Machine Learning System for Asthma Severity Detection Based on Support Vector Machine

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ABSTRACT
Detecting the severity of contagious respiratory illnesses early is essential for effective treatment and healthcare planning. This study explores how machine learning, specifically Support Vector Machine (SVM) and Random Forest (RF), can help classify and predict illness severity based on patient symptoms and clinical data. The system is developed using Python programming language on streamlit environment. The aim of this research is to classify the severity level of Asthma for informed decision and patient care. Random Forest regression and SVM models were successfully developed and trained, and its performance was evaluated using metrics such as Mean Squared Error (MSE) and R^2. The findings showed an MSE of 0.0173 and an R^2 of 0.6630. These results indicated that the model could predict the severity index of Asthma in a patient with a good degree of accuracy, capturing approximately 88.3% of the variance in the target variable. Our findings show that while both algorithms perform well, Random Forest provides more accurate predictions due to its ability to capture complex patterns in medical data.

Keywords: *Asthma, Severity, Respiratory Disease, Health, Machine Learning*

1. INTRODUCTION

Infectious respiratory disorders pose a major threat to public health worldwide and are usually spread via droplets and close human contact. They include less dangerous ailments like the common cold as well as more serious ones like pneumonia, Asthma, and COVID-19 (Ekong et al., 2022). Airborne particles emitted when an infected person coughs, sneezes, or talks are the primary means by which an infection is transmitted (Centers for Disease Control and Prevention [CDC], 2020). The severity and spread of these ailments might vary significantly depending on the underlying infection, environmental factors, and population vulnerability (Ekong et al., 2023). For instance, viral respiratory illnesses such as Asthma and coronaviruses can cause seasonal epidemics or even global pandemics since they are frequently very contagious (World Health Organization [WHO], 2021). This study analyzes the risk severity of Asthma, a respiratory illness that spreads quickly, using a machine learning approach (Edet et al., 2023). Asthma intensity can range from mild symptoms to severe, potentially lethal outcomes, particularly in high-risk groups like young children, the elderly, expectant mothers, and those with chronic illnesses (Ebong et al., 2024). Asthma can cause pneumonia, severe respiratory distress, and sometimes multi-organ failure. Seasonal flu viruses typically result in widespread outbreaks each year, which raise healthcare expenses and mortality rates, particularly during the colder months when flu season is at its worst (Uwah and Edet, 2024). Vaccination is still an essential way to reduce the severity of the illness and prevent complications because annual vaccines are designed to protect against the most prevalent Asthma strains that are circulating each season (Grohskopf). What problem have you identified in your geographical area or the society at large? The severity (Edet et al., 2024) and spread of respiratory illnesses are influenced by a variety of Asthma risk factors (Edet et al., 2024). The environment is crucial because factors like temperature, humidity, and air quality can influence how viruses spread (Moriyama, Hugentobler, & Iwasaki, 2020). For example, studies have shown that low humidity and cold temperatures, particularly in the winter, are conducive to the Asthma virus's spread (Harper, 1961). Additionally, in crowded areas where people regularly come into close touch with one another, urbanization and population density increase the rates of transmission (Cohen, Tohme, & Qin, 2017). If an infection occurs, people who are older or have pre-existing conditions like asthma or heart disease (Ekong et al., 2024) are also more likely to experience severe symptoms (WHO, 2021). It is common for infectious respiratory infections to spread rapidly throughout the community, overburdening healthcare systems in the process. For example, during the COVID-19 pandemic, hospitals worldwide faced unprecedented strain as the number of cases rose and medical resources were overextended (Ranney, Griffeth, & Jha, 2020). To stop the spread of high transmission rates, public health officials must also enforce regulations such as mask requirements, travel restrictions, and quarantines (Ekong et al., 2024)). These steps ensure that resources are accessible for critical cases by safeguarding high-risk groups and preventing the healthcare system from being overworked (Fong et al., 2020). Vaccination has been one of the most effective approaches to prevent or reduce the consequences of respiratory infections. In patients suffering from illnesses like Asthma and COVID-19, vaccines have shown a significant decrease in hospitalization rates and a decrease in the intensity of illness (Fauci, Lane, & Redfield, 2020). Annual flu shots are necessary because the virus can change and create new strains each season (Grohskopf et al., 2019). Similarly, booster doses have become crucial as COVID-19 variants that might partially evade immunity from early vaccines arise (WHO, 2021). The goal of vaccination campaigns is herd immunity, which reduces the number of susceptible hosts and limits virus transmission within the community (Omer et al., 2019). However, vaccine hesitancy and misinformation provide significant challenges to the fight against respiratory illnesses. Herd immunity is impacted and communities become more vulnerable to epidemics when vaccination rates are decreased due to misleading information regarding the efficacy and safety of vaccines (Salmon et al., 2015). The WHO lists vaccine reluctance as one of the top 10 threats to global health (WHO, 2019). To boost confidence in immunizations and public health programs, the fight against disinformation includes public education, open communication, and collaboration with community leaders (Dubé et al., 2021). Contagious respiratory diseases provide intricate problems that call for a variety of solutions, such as immunization, public education, and preventative measures. Developing successful management solutions for these disorders requires an understanding of the factors that affect transmission, severity, and prevention. Public health organizations keep modifying their tactics to lessen the spread of respiratory illnesses and the burden they place on the general public. Such strategies are essential for managing and ultimately eliminating epidemics of infectious respiratory diseases, along with strong public health infrastructure and community collaboration (Edet et al., 2024)). Contagious respiratory diseases can range greatly in severity, depending on the type of pathogen, the health of the individual, and the surrounding environment. Infections like Asthma and COVID-19, for example, can produce serious problems, especially in susceptible individuals, but the ordinary cold usually only causes minor symptoms. Disease outcomes are greatly influenced by age, pre-existing medical disorders, and weakened immune systems; older folks and people with long-term ailments like diabetes, asthma, or cardiovascular diseases are frequently more likely to have severe sickness and hospitalization (Centers for

