic asthma is not triggered by allergens but by factors such as stress, exercise, cold air, or viral infections. It is

generally more severe and less common than allergic asthma [22].

3. **Exercise-Induced Asthma (EIA):** EIA, or exercise-induced bronchoconstriction (EIB), occurs during or after physical activity due to the loss of heat and moisture in the airways. It is prevalent among athletes and individuals exposed to cold, dry environments [23].
4. **Occupational Asthma:** This type is caused by exposure to irritants in the workplace, such as chemicals, dust, and fumes. Occupational asthma is a significant public health concern, particularly in industries like construction, farming, and manufacturing [24].
5. **Cough-Variant Asthma:** This form is characterized predominantly by a chronic, non-productive cough without the classic symptoms of wheezing and shortness of breath. It is often underdiagnosed and mismanaged [25].
6. **Nocturnal Asthma:** Symptoms worsen at night, possibly due to a reclining position, cooler air, or hormonal variations. Nocturnal asthma significantly impacts the quality of life and sleep quality of patients [26].
7. **Aspirin-Induced Asthma (AIA):** This type is triggered by aspirin and other nonsteroidal anti-inflammatory drugs (NSAIDs), leading to severe respiratory issues. AIA is often associated with nasal polyps and chronic rhinosinusitis [27].

B. METRICS FOR MEASURING ASTHMA

Assessing asthma involves various clinical metrics and tools to gauge the severity, control, and impact on patients:

1. **Peak Expiratory Flow (PEF):** PEF measures the highest speed at which air can be expelled from the lungs. It is a simple, portable test that patients can use at home to monitor their asthma control [28].
2. **Forced Expiratory Volume in 1 Second (FEV1):** FEV1 measures the amount of air a person can forcefully exhale in one second. It is a standard measure in spirometry to assess lung function and severity of asthma [29].
3. **Asthma Control Test (ACT):** The ACT is a validated questionnaire that evaluates the patient's perception of their asthma control over the past four weeks. It is widely used in clinical practice to guide treatment adjustments [30].
4. **Asthma Quality of Life Questionnaire (AQLQ):** The AQLQ measures the impact of asthma on a patient's quality of life across several domains, including symptoms, activity limitations, emotional function, and environmental stimuli [31].
5. **Fractional Exhaled Nitric Oxide (FeNO):** FeNO is a biomarker that indicates airway inflammation. Elevated FeNO levels are associated with eosinophilic inflammation and asthma exacerbations [32].
6. **Symptom-Free Days (SFDs):** SFDs count the number of days without asthma symptoms, providing a straightforward measure of disease control and treatment efficacy [33].

C. MACHINE LEARNING MODELS

ML has revolutionized numerous fields by enabling computers to learn from data and make predictions. ML models can be broadly classified into several categories [34]: figure 1 illustrates the various ML for prediction models.

1. **Supervised Learning:** In supervised learning, models are trained on labeled data. Common algorithms include:
   a. **Linear Regression:** Used for predicting continuous values.
   b. **Logistic Regression:** Applied for binary classification tasks.
   c. **Decision Trees and Random Forests:** Suitable for both classification and regression tasks, these models are known for their interpretability and robustness.
   d. **Support Vector Machines (SVM):** Effective for high-dimensional spaces and widely used in classification problems.
   e. **Neural Networks:** Capable of capturing complex patterns in data, neural networks, including deep learning architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are used for tasks ranging from image recognition to natural language processing [35].
2. **Unsupervised Learning:** This category involves models identifying patterns in unlabeled data. Key algorithms include:
   a. **K-Means Clustering**: Partitions data into k clusters based on similarity.
   b. **Principal Component Analysis (PCA):** Reduces the dimensionality of data while preserving variance.
   c. **Hierarchical Clustering**: Builds nested clusters by progressively merging or splitting clusters based on distance metrics.
3. **Reinforcement Learning (RL)**: In RL, models learn to make decisions by receiving rewards or penalties. Prominent algorithms include Q-learning and Deep Q-Networks (DQN), which are used in applications ranging from game playing to robotic control [36].

D. OPTIMIZATION TECHNIQUES

Optimization techniques are essential for training ML models and solving various engineering problems. Key optimization methods include [37]:

1. **Gradient Descent:** An iterative approach to minimize a loss function by updating model parameters in the direction of the steepest descent. Variants include Stochastic Gradient Descent (SGD), Mini-batch Gradient Descent, Adam, and RMSprop, each offering

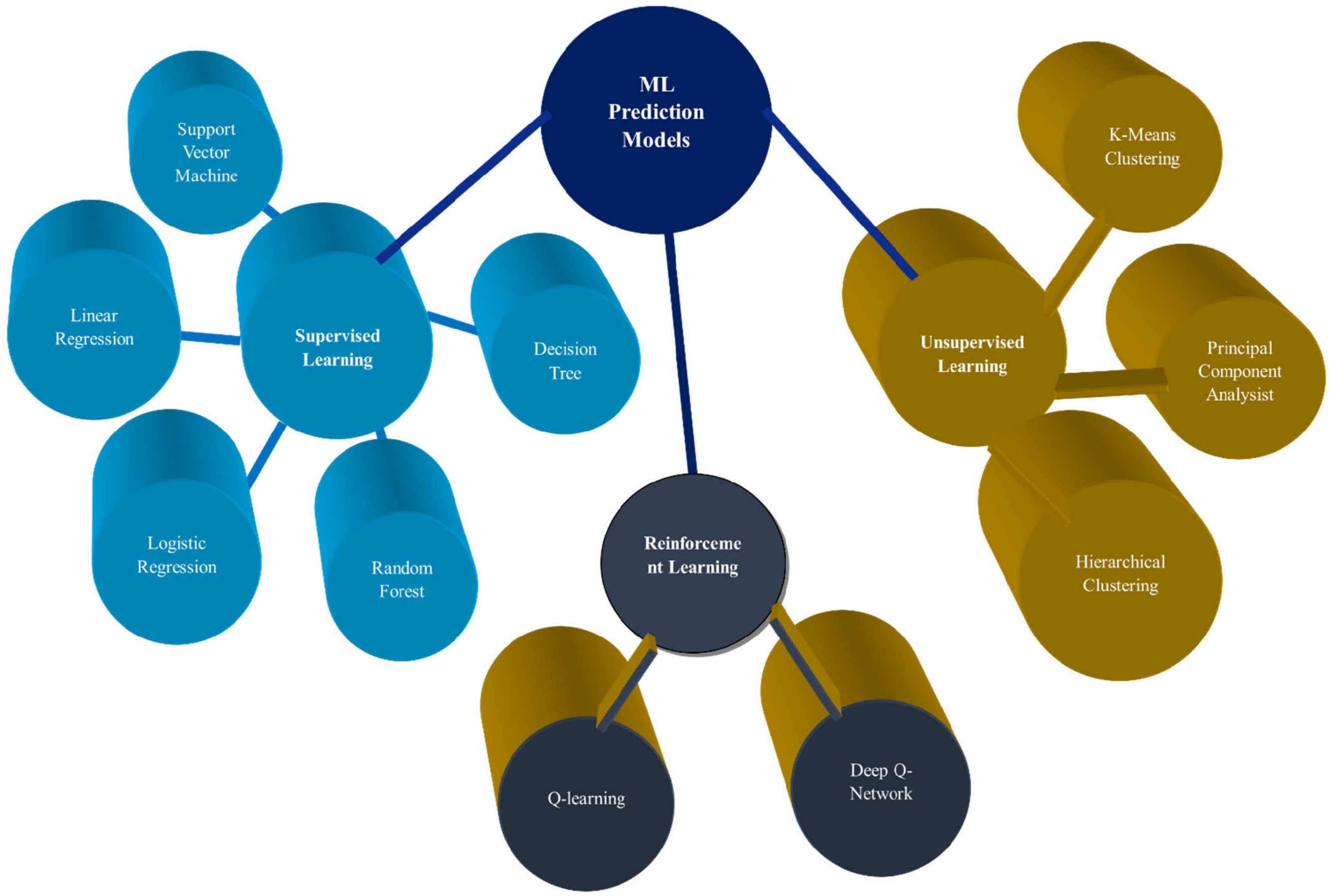

FIGURE 1. Various ML models for asthma prediction.

different trade-offs in terms of speed and convergence stability.

2. **Genetic Algorithms:** Inspired by natural selection, these algorithms evolve a population of solutions through operations like selection, crossover, and mutation to find optimal solutions.
3. **Simulated Annealing:** This technique mimics the annealing process in metallurgy, exploring the search space to find a global optimum by allowing occasional uphill moves to escape local minima.
4. **Bayesian Optimization:** Uses probabilistic models to optimize expensive-to-evaluate functions by focusing on promising areas of the search space.
5. **Particle Swarm Optimization:** Simulates social behavior patterns of birds flocking or fish schooling to explore the search space efficiently.

E. APPLICATION TO ASTHMA

ML models hold significant promise in asthma management, including predicting exacerbations, personalizing treatment plans, and identifying risk factors. Key metrics like PEF, FEV1, and ACT scores are integral inputs for these models, aiding in the development of predictive and diagnostic tools. Optimization techniques ensure that these models achieve optimal performance, enhancing clinical decision-making and improving patient outcomes [4].

III. METHODOLOGY

The technique employed in this systematic review functioned as the structural framework intended to provide strong, clear, and replicable results. This approach has been applied in previous systematic reviews across similar fields, evidenced by existing systematic literature review articles as documented in [38] and [39]. This section gives the review methodology, with recommendations in [40], [41], and [42] followed with great attention to detail. The methodology involves the exploration plan, criteria for selecting studies, inclusion and exclusion guidelines, and research questions.

A. SEARCH STRATEGY

A thorough search strategy was developed to locate relevant studies concerning optimization methods for asthma exacerbation models. The methodology involved online searches in key databases, which were Google Scholar, PubMed/MEDLINE, Scopus, and IEEE Xplore. The search employed a combination of relevant keywords and Boolean operators, specifically targeting the terms "Optimization," "Optimization Techniques," and "Optimizing" in conjunction with the terms "Asthma Exacerbation" or "Asthma Attacks" and "Prediction Models" or "Predictive Models." The search was restricted to articles published between January 1, 2014, and February 17, 2024, with a language filter applied to include only English-language publications.

