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Abstract :

This research investigates the association between various elements and the severity of asthma among individuals living in the Al Batinah North Governorate of Oman. It addresses both indoor and outdoor parameters that participate in the development of severity of asthma, with indoor elements including smoking, bakhoor (incense), perfume, and dust, while outdoor elements focus on pollution from nearby industrial areas such as Sohar Industrial Zone (SIZ), Majan Industrial Area (MIA), and Sohar Industrial Port (SIP). Additionally, other health-related factors are examined. The study uses the Knowledge Data Discovery (KDD) methodology to employ Artificial Intelligence (AI) and Machine Learning (ML) methods to identify hidden patterns that influence asthma severity. Additionally, a comprehensive analysis is conducted to find the association between parameters. The dataset of the study was acquired from an electronic health recording system at the Ministry of Health called Al-Shifa. For this study, the system encompasses patient records from three health centers in the Al Batinah North Governorate between 2014 and 2022. The findings indicate a significant positive relationship between proximity to MIA and the severity of asthma, with age also emerging as an influential factor in certain cases. This research aims to enhance asthma understanding and support personalized healthcare development, evidence-based policies, and effective management and prevention strategies for this population.

1. Introduction:

Chronic Respiratory Disease (CRD) asthma is a common ailment that reduces the quality of life of a large part of the global population (Dan et al., 2025; Naftel et al., 2025). It is a disease that flares up and then subsides and is defined by wheezing, difficulty in breathing, and chest constriction. Asthma has both genetic and environmental causes, making it difficult to diagnose and treat (Ma et al., 2025). Even as health researchers work around the clock to develop new cures and treatments, asthma remains one of the most prevalent chronic illnesses worldwide. According to the record of the World Health Organization (WHO), approximately 300 million people around the world have asthma (Maciag et al., 2020; Nanda et al., 2019), and the disease is responsible for about 250,000 deaths annually (Lundbäck et al., 2016).

Asthma is an inflammatory respiratory disease (Canonica et al., 2023; Makrufardi et al., 2023). It is a serious challenge to public health systems because it affects millions of people globally (Agache et al., 2024). Asthma develops due to a combination of genetic factors and environmental influences, making it a complex condition that is difficult to manage and treat effectively (Brusselle et al., 2022; Rodrigo et al., 2004). Asthma symptoms typically include temporary airway obstruction, bronchospasms, and increased inflammation in the airways, which can cause difficulty breathing, wheezing, coughing, and a tightness in the chest (Oyenuga et al., 2024). These symptoms can vary in severity, and asthma attacks can be triggered by various factors such as environmental pollution, allergens, physical activity, and infections (Žavbi et al., 2016). Asthma has been recognized as a leading cause of the healthcare burden, particularly in urban areas with high levels of environmental pollution (Žavbi et al., 2016). In Oman, asthma has rapidly become a pressing public health concerns that requires urgent attention.

Environmental factors, both indoor and outdoor, play a pivotal role in asthma onset and severity. Industrial development in parts of Oman, especially in Al Batinah North Governorate, has exposed the region to pollution from industrial zones such as Sohar Industrial Zone (SIZ) and Majan Industrial Area (MIA). Pollutants such as particulate matter, nitrogen dioxide, and volatile organic compounds trigger lung tissue inflammation by releasing oxidative stress markers, thereby worsening respiratory diseases. Moreover, Omani-specific indoor emissions including bakhoor and fragrances are additional types of indoor air quality (IAQ) pollutants that exacerbate asthma among residents. However, despite these environmental challenges, few studies have examined asthma in Oman with a focus on environmental factors and their association between demographic variables. The application of streaming data analysiscombined with Artificial Intelligence (AI) and Machine Learning (ML) in health analytics has provided new insights into complex, multifactorial diseases such as asthma. These technologies are well-suited for analyzing large datasets, enabling the identification of relationships that may be difficult to detect using conventional statistical methods. In Oman, the Al-Shifa Electronic Health Record (EHR) system offers a rich database for advanced analysis. To this end, this paper aims to use AI and ML to fill some essential research questions that remain unexplored in current asthma studies, such as the impact of environmental, demographic, and health factors on asthma severity. This research aligns with an increased global emphasis on precision medicine as well as precision population health. Realizing the different ways in which these exposures affect the severity of asthma is critical to the design and implementation of interventions. For example, studies have associated an increase in asthma rates with the geographical location near industrial areas; nevertheless, the pollutants and the exposure level that impacts the Omani people have not been well investigated.

Similarly, pollutants specific to indoor environments, such as mold and Volatile Organic Compounds (VOCs), can significantly impact the health, especially given Oman's cultural practices. In many Omani households, people spend a significant amount of time indoors, especially during the extreme heat of summer, which increases their exposure to indoor pollutants and exacerbates respiratory issues like asthma. The frequent burning of incense (bukhoor) and the use of scented oils and perfumes, both integral to Omani culture, release VOCs and particulate matter into the air, irritating the respiratory system and worsening conditions such as asthma and allergies (Agache et al., 2024). Additionally, strong cleaning chemicals and disinfectants, while necessary for maintaining hygiene, introduces additional VOCs into the indoor environment, negatively affecting respiratory health over time. The humid climate in many parts of Oman further promotes mold growth in indoor and mold spores triggering respiratory issues, particularly for individuals with asthma or chronic respiratory diseases. Furthermore, traditional home furnishings such as carpets and heavy upholstery trap dust, allergens, and VOCs, further degrading indoor air quality. By analyzing how indoor pollutants and cultural practices on asthma outcomes in Oman, this study highlights a unique and culturally relevant perspective.

Asthma remains a significant global public health challenge. This research makes a significant contribution to environmental health research by addressing critical gaps in understanding the relationship of asthma severity in Oman, particularly its links to environmental and demographic factors. This research highlights the critical role of outdoor and indoor pollutants in worsening asthma symptoms and emphasizes the advantages of using AI and ML techniques to uncover patterns that traditional statistical methods might miss. By utilizing the Oman's EHR system and adopting a Knowledge Discovery in Databases (KDD) framework, this study aims to bridge the research gap on asthma-related environmental and demographic factors. The findings will have broad implications, from informing clinical practices to shaping public policies and industrial regulations. Moreover, asthma poses an increasing public health and economic challenge, with significant costs associated with healthcare, hospitalizations, and lost productivity (Guilleminault et al., 2024; López-Tiro et al., 2022; van Boven et al., 2024). Thus, the study will provide valuable insights that can help to reduce the financial burden associated with asthma management. By identifying key environmental and demographic risk factors, this study will provide insights for policymakers to develop targeted interventions, such as improved air quality regulations and workplace safety measures, ultimately reducing the prevalence and severity of asthma cases. Ultimately, this research contributes to the growing emphasis on precision medicine and population health, offering valuable strategies for mitigating asthma risks and improving healthcare interventions in Oman and beyond.

The structure of this article is as follows: Section 2 comprehensively review of existing studies on asthma severity, environmental and demographic factors, and the application of AI and ML methodologies. Section 3 describes the dataset, including its origin, structure, and preprocessing steps. It also outlines the AI and ML techniques, feature selection process, and the methodological framework used to analyze asthma severity. Section 4 presents the study's findings, highlighting key predictors of asthma severity and their interactions. The experimental results are discussed in section 5. Section 6 interprets the findings, placing them in the context of existing literature. It also discusses the implications for public health policy, clinical practice, and future research directions. Limitations and future research opportunities are explored in Section 7. Section 8 summarizes the study's key findings and their practical applications, offering recommendations for healthcare professionals, policymakers, and industry stakeholders.