Disease Control and Prevention [CDC], 2020). Winter-loving viruses like Asthma are also more likely to spread due to environmental variables like low humidity and chilly temperatures (Moriyama, Hugentobler, & Iwasaki, 2020). One significant effect of respiratory infections' infectious nature is the burden they place on healthcare systems during severe outbreaks. Healthcare institutions frequently see spikes in patient volume during high-transmission scenarios, which puts a burden on medical personnel and causes shortages of medical supplies. For instance, the COVID-19 pandemic brought to light the devastating effects on hospitals around the world, as vital resources such as ventilators, PPE, and intensive care unit beds were overloaded (Ranney, Griffeth, & Jha, 2020). Public health measures like as mask requirements, social distance, and immunizations are therefore essential for halting the spread and reducing severe cases, particularly in susceptible groups. Together, these initiatives seek to lower hospitalization rates and improve the efficiency of healthcare systems during pandemics (World Health Organization [WHO], 2021).
With severity levels ranging from minor symptoms to severe, life-threatening disorders, Asthma offers a serious risk to health, particularly for vulnerable groups including the elderly, small children, and people with chronic illnesses. Conventional techniques for determining the severity of Asthma frequently depend on clinical judgment and symptom observation, which may not be accurate enough to identify high-risk individuals early. In addition to putting more demand on healthcare resources, this delay may impede prompt treatments that could lower hospitalization rates and avoid consequences. More accurate and effective methods to identify people at risk of serious illness are desperately needed, especially in light of the global impact of seasonal Asthma.

2. RELATED LITERATUE

Albretcht et al., 2024, This study explores forecasting models to predict hospital admissions in Auckland, New Zealand, during seasonal respiratory disease epidemics. The goal is to improve hospital management, especially during surges in acute respiratory illness, by accurately forecasting hospital bed requirements and guiding intervention strategies. By leveraging machine learning techniques, the study compares model accuracy against traditional seasonal forecasting methods and assesses the use of laboratory data from hospital surveillance of respiratory viruses. The dataset used is from active surveillance in two public hospitals, which includes systematic testing for nine respiratory viruses, including Asthma and RSV, based on the WHO's Severe Acute Respiratory Infection (SARI) definition. Machine learning models, including advanced generative transformers and artificial neural networks, outperformed traditional models in forecasting. Additionally, reducing the temporal resolution of forecasts improved prediction accuracy and the reliability of probabilistic forecasts. However, integrating laboratory data did not significantly improve forecast accuracy, as there were strong season-to-season variations in virus incidence, which seemed to correlate with hospitalization rates but did not enhance predictive performance.
Algarni et al., 2023, respiratory diseases are a leading cause of global mortality, responsible for nearly 900,000 deaths annually, emphasizing the need for early detection to reduce mortality rates. This review examines the use of machine learning (ML) and deep learning (DL) technologies in detecting and classifying respiratory diseases, highlighting significant advancements in these fields. It provides an overview of various ML and DL algorithms, including support vector machine (SVM), logistic regression, artificial neural networks (ANN), convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM). The performance of these models is evaluated using several metrics, such as accuracy, precision, recall, F1-score, and AUC. Among the models studied, the recurrent neural network (RNN) outperforms others with an accuracy of 83%, precision

of 87%, F1-score of 91%, and AUC of 91%. However, the artificial neural network (ANN) shows a superior recall rate of 96%, indicating its better ability to identify all relevant cases. This review underscores the potential of these advanced machine learning and deep learning techniques in enhancing the early detection and classification of respiratory diseases, ultimately improving outcomes and reducing mortality rates.

Patil et al., 2024, The increasing strain on global healthcare systems due to respiratory illnesses can be alleviated with advancements in medical image processing, which plays a crucial role in diagnosis, treatment, and early detection. This study focuses on the use of Deep Learning (DL) models to assist in diagnosing respiratory diseases such as COVID-19, pneumonia, and tuberculosis. The research emphasizes the significance of data balancing, data augmentation, and segmentation in improving medical image data. By using data augmentation and edge detection techniques, the study enhances the preprocessing of radiological images to locate regions of interest (ROI). It also proposes a custom-built Deep Neural Network (DNN), named RESP_DNN, designed for more accurate diagnostic support. The proposed methodology involves the creation of enhanced RESP datasets with improved radiological image preprocessing to identify ROIs. By modifying the architecture of deep neural networks, the model successfully classifies five categories: COVID-19, pneumonia, lung opacity, tuberculosis, and normal. The model achieves a high diagnostic accuracy of 95.52%, outperforming other recently published methods. This high level of accuracy provides a significant advantage in the early detection and classification of respiratory illnesses, enabling radiologists to quickly and accurately diagnose conditions like COVID-19, pneumonia, and tuberculosis. This approach represents a promising tool for improving diagnostic outcomes in clinical settings.