B. STUDY SELECTION

The study selection process commenced by identifying 362 records through comprehensive database searches, supplemented by nine records from manual searches, resulting in 371 articles. Mendeley was employed to check for duplicates, removing 58 redundant records and leaving 313 unique records for further screening. Subsequently, Rayyan was utilized for title screening, where 238 records were excluded due to a lack of relevance to asthma exacerbation prediction models, resulting in 75 remaining records. Further refinement during abstract screening using Rayyan excluded 40 records for not being related to asthma attack prediction models, leaving 35 records for full-text assessment. During this phase, seven articles were excluded: 4 studies utilized statistical methods instead of ML techniques, two had low assessments, and one book chapter did not meet the eligibility criteria. Additionally, one article was excluded due to inaccessibility. Consequently, 27 articles met the eligibility criteria. They were incorporated into the systematic literature review on optimization techniques for predicting asthma exacerbations.

C. INCLUSION CRITERIA

The inclusion criteria for this systematic literature review on optimization techniques for asthma exacerbation prediction models involved selecting English-language, peer-reviewed articles published between 2014 and 2024. These studies must specifically focus on asthma exacerbation prediction models.

D. EXCLUSION CRITERIA

The exclusion criteria for this systematic literature review encompassed studies unrelated to asthma exacerbation prediction or optimization techniques, non-peer-reviewed sources (such as abstracts, lecture notes, book chapters, editorials, etc.), publications not written in English, and research primarily focusing on treatments rather than prediction models.

E. RESEARCH QUESTION

This systematic literature review aimed to address the following research questions to provide comprehensive insights into the optimization of asthma exacerbation prediction models and their implications for personalized management strategies:

1. How effective were ML algorithms in predicting asthma exacerbations, and what were the key factors influencing their predictive performance?
2. What feature selection and model optimization techniques yielded the highest accuracy in the selected studies' asthma exacerbation prediction models, and how did these techniques contribute to improving the robustness and reliability of the models?
3. How did environmental and spatial factors, such as indoor air quality, weather conditions, and geographical location, impact the accuracy of the asthma exacerbation prediction models?
4. What are the implications for personalized asthma management strategies?

The research questions aimed to address key aspects of asthma exacerbation prediction models and their implications for personalized management strategies. These questions focused on evaluating the efficiency of ML algorithms, identifying optimal feature selection and model optimization techniques, understanding the impact of environmental and spatial factors on model accuracy, and exploring the implications for personalized asthma management. The review sought to provide valuable insights for researchers, clinicians, and policymakers by addressing these questions, aiming to improve predictive modeling approaches and patient healthcare outcomes in asthma management.

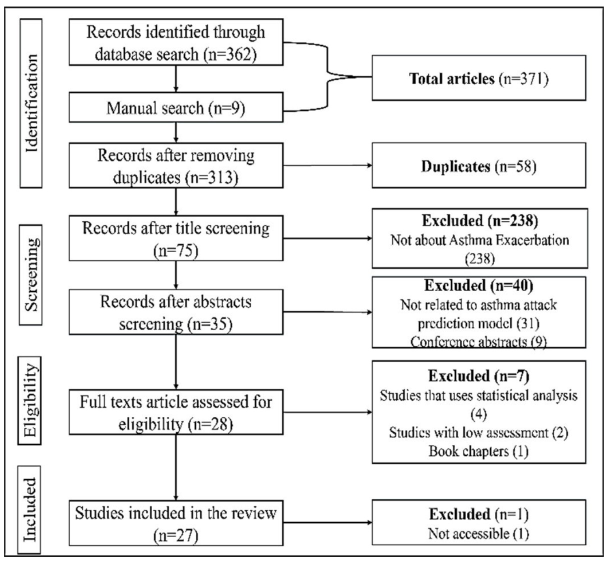

FIGURE 2. Visual breakdown of publication selection based on PRISMA guidelines.

IV. RESULTS

The systematic review's methodology functioned as the structural foundation, crafted to deliver dependable, transparent, and replicable results. Following the guidelines meticulously, this review outlined the detailed steps to address the research inquiries. This section offers a comprehensive account of the procedures employed in literature search, selection, analysis, and quality evaluation. Figure 1 provides a graphical representation of the process.

A. SEARCH RESULT

The search strategy in this review identified 371 articles, of which 313 were unique after removing duplicates. Screening for eligibility resulted in 28 full-text articles, with seven exclusions. Another one article was excluded due to lack of access. Ultimately, 27 eligible articles were included in the review.

B. STUDY CHARACTERISTICS

The analysis incorporated data from 27 studies conducted across 16 countries, this comprehensive dataset delved into various risk factors, including demographic, environmental, lifestyle, and clinical aspects. Notably, clinical factors were the most frequently discussed, with 18 studies covering this dimension, closely followed by demographic factors being featured in 16 studies. The combination of demographic and clinical factors emerged as the most prevalent theme, appearing in 14 studies. Environmental factors were also prominently explored and documented in 15 studies, while lifestyle factors were discussed in 11 studies. Overall, the dataset underscores the complexity of risk factor research, emphasizing the need to consider multiple dimensions when evaluating and addressing potential risks.

TABLE 1. Geographical distribution of selected papers on asthma exacerbation prediction models.

Country	Numbers
United States	6
Iran	3
South Korea	3
UK	3
India	2
Australia	1
Bangladesh	1
Belgium	1
China	1
France and the UK.	1
Global	1
Pakistan	1
Scotland	1
Sweden	1
Taiwan	1
USA and South Korea	1

Table 1 provides a concise overview of the representation of various countries across different continents. The United States is the country that appeared most frequently in the data, which was six times. This likely reflects the significant influence and global presence of the United States across various domains, including politics, economics, and culture. Iran, South Korea, and the United Kingdom are closely behind, each appearing three times, indicating the countries' relevance in the analyzed context, while India contributed two studies. The remaining 10 studies were distributed among China, Taiwan, Pakistan, France, Belgium, Australia, Scotland, and Bangladesh, as graphically illustrated in Figure 3. This distribution highlights the prominence of these countries in discussions or datasets related to the subject matter under consideration, whether it pertains to trade, geopolitics, or other areas of interest.

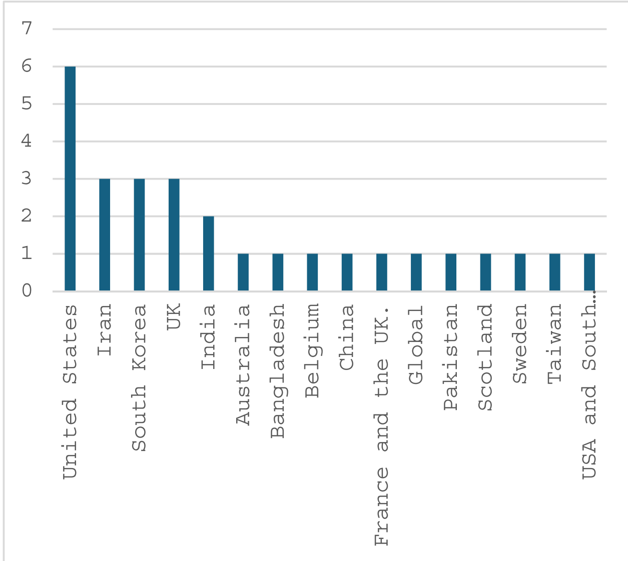

FIGURE 3. Geographical distribution of selected papers on asthma exacerbation prediction models.

When examining the distribution by continent, it becomes apparent that Asia holds a substantial presence in the table, with several countries from the region, such as India, China, Taiwan, Pakistan, and Bangladesh. This concentration underscores the region's significance in global affairs and highlights Asia's diverse range of countries. Additionally, the representation of the United Kingdom, France, Sweden, Belgium, and Scotland demonstrates Europe's continued relevance on the international stage. In addition, the inclusion of Australia serves as a nod to the importance of Oceania in global discussions, albeit with a lesser frequency than those of other continents. Overall, the table encapsulates a snapshot of global dynamics, reflecting the countries' varied contributions and the impacts across different regions.

TABLE 2. Publication trends for asthma exacerbation prediction models from selected studies (2014-2024).

Publication year	Numbers
2023	5
2024	2
2020	6
2022	2
2021	8
2019	5
2017	1
2018	1

Table 2 presents a breakdown of publication years and the corresponding number of publications. It reveals a distribution of publications across various years, indicating trends or patterns in content publication within the timeframe. Notably, 2021 stood out with the highest frequency of publications, recording eight instances. This suggests a peak in publishing activity during that particular year, possibly indicating a significant event, research breakthrough, or heightened interest in the subject matter. Additionally, 2020 followed closely

TABLE 3. Publication distribution across journals for asthma exacerbation prediction models from the selected studies.

Journal	Number of studies
PloS One	2
Journal of Translational Medicine	1
Environmental Monitoring and Assessment	1
Journal of Personalized Medicine	1
Journal of System and Management Sciences	1
BMC Pulmonary Medicine	1
Life	1
Computers in Biology and Medicine	1
Photodiagnosis and Photodynamic Therapy	1
Annals of the New York Academy of Sciences	1
Journal of Medical Systems	1
Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)	1
Scientific Reports	1
Journal of Asthma	1
Respiratory Medicine	1
ERJ Open Research	1
Journal of Medical Internet Research	1
Computer Methods and Programs in Biomedicine	1
Clinical and Experimental Allergy	1
Academic Emergency Medicine	1
AMIA Joint Summits on Translational Science Proceedings, AMIA Joint Summits on Translational Science	1
IEEE Access	3
BMJ Open	2
Heart & Lung	1
Science of the Total Environment	1

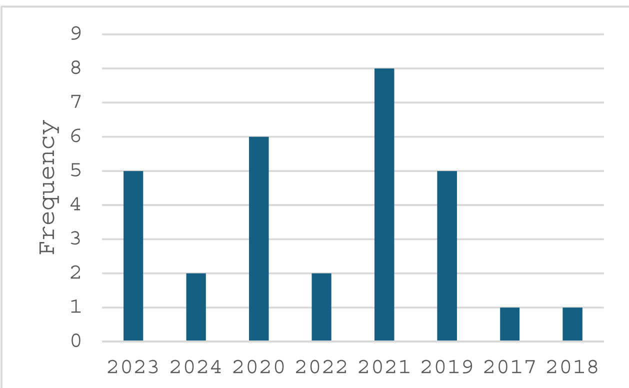

FIGURE 4. Publication trends for asthma exacerbation prediction models from selected studies (2014-2024).

behind with six publications, further indicating a period of notable activity in terms of content creation.

Furthermore, the table indicates that publication activity fluctuated across different years, with some years recording fewer publications. For instance, 2017 and 2018 had only one publication listed, suggesting relatively lower activity levels during those years. However, it is important to note that the table provides a snapshot of publication frequency and does not offer insights into the specific reasons behind the variations in publication numbers. Overall, the table provides valuable insights into the temporal distribution of publications, highlighting periods of heightened activity and potential trends in the publication landscape within the given timeframe.