2. Literature Review:

The SIP, MIA, and SIZ are essential to Oman's economic development. However, these industrial hubs contribute significantly to environmental pollution, particularly air pollution, which poses serious health risks. Exposure to airborne pollutants from these areas has been linked to respiratory diseases such as chronic obstructive pulmonary disease (COPD), asthma, and lung cancer (Guarnieri et al., 2014; Kim et al., 2018). Additionally, indoor pollutants, including smoking, incense burning (bakhoor), dust, perfumes, and emissions from household appliances, exacerbate air quality issues, further impacting respiratory health (Apte et al., 2016; Q. Li et al., 2017; Maciag et al., 2022). Understanding the interplay between environmental and indoor pollution, demographic factors, and genetic predispositions is crucial for assessing asthma risks and guiding public health policies and industrial regulations tailored to Oman's unique environmental and cultural landscape.

Cockcroft (2018) highlights that inhaled allergens, particularly Immunoglobulin E (IgE)-mediated ones, play a central role in airway inflammation, leading to Airway Hyper-Responsiveness (AHR). Occupational exposure to chemical sensitizers, short-term contact with potent irritants, and long-term pollutant exposure can cause chronic airway changes, aggravating asthma symptoms. Exposure to these allergens not only leads to AHR and inflammation but is also linked to the Late Asthmatic Response (LAR) (Bhat et al., 2024). Environmental tobacco smoke, a major risk factor, further compounds these effects. Varga et al. (2024) provide a meta-analysis focusing on childhood asthma, revealing that mold exposure in homes significantly increases asthma risk. While case-control studies show a 53% increased risk, cohort studies report a lower but still notable 15% increase. This discrepancy suggests that age, gender distribution, and study methodologies influence findings. Genetic susceptibility, particularly heightened airway sensitivity in children, underscores the complexity of asthma development. The challenge remains in distinguishing whether mold exposure is a causative factor or merely a trigger for pre-existing conditions (Lee et al., 2024; A. Li et al., 2024; Patti et al., 2024).

The relationship between air pollution and asthma is well-documented, with pollutants such as particulate matter (PM), nitrogen oxides (NO_2), ozone, and volatile organic compounds (VOCs) being primary culprits (Eguiluz$_2$ Gracia et al., 2020). More than 90% of the global population breathes air exceeding WHO pollution limits, increasing the prevalence and severity of asthma. Perinatal exposure to second-hand smoke is particularly detrimental, heightening asthma susceptibility in children. Climate change further exacerbates respiratory conditions by prolonging pollen seasons and altering allergen profiles. Zhou et al. (2024) explore the biological pathways through which air pollution aggravates asthma, emphasizing oxidative stress and inflammatory responses. Pollutants disrupt the airway barrier, enhance TH2 inflammatory activity, and disturb immune regulation, leading to persistent airway hypersensitivity. Notably, long-term pollution exposure induces epigenetic modifications, potentially predisposing individuals to asthma. Despite their comprehensive analysis, Zhou et al. (2024) note limitations, particularly the lack of geographical considerations and the exclusion of at-risk groups beyond children. Domingo et al. (2020) further expand on air pollution's impact by linking it to increased vulnerability to viral infections, including COVID-19. Their study suggests that prolonged exposure to pollutants weakens immune defenses, prolonging illness severity and increasing mortality rates among individuals with pre-existing respiratory conditions. These findings highlight the urgent need for global policy interventions to enhance air quality and mitigate health risks.

A study conducted by Nunes et al. (2017) found that asthma often commences in childhood. Although some patients recover from asthma as they grow up, it often persists throughout the life of the infected people, requiring ongoing management and treatment (Lommatzsch, 2024; Medeleanu et al., 2023). While there is currently no absolute cure for asthma, it can be effectively managed through three key factors: a combination of medications, lifestyle modifications, and avoidance of known triggers. Appropriate management can dramatically reduce the rate and intensity of asthma attacks, help prevent lasting lung damage, and enhance the quality of life for those living with asthma (Becker et al., 2017). Ongoing research into asthma pathophysiology, along with advancements in personalized medicine and environmental interventions, offers hope for improved treatments and better management strategies in the future. However, addressing the environmental determinants of asthma, particularly air pollution, is critical in preventing new cases and reducing the burden of the disease worldwide.

Particulate matter (PM), a major component of air pollution, affects the incidence, severity, and symptoms of asthma, as observed by Chatkin et al. (2022). In their review, they discussed the effects of PM10, PM2.5, PM0.1, NO_2, SO_2, CO, and O_3 on asthma addressing molecular and environmental pathophysiological mechanisms by which these pollutants affect asthma. An increase in density in and around urban areas and movement from rural to urban settings, in addition to changes in lifestyles of the people, particularly those in the low income bracket has led to increased exposure. PM0.1 or smaller PMs enter the alveolar region and cause oxidative stress and immunological changes. NO_2 and ozone cause exacerbation of asthma symptoms by the intensification of airway inflammation. Individual suffering from common childhood illnesses or some respiratory illnesses are at higher risk of being hospitalized than those with high mortality rates. Chatkin et al. (2022) pointed out that those regulatory measures aimed at decreasing exposure to air pollutants are urgently needed. However, greater emphasis should be made on the limitation of industrial and traffic emissions that, in turn, could improve respiratory health and, particularly, the health of individuals living in polluted cities. While this study provides a comprehensive review of the effects of particulate matter (PM) and other pollutants on asthma, several limitations must be noted. The study primarily relies on existing literature without incorporating new experiments, which limits its ability to establish causal relationships between pollutants and asthma outcomes. Additionally, although regulatory measures are suggested, the study lacks detailed policy recommendations or evidence-based strategies to implement these measures effectively.

The reviewed literature establishes a strong link between industrial and indoor air pollution and asthma exacerbation, particularly in vulnerable populations such as children. Given Oman's reliance on industrial expansion, developing policies to regulate emissions and improve indoor air quality is critical. In summary, the above studies provide valuable insights into the environmental and lifestyle factors contributing to asthma, but they exhibit notable weaknesses. Fist, none of the studies applied AI and ML to analyze data patterns, identify complex relationships, or predict asthma triggers and progression. Integrating advanced computational approaches could have provided deeper data-driven insights into the multifaceted causes and dynamics of asthma. The absence of advanced computational approaches limits the potential to uncover novel insights or verify existing hypotheses. Second, the lack of comprehensive datasets is another significant limitation. The datasets used in the above studies were not comprehensive, limiting the ability to draw robust, generalizable conclusions. The studies mainly relied on specific case-control or cohort datasets, which were not sufficiently diverse. This limitation reduces the representativeness of the findings and restricts their application across diverse populations. Third, none of the studies adequately addressed geographical variations or the role of proximity to population sources. These factors are critical for understanding regional differences in asthma prevalence and triggers. For example Cockcroft (2018) did not analyze the role of geographical differences in environmental exposures or asthma development. In addition, Varga et al. (2024) and Eguiluz2 Gracia et al. (2020) overlooked the influence of climatic and regional disparities in their studies on mold and air pollutants, respectively. Besides, Zhou et al. (2024) did not explore how geographical variations might affect the impact of air pollution on asthma. Fourth, several studies, such as Varga et al. (2024) and Agache et al. (2024), concentrated on childhood asthma or specific indoor pollutants, leaving gaps in understanding asthma triggers across broader demographic and environmental contexts. Fifth, there is a limited causal and mechanistic analysis in the reviewed studies. Most studies, including those by Nunes et al. (2017) and Eguiluz2 Gracia et al. (2020), relied on observational or cross-sectional methods, hindering causal inference. This methodological constraint restricts the understanding of how environmental and lifestyle factors directly contribute to asthma onset and exacerbation. Finally, the studies lacked sufficient longitudinal and predictive insights. While some studies long-term impacts of air pollution, climatic changes, and allergens on asthma were mentioned (e.g., Eguiluz2 Gracia et al. (2020)) they did not incorporate predictive modeling to quantify these effects robustly over time.

