Hybrid DQN–Greedy Tree Learning Framework for Air Pollution–Driven Health Impact and Asthma Prediction

SK. Mahaboob Basha[1], Banoth Akhila[1], Meduri Lahari[1], Meesala Ganesh[1], Pothuganti Rahul[1]

[1]Department of Computer Science and Engineering, [1]Sree Dattha Institute of Engineering and Science, Nagarjuna Sagar Road, Sheriguda, Ibrahimpatnam, Rangareddy Dist, 501510, Telangana, India.

ABSTRACT

Air pollution has evolved into one of the most critical public-health challenges of the decade, directly influencing respiratory and cardiovascular disease burdens across urban and semi-urban regions. While massive environmental datasets are now available, most existing monitoring platforms only visualize pollutant levels and fail to convert this information into actionable health-risk insights. Traditional systems rely heavily on static thresholds or rule-based estimates, which cannot adapt to dynamic pollution patterns, seasonal variations, or complex pollutant interactions. These approaches offer limited predictive accuracy, lack automated forecasting, and provide no deep correlation between air-quality indicators and real health impact metrics such as asthma or cardiovascular case surges. To address these shortcomings, there is a clear need for an intelligent, data-driven system that can continuously learn from environmental and medical datasets and produce real-time, user-friendly health-risk predictions. The proposed system introduces a full-stack machine learning platform capable of classifying health-impact severity and predicting disease case counts using a hybrid modeling approach. The backend integrates Random Forests (RF), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), and a Hybrid Deep Quality Network-Random Forest (DQN-RF) architecture to capture both linear and non-linear dependencies within pollution data. The system performs classification of health-impact categories and regression-based forecasting for respiratory and cardiovascular cases. Advanced preprocessing, feature scaling, automated training, performance evaluation, and batch prediction pipelines ensure reliability and scalability. A Flask-based web interface enables real-time predictions for both individual readings and entire datasets. This hybrid prediction framework significantly enhances public-health readiness by transforming raw air-quality data into early-warning health indicators. The system's ability to detect high-risk pollution patterns, forecast potential disease surges, and deliver actionable insights makes it valuable for environmental agencies, healthcare planners, and smart-city applications aiming to minimize pollution-related health impacts.

Keywords: Cardiovascular diseases, Behavioural indicators, Environmental complexity, Time-Series Prediction, Climate Variables.

1. INTRODUCTION

Air pollution can be defined as the presence in the air of substances harmful to humans and is associated with a high risk for premature deaths due to cardio-vascular diseases (e.g., ischaemic heart disease and strokes), chronic obstructive pulmonary disease, asthma, lower respiratory infections and lung cancer [1,2]. People living in developing and overpopulated countries disproportionately experience the burden of outdoor (ambient) air pollution with 91% of the 4.2 million premature deaths in 2016 occurring in low- and middle-income countries of the South-East Asia, Central Africa and Western Pacific regions where exposure is higher [1,3].

Asthma is a chronic health condition that affects all age groups globally and is characterized by a heterogeneous inflammatory disease of the lungs, with variable symptoms such as coughing, wheezing, shortness of breath, chest tightness, and variable airflow limitation. It is estimated that around 339 million people worldwide currently live with this condition, with many experiencing seasonal and daily variations in their symptoms, with different levels of severity throughout their lives [4]. Although most individuals manage to control their symptoms, there is a constant risk of acute crises that can lead to hospitalization and, in severe cases, death. Over the last 50 years, there has been a significant increase in the prevalence of asthma, especially in children in industrialized countries, largely due to growing environmental pollution and exposure to irritants. This reality makes it essential to study asthma in depth, not only in terms of its prevalence but also its mortality, to guide public health policies and mitigation strategies.