Table 3 thoroughly summarizes how the publications are distributed among different journals, offering insights into the frequency and diversity of publishing platforms within the field. Several journals listed only one publication, indicating a wide range of sources for disseminating research findings. These include journals such as the Journal of Translational Medicine, Environmental Monitoring and Assessment, Life, and the Journal of Asthma, among others. This diversity underscores the interdisciplinary nature of the subject matter, with research studies published across various specialized and generalist journals catering to different aspects of the field.

Moreover, certain journals stand out with multiple publications associated with them, indicating their prominence or popularity within the domain. For example, PloS One and IEEE Access each have multiple publications listed, suggesting a significant volume of research being published in these journals. BMJ Open also features multiple publications, further emphasizing its role as a prominent outlet for research dissemination. The presence of these journals with multiple publications highlights their importance as platforms for sharing findings and contributing to advancing knowledge within the field. The table provides valuable insights into the distribution of publications across various journals, reflecting the breadth and depth of research being conducted and disseminated within the given domain.

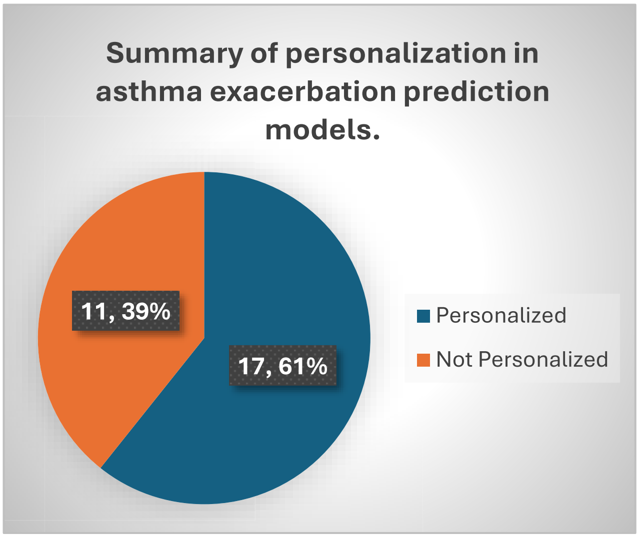

FIGURE 5. Summary of personalized models for asthma exacerbation prediction from selected studies.

Figure 5 below shows the summary of Summary of Personalized Models for Asthma Exacerbation Prediction from Selected Studies.

Figure 5 provides a breakdown of the frequency of personalized approaches used in the studies. A total of 61% were personalized approaches, while 39% were not, indicating a considerable emphasis on personalized approaches in the development of predictive models for asthma exacerbations. The distinction between personalized and non-personalized methods suggests that researchers actively explore tailored interventions or predictions that consider individual patient characteristics. The emphasis on personalization underscores the importance of individualized approaches in improving the accuracy and effectiveness of asthma management strategies.

C. MACHINE LEARNING APPROACHES

Recently, there has been significant interest in developing optimized prediction models for asthma exacerbations to improve patient healthcare outcomes and healthcare resource utilization. Diverse ML methodologies and optimization strategies have been utilized to augment the precision and dependability of predictive models. The study in [43] introduced the weighted feature averaging technique (WFAT) to identify crucial risk factors for asthma exacerbations. They explored ensemble ML techniques to improve classification performance. Similarly, [44] proposed the affinity graph enhanced classifier (AGEC), which effectively captured correlations between data samples, leading to more accurate predictions of asthma exacerbations. These studies highlight the importance of optimization techniques in leveraging ML approaches to develop robust prediction models for asthma management.

Furthermore, optimization techniques have been applied to traditional ML models, demonstrating the techniques' effectiveness in enhancing predictive accuracy and clinical relevance. The study in [45] utilized a range of ML algorithms and optimization techniques to forecast the necessity of hospital-level medical attention in pediatric patients with asthma, highlighting the value of systematic optimization in model selection and parameter tuning. Optimization techniques have also been used to address specific challenges in asthma exacerbation prediction, such as imbalanced datasets and feature selection. For instance, [46] utilized the ADASYN algorithm to balance class distributions and improve model performance. This underscores the importance of optimizing data preprocessing techniques for reliable asthma exacerbation prediction.

Advancements in optimization techniques, particularly in preprocessing, have led to the creation of innovative forecasting models for asthma exacerbations. The research conducted in [47] designed a cyber-physical system with dew-cloud assistance to investigate the correlation between meteorological data and the health status of individuals with asthma, highlighting the potential of optimization techniques to integrate environmental factors into prediction models. Similarly, [48] introduced a prediction tool for asthma risk utilizing ML, implemented as a mobile health application on smartphones and leveraging Internet-of-Things (IoT) resources. The approach, leveraging the convolutional neural network (CNN) architecture, showcases the utility of optimization techniques in enhancing predictive accuracy for personalized asthma risk assessment. These studies collectively emphasize the critical role of optimization techniques in advancing the field of asthma exacerbation prediction, facilitating more effective asthma management and improved patient healthcare outcomes.

D. FEATURE SELECTION AND MODEL OPTIMIZATION

In the realm of feature selection and model optimization for asthma exacerbation prediction, researchers have employed various techniques to enhance the performance and reliability of their predictive models. As mentioned, the study in [43] applied the weighted feature averaging technique to extract significant features in asthma risk identification, focusing on selecting prominent characteristics to increase classification accuracy. On the other hand, [44] employed dimensionality reduction and affinity graph learning to optimize their model for asthma prediction, preserving discriminative features and capturing correlations between samples. These studies highlight the significance of selecting features to enhance model accuracy and interpretability.

Moreover, optimization techniques have been applied to model architecture and implementation to enhance predictive performance further. The study in [49] utilized data transformation and regularization techniques to refine their feedforward deep neural network (FDNN) model for personalized asthma predictions, resulting in enhanced performance through reduced prediction errors. The study verified the accuracy of standard operational definitions of asthma and enhanced diagnosis through ML approaches, underlining the optimization of definitions and prediction models. The research studies in [50] and [51] utilized advanced methods, which were imbalanced sampling, transfer learning, and spatio-temporal modeling, to optimize algorithms and improve predictive performance, highlighting the importance of model optimization in addressing specific challenges in asthma exacerbation prediction.

Furthermore, researchers have incorporated various features and performed rigorous model evaluations to optimize predictive models for asthma exacerbation. The research conducted in [45] included varied patient variables in its prediction models, optimizing performance in identifying the requirement for hospital-level care in pediatric asthma patients. Similarly, [52] and [53] identified relevant features and employed data post-processing techniques, respectively, to optimize their machine learning algorithms for asthma self-management and severe exacerbation detection. These studies underscore the significance of feature selection, model optimization, and comprehensive evaluation in developing robust predictive models for asthma exacerbation prediction.

E. INTEGRATION OF ENVIRONMENTAL AND SPATIAL FACTORS

Environmental and spatial variables play a crucial role in asthma exacerbation prediction, and researchers have integrated these factors into their predictive models to enhance accuracy and effectiveness. The research study in [54] utilized location-based social network (LBSN) data and an artificial neural network (ANN) to simulate the temporal risk zone for respiratory disorders, illustrating the relevance of incorporating environmental and infrastructural aspects to find spatial associations with respiratory attacks. Similarly, [50] explored the relationship between indoor air quality and fluctuations in peak expiratory flow rate (PEFR), showing the necessity of including environmental parameters in predictive modeling for asthma-related outcomes.

Furthermore, researchers have incorporated various environmental factors, such as weather conditions, air quality, and geographic features, into their predictive models to improve asthma exacerbation prediction. The study in [45] integrated weather, neighborhood characteristics, and community viral load information into its predictive models for pediatric asthma patients, underscoring the significance of accounting for environmental factors when predicting the necessity for hospital-level care. Similarly, [55] integrated a wide range of environmental factors, such as distance to parks, rainfall, temperature, humidity, and air pollutant concentrations, into its random forest model to identify asthma-prone areas, illustrating the comprehensive approach to environmental integration in predictive modeling.

Moreover, studies have highlighted the importance of supplementing clinical information with environmental triggers to improve predictive models for asthma exacerbation risks. The study conducted in [5] augmented prior clinical data with extra information on environmental triggers, such as weather conditions, pollen levels, and air quality, to enhance the efficiency of its predictive models. Similarly, [47] investigated the association between meteorological and health metrics using IoT-enabled smart sensors, underlining the necessity for capturing extensive environmental factors to understand better their impacts on health outcomes, including asthma exacerbations. Reference [48] studied the link between indoor particulate matter, meteorological data, and PEFR values, seeking to forecast the likelihood of asthma episodes, which further underscores the need to integrate environmental elements into predictive modeling for asthma therapy.

F. PERSONALIZED MEDICINE AND RISK STRATIFICATION

Personalized medicine and risk stratification in asthma management have been significantly enhanced by integrating ML techniques, allowing for tailored interventions and individualized risk assessment. The study in [56] developed explainable ML models for personalized risk assessment of acute exacerbation of chronic obstructive pulmonary disease (COPD), providing insights into key features affecting disease outcomes and offering individualized risk predictions. Similarly, [57] implemented a personalized asthma prediction model using an improved Adam-based FDNN, demonstrating its effectiveness in providing individualized predictions based on demographic and weather factors.

Moreover, researchers have focused on providing personalized interventions and treatment evaluations based on predictive modeling outcomes. The study in [51] proposed a modeling framework for personalized asthma risk management to provide individualized interventions based on predictive models' outcomes. Reference [58] developed a predictive approach to assess the effectiveness of mite subcutaneous immunotherapy in asthma, offering a tailored strategy for treatment evaluation based on predictive modeling results. The study in [59] utilized ML tools to predict asthma risks and offered a tailored risk assessment methodology based on individual spectral variances.

Furthermore, personalized approaches have been employed in developing decision-support tools and early warning algorithms for asthma management. The study in [59] highlighted the promise of ML techniques in generating tailored decision support for telemonitoring systems for chronic diseases, including predicting asthma exacerbations before they occur. Similarly, [20] developed an ML model to predict future hospital contacts related to asthma, facilitating personalized asthma care management by proactively identifying high-risk patients and providing them with preventive healthcare services. Moreover, [46] developed a decision support system designed to assist in the early detection

TABLE 4. Summary of studies on predictive models for asthma exacerbations.