Kassaw et al., 2024, Acute Respiratory Infections (ARI) are a leading cause of death in children under five, particularly in developing countries like Ethiopia. To predict the factors contributing to ARI in the Amhara region, a study used machine learning models on data from the 2016 Ethiopian Demographic and Health Survey. Seven models, including logistic regression, random forests, decision trees, and support vector machines, were employed to forecast ARI determinants. Among these, the Random Forest algorithm demonstrated the highest accuracy, achieving 90.35% accuracy and an Area Under the Curve (AUC) of 94.80%. The study identified several significant factors associated with ARI in children under five. These included families with poorer wealth status, families with four to six children, children without a history of diarrhea, and mothers who had occupations. Additionally, children under six months of age, mothers with no education, rural residents, and families using wood as a cooking material were found to be at higher risk. The study also emphasized the importance of fewer children in a household and the absence of diarrhea in improving health outcomes for children in this region. Through Shapley Additive Explanations (SHAP) analysis, these factors were validated as critical contributors to ARI risk.

Kumar et al., 2023, Asthma, a seasonal respiratory illness, affects people of all ages, causing symptoms such as fever, chills, headaches, fatigue, cough, and muscle aches. While it can range from mild to severe, Asthma can also result in death. Early detection of Asthma is a critical area of research, as timely diagnosis can help mitigate its impact. Recent studies have shown that machine learning techniques are increasingly being used to detect Asthma early. This paper discusses the use of various machine learning methods, employing data from the Asthma Research Database and Human Surveillance Records. Ensemble-based stacked algorithms were implemented on the datasets to enhance predictive accuracy.

The study evaluates the performance of different machine learning models using various metrics and proposes efficient models that could serve as a cost-effective and rapid diagnostic tool for Asthma detection. These models aim to provide a quick, affordable alternative for diagnosing Asthma, potentially improving early detection and response during seasonal outbreaks.

Huang et al., 2024, This study aimed to develop machine learning models for accurately predicting the severity of neonatal respiratory distress syndrome (NRDS) to enhance clinical decision-making. Conducted as a double-blind cohort study, it included 230 neonates from Yantaishan Hospital's NICU between December 2020 and June 2023, with 119 diagnosed with NRDS. Clinical data, including lung ultrasound scores (LUS), oxygenation index (OI), respiratory index (RI), and sequential organ failure assessment (SOFA) scores, were analyzed. Predictor variables were identified using LASSO regression, and models were developed using logistic regression (LR), random forest (RF), artificial neural network (NN), and support vector machine (SVM).

The study found that LUS, SOFA, RI, and OI were critical variables for predicting NRDS severity, with significantly different values between severe and mild-to-moderate cases. Of the four models, the RF model demonstrated the best predictive performance, achieving an AUC of 0.894, accuracy of 0.808, and sensitivity of 0.706, outperforming LR, NN, and SVM. These findings suggest that RF provides the most reliable support for assessing NRDS severity, potentially improving neonatal care and outcomes. Machine learning have been used in health and other sectors such as security as described by (Edet et al., 2024) with commendable outcomes over the years.

3. METHODOLOGY

The proposed system leverages two powerful machine learning techniques Support Vector Machine (SVM) and XGBoost ensemble learning to efficiently classify Asthma cases and evaluate their severity. SVM is used for the primary task of detecting Asthma by drawing decision boundaries between Asthma and non-Asthma cases based on the dataset's key features such as fever, cough, and respiratory rate, which are indicative of the disease. This classification task benefits from SVM's ability to handle complex, high-dimensional data and achieve high accuracy, as demonstrated in past studies of respiratory disease detection. Once Asthma is detected, the system proceeds to evaluate its severity using an ensemble method, specifically the XGBoost algorithm, which excels at handling large datasets and making robust predictions by combining multiple weaker models to improve overall accuracy.

For the severity evaluation, only when Asthma is detected does the system assess the level of severity based on additional features, such as oxygen levels, comorbidities, and respiratory rate. XGBoost, as an ensemble method, processes these features in a way that allows the system to categorize the severity into different classes mild, moderate, or severe. The algorithm uses boosting to focus on misclassified cases from earlier iterations, making it highly effective in distinguishing between varying levels of severity. This step ensures that the system not only detects Asthma but also provides valuable insights into the urgency of medical intervention required, as noted. If the system does not detect Asthma, no severity assessment is performed, avoiding unnecessary computation and focusing resources on actual cases.

By integrating both SVM for classification and XGBoost for severity assessment, the system aims to deliver a rapid, cost-effective diagnostic tool that can be deployed in clinical settings. The model is trained on a comprehensive dataset sourced from the Kaggle repository, which includes a rich set of features representing Asthma symptoms and severity indicators. This approach allows for both quick detection and nuanced evaluation of the disease's impact, ensuring that healthcare providers can prioritize patients based on the severity of their conditions. The proposed system, therefore, not only serves as an early detection tool but also as a decision-support system that improves patient management and healthcare resource allocation during Asthma outbreaks.