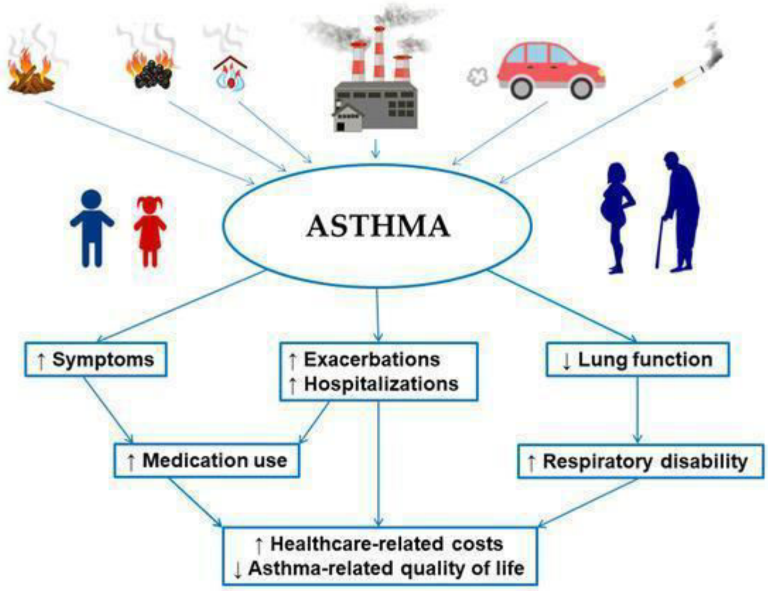


Fig. 1: Asthma triggers, and health consequences.

Asthma not only represents a significant public health challenge but is also associated with alarming mortality rates. In 2019, approximately 461,000 people died from asthma-related complications worldwide, which demonstrates the severity of the condition [5]. In addition to its prevalence, which affects around 262 million individuals, asthma is a chronic disease that profoundly impacts patients' quality of life, as it currently has no definitive cure. Epidemiological studies have shown a strong association between exposure to air pollutants and the worsening of asthma, suggesting that environmental factors play a crucial role in the progression of the disease. The literature also points out that elements such as air pollution, tobacco smoke, climatic conditions, allergens such as pollen, and pathogens such as influenza viruses are among the main factors that exacerbate asthma [6]. In the face of climate change, the situation becomes even more critical, since these changes affect air quality and the production of allergens, contributing to an increase in asthmatic episodes and allergic respiratory diseases. In Brazil, asthma represents a significant public health problem due to limitations in access to standardized treatment, which overloads the capacity for hospital admissions, as evidenced in several studies [7]. Several studies studying the correlation between environmental variables and respiratory diseases have been carried out in different cities in Brazil. An epidemiological analysis carried out between 2016 and 2020 revealed a significant reduction in the number of hospitalizations for asthma during the COVID-19 pandemic (2019–2020), although the northeast region of Brazil recorded the highest number of hospitalizations in the 2016–2020 period, with 2248 deaths associated with the disease during the period. According to these authors, the higher number of asthma hospitalizations may be associated with increased temperatures and lower latitudes. Furthermore, when all mentions of asthma on death certificates are considered, in 2000, there was an increase of approximately 50% in mortality rate, ranging from 36% in the state of Ceará to 76% in the state of Rio Grande do Sul, with women and the elderly showing the highest rates [8]. The prevalence of asthmatic symptoms also stands out, with significant variations observed between Brazilian states; for example, the prevalence of active asthma was 14.8% in Maceio, a city on the coastal strip of the northeast region with a hot and rainy climate, compared to 30.5% in Vitória da Conquista, a city in the interior of Northeast Brazil with a high-altitude humid climate. These data indicate not only the severity of the condition, but also the urgent need for monitoring and effective interventions, especially in regions such as the northeast, where asthma research is still scarce and needs greater attention. Air pollution is a major public health concern, as pollutants like PM2.5, PM10, NO2, SO2, and O3 have direct and severe effects on respiratory and cardiovascular health, including an increased risk of asthma and other chronic diseases. While large-scale environmental and health datasets are available, predicting the severity of health impacts and estimating disease cases remains a complex challenge due to nonlinear interactions among multiple pollutants, meteorological factors, and human responses.

2. LITERATURE SURVEY

2.1 Impact of Air Pollution on Asthma

Tiotiu et al. [9] examined the influence of both indoor and outdoor pollutants on asthma outcomes, identifying traffic-related pollution, nitrogen dioxide, and second-hand smoke as major contributors, particularly in children. Their study highlighted that such exposures lead to increased symptoms, reduced lung function, and higher healthcare utilization. Olaia et al. [10] conducted a comprehensive review exploring the pathological mechanisms through which pollution contributes to asthma onset and exacerbation. The study emphasized the need for global interventions to improve air quality and reduce health risks. Zhou et al. [11] analyzed the biological pathways linking air pollution to asthma, focusing on inflammatory responses, oxidative stress, and epithelial barrier dysfunction. Their findings showed that pollutants intensify immune responses and contribute to disease progression.