Ref.	Personalized	Algorithm Used	Dataset	Population	Intervention	Outcome	Limitations	Contributions
[5]	No	ML classifiers	Electronic medical records and national registers	Asthma patients	ML models for exacerbation prediction	Validation resulted in AUPRC of 0.007, suggesting historical clinical data alone may not adequately predict exacerbations	Limited to historic clinical data, may require supplementation with additional environmental and wearable data for improved performance	Created ML models to predict asthma exacerbation risks, emphasizing necessity of additional data sources for enhanced predictive accuracy
[20]	No	ML model	Patient data from Intermountain Healthcare and University of Washington Medicine	Adult patients with asthma	ML model for asthma hospital encounter forecasting	Achieved AUC of 0.902 for forecasting asthma hospital encounters, with 90.6% accuracy and 70.2% sensitivity	Limited to patient data from two healthcare systems; may not generalize to other populations or healthcare settings	Evaluated generalizability of ML model for forecasting asthma hospital encounters across different healthcare systems, demonstrating promising results for clinical application
[43]	No	WFAT and ensemble ML	Two diverse datasets	Not specified	WFAT	Classification accuracy was 85% (91% with a reduced feature set)	Not specified	Introduced novel weighted feature averaging technique and ensemble ML model with high classification accuracy for asthma prediction
[44]	No	AGEC	Clinical dataset with 152 samples	Not specified	AGEC	Accuracy of 72.50% exceeded other models' performance	Limited by small dataset size and specific features used; no external validation mentioned	Introduced AGEC model for asthma prediction, which showed superior performance compared with those of existing models, particularly in capturing sample correlations
[45]	Yes	Decision Tree, LASSO LR, RF, and GBM	Children aged 2 to 18 experiencing asthma exacerbation	Pediatric patients with asthma	Integrated clinical data, weather conditions, neighborhood attributes, and community viral load	GBM outperformed alternative approaches, achieving an AUC of 0.84	Limited to pediatric patients with asthma exacerbation; retrospective analysis of emergency department data	
[46]	Yes	SVC, RF, GBC, XGB, ANN, LDA, QLDA, NB, DT, and KNN	Asthma dataset	Not specified	BOMLA detector with ten classifiers and ADASYN algorithm	Achieved greatest accuracy and Matthews's correlation coefficient for asthma detection	Not specified	Proposed BOMLA detector with multiple classifiers and ADASYN algorithm for early detection of asthma
[47]	Yes	Weighted NE and adaptive neuro-fuzzy inference	IoT-assisted smart sensor data from four	Individuals affected by irregular	Cyber-physical system (CPS) aided by dew-	Proposed model for assessing link between climatic	Not specified	Proposed dew-cloud-assisted CPS to examine correlation between

TABLE 4. ***(Continued.)*** **Summary of studies on predictive models for asthma exacerbations.**

		system (ANFIS)	schools in Jalandhar, India	meteorologica l factors	cloud technology	and health parameters.		meteorological and health parameters using IoT-based smart sensors
[48]	Yes	CNN	Data from IoT systems, including indoor particulate matter (PM), outdoor weather, and PEFR	Not specified	ML-based tool for predicting asthma risk	Outperformed contemporary deep neural network (DNN) methods	Limited to indoor PM, outdoor weather, and PEFR data	Developed ML-based asthma risk prediction tool utilizing data from IoT system implemented as smartphone app
[49]	Yes	XGBoost	Patients from Seoul St. Mary's Hospital and Seoul St. Paul's Hospital, Seoul, Korea	Patients with and without asthma	Traditional operational description and ML methods	XGBoost model attained 87.1% accuracy, 93.0% AUC, 82.5% sensitivity, and 97.9% specificity	Limited to a hospital setting; no external validation mentioned	Established appropriate operational definition of asthma using ML; XGBoost model showed high accuracy in asthma diagnosis
[50]	No	Deep learning, LR, and quantile regression	Real datasets	Not specified	Deep learning, variable sliding window, LR, and quantile regression	Improved model classification accuracy and low relative errors; presented modeling framework	Lack of external validation specific to asthma risk management system, no discussion on clinical implementation	
[51]	Yes	Imbalanced sampling and transfer learning	Not specified	Asthma patients	Imbalanced sampling and transfer learning	Achieved balanced accuracy median of 66%–76% and 68%–78% for TL1_IS and TL2_IS, respectively	Lack of external validation specific to prediction of change in PEFR due to indoor air exposure	Demonstrated effectiveness of transfer learning with imbalanced sampling in predicting change in PEFR due to indoor air exposure
[52]	Yes	LR and naïve Bayes (NB) classifiers	Asthma Mobile Health Study (AMHS) dataset	Asthma patients	ML techniques utilized in early alert system	LR and NB classifiers achieved high accuracy (>0.87) in differentiating stable and unstable periods	Limited to data from mobile health study; may not generalize to broader populations	Created predictive models for asthma self-care via ML on mHealth data, delivering personalized guidance promptly
[53]	No	LR	Daily monitoring data from SAKURA study	Adults with persistent asthma	ML algorithm for exacerbation detection	Achieved 0.85 AUC, 90% sensitivity, and 83% specificity for severe asthma exacerbation detection with LR	Limited to daily self-monitoring data from SAKURA study; may not generalize to other populations or data sources	Developed ML algorithm to promptly identify severe asthma exacerbations, utilizing easily accessible daily monitoring data to improve outcomes
[54]	No	Multilayer-perceptron ANN	Data for five years from Dec. 2013 to Dec. 2018 in Tehran, Iran	Not specified	LBSN data and ANN	Identified air pollution, exposure to contaminated places, and land use as decisive determinants for respiratory disorders	Limited to specific geographical region and data source (Tehran, Iran); no validation on other regions or datasets	

TABLE 4. ***(Continued.)*** **Summary of studies on predictive models for asthma exacerbations.**

[55]	No	RF	Utilized 872 instances of pediatric asthma cases and investigated 13 environmental factors influencing disease	Children with asthma in Tehran, Iran	Geographic Information System (GIS) and RF model	RF model accurately identified asthma-prone areas (AUC of 0.987 for training, 0.921 for testing)	Limited to a specific geographic area (Tehran, Iran)	Utilized environmental and spatial factors to identify asthma-prone areas in Tehran, Iran, offering insights for targeted public health interventions to mitigate asthma risk
[56]	Yes	Gradient boosting machine (GBM)_ and SVM	Retrospectively examined 606 patients with COPD	Patients with COPD	Predicting first-time acute exacerbation of COPD	ML models accurately predicted first-time AECOPD SHAP values for feature importance interpretability	Limited to retrospective study specific to COPD patients from a single hospital	Developed accurate ML models for predicting first-time AECOPD and provided interpretable explanations of model decisions based on SHAP values
[57]	Yes	Enhanced FDNN utilizing Adam optimization algorithm	General dataset	Asthma patients	Data transformation (standardization, normalization) and regularization (dropout, max-norm constraint)	Improved prediction with low loss value and higher accuracy rate than those of other optimizers	Limited discussion on external validation, specific to asthma predictions based on demographics and weather	Presented enhanced FDNN model using Adam optimization for personalized asthma forecasting, emphasizing data transformation and regularization
[58]	Yes	Dispersed-foraging salp swarm algorithm–kernel extreme learning machine (DFSSA-KELM)	Clinical information collected from 390 pediatric asthma patients aged between 4 and 17 years	Children with asthma	Allergen immunotherapy	Predicted efficacy of mite subcutaneous immunotherapy with 87.18% accuracy and 93.55% sensitivity	Limited to children aged 4 to 17 with asthma, specific to mite subcutaneous immunotherapy	Introduced DFSSA-KELM model for predicting success of mite subcutaneous immunotherapy in children with asthma; identified key predictors for treatment outcome
[59]	Yes	NB classifier, adaptive Bayesian network, and SVM	Daily self-monitoring reports from adult asthma patients during home telemonitoring	Adult asthma patients	ML algorithms for predicting asthma exacerbations	Achieved sensitivity (0.80–1.00), specificity (0.77–1.00), and accuracy (0.77–1.00) within varying ranges	Limited to telemonitoring data; may not capture all factors influencing exacerbations	Demonstrated telemonitoring and ML predicting asthma exacerbations, emphasizing personalized decision support in chronic disease management
[80]	No	SVM, ANN, and RF	Raman spectra from 150 samples of blood serum from individuals with asthma and 52 samples from healthy controls	Patients with asthma and healthy controls	Raman spectroscopy, SVM, ANN, and RF	SVM demonstrated superior performance in classifying asthma patients	Limited to blood serum samples specific to classification of asthma patients	Showed effectiveness of SVM combined with Raman spectroscopy for machine-based categorization of asthma patients, demonstrating encouraging accuracy
[81]	Yes	Ensemble learning algorithm	96 asthma patients from specialized	Asthma patients	Suggested algorithm for detecting	Proposed model achieved 91.66% accuracy in	Limited to data from single specialized	Integrated medical insights and ML for precise asthma

TABLE 4. ***(Continued.)*** **Summary of studies on predictive models for asthma exacerbations.**

		(combining rule-based classifier and supervised learning algorithms)	pulmonary diseases hospital in Tehran		asthma control levels	detecting asthma control level	hospital; may not generalize to other populations	control classification, offering real-time decision support and personalized alerts
[82]	No	LR	Prospective observational study data	Untreated patients with symptoms suggestive of asthma	Diagnostic performance assessment	Combined wheezing intensity scale with spirometry and FENO to improve asthma diagnosis accuracy	Limited to observational study data; potential for selection bias and generalizability to broader populations	Combined symptom intensity scales with objective measures to aid in asthma diagnosis, potentially improving diagnostic accuracy in clinical practice
[83]	No	KNN, RF, AdaBoost, and feature-based dissimilarity space classifier	Forced oscillation technique (FOT) parameters	Individuals with and without airway obstruction	ML classifiers for FOT in asthma diagnosis	Achieved AUCs ranging from 0.81 to 0.91, improving diagnostic accuracy of FOT parameters for airway obstruction	Limited to FOT data and may require further validation in clinical settings	Developed ML classifiers to enhance asthma patients' airway obstruction diagnosis, employing forced oscillation technique parameters
[84]	No	LR	Manchester Asthma and Allergy Study (MAAS) data	Children	Asthma prediction tool (MAAS APT)	Developed simple asthma prediction tool (MAAS APT) with high ratio of positive and negative likelihoods	Limited to children from birth cohort study; may require validation in other populations and healthcare settings	Developed easily applicable asthma prediction tool (MAAS APT) based on characteristics at age 3, facilitating early identification of asthma risk
[85]	Yes	Supervised learning approaches, mixtures of semi-Markov models	Electronic health records (EHRs)	Asthma patients	Modeling asthma exacerbations from EHRs	Achieved AUC of approximately 0.77 for predicting asthma exacerbations	Limited to EHR data; may not capture all relevant information for predicting exacerbations	Created EHR-based algorithm for asthma exacerbation phenotyping, identifying distinct patient subpopulations with varied exacerbation patterns for improved asthma understanding and management
[86]	Yes	Various ML techniques (e.g., LR and one-class and two-class classifiers)	Optimum Patient Care Research Database	Individuals aged 8 to 80 years actively receiving treatment for clinician-diagnosed asthma	Developed predictive tool to recognize patients prone to asthma attacks	Evaluation of various ML techniques for predicting asthma attacks and comparison with LR model	Not specified	Aimed to create prognostic tool for identifying high-risk asthma patients in primary care settings, utilizing ML advancements
[87]	Yes	Generalized linear mixed models	Data from fitness tracker sleep data	Women with poorly managed asthma	Employed sleep data from fitness trackers to build models for predicting daily asthma-specific wakening and FEV1 control	Demonstrated predictive capacity for daily asthma outcomes	Not specified	Sleep data from fitness trackers showed predictive potential for daily asthma outcomes

of asthma. Also, [48] presented an asthma risk prediction tool implemented as a mobile health application, providing personalized risk prediction for asthma attacks based on an individual's PEFR values and environmental factors.