In general, the above studies fall short in leveraging advanced computational techniques, comprehensive datasets, and geographically inclusive analyses. Addressing these limitations in future research—particularly through AI, ML and diverse, large-scale datasets—can significantly enhance the precision, scope, and applicability of asthma studies. Additionally, bakhoor and perfumes are cultural habits that are still unexplored but highly influential causes of indoor air pollution in the Middle East. This research therefore seeks to fill this gap using superior technologies in AI and ML to analyze environmental, demographic, and health data from Oman's Al-Shifa EHR system. By doing so, this research aims to close the existing research-practice gap regarding predictors of asthma severity.

3. Materials and Methods:

3.1. Data Collection

The dataset used in this study was obtained from the national Al-Shifa Electronic Health Record System (AEHR) in Al Batinah North Governorate. Data collection was conducted at three healthcare centers in Liwa, Falaj Al Qabail, and Nabr. These centers were chosen because of their close proximity to the industrial areas and the high number of asthma cases recorded in their patient databases, ensuring the dataset was representative of the affected population. The dataset covers the period from 2014 to 2022, allowing for a robust analysis.

The 2014–2022 timeframe was selected to capture all asthma-related visits, ensuring a broad representative, and reliable dataset. Previous studies, such as Al-Wahaibi et al. (2015) and Al-Busaidi et al. (2015), only analyzed data up to 2014, highlighting the need for updated research. As the dataset was collection in 2023, it includes records only up to the year 2022.

The dataset comprises 410 patients with 50 parameters. Here, the number of patients represents the sample size, while the parameters serve as features. The majority of features are categorical (41 features), with only nine being numerical. Throughout the data collection process, patient security and privacy were prioritized, adhering to all relevant guidelines and securing the necessary approvals to maintain confidentiality.

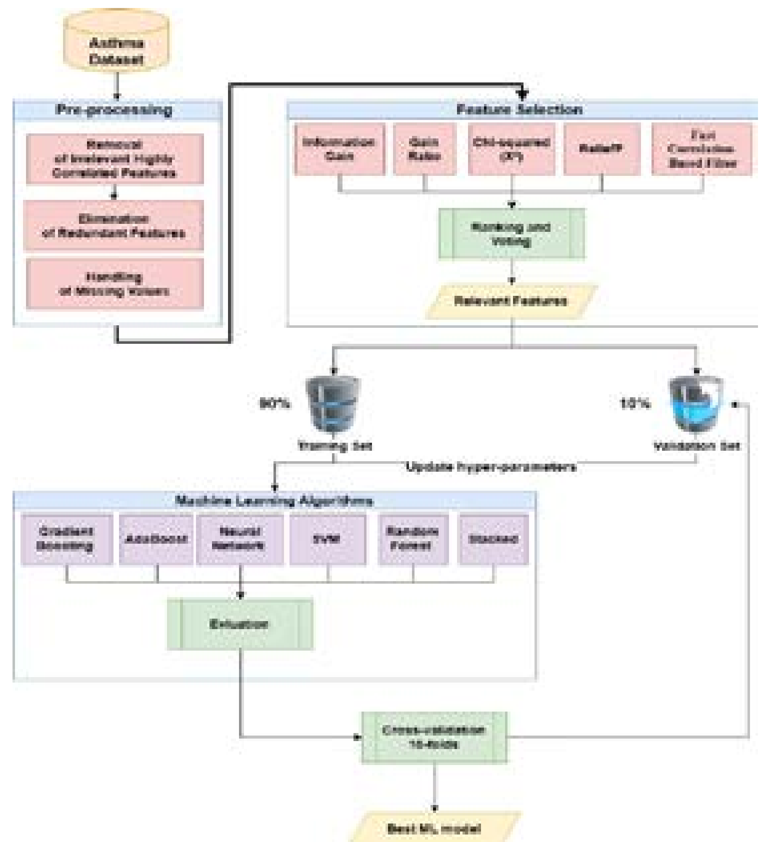
3.2. Ethical Statement

Approval for ethical considerations and data-sharing agreements was obtained from the Research and Ethical Review & Approval Committee at Ministry of Health. The aapproval code is **MoH/DGPS/CSR/PROPOSAL_APPROVED/&/2018**. Besides the research was carried out following the guidelines of the Ethic and Biosafety committee at the College of Medicine and Health Sciences, National University of Science and Technology. The Protocol Code is **NU/COMHS/EBC0058/2022**.

3.3. Methodology

Asthma is a prevalent health issue in Oman, with varying impacts on individuals depending on the disease severity. This study employs the KDD methodology (Debuse et al., 2001; Debuse et al., 2000) to investigate how AI and ML can enhance our understanding of asthma severity as shown in Figure 1. The KDD methodology is well-regarded in academic research for its capacity to yield accurate and actionable insights (Rahman et al., 2014; Williams et al., 1996).

Figure 1. Our methodology as KDD architecture



In the original dataset, all patients were identified as having asthma at different severity levels: 218 were classified as moderate, 108 as mild, and 84 as severe. Upon consultation with domain experts, it was determined that mild and moderate cases could be combined, resulting in a final classification of 326 moderate patients and 84 severe patients.

The workflow illustrated in Figure 1 presents a structured approach to build a machine learning (ML) model for analyzing an asthma dataset. The workflow is divided into several stages: Pre-processing, Feature Selection, and Model Training and Validation.

3.3.1 Preprocessing

This stage aims to prepare the raw dataset for analysis. It begins with removing of irrelevant, highly correlated features. Parameters such as Asthma Severity, Combined Severity Asthma, and Asthma_Severity (Filter) were highly correlated with the target class, which could introduce potential bias. These features were removed to ensure a unbiased model development. Next, redundant features were eliminated. For instance, Age Range 1 and Age Range 2 were found to be identical, with the latter grouping samples into 15-year intervals, so Age Range 2 was excluded. Similarly, Covid Vaccine 1 and Covid Vaccine 2 were duplicates, leading to the removal of Covid Vaccine 2. Smoke Status 1 and Smoke Status 2 also conveyed identical information, resulting in the removal of Smoke Status 2.

