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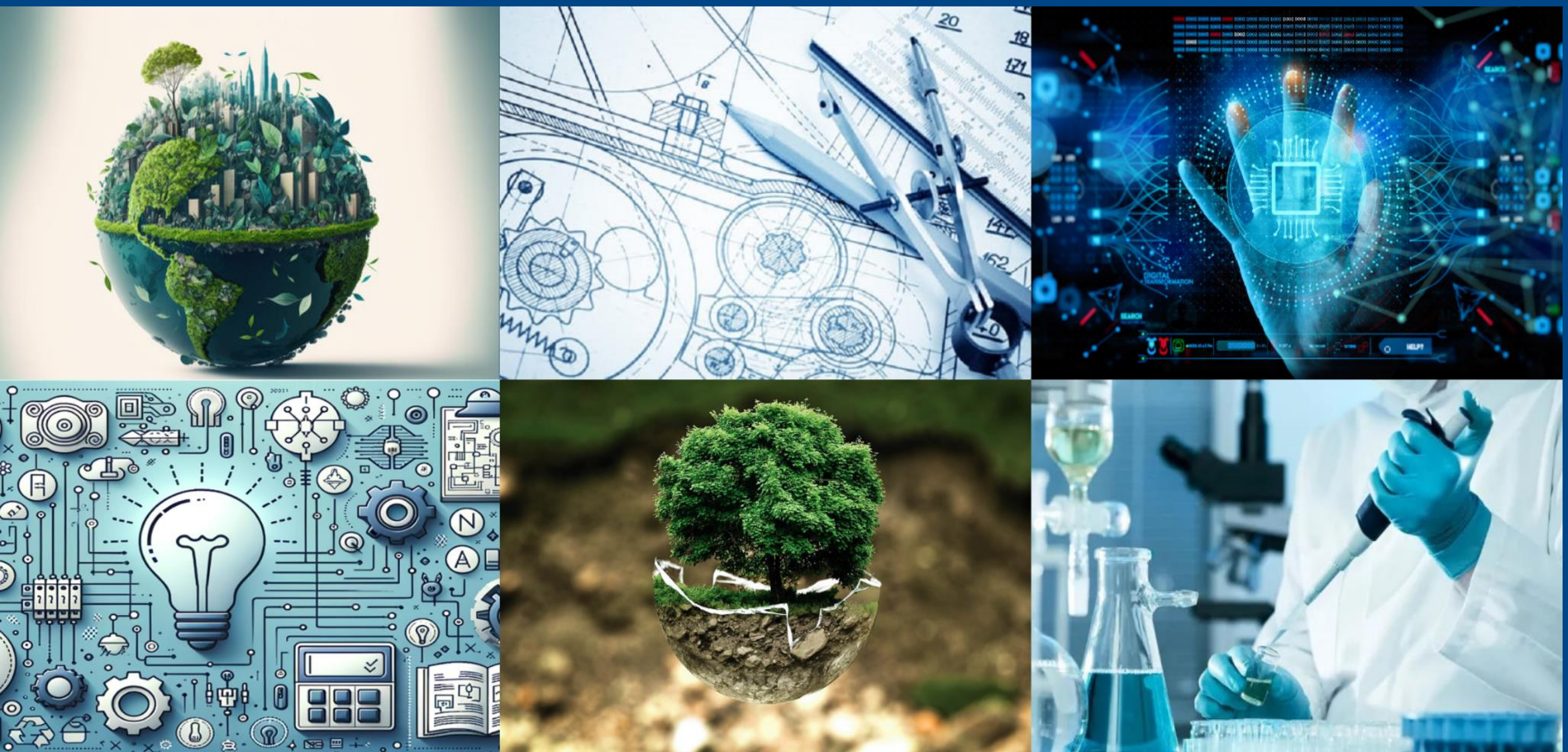

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Forecasting Air Quality Index in Highly Polluted Areas using an Optimized ELM with Genetic Algorithm