G. OPTIMIZATION TECHNIQUES IN ASTHMA EXACERBATION PREDICTION MODELS

Optimization techniques are crucial in refining predictive models for asthma exacerbations by fine-tuning model parameters, optimizing feature selection, and improving algorithm performance [60], [61]. These techniques encompass various methodologies, including ML algorithms, statistical modeling approaches, and computational optimization methods [62], [63]. Various ML methodologies, such as random forest (RF), support vector machine (SVM), and neural network, have been extensively utilized in creating prediction models for asthma exacerbations [61], [64]. These algorithms utilize extensive datasets to understand intricate patterns and connections between predictor variables and the outcomes of asthma exacerbations. Statistical modeling approaches, including logistic regression (LR) and Cox proportional hazards models, have also been utilized to develop predictive models based on predefined risk factors and covariates [65], [66]. Additionally, optimization approaches, such as genetic algorithm, particle swarm optimization, and simulated annealing, have been utilized to optimize model parameters and increase predictive accuracy [67], [68], [69].

H. EFFECTIVENESS OF OPTIMIZATION TECHNIQUES

Several studies have evaluated the effectiveness of optimization techniques in improving the predictive accuracy of asthma exacerbation prediction models. For example, [70], [71], [72] compared various ML algorithm performances in forecasting asthma exacerbations using clinical and environmental factors. The study found that RF outperformed SVM regarding predictive accuracy and model generalizability. Similarly, [73] undertook a systematic review and meta-analysis of studies examining predictive modeling for asthma exacerbations. It found that models incorporating feature selection techniques, such as recursive feature elimination, achieved a higher predictive accuracy than those of models using all available predictor variables.

I. CHALLENGES AND CONSIDERATIONS

Despite the promise of optimization techniques in improving asthma exacerbation prediction models, several challenges and considerations must be addressed. One challenge is the accessibility and reliability of the data utilized for training and validating predictive models. Many studies relied on retrospective electronic health record data, which may contain missing or inaccurate information [74]. Furthermore, the generalizability of predictive models across different patient populations and healthcare settings remains a concern [75], [76]. Additionally, the interpretability of complex ML models poses challenges for clinical implementation and decision making [77], [78], [79].

The study identified 371 articles, removed duplicates to leave 313 unique records, excluded irrelevant ones through screening processes, and ultimately included 27 articles in a systematic literature review on optimization techniques for predicting asthma exacerbations. Table 4 presents a comprehensive overview of included studies on optimization techniques for asthma exacerbation prediction models. Each study was examined based on several key aspects, which were personalized medicine, algorithms employed, dataset, population studied, intervention strategies, outcomes measured, limitations, and contributions. These aspects provide a detailed analysis of the methodologies and approaches employed in optimizing asthma exacerbation prediction models, highlighting the diversity of techniques and their implications for improving patient healthcare outcomes and healthcare resource utilization.

1. **Use of personalized medicine**: Several studies, such as [51], [56], [57], and [88], incorporated personalized medicine approaches in their models, tailoring predictions to individual patients' characteristics and needs. These studies highlight how personalized approaches enhance the accuracy and effectiveness of asthma exacerbation prediction models.
2. **Algorithms employed**: Many ML techniques were utilized, including logistic regression, support vector machine, random forest, neural network, and ensemble learning methods, with selection criteria tailored to individual research aims and the unique features of the datasets under examination. This comprehensive approach underscores the importance of aligning algorithmic selection with specific objectives and characteristics of data to optimize asthma exacerbation prediction models effectively.
3. **Dataset and population**: The studies utilized diverse datasets, ranging from clinical data to electronic health records and IoT sensor data. Similarly, the population studied varied, including children, adults, asthma patients, and individuals with specific symptoms suggestive of asthma.
4. **Intervention strategies and outcomes**: Various intervention strategies were employed, such as feature selection, model optimization, environmental factor integration, and personalized risk assessment. These interventions aimed to enhance the asthma exacerbation prediction models' accuracy, robustness, and dependability, resulting in improved performance metrics, such as classification accuracy, specificity, sensitivity, and area under the receiver operating characteristic curve (AUC).
5. **Limitations and contributions**: Each study acknowledged constraints, such as small dataset sizes, particular patient cohorts, absence of external validation, and restricted generalizability. Notwithstanding these

constraints, the studies presented notable advancements by introducing innovative methodologies, algorithms, and predictive models for asthma exacerbation prediction. These contributions enhance our comprehension of asthma management and facilitate the development of more efficient personalized intervention strategies.

Overall, the analysis highlighted the diversity of approaches and methodologies employed in optimizing asthma exacerbation prediction models, emphasizing the importance of personalized medicine, and integrating environmental factors for improved predictive accuracy and clinical outcomes.

J. SUPPORTING SDGs 3, 11, AND 13

Sustainable Development Goals offer a comprehensive framework to tackle global challenges and promote sustainable development. Hence, this review also investigated the role of research in advancing SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action).

The objective of SDG 3 is to guarantee the health and well-being of every individual. Studies have stressed the role of access to healthcare services and community-based health programs in improving health outcomes [43], [44]. Furthermore, the progress made in ML algorithms has facilitated the creation of prognostic models for asthma exacerbations, hence improving the timely identification and treatment of this condition [20], [57].

SDG 11 focuses on establishing inclusive, safe, resilient, and sustainable cities and communities. Sustainable urban development techniques, such as green infrastructure implementation and social equality considerations in urban design, contribute to environmental sustainability and public health [45], [46]. Furthermore, ML approaches applied to urban data have facilitated the identification of asthma-prone locations and informed targeted public health interventions [47], [55].

SDG 13 stresses the urgent need for climate action to combat climate change and its implications. Mitigating greenhouse gas emissions and developing renewable energy sources are crucial actions. ML models have been utilized to estimate the health co-benefits of climate action, such as reducing air pollution and improving respiratory health outcomes [6], [48]. Additionally, innovative methodologies, including cyber-physical systems and IoT technology, have been applied to explore the link between climatic conditions and health parameters, defining adaptive solutions for climate resilience [47], [49].

The integration of ML models in identifying environmental triggers of asthma exacerbations significantly supports efforts toward SDG 13 by contextualizing the health impacts of climate change. Climate change exacerbates environmental conditions such as increased air pollution, extreme weather events, and changing patterns of allergens, all of which can trigger asthma exacerbations.

Identifying Environmental Triggers Exacerbated by Climate Change:

1. **Air Pollution:** Climate change contributes to higher levels of air pollutants such as ground-level ozone and particulate matter. ML models can predict the impact of these pollutants on asthma patients by analyzing data from environmental monitoring systems and health records, enabling timely interventions to reduce exposure [6], [48].
2. **Extreme Weather Events:** Increasing frequency and intensity of extreme weather events, including heatwaves, wildfires, and storms, are linked to climate change. These events can worsen air quality and increase respiratory problems. ML models can help in predicting the health impacts of such events on asthma patients, providing critical insights for emergency preparedness and response strategies [47], [49].
3. **Allergen Patterns:** Climate change affects the distribution and potency of allergens, such as pollen, which can trigger asthma attacks. ML models can analyze trends in allergen levels in relation to climate variables, helping to forecast periods of high risk and allowing individuals and healthcare providers to take preventive measures [47].

By identifying and analyzing these environmental triggers, ML models facilitate adaptive solutions that enhance climate resilience. These models inform policymakers and healthcare providers about the specific climate-related risks to asthma patients, leading to targeted actions that mitigate these risks and improve public health outcomes.

The studied works in the literature underline the interconnectivity of SDGs 3, 11, and 13 and the necessity of integrated approaches in promoting health, urban sustainability, and climate resilience. By harnessing breakthrough technology and interdisciplinary cooperation, policymakers and practitioners may promote sustainable development objectives and create healthier, more resilient communities. Efforts to address health inequities, promote sustainable urban planning, and mitigate climate change consequences are mutually reinforcing, underscoring the necessity of a holistic approach to reaching the SDGs.

Incorporating predictive models that identify environmental triggers exacerbated by climate change not only advances SDG 13 but also strengthens the goals of SDG 3 and SDG 11. This integrated approach ensures that efforts to combat climate change simultaneously enhance public health and promote sustainable urban development, contributing to a more sustainable and resilient future.

Table 5 shows the characteristics of the studies in asthma exacerbation prediction models. The table uses 1s to indicate the inclusion and 0s to indicate the exclusion of various risk factors (demographic, environmental, lifestyle, and clinical) and methodological rigor elements (study design, sample size, and data collection method) in each study. Several key insights emerged from Table 5 when focusing on improving model performance based on risk factors and methodological

TABLE 5. Characteristics of selected studies in asthma exacerbation prediction models.