3.1 SVM Algorithm of the Proposed System

1. Load and Preprocess Data:
- Load the dataset (features and labels)
- Split the data into training and testing sets
- Normalize the features (optional but recommended)
2. Define the SVM Model:
- Initialize the SVM model with a kernel (linear, polynomial, or RBF)
- Set the hyperparameters (C, kernel type, gamma, etc.)
3. Train the Model:
- For each data point, calculate the dot product of the input features
- Maximize the margin between classes using optimization techniques
- Minimize the objective function:
*- Objective: 0.5 * ||w||^2 + C * Σ(ξ_i)*
- Where w is the weight vector, C is the regularization parameter, and ξ_i are slack variables
4. Find the Optimal Hyperplane:
- The optimization will yield the weight vector (w) and bias term (b)
*- The decision function will be: f(x) = w*x + b*
- Where x is a test input sample
5. Make Predictions:
- For each test sample, compute the decision function f(x)
- If f(x) > 0, classify as one class (e.g., Asthma detected)
- If f(x) <= 0, classify as the other class (e.g., not Asthma)
6. Evaluate the Model:
- Use performance metrics like accuracy, precision, recall, F1-score, etc.
- Calculate confusion matrix to evaluate true positives, false positives, true negatives, and false negatives
7. Fine-tuning and Hyperparameter Optimization (Optional):
- Use techniques like Grid Search or Random Search to optimize the hyperparameters (C, kernel, gamma)
8. Deploy the Model:
*- Once optimized and evaluated, deploy the SVM model for real-time prediction of new samples (*Udoetor et al., 2024)

4. RESULTS AND DISCUSSION

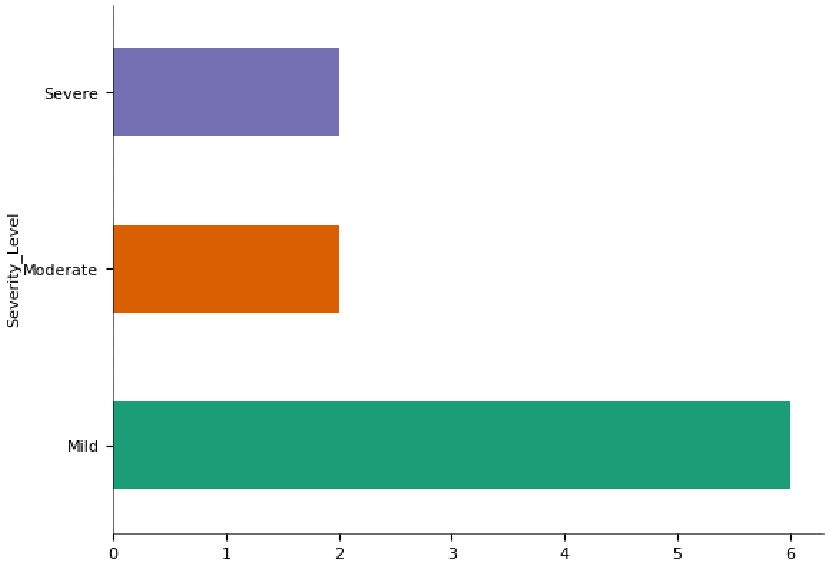

Fig.1: Asthma Severity Class Levels

Asthma severity is classified into three main levels: mild, moderate, and severe, based on symptom frequency, lung function, and response to treatment. Mild asthma is characterized by occasional symptoms that do not significantly interfere with daily activities. Patients may experience mild shortness of breath, wheezing, or coughing, particularly at night or after exposure to triggers. Symptoms are usually well-controlled with minimal use of reliever medications, and lung function remains close to normal. However, if left unmanaged, mild asthma can progress to more severe stages. Moderate asthma presents with more persistent symptoms, requiring regular medication to maintain control. Individuals with moderate asthma experience breathing difficulties more frequently, and their lung function shows moderate impairment. Activities such as exercise, exposure to allergens, or respiratory infections can easily trigger symptoms. Patients in this category often require daily use of inhaled corticosteroids and bronchodilators to prevent exacerbations. Additionally, moderate asthma can lead to sleep disturbances and occasional emergency visits if symptoms worsen suddenly. Severe asthma is the most serious form of the condition, significantly impacting a person's daily life and overall health. Individuals with severe asthma have persistent symptoms that do not respond well to standard medications. They may experience frequent and intense attacks, requiring hospitalization and high doses of corticosteroids for management. Their lung function is significantly reduced, and even minor triggers can lead to life-threatening exacerbations. Severe asthma often requires advanced treatment options such as biologic therapies and long-term medication regimens to prevent complications. The severity of asthma is influenced by multiple factors, including peak expiratory flow (PEF), which measures the ability to exhale air from the lungs. A lower PEF value indicates more severe airway obstruction, making it a crucial determinant in classifying asthma severity. Other contributing factors include environmental triggers, genetic predisposition, lifestyle choices, and underlying health conditions. Proper asthma management, including trigger avoidance, medication adherence, and regular monitoring of PEF, is essential in preventing severe complications and improving the quality of life for individuals living with asthma.