2.2 Environmental and Climate-Based Asthma Prediction

Reis et al. [12] developed predictive models for asthma cases using meteorological and pollution data. Among several machine learning methods evaluated, Random Forest demonstrated superior performance, highlighting the importance of environmental variables such as temperature and sulfur dioxide. Barrera-Heredia et al. [13] systematically reviewed the role of air quality indices (AQIs) in asthma research, identifying particulate matter, nitrogen dioxide, and ozone as the most influential pollutants. The study also emphasized the growing impact of climate change on asthma prevalence and severity. Clougherty et al. [14] investigated the relationship between perceived and actual air pollution exposure and asthma outcomes. Their findings indicated that perceived air quality had a stronger association with asthma symptoms than objective pollution measurements.

2.3 AI and Hybrid Models for Pollution and Health Prediction

Subramaniam et al. [15] explored various artificial intelligence and machine learning approaches for environmental pollution forecasting and early-warning systems. Their study concluded that hybrid models outperform individual models in accuracy and reliability, particularly for predicting major pollutants. Necula et al. [16] proposed a hybrid forecasting model combining SARIMA and BiLSTM with attention mechanisms to capture both linear and nonlinear patterns in pollutant data. Their approach demonstrated superior performance across multiple forecasting horizons.

2.4 Risk Assessment and Neural Network-Based Studies

Souad Mahmoud Al Okla et al. [17] developed a neural network-based model for predicting asthma risk, achieving high accuracy. The study identified environmental proximity, smoking exposure, and wind direction as significant contributing factors

3. PROPOSED METHODOLOGY

The proposed system for predicting air-pollution-driven health impacts and asthma brings everything together into a single, streamlined pipeline that runs end-to-end. It starts with data gathered from multiple sources such as pollutant sensors (PM2.5, PM10, NO_2, SO_2, O_3, AQI), hospital health records, and meteorological parameters like temperature, humidity, and wind speed. This heterogeneous data flows into a preprocessing module that handles cleaning, missing-value treatment, label encoding, and extraction of the most relevant features representing pollution exposure and related health indicators. After scaling and normalization, the data enters the modelling core where a hybrid DQN–Greedy Tree framework powers both classification and regression tasks leveraging a Deep Q-Network for capturing complex patterns and a greedy tree ensemble for structured decision-making. Alongside this hybrid model, baseline learners including RF, GB, and XGBoost are trained for fair comparison. Models are evaluated using accuracy, precision, recall, and F1-score for classification, and MAE, MSE, RMSE, and R^2 for regression as shown Fig. 2. Once validated, the system stores trained models, scalers, and preprocessing objects for fast real-time inference.

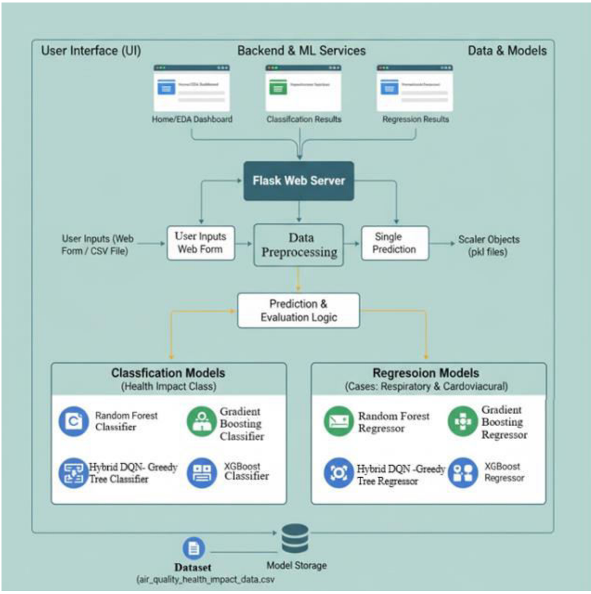


Fig. 2. Proposed System architecture of asthma prediction

A major strength of this architecture is its integration with a Flask web server, which acts as the central bridge connecting the UI, backend logic, and stored ML models. Flask handles user inputs (form or CSV uploads), routes them into preprocessing, triggers the appropriate model pipeline, and returns predictions instantly through clean, interactive web pages. It also supports batch predictions, result visualization, and rendering of EDA dashboards, making the system accessible to researchers, healthcare teams, and policymakers without needing coding expertise. Flask's modular routing and lightweight design keep the system fast, scalable, and super beginner-friendly for deployment, enabling round-the-clock access to insights on health impact classes, asthma risk levels, and predicted case counts. Overall, the architecture stays flexible, interpretable, and future-proof ready to plug in new data sources, improved ML models, or real-time IoT sensor feeds.