Ref.	Risk factors				Methodological rigor		
	Demographic	Environmental	Lifestyle	Clinical	Study design	Sample size	Data collection method
[5]	1	1	1	1	Used ML techniques, including RF, XGBoost, LightGBM, RNN, and LR, with different regularization methods	29,396 asthma patients in Sweden without specified comorbidities	Utilized electronic medical records linked with Swedish national health registers, incorporating clinical data and creating over 25,000 variables
[20]	1	1	1	1	Secondary analysis of clinical and administrative data from adult asthma patients at University of Washington Medicine (UWM) facilities	Cohort of adult asthma patients who visited UWM facilities during specified period	Information from UWM's enterprise warehouse comprised clinical and administrative records from three hospitals and twelve clinics
[43]	1	1	1	1	Utilized retrospective and cross-sectional data from ISAAC asthma dataset	6,242 samples into balanced dataset of 142 samples	
[44]	0	0	0	1	Focused on developing an AGEC model for predicting asthma using clinical indicators extracted from blood samples	Dataset comprising 152 samples	Extracted 24 clinical indicators from blood samples as candidate predictors in classification procedure; diagnosis results were used as labels
[45]	1	1	1	0	Retrospective analysis of pediatric emergency department patients assessed for asthma exacerbation	29,354 asthma visits of patients aged 2 to 18 years over four years	Data collection involved patient features, triage-available illness severity measures, weather features, and CDC influenza patterns
[46]	0	0	0	1	Development of BOMLA framework for asthma detection using ML	389 individuals from clinical study in Khulna, Bangladesh	Administered a semi-structured questionnaire; research assistants were trained with consent
[47]	0	1	0	1	Develop real-time monitoring framework inspired by dew computing for early prediction of asthma symptoms	Four schools with 28 students were selected based on various characteristics	Utilized IoT devices, smart wearables, and environmental sensors for manual and automatic data acquisition
[48]	0	1	0	1	Focused on developing ML-driven tool for forecasting asthma risk	Not provided	Data from IoT systems, including indoor PM, outdoor weather, and PEFR
[49]	0	0	0	1	Identified asthma patients at two hospitals from January 2017 to January 2018 using traditional operational description	Analyzed 4,235 asthma patients, including 353 selected for additional investigation	Reviewed medical charts to validate precision of conventional asthma definition and employed ML for enhanced diagnostic accuracy
[50]	0	1	0	0	Employed daily data on indoor air quality and PEFR from adult patients with asthma and their homes	25 patients	Incorporated integrated indoor air quality data from monitors and daily PEFR values, distinguishing the study from others
[51]	1	1	1	1	Implemented asthma risk management system with real-time data acquisition and interventions	ESCORT study enlisted 19 adult participants diagnosed with asthma, ranging in age from 34 to 83 years	Collected daily PEFR values, indoor air quality, daily activities, and categorical data from participants
[52]	1	1	0	1	ML on AMHS dataset	5,875 patients with 75,795 daily entries and 13,614 weekly survey entries	Daily and weekly questionnaires by asthma patients
[53]	0	0	0	1	Employed randomized controlled trial (RCT) design, specifically adopting international multicenter RCT approach	728,535 records from 2010 patients	Participants recorded various daily metrics, including peak expiratory flow, symptom scores, reliever inhaler usage, and other relevant variables, in paper diary

rigor. Regarding risk factors, it is evident that studies vary in the extent to which they incorporate demographic, environmental, lifestyle, and clinical factors into their predictive models. Studies such as [43], [57], and [82] encompassed a comprehensive range of risk factors, potentially leading to more robust prediction models. On the other hand,

TABLE 5. ***(Continued.)*** **Characteristics of selected studies in asthma exacerbation prediction models.**

[54]	0	1	0	0	Employed LBSN data and ANN for spatio-temporal modeling of respiratory exacerbation and environmental correlates	Over five years of data	Daily data collection over five years from Dec. 2013 to Dec. 2018 in Tehran, Iran
[55]	0	1	0	0	Spatial database consisting of 872 locations of pediatric asthma cases and 13 environmental variables	872 locations	Utilized RF to examine spatial connections between asthma and environmental factors, assessed via ROC and sensitivity analysis
[56]	1	0	0	1	Used ML models to predict first-time acute exacerbation in COPD patients	509 patients meeting the inclusion criteria	Utilized data collected from Changhua Christian Hospital's clinical research database, including demographic, clinical, and prescription data
[57]	1	1	0	0	Developed Adam-based FDNN model for personalized asthma predictions	Training set comprised 1,616 samples and testing set comprised 404 samples	Collected real-time asthma data via mHealth app Weather Asthma (WEA), comprising weather and demographic features alongside asthma control test (ACT) scores
[58]	1	1	1	1	Clinical dataset from Affiliated Hospital of Wenzhou Medical University to predict effectiveness of immunotherapy in individuals with asthma	Dataset comprised 390 children (aged 4 to 17) who underwent allergen immunotherapy for asthma	Collected data encompassed immunotherapy responses, serum tIgE and sIgE levels, full blood count, basic demographics (age, sex, height, weight), atopic family history, tobacco smoke exposure, and respiratory symptom onset time
[59]	0	0	0	1	Used telemonitoring data from adult asthma patients to predict asthma exacerbations	7,001 adult asthma patients	Collected data via telemonitoring, capturing asthma symptoms, medication usage, exposure to triggers, and lung function
[80]	1	0	1	1	Employed comparative design to analyze Raman spectral data from asthma patients and healthy individuals	150 asthma patients and 52 healthy individuals as part of dataset for analysis	Raman spectra from participants' blood sera samples
[81]	1	1	1	1	Conducted with 96 asthmatic patients over nine months	Collected 2,870 records from 96 asthma patients through daily assessments of asthma control	Used standard registry forms, allergy skin tests, lung function tests, peak flow meter measurements, asthma control test questionnaires, environmental stimuli data, and daily symptom monitoring over 4–12 weeks
[82]	1	1	1	1	Utilized odd months for training and even months for validation to mitigate bias	303 untreated patients with suspected asthma	Employed patient-reported outcomes, spirometry, and exhaled nitric oxide fraction (FENO) measurements
[83]	1	0	1	0	Conducted within Brazilian population at sole practice location; highlighted the need for multicenter studies to enhance generalizability	Not explicitly mentioned	Applied standard inclusion criteria and clinical procedures, analyzing data with ML for airway obstruction diagnosis
[84]	1	0	0	1	Analyzing Manchester Asthma and Allergy Study (MAAS) birth cohort data	Initially, 1,184 families and 995 children of age 3	Questionnaires, skin prick tests, and medical records
	1	0	0	1	Algorithm development for asthma exacerbation phenotyping and prediction from electronic health records (EHRs)	28,101 asthma patients	Utilized EHRs from University of Wisconsin's health system clinical data warehouse
[86]	0	0	0	1	Retrospective cohort study utilizing Optimum Patient Care Research Database	Patients aged 8 to 80 with actively managed asthma	Examined continuous data from each patient's three most recent years

TABLE 5. *(Continued.)* **Characteristics of selected studies in asthma exacerbation prediction models.**

[87]	1	1	1	1	Recruitment of women with poorly controlled asthma New York primary care system, home visits for surveys, spirometry, sensor placement, and record review	Data from participants	43	Data collection included surveys, sensors, diaries, and medical records covering asthma control, quality of life, spirometry, sleep, and environment

TABLE 6. **Performance metrics of selected studies in asthma exacerbation prediction models.**

Ref.	Model performance metrics							Validation metrics		Comparison with baseline models	Generalizability	Bias and confounding
	Accuracy	Sensitivity	Specificity	AUC	MAE	MSE	RMSE	CV	EV			
[5]	0	0	0	1	0	0	0	1	1	1	1	1
[20]	1	1	1	1	0	0	0	1	1	1	1	1
[43]	1	0	0	1	0	0	0	1	0	1	1	1
[44]	1	0	0	1	0	0	0	1	0	1		0
[45]	0	1	1	1	0	0	0	0	0	0	0	0
[46]	1	1	0	1	0	0	0	1	0	1	1	1
[47]	1	1	1	0	0	0	0	0	0	0	0	0
[48]	1	0	0	0	1	1	1	0	0	0	0	0
[49]	1	1	1	1	0	0	0	1	0	1	0	0
[50]	1	1	1	1	0	0	0	1	0	1	1	0
[51]	1	1	1	1	0	0	0	1	1	1	1	1
[52]	0	1	1	1	0	0	0	1	0	1	0	0
[53]	1	1	1	1	0	0	0	1	0	0	0	0
[54]	1	0	0	0	0	0	1	1	1	0	0	0
[55]	1	1	1	1	1	1	1	1	0	0	0	0
[56]	1	1	1	1	0	0	0	0	0	0	1	1
[57]	0	0	0	0	1	1	1	1	1	1	1	1
[58]	1	1	0	0	0	0	0	1	0	1	1	1
[59]	0	1	1	1	0	0	0	1	1	1	1	0
[80]	1	1	1	1	0	0	0	1	0	0	0	0
[81]	1	1	1	0	0	0	0	1	0	1	1	1
[82]	0	1	1	1	0	0	0	1	0	1	0	1
[83]	0	1	1	1	0	0	0	1	0	1	1	1
[84]	1	1	1	1	0	0	0	0	0	1	0	0
[85]	0	0	0	1	0	0	0	1	1	1	1	1
[86]	0	0	0	0	0	0	0	1	0	1	1	0
[87]	0	0	0	1	0	0	0	1	0	1	0	1

studies such as [44] and [54] focused more narrowly on specific clinical or environmental factors, which may limit the generalizability of their models.

Regarding methodological rigor, factors of study design, sample size, and data collection methods played crucial roles in ensuring the reliability and validity of the predictive models. Studies with larger sample sizes, such as [5] and [20], were likely to produce more reliable models due to the greater diversity and representation within the dataset. Additionally, studies that utilized real-time or longitudinal data collection methods, such as [51] and [57], may capture dynamic changes in asthma exacerbation risk more effectively, leading to more accurate predictions.

Moreover, studies that employed advanced ML techniques and optimization algorithms, such as [5] and [82], demonstrated a commitment to maximizing model performance. By leveraging state-of-the-art methodologies, these studies were better positioned to uncover complex patterns and relationships within the data, potentially resulting in superior predictive accuracy.

However, there are also opportunities for improvement across the board. For instance, some studies, such as [53] and [83], lack explicit information regarding certain methodological aspects, which could hinder reproducibility and transparency. Additionally, while many studies incorporated a wide range of risk factors, there may be room to explore novel data sources or integrate additional variables to enhance model performance further.

In summary, to improve model performance in asthma exacerbation prediction, researchers should strive to incorporate diverse risk factors, employ rigorous methodological approaches, leverage advanced ML techniques, and continuously seek opportunities for innovation and optimization in data collection and analysis.

Table 6 presents the performance metrics of the selected studies evaluating asthma exacerbation prediction models. Each row represents a study, detailing its performance metrics (accuracy, sensitivity, specificity, area under the curve (AUC), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE)), validation metrics (cross-validation (CV) and external validation (EV)), comparison with baseline models, generalizability, and considerations of bias and confounding. In the table, the 1s indicate the presence or inclusion of specific model performance metrics, comparisons with baseline models, assessments of generalizability, or evaluations of bias and confounding factors for each model, while the 0s indicate their absence.