Additionally, the features Number of Resident Years and Resident_Years_Range were redundant, with the latter presenting data in ranges; therefore, Resident_Years_Range was discarded. Since Age Range features were included, both Age in Years and Date of Birth were deemed redundant and removed. Lastly, the handling of missing values was addressed. Features such as Number of Family Members, Family Members Range, Marital Status, Level of Education 1 and 2, and Occupation contained a significant amount of missing data and were excluded from further analysis.

3.3.2 Feature Selection

After preprocessing, relevant features were identified through a combination of methods. To determine the most significant features contributing to the target class prediction, five widely recognized feature selection algorithms were employed. InfoGain and Gain Ratio measure the reduction of uncertainty (entropy) following a dataset split, with Gain Ratio adjusting for split complexity. The Gini Index, utilized in decision trees, assesses dataset purity, where lower Gini values indicate more homogeneous subsets. The Chi-squared (X) Test is a statistical method that evaluates the independence of variables and examines the relationship between a feature and the target variable. ReliefF gauges feature relevance by comparing instances and adjusting feature weights based on their effectiveness in distinguishing similar examples. Lastly, the Fast Correlation-Based Filter (FCBF) identifies features with a strong correlation to the target class while minimizing redundancy with other features, thereby refining the dataset for further analysis.

By employing these scoring methodologies, we aimed to ensure a robust foundation for our AI and ML analyses, facilitating accurate predictions regarding asthma severity in Oman. The majority of the scoring methods ranked the Age Range parameter as the most influential predictive factor, followed by four outdoor factors (e.g., distance from the industrial pollution) and then indoor factors. The top 10 parameters are considered for the classification algorithms, as agreed by the majority of the selected scoring methods.

3.3.3 Model Training and Validation

As for the model validation technique, during the training phase, we validated the models using a cross-validation technique called stratified 10-fold. Such a validation helped in mitigating the risk of excluding cases from either the training or validation stages. In addition, it assessed in mitigating the effect of an imbalanced dataset. In this iterative process, the dataset was divided into 10 subsets. In each iteration, 90% of the selected instances were left out for training, while the remaining 10% were considered as new, unseen instances. This ensured that each instance was used for training and testing in one of the ten iterations. Each iteration built and assessed a classifier model after which a general average metric was taken. Such processes fostered generalizability and helped prevent overfitting or boosting. Furthermore, it was confirmed that the class distribution in the dataset was preserved across all folds thereby providing the model with an accurate indication of its performance due to cross-validation being used. This process served to ensure the robustness and generalizability of the model. This process reduced the likelihood of overfitting or underfitting by averaging model performance through numerous splits.

Regarding the machine learning algorithm, supervised classification algorithms were employed to achieve optimal classification that could successfully identify a set of known features and unknown tags. Several classification models radically exposed an intense theory in representing knowledge as a precise pattern. To ensure the diversity in applying different structures, a collection of supervised classification algorithms belonging to different classes was employed including Functions, Meta, and Tree.

A classifier is a function that maps input features to their correct output labels. This function can be of any form, ranging from linear and nonlinear representations. This paper considered nonlinear functions of MLP and linear SVM as they have more advantages and abilities. MLPs are good at finding nonlinear correlations hidden in high-dimensional data. They offer flexibility, scalability, and feature extraction of data. Noisy or sparse environments, small to medium dataset sizes, robust generalization, and interpretability are the strengths of SVMs. Additionally, the kernel approach strengthens an SVM's work in nonlinear problem-solving.

In the meta model category, the main concept was to create a strong classifier from a pool of weak classifiers combined in a way that the prediction of the label was decided by the majority of classes or the average of continuous classes. Mainly we employed two techniques, bagging and boosting. In bagging techniques, the training data was sampled with replacement in order to obtain k samples. Each sample trained a classifier, usually the J48 algorithm. During testing, the outputs of all classifiers were combined in a voting or averaging process. Boosting methods generated a classifier in sequence, with subsequent classifiers paying more attention to the errors made by the previous weak classifier. In this paper, we used Random Forest (RF) technique as bagging method. This is because in term of the structured data, random forests yield robust, accurate, and interpretable results.

The experiments relied on the use of Gradient Boosting and AdaBoost. This is because both techniques are flexible, work well with structured data. In addition, they have very good predictive power, making them ideal for experiments where accuracy and the ability to address intricate data relationships are critical. Gradient Boosting minimizes errors by optimizing the loss function. This helps Gradient Boosting perform effectively in catching complicated patterns in data and managing nonlinear relationships between independent variables and outcomes. AdaBoost, on the other hand, assigns higher weights to misclassified instances in subsequent iterations; thus, it is more capable of focusing on difficult cases.

Tree-based models leverage the concept of randomness or impurity, using entropy as a crucial feature. The selection of attributes from within the training set was based on the level of impurity that would lead to a subset generation in the tree. The best attribute was, therefore, considered as the one which generated a tree whose leaf nodes were pure classes. Each of these classifiers was a tree, where each node represented the most beneficial feature at that level, and the branches represented the possible values of that feature. Among these, the J48 decision tree model, which was a weak classifier, was used in the random forest model. We further used and a Stacked model (ensemble method combining multiple models).

Finally, based on the cross-validation results, the best-performing model was selected as the final machine learning model for the asthma dataset. This comprehensive architecture exemplified a thorough approach to building a predictive model, highlighting the importance of data quality, relevant feature selection, and rigorous model validation.

4. Experimental Results

As stated above, the experimental results presented in this study are based on the selection of the most crucial features, which contribute to the model's predictive performance. To identify these key features, we employed five feature selection methods, and the top 10 most crucial features were selected based on the average ranking across all methods. The crucial features that contribute to the prediction of asthma severity include Age Range, distance to the industrial areas, Smoke, Dust, etc.

4.1. Experimental Analysis

The features in the used dataset each represent various aspects and perspectives of the variables affecting the prevalence of asthma. This section highlights how these characteristics affect the prevalence of asthma, particularly in different demographic groups. We used 10 key features from the dataset that were found using feature selection techniques to guarantee a targeted analysis. Numerous important groups of interest were identified by the analysis, including each demographic group's level of exposure to contaminants, age, geographic location, history of diseases, and vaccination status.

One crucial area is the vaccination status feature; thus, we examined the effects of influenza and COVID-19 vaccinations on the severity of asthma. Figure 2, which demonstrates the connection between vaccination and asthma severity, shows the impact of these vaccinations on asthma severity. According to the results, there was a significant relation among those who had both the influenza and COVID-19 vaccinations whereas the dataset ensures that 79.5% of people with moderate asthma severity had received both vaccines. The result suggests a robust correlation between vaccination and less severe asthma. The results highlight the value of vaccination in preventing respiratory infections as well as reducing the frequency and intensity of asthma exacerbations.