Hybrid DQN-RF(CART)

The Hybrid DQN–RF (CART) framework combines the adaptive learning capabilities of DQN with the robust, ensemble decision-making of RF (CART). In this hybrid model, the DQN learns optimal strategies or adjustments for predictions based on the current state of air pollution and health metrics, while the RF aggregates multiple CART trees to provide stable, interpretable outputs. The final prediction is a weighted combination of DQN outputs and RF predictions, enhancing both accuracy and robustness for classification (health impact classes) and regression (asthma/cardiovascular case counts) as shown in Fig. 3.

The first step identifies the features representing the environment, including AQI, PM2.5, PM10, NO_2, O_3, temperature, humidity, and wind speed. These features are standardized and normalized to provide consistent input for both the DQN network and RF ensemble. Each state corresponds to a snapshot of pollution conditions and health indicators. A DQN is initialized with dense layers and dropout for approximating Q-values, while a RF (ensemble of CART trees) is initialized with pre-defined depth, number of trees, and feature selection method. This dual initialization allows the DQN to learn adaptive adjustments and the RF to ensure structured, ensemble predictions. Using a greedy policy, the DQN selects actions, which correspond to potential predictions or adjustments. After executing an action, a reward is calculated based on prediction improvement, and the experience tuple (state, action, reward, next state) is stored in the replay buffer for later training. Mini-batches are sampled from the replay buffer, and the DQN is trained using temporal-difference loss. The target network is updated periodically to stabilize learning, ensuring that the Q-value estimates converge. This step allows the DQN to iteratively refine predictions based on experience.

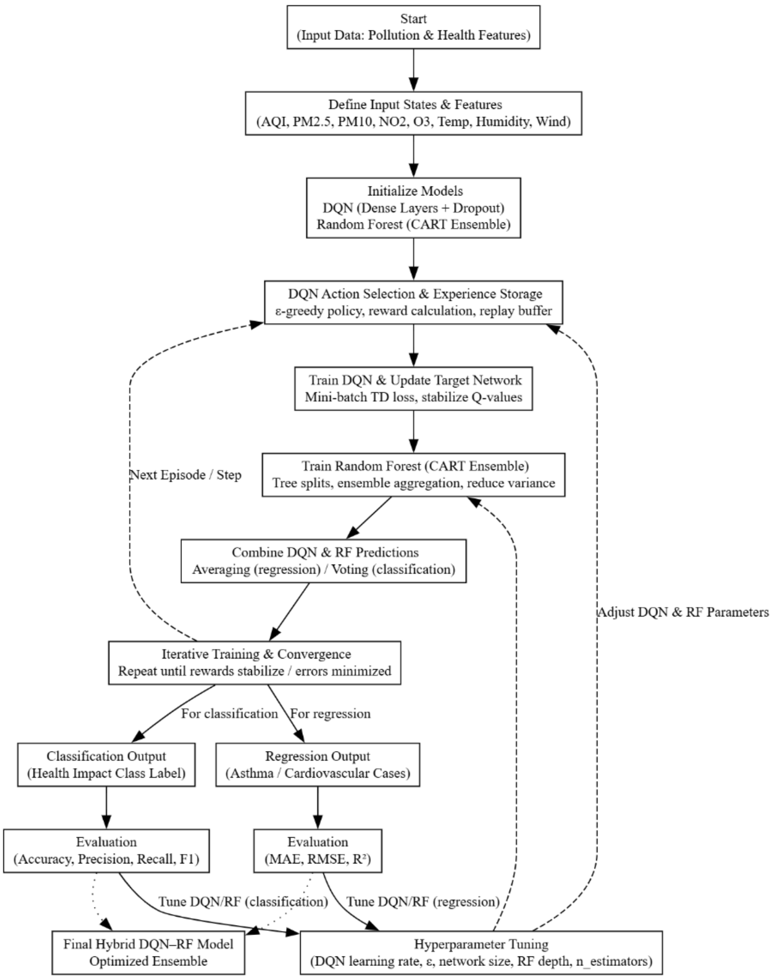


Fig. 3. Internal workflow of hybrid DQN – RF CART model

The RF is trained on the same input features to predict health outcomes directly. Each tree in the forest splits data based on feature importance, providing an ensemble decision that reduces variance and increases robustness for both classification and regression tasks. The predictions from DQN and RF are combined, usually by averaging (for regression) or voting (for classification). This hybrid combination leverages the adaptive learning from DQN and the ensemble stability from RF to generate robust final outputs. The hybrid system iterates over multiple training episodes, continuously updating the DQN policy and retraining the RF if necessary. Convergence is reached when rewards stabilize and prediction performance no longer improves, yielding a highly accurate and resilient model for both classification and regression tasks.