1. **Model performance metrics**: The availability of the performance metrics of accuracy, sensitivity, specificity, and AUC allows researchers to evaluate the effectiveness of predictive models. Models with higher values in these metrics are generally considered better performers. For example, the models in [51] and [56] showed high scores across these metrics, indicating strong performances.
2. **Validation metrics**: Validation metrics, such as CV, and EV, help assess the robustness and reliability of models. Models with better cross-validation and external validation metrics are preferred, as they demonstrate better predictive accuracy. For error metrics, lower values indicate better performance, whereas for accuracy metrics, higher values are preferred [89], [90]. Additionally, models with higher degrees of cross-validation are more likely to generalize well to unknown data [91].
3. **Comparison with baseline models**: Comparing a model's performance against those of baseline models provides insights into its effectiveness. Models that significantly outperform baseline models are considered more reliable. For instance, the models in [43] and [49] showed improvements over baseline models, indicating their potential utility.
4. **Generalizability**: Generalizability refers to the ability of a model to perform well on unknown data or in different settings [92]. Models with high generalizability are preferred, as they are more likely to be applicable in real-world scenarios. Ensuring that a model performs consistently across different datasets or validation sets is crucial for its practical utility [93].
5. **Bias and confounding**: Identifying and addressing biases and confounding factors in the data is essential for improving a model's performance and fairness. Models that account for biases and confounding variables are more likely to provide accurate predictions. It is important to assess how well a model handles these issues to ensure reliability and applicability in diverse contexts [94], [95].

In summary, the table highlights the critical factors influencing the performance of the asthma exacerbation prediction models. The availability of comprehensive model performance metrics, including accuracy, sensitivity, specificity, and AUC, provided insights into the effectiveness of the models in predicting asthma exacerbations. Additionally, validation metrics, such as MAE, MSE, RMSE, and CV, contributed to assessing the robustness and reliability of the models. Comparison with baseline models helped gauge the improvement achieved by the proposed models. Considerations of generalizability ensured their applicability in diverse settings. Moreover, addressing biases and confounding factors was essential to enhance the reliability and fairness of the models. By carefully considering these factors, researchers can develop more accurate and reliable asthma exacerbation prediction models, ultimately improving patient healthcare outcomes and healthcare management strategies.

V. DISCUSSION

The empirical findings from the results section are critically analyzed in this section, with specific emphasis placed on the utilization of ML models and psychophysiological data to comprehend patient responses and disease progression. These findings are contextualized in the wider academic conversation, with an exploration of the use of ML algorithms in predicting asthma exacerbations with considerations of demographics, environment, and clinical indicators. Additionally, the implications of these findings for personalized asthma management strategies are discussed in this review, highlighting the potential for more proactive and tailored approaches to asthma care. Furthermore, the review identified the methodological limitations of class imbalance issues, risk of bias, and challenges related to data integration and model interpretability in the studies discussed. These limitations highlight the necessity for additional research to tackle the challenges and improve the reliability and efficacy of predictive models. Moreover, future research directions are outlined, emphasizing the importance of interdisciplinary collaboration, large-scale validation studies, and transparency in model development. By critically analyzing the current state of research and identifying avenues for future exploration, the discussion plays a crucial role in advancing our comprehension of asthma exacerbation prediction and its implications for personalized healthcare by addressing class imbalance issues and minimizing the risk of bias.

Imbalanced Classes: Imbalanced classes, a common challenge in predictive modeling, are evident in several studies across the selected papers focusing on asthma exacerbation prediction [96]. Imbalanced classes occur when one class (for instance, asthma exacerbation) is significantly more prevalent than another class (for example, no exacerbation) within a dataset [97]. This imbalance may result in biased model performance, where the accuracy in predicting the majority class is high and the model struggles to detect the minority class [98], [99].

Addressing imbalanced classes is crucial for developing reliable predictive models for asthma exacerbation. Various techniques, such as resampling methods (e.g., oversampling of the minority class or undersampling of the majority class), ensemble methods (e.g., boosting or bagging), and cost-sensitive learning algorithms can help mitigate the impact of class imbalance [100]. Additionally, the inclusion of suitable performance metrics, such as precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC), are crucial for accurately assessing model performance, particularly when dealing with imbalanced class distributions [101], [102].

Furthermore, some studies employed specific sampling strategies or algorithmic adjustments for imbalanced classes. For instance, using retrospective and cross-sectional data from large asthma datasets allowed for the generation of a balanced dataset in some studies, thus mitigating the effects of class imbalance during model training and evaluation [103], [104], [105], [106], [107]. Addressing imbalanced classes is essential for developing robust and reliable predictive models for asthma exacerbation, ensuring that the models can effectively identify individuals at risk of exacerbation and facilitate timely interventions to improve patient healthcare outcomes.

Risk of Bias: Assessing the risk of bias is crucial when evaluating the reliability and validity of studies focusing on asthma exacerbation prediction. Across the selected papers, various factors contributed to the risk of bias in these studies. One major contributor to bias could be the potential absence of representativeness in the samples used for the studies. For example, some studies may include specific demographic groups or patient populations, limiting the generalizability of their findings to broader asthma populations [108], [109], [110]. Additionally, the use of convenience sampling methods or the inclusion of only certain types of asthma patients may introduce selection bias, affecting the external validity of the results [111], [112].

Furthermore, the choice of study design and data collection methods can influence the risk of bias in asthma exacerbation prediction studies. Studies relying on retrospective data analysis or electronic health records may be susceptible to information bias, as the accuracy and completeness of the recorded data could vary [113], [114]. Furthermore, studies employing ML algorithms for prediction may encounter the challenge of model overfitting. In such cases, the models performed well in training the data but faced challenges in generalizing unseen data, leading to exaggerated estimates of predictive accuracy [115], [116], [117].

Moreover, potential conflicts of interest or funding sources should also be considered when assessing the risk of bias in asthma exacerbation prediction studies. Studies funded by pharmaceutical companies or other commercial entities may be more likely to report positive findings, introducing publication bias and affecting the overall reliability of the evidence [118], [119], [120]. Additionally, the use of proprietary algorithms or datasets without transparent reporting can hinder the reproducibility of study findings and raise concerns about the validity of the results [121], [122]. Overall, careful consideration of sources of bias is essential for accurately interpreting the findings of asthma exacerbation prediction studies and informing evidence-based clinical practice and policy decisions, thus answering this review's research questions, as elaborated in the subsequent subsections. This ensures a comprehensive understanding of the implications of asthma exacerbation prediction and its role in personalized healthcare.

A. EFFECTIVENESS OF MACHINE LEARNING ALGORITHMS IN PREDICTING ASTHMA EXACERBATIONS AND KEY PREDICTIVE FACTORS (RQ1)

ML algorithms exhibit varying effectiveness in predicting asthma exacerbations, as indicated by the diverse performance metrics reported across the studies. While some studies achieved high accuracy, sensitivity, specificity, and AUC values, reflecting robust predictive performance, others reported lower metrics, suggesting less effective models. Several key factors influence the effectiveness of ML algorithms. Firstly, the quality and size of the dataset used for training play a pivotal role, with larger and more comprehensive datasets often leading to better performance. Additionally, selecting relevant features spanning demographic, environmental, lifestyle, and clinical indicators significantly impacts predictive accuracy. The choice of ML algorithms and model complexity also affects performance, with more advanced models and ensemble methods yielding improved results. Hence, ensuring the generalizability of models to unseen data, addressing bias and confounding factors, and conducting comparative analyses with baseline models are also crucial for developing reliable predictive models.

Moreover, the efficacy of ML algorithms in predicting asthma exacerbations hinges on their ability to account for various contextual factors and adapt to diverse patient profiles [123], [124]. Optimizing model performance includes incorporating real-time data from wearable devices and environmental sensors, integrating clinical data from electronic health records, and leveraging advanced feature engineering techniques [125], [126]. Furthermore, adopting transparent model evaluation methodologies, such as cross-validation and external validation on independent datasets, fosters confidence in the predictive capabilities of these algorithms [127]. By systematically addressing these factors and continually refining model architectures, ML has significant potential to enhance the early identification and treatment of asthma exacerbations. This can ultimately enhance patient healthcare outcomes and optimize healthcare resource allocation.

B. FEATURE SELECTION AND MODEL OPTIMIZATION TECHNIQUES FOR IMPROVING ACCURACY IN ASTHMA EXACERBATION PREDICTION MODELS (RQ2)

Feature selection and model optimization techniques varied across the selected studies. However, several approaches demonstrated efficacy in improving the accuracy of asthma exacerbation prediction models. One notable technique was incorporating comprehensive feature sets encompassing various demographic, environmental, lifestyle, and clinical indicators associated with asthma exacerbations. Studies that employed a wide array of relevant features tended to achieve higher accuracy, as they captured the multifaceted nature of asthma triggers and risk factors [128], [129]. Additionally, sophisticated feature selection techniques, such as recursive feature elimination or feature importance ranking, can aid in pinpointing the most crucial predictors for asthma exacerbations [130], [131]. By prioritizing pertinent features, these techniques can reduce noise, enhance model interpretability, and contribute to a more robust and reliable predictive performance [132], [133].

Furthermore, model optimization strategies, including hyperparameter tuning, ensemble learning, and cross-validation, can significantly enhance the accuracy and generalizability of asthma exacerbation prediction models. Hyperparameter tuning involves systematically searching for the optimal configuration of model parameters, such as learning rate or regularization strength, to improve model performance [134]. Ensemble learning techniques, such as random forest or gradient boosting, amalgamate multiple models to harness their combined predictive strength, resulting in superior accuracy and robustness [135]. Cross-validation techniques, such as k-fold or leave-one-out cross-validation, validate model performance on separate datasets, ensuring generalizability to new data [136]. By integrating these feature selection and model optimization techniques, asthma exacerbation prediction models can achieve higher accuracy, reliability, and clinical utility, ultimately facilitating early intervention and personalized management strategies for asthma patients.

C. IMPACT OF ENVIRONMENTAL AND SPATIAL FACTORS ON ASTHMA EXACERBATION PREDICTION MODELS (RQ3)

Environmental and spatial factors play crucial roles in influencing the accuracy of asthma exacerbation prediction models. Studies incorporating variables related to indoor air quality, weather conditions, and geographical location showed improved predictive performances due to their significant impact on asthma exacerbations. Indoor air quality, often assessed through various measures, such as particulate matter concentration and allergen levels, directly affects respiratory health and can trigger asthma symptoms [137], [138]. Models incorporating real-time indoor air quality data provided valuable insights into environmental triggers, leading to more accurate predictions of asthma exacerbations [139].