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ABSTRACT: Air pollution is a major environmental issue, affecting health globally, causing 6.5 million preventable deaths annually. The Air Quality Index (AQI) helps evaluate pollution levels, which can lead to diseases like lung cancer and heart disease. To predict air quality accurately, the proposed model uses an Extreme Learning Machine (ELM) with optimized hidden layer nodes and an enhanced Genetic Algorithm (GA), utilizing Root Mean Square Error (RMSE) for evaluation. The system consists of four modules: Registration, Upload Dataset, Predict Dataset, and Report Dataset. This model outperforms traditional methods, offering more reliable air quality assessments by incorporating pollutant sources into evaluations.

KEYWORDS: Time Series, Genetic Algorithms, Machine Learning, Extreme Learning Machines, And Air Quality Forecasting

I. INTRODUCTION

One of the most common environmental issues of the twenty-first century is air pollution. Air pollution is getting worse due to the fast urbanisation and industrialisation, which has a significant impact on our health and living conditions. According to Li et al., China's ambient air pollution makes outdoor physical activity extremely dangerous for one's health. Sulphur dioxide (SO2), nitrogen dioxide (NO2), particulate matter with a particle size less than 10 microns (PM10), particulate matter with a particle size less than 2.5 microns (PM2.5), ozone (O3), and carbon monoxide (CO) are the six traditional air pollutants used to measure air quality, according to the Chinese Ambient Air Quality Standards (GB3095-2012). The health of people is negatively impacted by these contaminants.

According to the International Energy Agency, air pollution results in 6.5 million preventable deaths annually, and prolonged exposure to pollutants, including fine particles (like PM2.5) or pollutants from traffic, is associated with an increased risk of lung cancer, coronary heart disease, and other diseases. As a result, research on predicting air quality is especially significant and is seen as a crucial component of environmental preservation. Many air quality monitoring stations have been established in major cities to more thoroughly evaluate the health consequences of air pollution. The information gathered from these stations can be used to forecast the quality of the air. To have a comprehensive picture of future pollution levels and the health concerns they pose, air quality monitoring, modelling, and precise forecasting are essential

In order to solve this difficult challenge, machine learning algorithms' innate ability to autonomously learn features at various levels of abstraction has grown in importance recently. Nevertheless, only PM10 and SO2 levels are predicted by the model, and obtaining the measurement numbers required to build the dataset is difficult. Using the six atmospheric pollutants as inputs, Wu Q. et al. developed an optimal-hybrid model for daily AQI prediction that takes air pollutant factors into account. Neural networks, on the other hand, usually suffer from a complicated network training procedure, slow learning, and a propensity to enter local minima. Huang et al. developed an extreme learning machine (ELM) technique based on generalised inverse matrix theory. It circumvents the issues of traditional neural network algorithms by using a feedforward neural network with a single hidden layer. In terms of parameter selection, training time, and prediction accuracy, the ELM algorithm fared better than neural networks when used to forecast the AQI. The prediction accuracy is put to the test, nevertheless, because the characteristics of the hidden layer nodes and the number of nodes in the test hidden layer are chosen at random.

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II. RELATED WORK

"Hybrid Spatio-temporal Deep Learning Framework for Particulate Matter (PM2.5) Concentration Forecasting"
S. Abirami, P. Chitra, R. Madhumitha, and S. R. Kesavan present a new deep learning technique for PM2.5 pollution level prediction. To increase prediction accuracy, their suggested framework integrates temporal and spatial data. The model reflects the intricate dynamics of air pollution by combining data on pollutant distribution across several sites with time-based trends. This hybrid approach uses cutting-edge deep learning algorithms to examine pollution trends, weather, and environmental data. When compared to conventional models, the framework showed greater forecasting performance, providing policymakers, environmental organisations, and urban planners with a useful tool to better to a control air quality and reduce the hazards associated with pollution