4. RESULTS DESCRIPTION

Fig 4 illustrates the hybrid DQN-RF model's classification performance, with an accuracy of 0.9602 and a precision of 0.9528. It features a confusion matrix and a classification report showing precision, recall, F1-score, and support for each health impact class. The layout uses a blue header with white data cells, emphasizing the model's superior performance, particularly for the Very High class with 3817 instances, showcasing the effectiveness of the hybrid approach


Hybrid DQN-RF

Accuracy (A) 0.9602 | Precision (P) 0.9528 | Recall (R) 0.9602 | F1-Score (F1) 0.9546

Confusion Matrix (CM)

	Very High	High	Moderate	Low	Very Low
Very High	3891	2	0	0	0
High	37	390	0	0	0
Moderate	0	54	155	0	0
Low	0	0	48	28	0
Very Low	0	0	40	4	0

Classification Report (CR)

Class	Precision	Recall	F1-Score	Support
Very High	0.9906	0.9995	0.9950	3893
High	0.8744	0.9133	0.8935	427
Moderate	0.6379	0.7416	0.6858	209
Low	0.8750	0.3684	0.5185	76
Very Low	0.0000	0.0000	0.0000	44
Weighted Avg	**0.9528**	**0.9602**	**0.9546**	**4649**

Fig. 4. Health impact classification analysis (hybrid DQN-RF).

Fig. 5 highlights the Hybrid DQN-RF regression analysis for asthma cases, with MAE (1.3006), MSE (2.6672), RMSE (1.6332), and an R² score of 0.7177. It features a scatter plot of actual versus predicted values with a red ideal line and blue data points, showing a tighter alignment. The blue header and white background design emphasize the hybrid model's superior predictive accuracy and strong correlation with actual asthma cases

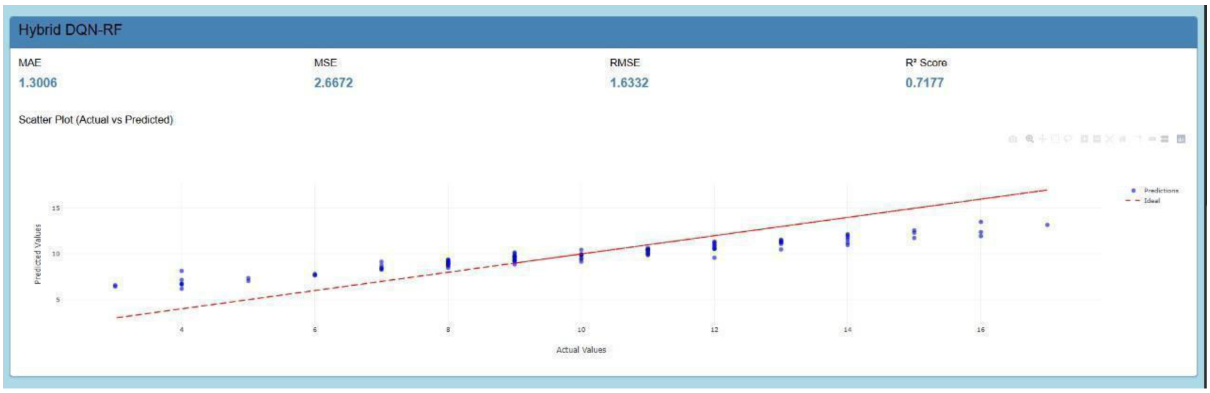


Fig. 5. Scatter plot obtained for asthma cases using proposed DQN – RF model

Fig 6 highlights the Hybrid DQN-RF regression analysis for cardiovascular cases. It provides metrics such as MAE (0.9313), MSE (1.4206), RMSE (1.1919), and an R² score of 0.7105, indicating a strong predictive performance compared to other models. The "Scatter Plot (Actual vs Predicted)" features blue dots for predictions against actual values, with a red ideal line showing a closer alignment of data points. This section is accessible under the "Cardiovascular Cases" navigation in the Air Quality Health Analysis tool. The high R² score underscores the hybrid model's superiority in capturing the relationship between air quality and cardiovascular cases. The design supports the project's innovative approach, offering a robust visualization for data-driven health insights