Case Study 1: A study conducted in four schools in Jalandhar, India, utilized IoT-assisted smart sensors to capture indoor environmental data and analyzed the correlation with health parameters using the Adaptive Neuro-Fuzzy Inference System (ANFIS). This study demonstrated the effectiveness of real-time monitoring and analysis in predicting asthma exacerbations caused by indoor air quality [58].

Moreover, weather conditions, including temperature, humidity, and air pollution levels, have been identified as important determinants of asthma exacerbations [140], [141], [142]. Fluctuations in these factors can exacerbate airway inflammation and increase respiratory symptoms among asthma patients. Models that integrated weather data, particularly through spatio-temporal modeling approaches, captured the dynamic nature of environmental exposures and their impact on asthma outcomes, resulting in more accurate predictions [143], [144].

Case Study 2: A pediatric asthma study included weather features such as temperature, humidity, and air pollution. The study compared four machine learning models (decision trees, logistic regression, random forests, and gradient boosting machines) and found that weather-related features significantly improved the prediction of hospitalization needs for pediatric asthma patients [59].

Case Study 3: A study at Intermountain Healthcare and the University of Washington Medicine evaluated the generalizability of a machine learning model that incorporated weather data to forecast asthma hospital encounters. The model showed excellent performance and highlighted the importance of weather conditions in predicting asthma-related hospital visits [81].

Additionally, geographical location plays a critical role in asthma exacerbation risk due to variations in environmental exposures, healthcare access, and socio-economic factors [145]. Models that accounted for spatial variability in environmental factors and population characteristics better captured localized asthma exacerbation patterns, leading to more precise predictions and tailored interventions [146].

Case Study 4: A study compared the performance of ten machine learning techniques to predict the association between indoor air quality and asthma symptoms, considering geographical variations. The study used advanced imbalanced sampling methods to enhance prediction accuracy and demonstrated how geographical factors influence asthma outcomes [80].

Hence, incorporating environmental and spatial factors into asthma exacerbation prediction models enhances their accuracy by accounting for the complex interplay between environmental exposures and respiratory health outcomes.

D. IMPLICATIONS FOR PERSONALIZED ASTHMA MANAGEMENT STRATEGIES (RQ4)

Personalized asthma management strategies are profoundly influenced by the insights from predictive models, as evidenced by the studies analyzed. By leveraging ML algorithms and incorporating various demographic, environmental, lifestyle, and clinical factors, these models offered tailored approaches for asthma management that can significantly improve patient healthcare outcomes [147], [148]. Identifying key predictors of asthma exacerbations, such as indoor air quality, weather patterns, and demographic characteristics, allows healthcare providers to develop individualized intervention plans to mitigate trigger exposure and optimize treatment regimens [149], [150], [151]. Additionally, integrating real-time data collection methods, including IoT devices and mobile health applications, enables continuous monitoring of asthma symptoms and environmental exposures, facilitating timely adjustments to treatment plans based on personalized risk profiles [152].

Furthermore, implementing personalized asthma management strategies holds promise for enhancing patient engagement and self-management behaviors [153]. By empowering individuals with personalized insights into their asthma triggers and symptom patterns, these strategies promote proactive health management and adherence to prescribed therapies [154], [155]. Moreover, integrating telemonitoring technologies and remote patient monitoring systems enables efficient communication between patients and healthcare providers, leading to timely interventions and mitigating the need for asthma-related hospitalizations and emergency department visits [156]. Adopting personalized asthma management strategies informed by predictive models represents a paradigm shift towards precision medicine, where interventions are tailored to individual patient needs, leading to better asthma control, lower healthcare utilization, and a higher quality of life.

The findings from this review on optimization strategies in asthma exacerbation prediction models not only can improve individualized asthma care but also correspond with SDGs linked to health, innovation, and sustainability. By establishing useful predictive models, the review provides the framework for personalizing interventions to individual asthma patients, thereby improving their health outcomes and contributing to SDG 3. Integrating environmental and spatial factors into prediction models, as recommended by this review, not only improves asthma care but also adds to achieving SDG 11 by supporting sustainable urban development practices. By addressing individual patients' needs and considering environmental concerns, healthcare systems can improve resilience and sustainability in urban environments, thus promoting broader SDG objectives.

VI. LIMITATIONS OF STUDIES

In the discussion section, the review's empirical findings were critically analyzed, focusing on the use of ML models and psychophysiological data to understand patient responses and disease progression. These findings were situated within the wider academic discourse, exploring the application of ML algorithms in predicting asthma exacerbations while considering demographics, environmental factors, and clinical indicators. The implications for personalized asthma management strategies were discussed, emphasizing the potential for proactive and tailored approaches to care.

However, several methodological limitations were identified within the studies reviewed. A significant challenge was the issue of class imbalance, which was evident in studies such as [57] where the minority class, representing patients with severe asthma exacerbations, constituted less than 10% of the dataset. This imbalance can lead to biased model predictions that favor the majority class. For example, in [58], the authors employed oversampling techniques to address this issue, which improved sensitivity but at the cost of increased risk of overfitting.

Different strategies for addressing class imbalance were observed across the studies. Oversampling, as seen in [59], increases the representation of the minority class by duplicating samples, which can lead to overfitting as the model may learn the noise along with the signal. Conversely, undersampling, as used in [80], reduces the majority class to balance the dataset but may result in loss of valuable information, potentially degrading the model's overall performance. An alternative approach, Synthetic Minority Over-sampling Technique (SMOTE), was utilized in [81], creating synthetic samples to balance the classes, which showed promise in mitigating the trade-offs between oversampling and undersampling.

Data integration challenges were also prevalent, particularly when combining datasets from different sources, as noted in [82]. In this study, discrepancies in data formats and measurement standards posed significant hurdles, leading to potential biases in the resulting predictive models. The integration of heterogeneous data remains a complex issue, underscoring the need for standardized data collection and reporting practices.

Additionally, biases in sampling, as observed in [83], and the risk of model overfitting, highlighted in [84], were recurring issues. These limitations stress the need for large-scale, multi-center studies with diverse populations to improve the generalizability and reliability of predictive models.

Future research directions should focus on interdisciplinary collaboration and large-scale validation studies to address these methodological challenges. By improving data integration processes and developing more sophisticated techniques to handle class imbalance, future efforts can enhance the reliability and accuracy of asthma exacerbation prediction models, thus promoting more effective asthma management practices. This approach aligns with Sustainable Development Goal (SDG) 3 by advancing health and well-being, and SDG 9 by fostering innovation in healthcare technology and methodologies.

VII. CHALLENGES AND FUTURE DIRECTIONS

Despite the progress in optimizing asthma exacerbation prediction models, several challenges persist. The study in [5] highlighted the need for additional data sources, such as environmental triggers and wearable device data, to improve short-term predictive models. Moreover, [157] emphasized the importance of real-time big data and predictive model reliability for developing preventive guidelines, suggesting that IoT and deep learning methodologies could improve risk prediction and intervention strategies. Future research should address data limitations, refine predictive models, and translate findings into actionable insights to improve asthma outcomes.

The studies presented in Table 2 showcase advancements in asthma exacerbation prediction, leveraging various methodologies ranging from ML algorithms to environmental and demographic data analysis. However, several challenges persist, pointing towards future directions for research and innovation.

One prominent challenge is the integration and standardization of heterogeneous data sources. While some studies utilized electronic health records or clinical databases, others relied on environmental sensor data, patient-reported outcomes, or social media data. Integrating these diverse data streams poses technical and methodological challenges, including data preprocessing, interoperability, and privacy concerns. Future research efforts could focus on developing robust frameworks for data integration and harmonization to maximize the utility of available data for asthma exacerbation prediction.

Moreover, the generalizability and scalability of prediction models remain critical areas for improvement. Many selected studies demonstrated high predictive accuracy within specific populations or settings. However, when applied to diverse populations or real-world clinical settings, they may lack external validity. Enhancing the generalizability of prediction models requires large-scale validation studies across diverse patient populations, geographic regions, and healthcare settings. Additionally, deploying prediction models in clinical practice necessitates user-friendly interfaces, integration with existing health information systems, and clinician engagement to facilitate adoption and implementation.

Furthermore, addressing the interpretability and explainability of ML models is essential for fostering trust and acceptance among clinicians and patients. Black-box models may achieve high predictive performance but offer limited insights into the underlying mechanisms driving predictions, hindering their clinical utility. Future research endeavors could focus on developing interpretable ML models and decision support systems that provide clinicians with actionable insights and recommendations, while transparently conveying the rationale behind predictions.

The review not only highlights present difficulties but also recommends future research avenues to address them in alignment with SDG 3. By focusing on enhancing model dependability and advancing customized healthcare understanding, the review establishes a roadmap for future research endeavors that contribute to reaching SDG 3. For example, the review advises exploring novel optimization strategies and combining other data sources to boost forecast accuracy and clinical value. These activities fit with SDG 9 by stimulating innovation in healthcare technology and methodology, ultimately supporting the objective of ensuring healthy lives and promoting well-being for everyone.

In conclusion, addressing these hurdles necessitates interdisciplinary teamwork involving clinicians, data scientists, engineers, and policymakers. This collaboration is vital to fully harness the capabilities of data-driven methods in predicting asthma exacerbations. By addressing these challenges and embracing emerging technologies and methodologies, future research endeavors hold promise for advancing personalized asthma management and improving patient healthcare outcomes.

VIII. CONCLUSION

In summary, the studies highlighted the significant progress made in asthma exacerbation prediction through various approaches, such as ML algorithms, environmental monitoring, and demographic analysis. These studies demonstrated promising results in predicting asthma exacerbations, with many achieving high accuracy, sensitivity, and specificity levels. Additionally, they identified key factors influencing predictive performance, including demographic characteristics, environmental factors, and clinical indicators in line with SDGs 3, 11, and 13.

However, several challenges and areas for improvement have been identified. These include integrating heterogeneous data sources, enhancing the generalizability and scalability of prediction models, improving model interpretability and explainability, addressing class imbalance issues, and mitigating the risk of bias. By addressing these challenges and embracing interdisciplinary collaboration, researchers can improve the effectiveness and reliability of predictive models, resulting in more proactive and tailored approaches to asthma care. Future research efforts should focus on developing robust frameworks for data integration, conducting large-scale validation studies across diverse populations and settings, as well as enhancing the transparency and interpretability of predictive models.

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