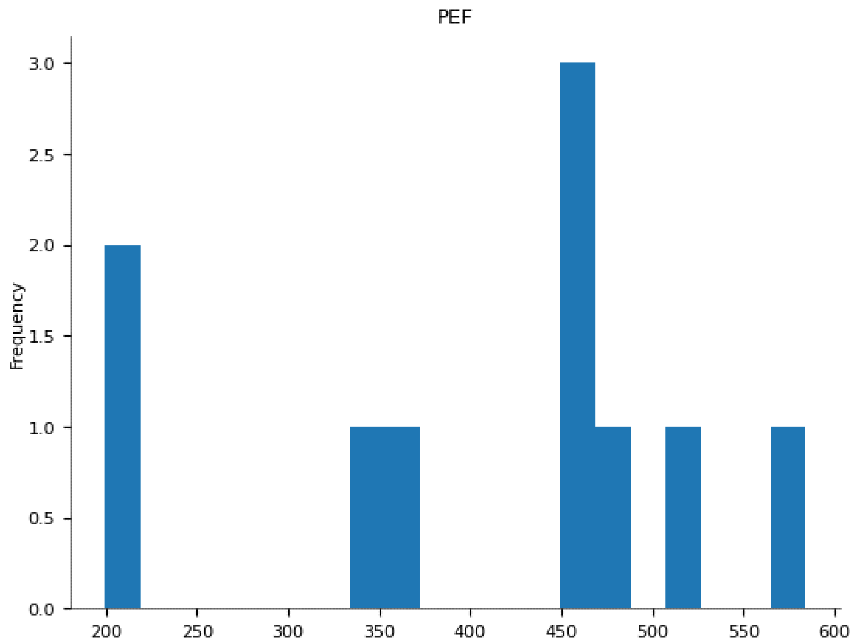

Fig. 2: PEF and its Frequency

Peak Expiratory Flow (PEF) is a crucial measure in determining asthma severity as it reflects the degree of airway obstruction. PEF measures the maximum speed at which a person can exhale air after taking a deep breath, and lower values indicate restricted airflow due to inflammation and narrowing of the airways. Individuals with mild asthma typically have near-normal PEF readings, while those with moderate asthma may experience moderate fluctuations in their PEF, especially during symptom episodes. In severe asthma, PEF values are significantly reduced and can drop dangerously low during exacerbations, signaling an increased risk of respiratory distress. Regular monitoring of PEF helps in assessing asthma control and detecting worsening conditions before they lead to severe attacks. The frequency of PEF fluctuations is also a key indicator of asthma severity. In well-controlled asthma, PEF values remain relatively stable, with minimal variations throughout the day. However, in moderate and severe cases, PEF readings may show significant variability, often dropping in response to triggers such as allergens, exercise, or respiratory infections. Frequent PEF reductions indicate poor asthma control and a higher risk of sudden exacerbations, which can lead to emergency situations if not managed properly. Tracking PEF over time allows individuals and healthcare providers to adjust treatment plans, ensuring that medications and lifestyle modifications effectively reduce symptom severity and prevent life-threatening attacks.

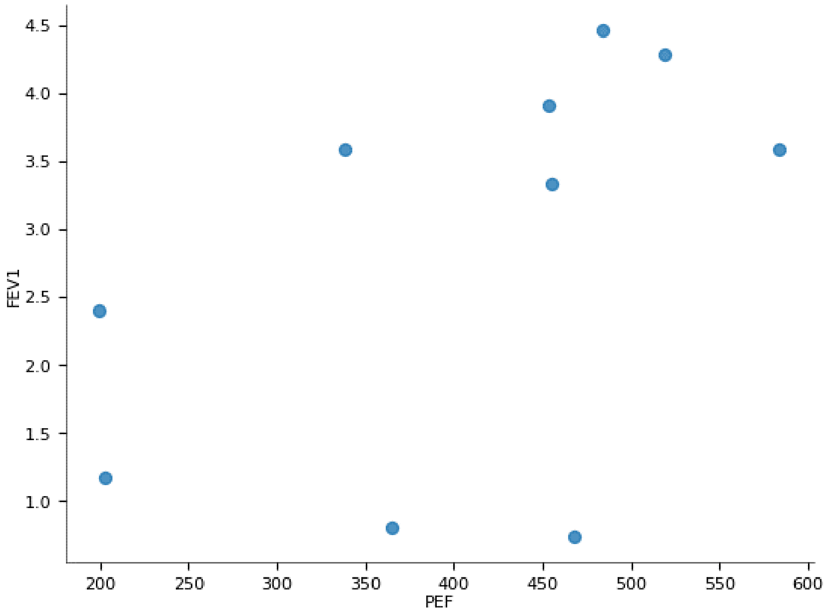

Fig.3: PEF and FEV1 Scatter Plot

A scatter plot of Peak Expiratory Flow (PEF) and Forced Expiratory Volume in One Second (FEV1) is a valuable tool for assessing lung function and diagnosing respiratory conditions like asthma. PEF represents the maximum airflow achieved during a forced exhalation, while FEV1 measures the amount of air exhaled in the first second of a forced breath. In healthy individuals, PEF and FEV1 values tend to correlate positively, as higher PEF readings usually indicate better lung function and greater FEV1. However, in asthma patients, this relationship may vary depending on the severity of airway obstruction. A scatter plot can visually display the distribution of these values, showing trends and deviations that help in identifying different levels of lung impairment. In patients with mild asthma, the scatter plot may show a tight clustering of data points, reflecting relatively stable lung function. As asthma severity increases, greater variation and lower values for both PEF and FEV1 may be observed, leading to a more scattered distribution of data points. Patients with moderate to severe asthma often exhibit a downward trend in the scatter plot, with more points falling in the lower PEF and FEV1 ranges. This pattern indicates increased airway obstruction and reduced lung capacity. By analyzing the scatter plot, healthcare providers can monitor asthma progression, adjust treatment strategies, and identify patients at risk of severe exacerbations.