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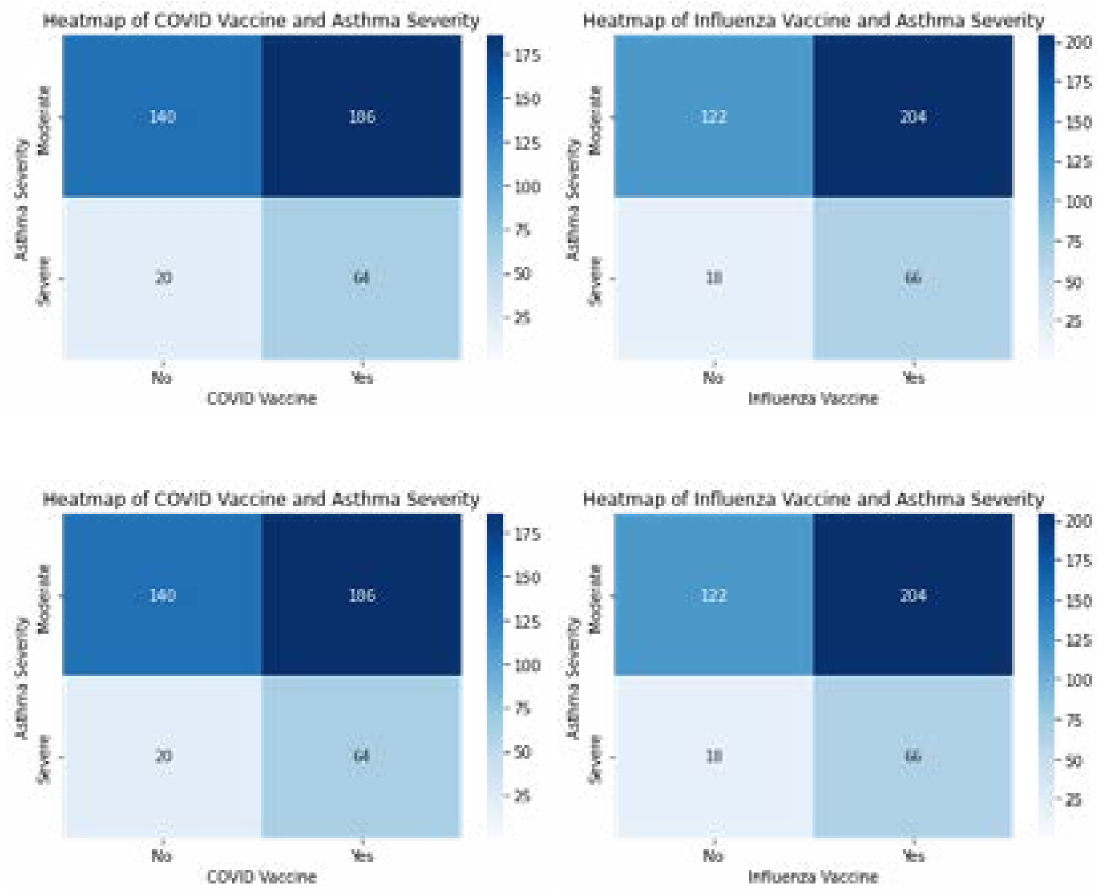
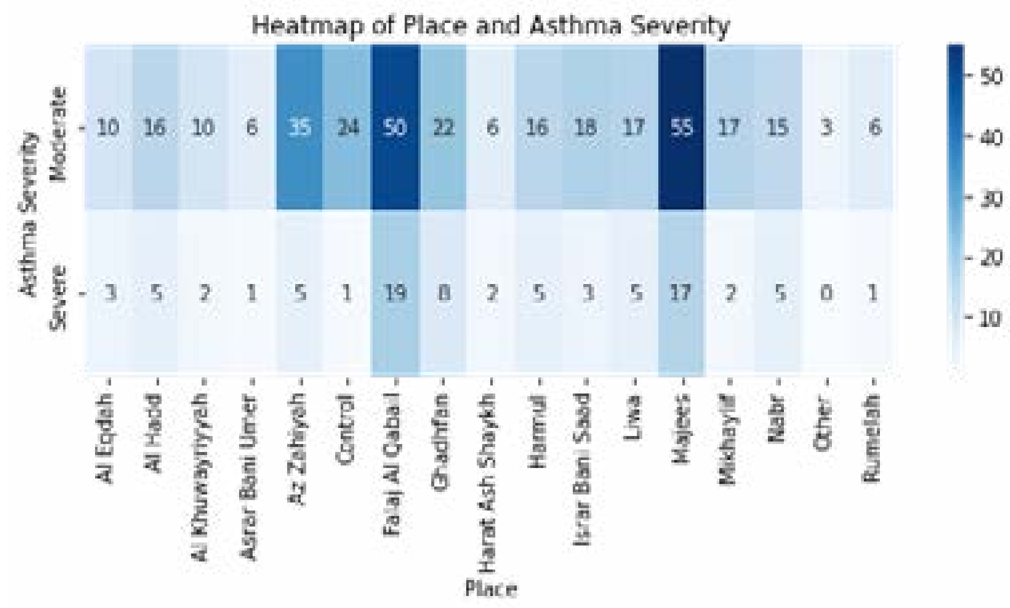
Figure 2: The impact of Vaccination status on Asthma Severity



We examine the possible effects of a marine site in Oman on the health of people who live nearby, focusing on the prevalence of asthma, from a location-based perspective. With 17 sites disseminated across different distances from the marine center, the study allows for a detailed investigation of the connection between geographic proximity to the site and health effects, particularly asthma. The results of the analysis show a strong relationship between the higher prevalence of asthma and how close a person's home is to the marine site. The number of asthma cases at each of the 17 sites, divided by distance from the marine site, is shown in Figure 3. Falaj Al Qabail and Majees are the two locations closest to the marine center, and both have the highest asthma prevalence rates. The figure not only reveals the increase in asthma prevalence near the marine center but also shows geographic signs in the allocation of asthma cases, with higher rates detected in areas nearest to the site among the 17 locations. Specifically, Majees has a marginally higher asthma prevalence rate of 17.5% than Falaj Al Qabail, which has a rate of 16.8%. These higher prevalence rates in the vicinity of the marine site point to a possible environmental factor that could be responsible for the increased incidence of asthma in these regions. People who live in these areas appear to be more susceptible to asthma than people who live further away from the marine site.

The results indicate that environmental factors related to the marine site, such as air quality, allergens, or marine pollutants, impact the increased percentage of asthma among residents. This ensures further investigation into the specific environmental variables that could be contributing to these health effects. In addition, the study ensures to dive into other socio-environmental factors in the surrounding areas, such as urbanization, traffic pollution, or industrial emissions that impact defects with asthma. These results show the importance of evaluating environmental exposure in the study of respiratory conditions such as asthma, particularly in the context of nearness to marine environments.