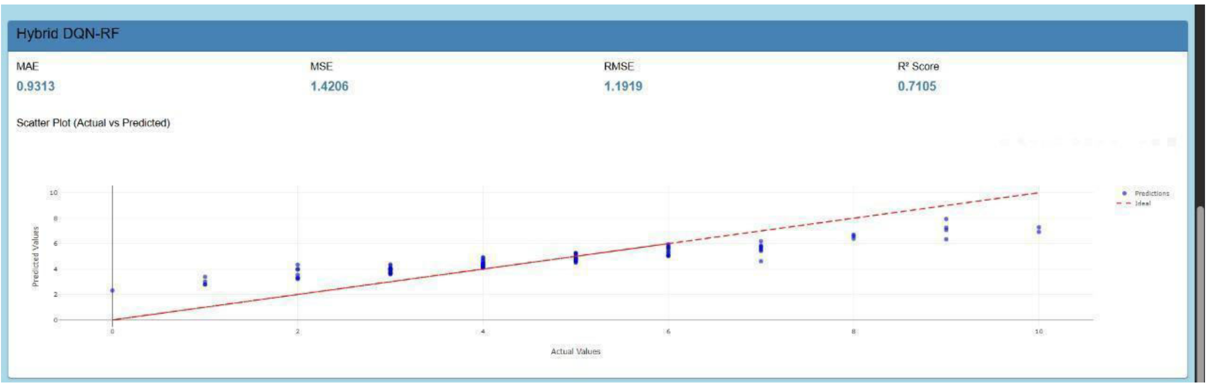
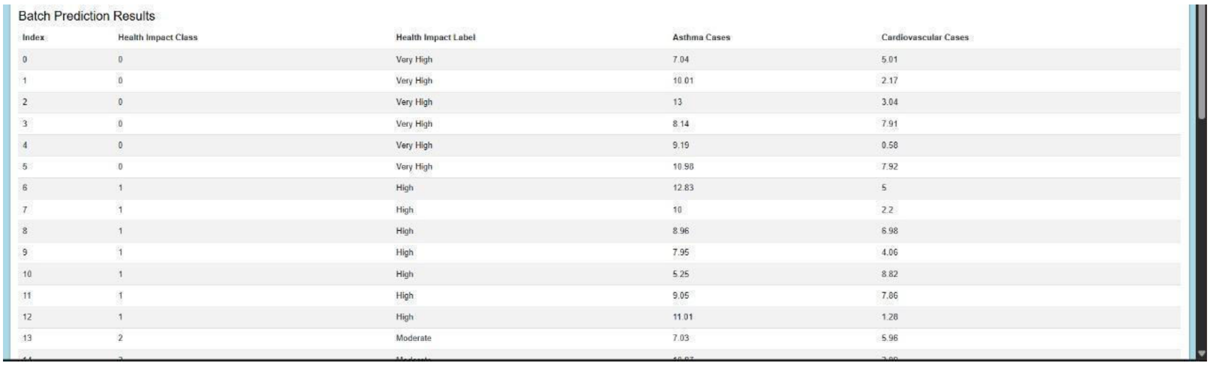


Fig. 6. Scatter plot obtained for cardio vascular cases using proposed DQN – RF model

Fig 7 illustrates the batch prediction interface of the Air Quality Health Analysis tool. Users can upload a CSV file containing columns like AQI, PM10, PM2.5, NO2, SO2, O3, Temperature, Humidity, and Wind speed, with a "Choose File" option and "Upload Prediction" button. The results table displays batch predictions, including Health Impact Class (0-4), corresponding labels (Very High to Very Low), Asthma Cases, and Cardiovascular Cases for each index. The table is neatly organized with white rows on a light background, showcasing multiple predictions (e.g., Index 0: Very High, 7.04 Asthma, 5.17 Cardio). This feature enables bulk analysis, aligning with the project's goal of providing comprehensive insights for urban health strategies.



Batch Prediction Results

Index	Health Impact Class	Health Impact Label	Asthma Cases	Cardiovascular Cases
0	0	Very High	7.04	5.01
1	0	Very High	10.01	2.17
2	0	Very High	13	3.04
3	0	Very High	8.14	7.91
4	0	Very High	9.19	0.58
5	0	Very High	10.98	7.92
6	1	High	12.83	5
7	1	High	10	2.2
8	1	High	8.96	6.98
9	1	High	7.95	4.06
10	1	High	5.25	8.82
11	1	High	9.05	7.86
12	1	High	11.01	1.28
13	2	Moderate	7.03	5.96

Fig 7. Batch prediction for data driven insights into asthma and air pollution associations.