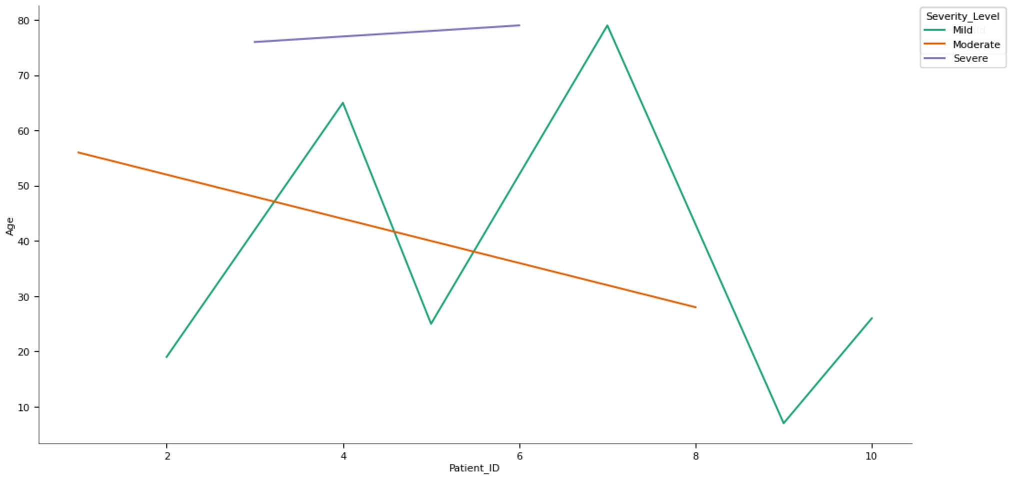

Fig. 4: Patient Age in Records

Age plays a significant role in the development, progression, and management of asthma. In children, asthma is often triggered by allergies, viral infections, and environmental factors. Their airways are smaller and more reactive, making them more susceptible to inflammation and obstruction. Childhood asthma symptoms often include wheezing, coughing, and shortness of breath, particularly at night or after physical activity. Many children experience intermittent asthma, where symptoms occur sporadically, but some may develop persistent asthma that requires ongoing treatment. As they grow older, some children may outgrow asthma symptoms, while others continue to experience the condition into adulthood. In adults, asthma can be either a continuation from childhood or develop later in life, known as adult-onset asthma. Unlike childhood asthma, which is often allergy-driven, adult asthma is frequently linked to environmental exposures, occupational hazards, obesity, and respiratory infections. Older adults with asthma may face more severe symptoms due to age-related lung function decline, making management more challenging. Additionally, asthma in older individuals can be complicated by other conditions like chronic obstructive pulmonary disease (COPD), making diagnosis and treatment more complex. Age-related factors such as medication tolerance, immune system changes, and overall lung elasticity play a crucial role in determining asthma severity and response to treatment across different age groups.

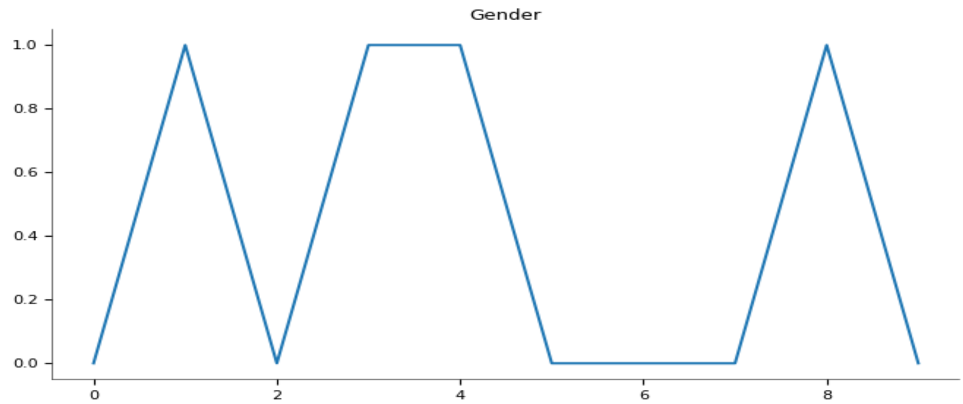

Fig.5: Gender Plot

Gender differences play a significant role in the prevalence, severity, and management of asthma. During childhood, asthma is more common and severe in boys than in girls, largely due to anatomical and physiological factors. Boys typically have smaller airway diameters relative to lung size, making them more susceptible to airway obstruction and inflammation. Additionally, hormonal differences and immune system variations may contribute to the higher incidence of childhood asthma in boys. However, as they approach adolescence, these differences begin to shift, and the prevalence of asthma in males decreases, while it increases in females. In adulthood, women are more likely to develop and experience severe asthma compared to men. Hormonal fluctuations, particularly those related to menstruation, pregnancy, and menopause, can influence airway inflammation and asthma control in women. Estrogen and progesterone have been linked to changes in lung function, sometimes worsening symptoms during certain phases of the menstrual cycle. Additionally, women with asthma are more likely to experience respiratory issues triggered by environmental factors, stress, and obesity. Understanding these gender-based differences is crucial for personalized asthma management and treatment approaches tailored to each patient's unique physiological and hormonal profile.