Figure 3: The impact of Place on Asthma Severity

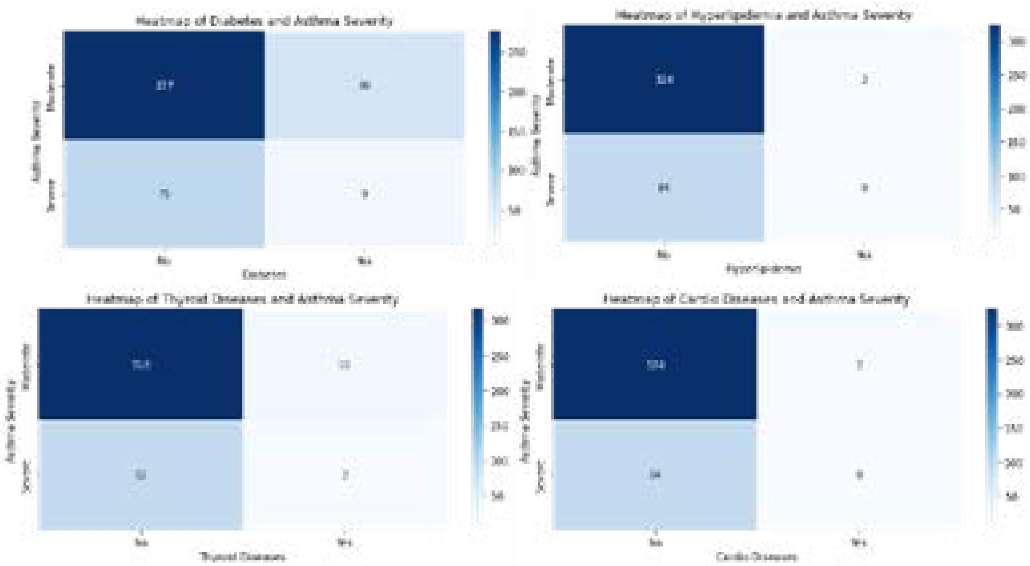


With a focus on a demographic ranging from 11 to over 80 years old, the analysis explores the impact of various age groups on the severity of asthma among people living in maritime areas. This wide range of ages makes it possible to fully comprehend how the severity of asthma may change with age. Comparing the trends in asthma severity across age groups when the gathered age data is methodically arranged into 10-year intervals, the 11-20 age group demonstrates the highest incidence of moderate asthma, with 85 cases. These results suggest that younger individuals in the marine area may be more susceptible to moderate asthma, potentially due to environmental or occupational factors.

In general, the severity of asthma tends to decrease with age across all categories, with fewer moderate and severe asthma cases observed in older age groups. Nonetheless, the most general category for individuals of all ages is still moderate asthma, suggesting that its impact is comparable among those living in the maritime region. The relative abnormality of severe asthma cases suggests that severe respiratory problems are less common in the general population. With 12 cases, the 11–20 age group once again has the highest number of severe asthma cases. Regardless, the number is still much lower than that for moderate asthma, emphasizing the lower prevalence of severe asthma, even in younger people. It is important to note that the ages between 21 and 50 have the highest asthma severity levels indicating that people in this age range are more likely to work longer hours in maritime settings having a greater negative influence on respiratory health. According to this data, working in maritime environments for extended periods and occupational exposure may make asthma worse, particularly in this crucial working-age group.

Asthma severity, in addition to being influenced by various external factors, can also have a significant impact on individuals with historical medical issues such as diabetes, hyperlipidemia, thyroid disorders, and cardiovascular diseases. Figure 4 illustrates the distribution of individuals with medical issues with moderate to severe asthma. Significant effects are shown, with a 14% decrease in the severity of asthma in those with a history of medical issues. This indicates that the patients have proactive behavior to control their health, such as avoiding high-pollution areas that may cause respiratory symptoms. Furthermore, as people with severe asthma attempt to decrease their exposure to pollutants, this avoidance behavior may have wider ramifications for public health planning.

Figure 4: The impact of Previous Diseases on Asthma Severity



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4.2. Machine learning Validation and Results

The asthma severity in Oman is evaluated using a variety of machine learning algorithms, including Neural Network, Support Vector Machines (SVM), AdaBoost, Random Forest, Gradient Boosting, Decision Trees and Naïve Bayes. The learning theory behind each algorithm yields in identifying the patterns from the input independent features of multifactorial aspects and focusing on valuable insights into the factors contributing to Asthma severity among Omani patients. To validate the experiment results, a 10-fold cross-validation technique is used to splits the dataset into ten folds and iteratively uses one-fold for validation while the others for training. This technique ensures participating each instance in training and testing phases. In the realm of evaluation analysis, the effectiveness of ML algorithms is evaluated using a test set, while the quality of the results is measured using several metrics. We use well-known metrics to evaluate effectiveness of models, which include Accuracy, F-Measure, Precision, Sensitivity (Recall), MCC, ROC Area, and PRC Area (Naidu et al., 2023).

The performance of different machine learning algorithms was evaluated via a number of theoretical foundations as shown in Table 1. With a satisfactory accuracy rate of 82.1%, the proposed stacked model - a hybrid ensemble that capitalizes on the stability of random forest and gradient boosting - performs superior to other models. Even though the RF, a tree-based ensemble model, gained a lower accuracy of 74.3%, it performs well and produces valuable results when integrated as a component model into the hybrid ensemble stacked model. Even though the RF model performs less well as a stand-alone model, it improves the prediction accuracy of the stacked model ensuring the crucial model integration to exploit the complementary advantages of various algorithms.

Table 1. The Results of the Evaluation Metrics

Algorithm	AUC	Accuracy	F1	Precision	Recall	MCC
Stack	0.749	0.821	0.804	0.814	0.821	0.484
Gradient Boosting	0.757	0.807	0.800	0.798	0.807	0.465
Neural Network	0.751	0.797	0.790	0.787	0.797	0.438
AdaBoost	0.708	0.767	0.764	0.762	0.767	0.377
Random Forest	0.653	0.743	0.633	0.552	0.743	0.000
SVM	0.759	0.743	0.633	0.552	0.743	0.000

The gradient boosting and neural network models perform well, with accuracy values of 80.7% and 79.7%, respectively. These models reveal competitive results with the stacked model, although they do not surpass its performance. The slight difference in accuracy between the stacked model and the two models indicates that integrating models can also yield better generalization and robustness. On the other hand, the Support Vector Machine (SVM) and AdaBoost models obtain low effectiveness when evaluated against other ML algorithms on precision, recall, F1 score, and accuracy metrics. These lower results highlight the importance of choosing the most appropriate algorithm, considering both its learning theory and the specific evaluation criteria. The evaluation metrics are consistent with the accuracy values reported for each model. These also include other standard classification metrics such as precision, recall, F1 score, and area under the ROC curve (AUC), which confirm the tendencies followed in accuracy. Finally, while models like gradient boosting and neural networks obtain proper performance, the stacked model reaches the highest accuracy and robustness, highlighting the possibility for enhanced performance through model integration.

5. Discussion:

Initial findings from our research indicate that several factors play significant roles in influencing asthma severity among Omani patients in the Al Batinah North Governorate. The experimental results of the ML algorithms on the asthma dataset provide a comprehensive view of asthma severity across different age groups, distances from key industrial areas, smoking habits, and geographic coordinates. These results highlighted complex interactions among these factors and extracted important patterns and trends that are crucial for improving the understanding and management of this chronic respiratory condition. Our results align with global data provided by the World Air Quality Index (WAQI), which offers transparent real-time air quality monitoring for over 500,000 stations worldwide (Scale, 2025). According to WAQI, air quality levels near MIA, SIP and SIZ range from moderate to unhealthy, signifying serious pollution levels, particularly hazardous to individuals with respiratory diseases. However, WAQI's outdoor pollution data does not capture critical factors such as age and proximity to industrial areas, which our study addresses by uncovering deeper patterns of asthma severity.