Comparative analysis plays a vital role in evaluating the performance and effectiveness of different machine learning models used in air pollution–driven health impact prediction. In this project, multiple models including RF, Gradient Boosting (GB), XGBoost (XGB), Deep Q-Network (DQN), and the proposed Hybrid DQN–RF (CART) — are trained and tested on the same dataset to assess their predictive performance in both classification and regression tasks. The classification models are designed to predict health impact classes (Very Low, Low, Moderate, High, Very High), while regression models estimate continuous outcomes such as asthma (respiratory) and cardiovascular cases. Each model is evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-Score for classification, and MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and R² Score for regression. From the experimental results, traditional models like RF and Gradient Boosting performed well in identifying general patterns, but they lacked adaptability and sensitivity to non-linear variations in pollutant–health interactions. XGBoost improved performance due to its boosting mechanism but still showed limited robustness with noisy data. The deep q-network, based on reinforcement learning, demonstrated strong feature representation capabilities but was computationally intensive. The hybrid dqn–rf model outperformed all baseline methods, achieving the highest classification accuracy and lowest regression error rates. By combining DQN's deep learning ability to extract complex temporal and non-linear patterns with RF's ensemble-based decision aggregation, the proposed hybrid model achieved enhanced generalization, stability, and predictive precision. This improvement highlights the advantage of integrating reinforcement learning and decision tree principles into a unified hybrid framework.

Table. 1. Comparative analysis of classification models for air pollution–driven health impact prediction.

Model	Accuracy	Precision	Recall	F1-Score
RF	0.8413	0.7721	0.8413	0.7731
GB	0.8576	0.8157	0.8576	0.8135
XGBoost	0.8374	0.7012	0.8374	0.7633
hybrid DQN–RF	0.9602	0.9528	0.9602	0.9546

Table. 2. Comparative Analysis of Regression Models for Asthma and Prediction.

Model	Target	MAE	MSE	RMSE	R² Score
RF	Asthma Cases	2.4347	9.3620	3.0597	0.0091
GB	Asthma Cases	2.4293	9.3833	3.0632	0.0068
XGBoost	Asthma Cases	2.4324	9.4004	3.0660	0.0050
hybrid DQN–GT	Asthma Cases	1.3006	2.6672	1.6332	0.7177

Table. 3. Comparative Analysis of Regression Models for Cardiovascular Case Prediction.

Model	Target	MAE	MSE	RMSE	R² Score
RF	Cardiovascular Cases	1.7224	4.8521	2.2028	0.0112
GB	Cardiovascular Cases	1.7250	4.8815	2.2094	0.0052
XGBoost	Cardiovascular Cases	1.7258	4.8879	2.2109	0.0039
hybrid DQN– GT	Cardiovascular Cases	0.9313	1.4206	1.1919	0.7105

5. CONCLUSION

The proposed Hybrid DQN–Greedy Tree Learning Framework for Air Pollution–Driven Health Impact and Asthma Prediction successfully integrate deep reinforcement learning and ensemble-based decision modelling to achieve superior predictive performance. The system efficiently analyses air pollution parameters such as PM2.5, NO_2, and CO levels to predict associated health impacts, including asthma and cardiovascular conditions. Comparative analysis demonstrates that the proposed Hybrid DQN–RF model significantly outperforms traditional models like RF, GB, and XGBoost in terms of accuracy, precision, and robustness. The model's ability to adaptively learn complex nonlinear dependencies between pollutants and health metrics enhances its generalization capability. Furthermore, the integration of DQN-based optimization enables dynamic adjustment of feature weights, improving both prediction reliability and computational efficiency. The developed framework provides valuable insights for healthcare authorities and environmental policymakers to forecast health risks based on pollution data. The deployment through a Flask-based web interface ensures real-time accessibility and usability. Overall, the project contributes to building an intelligent, data-driven health monitoring system that supports preventive healthcare decisions and environmental management.

REFERENCES

[1] World Health Organization. Ambient (Outdoor) Air Pollution. Available online: **https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health** (accessed on 14 August 2020).

[2] Liu, Y.; Pan, J.; Zhang, H.; Shi, C.; Li, G.; Peng, Z.; Ma, J.; Zhou, Y.; Zhang, L. Short-Term Exposure to Ambient Air Pollution and Asthma Mortality. *Am. J. Respir. Crit. Care Med.* **2019**, *200*, 24–32. [**Google Scholar**] [**CrossRef**]

[3] World Health Organization. Ambient Air Pollution. Available online: **https://apps.who.int/gho/data/node.main.151?lang=en** (accessed on 13 June 2020).

[4] Khanam, U.A.; Gao, Z.; Adamko, D.; Kusalik, A.; Rennie, D.C.; Goodridge, D.; Chu, L.; Lawson, J.A. A scoping review of asthma and machine learning. *J. Asthma* **2023**, *60*, 213–226.