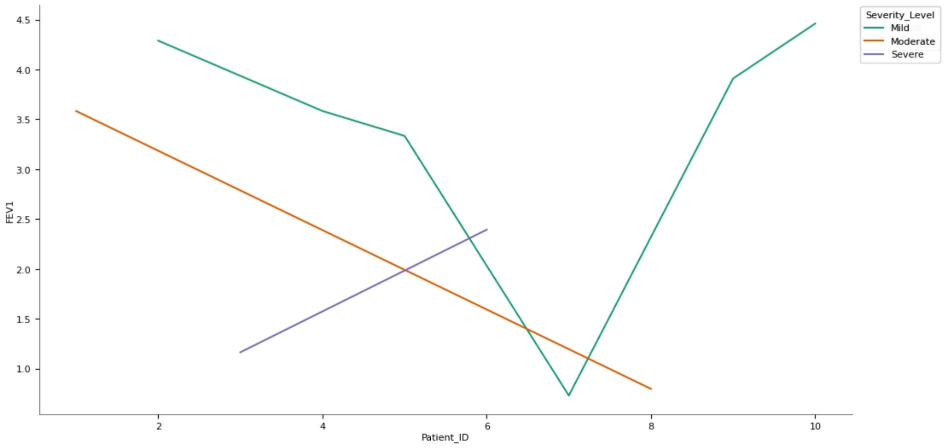

Fig. 6: PEV1 and Severity Level

Forced Expiratory Volume in one second (FEV1) is a crucial pulmonary function parameter used to assess airway obstruction and classify the severity of asthma. FEV1 measures the amount of air a person can forcefully exhale in one second after taking a deep breath. It serves as a key indicator of lung function, with lower FEV1 values reflecting greater airway obstruction. In asthma management, FEV1 is often expressed as a percentage of the predicted normal value based on age, height, gender, and ethnicity. A higher FEV1 percentage indicates better lung function, while a lower value suggests more severe airway restriction and increased asthma severity. The severity of asthma is classified into mild, moderate, and severe categories based on FEV1 values and symptom frequency. Patients with mild asthma typically have FEV1 values above 80% of the predicted normal, indicating minimal airway obstruction. Moderate asthma is associated with FEV1 values between 60% and 80%, suggesting significant airflow limitation. Severe asthma, on the other hand, is characterized by FEV1 values below 60%, indicating marked airway obstruction and poor lung function. In these cases, patients experience frequent exacerbations, persistent symptoms, and reduced responsiveness to standard treatment, often requiring higher doses of medication and additional interventions. Monitoring FEV1 over time is essential for assessing asthma progression and treatment effectiveness. A decline in FEV1 may signal worsening disease control, prompting the need for treatment adjustments. Regular spirometry testing helps healthcare providers identify patterns in lung function, ensuring timely intervention to prevent severe asthma attacks. Additionally, combining FEV1 with other parameters, such as Peak Expiratory Flow (PEF) and symptom tracking, provides a comprehensive assessment of asthma severity, enabling a more personalized and effective management plan.

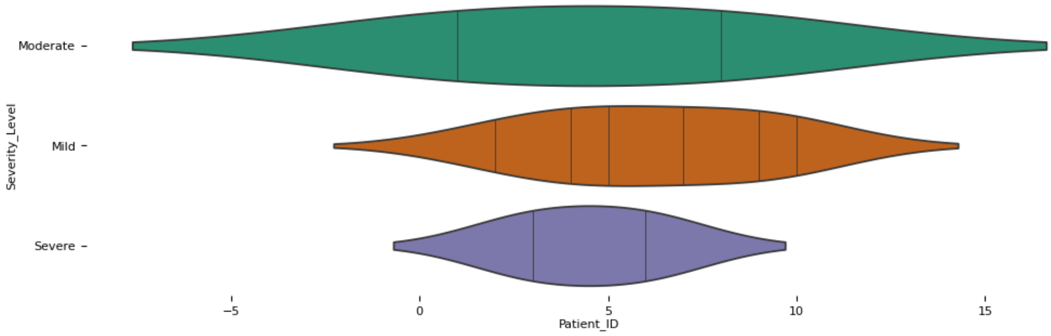

Fig. 7: Severity Level Per Patient ID

The severity level of asthma per Patient ID is determined by evaluating the Peak Expiratory Flow (PEF) values, which indicate the degree of airway obstruction. Each patient is assigned a severity category—mild, moderate, or severe—based on their PEF measurements relative to predicted normal values. Patients with higher PEF readings generally fall into the mild category, experiencing minimal airflow restriction and occasional symptoms. Moderate severity is associated with fluctuating PEF values, reflecting noticeable airflow limitation and more frequent symptoms. Severe cases are marked by significantly reduced PEF values, indicating persistent and severe airway obstruction, often requiring intensive medical intervention. Tracking severity per Patient ID over time helps monitor disease progression, assess treatment effectiveness, and guide clinical decisions for improved asthma management.

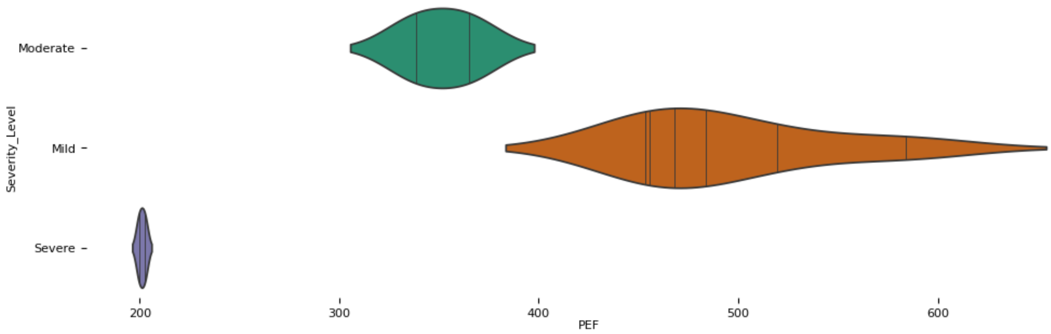

Fig. 8: Severity Level Vs PEF

Peak Expiratory Flow (PEF) is a critical determinant of asthma severity, as it measures the maximum speed at which a person can exhale air. A higher PEF value typically indicates better lung function and a lower risk of severe asthma symptoms, whereas a lower PEF value suggests significant airway obstruction and increased severity. Patients with mild asthma generally exhibit PEF values close to the predicted normal range, with minimal airflow restriction. In contrast, those with moderate asthma experience noticeable fluctuations in PEF, indicating inconsistent lung function. Severe asthma is characterized by persistently low PEF values, reflecting chronic airway constriction and a higher likelihood of exacerbations. The relationship between PEF and severity level is crucial for asthma management and classification. Regular monitoring of PEF allows healthcare providers to assess disease progression and adjust treatment accordingly. A sharp decline in PEF may signal an impending asthma attack, prompting early intervention to prevent severe complications. By categorizing severity levels based on PEF measurements, physicians can tailor treatment plans to ensure effective symptom control. Furthermore, patients can use home PEF monitoring to track their lung function and recognize patterns that may indicate worsening asthma, allowing for timely medical attention.