Our findings extend existing research by emphasizing the combined effects of age, geographic proximity, and indoor pollution factors such as smoking on asthma severity. Our study revealed that asthma severity is significantly affected by patient age combined with proximity to major industrial areas like MIA and SIZ. Specifically, patients aged 21 to 50 or 61 to 80 years, residing approximately 7.61 kilometers from MIA or 25.65 kilometers from SIZ, consistently reported experiencing moderate asthma symptoms. For patients within the same age groups, living at a distance of less than 25.65 kilometers from SIZ generally correlates with a reduced likelihood of severe asthma unless they are exposed to indoor pollution (smoking). This insight highlights the role of smoking as a worsening factor in regions closer to industrial pollution. Smoking appears to increase respiratory issues in patients exposed to industrial pollutants (Beyene et al., 2022; Noah et al., 2023), signifying that indoor pollutions can substantially alter asthma outcomes for those living in industrial areas. This conclusion is aligned with the findings in (Cockcroft, 2018; Soendergaard et al., 2024). Patients aged 31 to 50 years living within a 4.6-kilometer radius of the SIP, regardless of gender, are highly likely to experience severe asthma. Additionally, patients aged 21 to 30 years residing in the area between SIP and MIA—specifically those located less than 8 kilometres from MIA or less than 4 kilometres from SIP—are also at significant risk of severe asthma. The experimental results did not highlight any indoor parameters for SIP, strongly indicating that outdoor pollution is a major contributing factor to the observed severity of asthma. This finding underscores the profound impact of environmental pollution, such as industrial emissions and urban pollutants, on respiratory health.

Unlike Varga et al. (2024) and Zhou et al. (2024), the our results call for special attention to older patients, particularly those aged 61 to 80 years old. It has been found that this age group face a heightened risk of severe asthma if they live within a close 7.61-kilometer radius of MIA. This indicates that proximity to this industrial area introduces environmental factors possibly including particulate matter or gaseous pollutants that exaggerate asthma symptoms in older patients. The model shows that older individuals have less respiratory resilience, which, combined with environmental exposure, significantly increases asthma severity. Thus, targeted interventions for elderly patients in these areas may be crucial. Longitude also plays an important role in asthma severity. Patients aged 31-50 or older than 80 years old, who smoke and live at a longitude higher than 56.60 are particularly susceptible to severe asthma. This highlights that geographic elements, possibly associated with air quality variations, interact with smoking to escalate asthma risk. On the other hand, those within the same age range but do not smoke, generally experience moderate asthma, highlighting the protective effect of indoor pollution (smoking) even in higher-risk geographic zones. In the age range of 41-50 years old, patients living at a longitude of 56.60 or above are likely to have severe asthma, regardless of smoking status, indicating that other environmental factors unique to this longitude may escalate symptoms in this age range. Alternatively, patients aged 31-40 or over 80 years old and live in the same longitude range tend to have moderate asthma, pointing to possible age-related resilience elements that reduce asthma severity in these groups. This finding emphasizes the significance of age-specific respiratory resilience.

Quite the opposite the findings of Nunes et al. (2017), the experimental results of the AI and ML further identify unique trends in younger patients. Children younger than 10 years old consistently exhibit moderate asthma, which could be due to a combination of lesser environmental exposure time and possibly better response to early intervention measures. Whereas youths aged 11 to 20 years old exhibit a different trend: those who live more than 7.96 kilometers from SIZ and at least 9.56 kilometers from MIA show severe asthma, indicating that specific environmental prompts within this radius range may contribute to greater respiratory sensitivity in this age group. Remarkably, severe asthma is also observed in teenagers living closer to MIA (less than 8.84 kilometers), indicating a sensitivity to industrial pollutants at shorter distances for this age group. Among middle-aged patients, particularly those aged 51 to 60 years old, the majority exhibit moderate asthma. This trend points out that this age group may have built some

level of respiratory resilience or possibly benefit from intervention measures. However, outdoor and indoor pollutions may still contribute to moderate symptomatology, though not to the severity observed in younger or older groups under similar environmental conditions.

Generally, this study bridges critical gaps in understanding the multifaceted impacts of air pollution on asthma severity by integrating demographic, geographic, and environmental factors. By identifying age-specific vulnerabilities and the significant role of indoor pollution, our findings provide a strong foundation for targeted public health interventions and policies aimed at mitigating the burden of asthma in industrial regions. The findings emphasize how cultural practice in Oman increases indoor air quality and health outcomes. The burning incense (bukhoor) and using scented oils and perfumes, which are integral to Omani traditions, contributes significantly to indoor pollution by releasing VOCs and particulate matter, aggravating asthma and allergies. The widespread use of strong cleaning chemicals and disinfectants introduces additional VOCs into the air, while traditional architectural designs with limited ventilation promote the accumulation of pollutants, including mold caused by humidity and poor air circulation. Additionally, the humid climate in Oman exacerbates mold growth in indoor spaces, with spores triggering respiratory issues. The traditional use of carpets and heavy upholstery further compounds the problem by trapping dust, allergens, and VOCs, which degrade indoor air quality. By highlighting these culturally specific practices, this study offers a distinct and culturally relevant perspective, providing valuable insights into the unique challenges faced by the Omani population. These findings not only contribute to the broader understanding of asthma management but also inform culturally tailored public health strategies to improve indoor air quality and reduce asthma severity in Oman.

6. **Implication:**

The implications of these findings are significant, as they highlight the need for targeted interventions and stricter environmental regulations in heavily industrialized and urbanized regions. The study offers a dual contribution, delivering both theoretical insights and practical applications that hold considerable importance for researchers, healthcare professionals and policymakers.

6.1 Theoretical Implications:

This research provides a novel theoretical framework that explores the complex relationships between geographic proximity, environmental pollutants, lifestyle factors, and asthma severity across different age groups. Public health initiatives focusing on pollution control, alongside monitoring air quality in areas surrounding SIP and MIA, are essential to mitigating the adverse health impacts. Furthermore, the data emphasize the necessity of tailoring asthma prevention strategies to specific geographical and demographic contexts, ensuring the development of comprehensive policies that address the unique risks faced by residents in proximity to industrial and urban zones. By integrating advanced AI and ML techniques, the study bridges the gap between traditional epidemiological models and modern data-driven approaches, presenting a pioneering perspective on asthma management. It emphasizes the role of spatial analysis in understanding asthma severity, introducing a methodological advancement in evaluating the environmental and demographic factors that contribute to health outcomes. This framework can serve as a foundation for future research investigating similar health conditions influenced by environmental and lifestyle variables. The study introduces nuanced demographic categorizations (e.g., age groups, geographic distances) and their specific sensitivities to environmental factors, which enrich existing theoretical models of asthma pathophysiology and management strategies.

6.2 Practical Implications:

From a practical perspective, the model introduced in this study is both dynamic and flexible, making it highly suitable for diagnosing future diseases. Its adaptability can greatly accelerate the diagnostic process, helping to minimize the occurrence of severe cases. Furthermore, the framework's application extends beyond asthma, highlighting its potential as a critical tool in combating emerging diseases. This enhances our ability to respond promptly and effectively to healthcare challenges. Overall, the practical implications of the proposed model are summarized as follow:

- **For Policymakers:** The findings provide actionable insights to design evidence-based policies aimed at mitigating the severity of asthma. For instance, targeted interventions, such as stricter regulations on industrial emissions in high-risk zones and public health campaigns about indoor pollution (e.g., smoking), can significantly reduce the burden of asthma.
- **For Healthcare Providers:** The results highlight the need for tailored healthcare approaches that address the unique risk profiles of patients based on their age, proximity to industrial zones, and lifestyle factors. Healthcare practitioners can use this information to personalize asthma prevention and management strategies, ensuring that vulnerable populations, such as children and elderly individuals near industrial areas, receive timely interventions.
- **Community Awareness Programs:** This study underscores the importance of community-level interventions, such as educational campaigns focusing on indoor pollution reduction and lifestyle modifications, to combat asthma severity effectively.
- **Strategic Planning for Public Health:** The insights can assist health authorities in resource allocation, prioritizing areas and demographics with higher risks of severe asthma, thereby optimizing the impact of public health initiatives.