[5] Tsang, K.C.H.; Pinnock, H.; Wilson, A.M.; SHAH, S.A. Application of Machine Learning Algorithms for Asthma Management with mHealth: A Clinical Review. *J. Asthma Allergy* **2022**, *15*, 855–873.

[6] Anderson, H.R.; Gupta, R.; Kapetanakis, V.; Asher, M.I.; Clayton, T.; Robertson, C.F.; Strachan, D.P. International correlations between indicators of prevalence, hospital admissions and mortality for asthma in children. *Int. J. Epidemiol.* **2008**, *37*, 573–582.

[7] Ebmeier, S.; Thayabaran, D.; Braithwaite, I.; Bénamara, C.; Weatherall, M.; Beasley, R. Trends in international asthma mortality: Analysis of data from the WHO Mortality Database from 46 countries (1993–2012). *Lancet* **2017**, *390*, 935–945.

[8] Razavi-Termeh, S.V.; Sadeghi-Niaraki, A.; Choi, S.M. Asthma-prone areas modeling using a machine learning model. *Sci. Rep.* **2021**, *11*, 1912.

[9] Tiotiu AI, Novakova P, Nedeva D, Chong-Neto HJ, Novakova S, Steiropoulos P, Kowal K. Impact of Air Pollution on Asthma Outcomes. Int J Environ Res Public Health. 2020 Aug 27;17(17):6212. doi: 10.3390/ijerph17176212

[10] Olaia Bronte-Moreno, Francisco-Javier González-Barcala, Xavier Muñoz-Gall, Ana Pueyo-Bastida, Jacinto Ramos-González, Isabel Urrutia-Landa, Impact of Air Pollution on Asthma: A Scoping Review, Open Respiratory Archives, Volume 5, Issue 2, 2023, 100229, ISSN 2659-6636, https://doi.org/10.1016/j.opresp.2022.100229

[11] Zhou X, Sampath V, Nadeau KC. Effect of air pollution on asthma. Ann Allergy Asthma Immunol. 2024 Apr;132(4):426-432. doi: 10.1016/j.anai.2024.01.017

[12] Reis, J.S.d.; Costa, R.L.; Silva, F.D.d.S.; de Souza, E.D.F.; Cortes, T.R.; Coelho, R.H.; Velasco, S.R.M.; Neves, D.J.D.; Sousa Filho, J.F.; Barreto, C.E.C.; et al. Predicting Asthma

Hospitalizations from Climate and Air Pollution Data: A Machine Learning-Based Approach. *Climate* **2025**, *13*, 23. https://doi.org/10.3390/cli13020023

[13] Barrera-Heredia, A.D.; Zafra-Mejía, C.A.; Cañas Arboleda, A.; Fernández Sánchez, M.J.; López-Kleine, L.; Rojas Moreno, A. Trends in the Use of Air Quality Indexes in Asthma Studies. *Atmosphere* **2024**, *15*, 847. https://doi.org/10.3390/atmos15070847

[14] Clougherty, J.E.; Ocampo, P. Perception Matters: Perceived vs. Objective Air Quality Measures and Asthma Diagnosis among Urban Adults. *Int. J. Environ. Res. Public Health* **2023**, *20*, 6648. https://doi.org/10.3390/ijerph20176648

[15] Subramaniam, S.; Raju, N.; Ganesan, A.; Rajavel, N.; Chenniappan, M.; Prakash, C.; Pramanik, A.; Basak, A.K.; Dixit, S. Artificial Intelligence Technologies for Forecasting Air Pollution and Human Health: A Narrative Review. *Sustainability* **2022**, *14*, 9951. https://doi.org/10.3390/su14169951

[16] Necula, S.-C.; Hauer, I.; Fotache, D.; Hurbean, L. Advanced Hybrid Models for Air Pollution Forecasting: Combining SARIMA and BiLSTM Architectures. *Electronics* **2025**, *14*, 549. https://doi.org/10.3390/electronics14030549

[17] Al Okla, S.M.; Al Rasbi, F.A.Z.K.; Al Marhubi, H.S.; Al Mataani, S.S.; Al Sawai, Y.M.; Mohammed, H.I.; Al Mamari, M.A.S.; Al Balushi, S.A.A.; Abbady, A.Q. The Impact of Air Pollution on Asthma Severity among Residents Living near the Main Industrial Complex in Oman: A Cross-Sectional Study. Int. J. Environ. Res. Public Health 2024, 21, 553. https://doi.org/10.3390/ijerph21050553