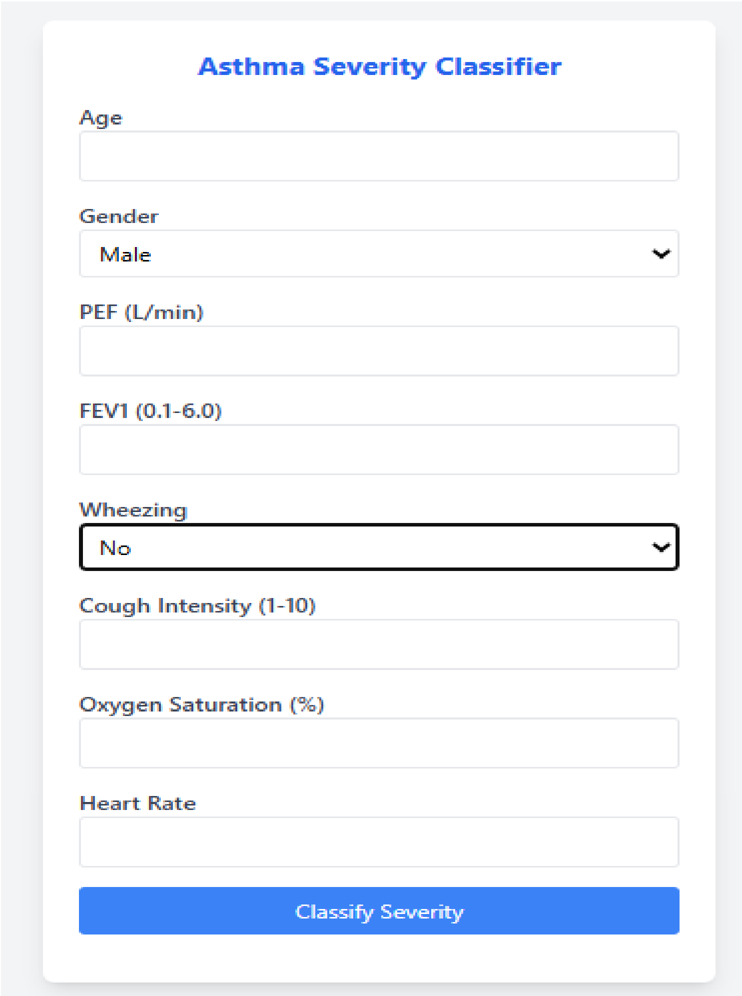

Fig.9: Program Interface for Asthma Severity Classification

The Program Interface for Asthma Severity Classification will include several key features that contribute to determining the severity of asthma. Age and Gender will provide demographic information about the patient, which can help contextualize the severity level. PEF (Peak Expiratory Flow) and FEV1 (Forced Expiratory Volume in 1 second) are critical measures of lung function, and they will play a significant role in determining the severity level. Wheezing and Cough Intensity will be used to assess the presence and severity of respiratory symptoms, while Oxygen Saturation and Heart Rate will provide vital information about the patient's current health status, particularly in relation to oxygen levels and cardiovascular response. Once the user fills out the input fields, the program will classify asthma severity into three levels: Mild, Moderate, or Severe. The other features will contribute contextually, helping to refine the classification. For example, a low FEV1, low Oxygen Saturation, or high Cough Intensity may indicate worsening asthma control, while Heart Rate and Wheezing will help assess if the patient is at higher risk. Based on the inputs, the program will provide an outcome that reflects the asthma severity and can guide healthcare professionals in making informed decisions.

5. CONCLUSION

In conclusion, this research successfully demonstrates the application of machine learning techniques, specifically Random Forest regression, to predict the severity index of Asthma based on key physiological indicators. Through careful data collection, preprocessing, and model development using features such as PEF, FEV1, Wheezing, Oxygen Saturation, Coughing, the study achieved promising results with an MSE of 0.0173 and an R^2 value of 0.6630. These findings underscore the potential of leveraging physiological parameters to assess and predict the severity of Asthma, offering a novel, data-driven approach to understanding the progression of this contagious respiratory disease. The integration of feature importance analysis and visualizations further provided insights into how specific biological markers contribute to predicting the disease's severity. The findings of this research have important practical implications for early diagnosis, intervention, and resource allocation within the medical sector. The model can serve as an effective tool for identifying high-risk individuals, enabling early and accurate detection of severe cases. Additionally, the research highlights the importance of adopting machine learning approaches for disease severity prediction, contributing to improved clinical decision-making and public health strategies. Future studies could explore larger, more diverse datasets and consider integrating other machine learning models to strengthen predictive accuracy. Overall, this work represents a significant step toward a proactive, evidence-based response to managing Asthma and similar respiratory diseases.

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