Beyond its practical applications, the findings of this research have substantial economic implications. The ability to predict and mitigate asthma severity through AI and ML-driven models can lead to significant cost savings in healthcare. Early diagnosis and intervention reduce the frequency of hospital visits, emergency care utilization, and long-term medication dependency, alleviating the financial strain on both healthcare systems and patients. From a broader societal perspective, optimizing public health resources based on data-driven insights ensures efficient allocation of funds, minimizing unnecessary expenditures on reactive healthcare measures. By prioritizing preventive care and risk-based resource distribution, governments can reduce the long-term economic impact of chronic respiratory diseases, fostering a more sustainable healthcare system. Ultimately, these economic benefits extend beyond healthcare, positively influencing workforce sustainability, national productivity, and overall economic resilience.

In conclusion, this study not only advances theoretical understanding but also equips decision-makers in health and governance sectors with the tools to implement targeted strategies, ultimately reducing asthma severity and improving the quality of life for affected individuals in Al Batinah North Governorate. By addressing the interplay of environmental, demographic, and lifestyle factors, the research provides a holistic approach to tackling asthma in vulnerable populations.

7. Limitations and Future Work:

Future research should address several important factors to enhance our understanding of asthma severity and its environmental triggers among residents near industrial areas. A key limitation of this study was the absence of control cases, as only individuals with moderate to severe asthma were included. To obtain a more comprehensive view of asthma risk, future studies should include a control group of individuals without asthma, enabling a comparison of specific environmental or lifestyle conditions that may prevent asthma onset or reduce its severity.

Moreover, future studies should incorporate detailed geographic and environmental variables, such as residents' home locations, prevailing wind directions, and distances from the industrial complex. Analyzing these factors can help clarify how pollutant dispersion patterns contribute to asthma incidence and severity. For example, variations in wind direction and speed may either concentrate pollutants in certain areas or disperse them, potentially exposing certain neighborhoods more than others. Examining these variables may reveal which environmental characteristics are associated with higher or lower asthma rates, providing valuable insights for developing effective preventive strategies.

8. Conclusion:

This study marks a groundbreaking effort in the thorough analysis of the factors influencing the severity of asthma among Omani patients, with a specific focus on the Al Batinah North Governorate. Our research has extracted valuable insights into the complicated interrelationship between geographic location, age, indoor pollutions and the severity of asthma among different patient groups. By employing state-of-the-art ML and AI techniques, we have simplified the complexities surrounding this issue, highlighting the unquestionable impact of environmental factors on asthma severity. These findings highlight the critical need to consider geographic location and industrial pollution sources in the comprehensive management and prevention of asthma, particularly for vulnerable populations living in close proximity to such areas.

In summary, the experiential results provide a detailed perspective on how asthma severity varies with age, outdoor elements (geographic proximity to industrial zones), and indoor elements (lifestyle factors such as smoking). Patients who are 21 to 50 and 61 to 80 years old living around 7.61 kilometers from MIA and 25.65 kilometers from SIZ generally experience moderate asthma. Those under 25.65 kilometers from SIZ are less likely to have severe asthma unless they are exposed to smoking indoor elements, highlighting the exacerbating impact of smoking. Older patients who live closer to MIA are more likely to suffer from severe asthma, indicating sensitivity to industrial pollution in this age group. It is important to mention that severe asthma risk increases for patients who are 31-50 years old and older than 80 years old if they smoke and live at a longitude higher than 56.60. Children under 10 typically exhibit moderate asthma, whereas youths11-20 years old show a higher likelihood of severe asthma if located between specific distance ranges from SIZ and MIA. Most patients aged 51 to 60 display moderate asthma, possibly due to resilience or effective management strategies. These results provide actionable insights, suggesting targeted intervention strategies tailored to specific patient demographics and their associated risk factors, ultimately aiding in the reduction of asthma severity across diverse age groups and environmental settings. The absence of any notable indoor pollution parameters in the analysis of SIP emphasizes the role of outdoor environmental pollution, including industrial emissions and urban pollutants, as a major driver of asthma severity.

We believe our findings will play a key role in expanding the understanding of asthma within this community. This finding highlights the importance of managing indoor air quality, particularly in high-risk areas, to potentially reduce the severity of asthma symptoms and improve patients' quality of life. There is a critical need to raise awareness about the harmful effects of indoor pollution on respiratory health, particularly asthma severity. Community-level interventions, such as educational campaigns, are essential to inform individuals about the impact of cultural practices like burning incense, using scented products, and employing strong cleaning chemicals. By promoting lifestyle modifications and practical steps to reduce indoor pollution such as improving ventilation, managing humidity, and reducing exposure to VOCs this study emphasizes the importance of empowering communities to adopt healthier practices that mitigate asthma severity and enhance overall well-being.

In general, the obtain insights can form the basis for creating evidence-based policies and effective strategies that will improve how asthma is managed and prevented. By addressing the unique needs of this population and its environmental challenges, we hope to enhance the quality of life for those affected by asthma. Our research assists in making strategic plans and offers valuable resources for healthcare providers and policymakers, ultimately contributing to a healthier future for asthma patients in the Al Batinah North Governorate.

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Abstract :

This research investigates the association between various elements and the severity of asthma among individuals living in the Al Batinah North Governorate of Oman. It addresses both indoor and outdoor parameters that participate in the development of severity of asthma, with indoor elements including smoking, bakhoor (incense), perfume, and dust, while outdoor elements focus on pollution from nearby industrial areas such as Sohar Industrial Zone (SIZ), Majan Industrial Area (MIA), and Sohar Industrial Port (SIP). Additionally, other health-related factors are examined. The study uses the Knowledge Data Discovery (KDD) methodology to employ Artificial Intelligence (AI) and Machine Learning (ML) methods to identify hidden patterns that influence asthma severity. Additionally, a comprehensive analysis is conducted to find the association between parameters. The dataset of the study was acquired from an electronic health recording system at the Ministry of Health called Al-Shifa. For this study, the system encompasses patient records from three health centers in the Al Batinah North Governorate between 2014 and 2022. The findings indicate a significant positive relationship between proximity to MIA and the severity of asthma, with age also emerging as an influential factor in certain cases. This research aims to enhance asthma understanding and support personalized healthcare development, evidence-based policies, and effective management and prevention strategies for this population.

تحليل متعمق لعوامل شدة الربو لدى المرضى العمانيين باستخدام الذكاء الاصطناعي وتعلم الآلة

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تحليل متعمق لعوامل شدة الربو لدى المرضى العمانيين باستخدام الذكاء الاصطناعي وتعلم الآلة