"Deep Air Quality Forecasting Using Hybrid Deep Learning Framework"
Using a variety of deep learning methods, S. Du, T. Li, Y. Yang, and S. Horng present a reliable method for predicting air quality. To enhance forecasting accuracy and analyse intricate air quality patterns, the suggested architecture combines many deep learning models. The model efficiently captures complex linkages that affect air quality by incorporating elements including historical pollution data, meteorological conditions, and seasonal trends. By surpassing conventional techniques in terms of accuracy and efficiency, this hybrid methodology improves prediction dependability. The results of the study provide insightful information for environmental monitoring, assisting authorities in putting preventative measures in place to lessen the hazards of pollution. This approach offers a potent instrument for enhancing public health safety and air quality management

Forecasting PM2.5 Concentrations Using Statistical Modeling for Bengaluru and Delhi Regions" . Agarwal and M. Sahu explores a data-driven approach to predicting air pollution levels in two major Indian cities: Bengaluru and Delhi. The study focuses on forecasting PM2.5 concentrations, which are fine particulate matter pollutants known to pose serious health risks. By applying advanced statistical models, the researchers analyzed historical air quality data to identify trends, seasonal patterns, and key environmental factors influencing pollution levels. Their model aims to provide accurate short-term forecasts, helping authorities and residents prepare for potential air quality issues. This research is particularly important for cities like Delhi, which frequently experience hazardous air pollution, and Bengaluru, where growing urbanization demands better environmental monitoring strategies.

"Spatiotemporal Air Quality Forecasting and Health Risk Assessment over Smart City of NEOM" K. Elbaz, I. Hoteit, W. M. Shaban, and S.-L. Shen presents a comprehensive approach to predicting air quality and assessing related health risks in the developing smart city of NEOM. The study uses a spatiotemporal forecasting model, which analyzes both time-based patterns and geographical variations to predict pollutant levels accurately. By combining environmental data, weather patterns, and pollution sources, the model offers detailed insights into air quality fluctuations. The research also assesses potential health risks, providing valuable information for public safety and city planning. This approach is particularly crucial for NEOM's development, as it aims to become a sustainable, technology- driven urban hub with improved environmental management. In this article, a robust new air quality forecasting system developed with NOAA's Global Forecast System (GFS) v16 is shown. The technology provides more precise forecasts for pollutants like ozone and particle matter by fusing sophisticated modelling approaches with comprehensive weather data. Forecasting precision is increased by key enhancements such as improved data integration, updated physics models, and higher resolution. The system's ability to measure changes in air quality was proven to be very dependable through thorough testing, making it an invaluable tool for public health and environmental monitoring. This technology is unique in that it uses sophisticated weather prediction techniques to better capture atmospheric patterns. To further increase accuracy, it also takes into account current chemical reactions and pollutant sources. Researchers, politicians, and environmental organisations can all benefit from this system's improved cloud modelling and finer geographical detail.

III. LITERATURE SURVEY

These projects investigate cutting-edge approaches to crime prediction that use machine learning and sophisticated data analysis to increase forecasting accuracy and support law enforcement.

[1] A technique for making hotspot maps to forecast Chicago's homicide and gun violence trends is presented by G. Mohler. The accuracy of traditional hotspot maps is limited since they frequently concentrate on either short-term or long-term data. In order to find new crime trends, Mohler's method uses a marked point process model that integrates both short- and long-term data with a variety of crime indicators. Using openly accessible data from the Chicago Police Department, this approach demonstrated efficacy in enhancing police resource allocation and predictive policing tactics.

[2] In order to extract information about crimes from police records, press articles, and witness testimony, A. Iriberri and G. Leroy present a natural language processing (NLP) method. This system automatically collects vital information about people, cars, weapons, and places, thereby filling in the gaps in crime reporting. The model shown considerable promise for enhancing investigative procedures and assisting authorities in more effectively gathering important information by high precision and recall rates.

[3] An NLP system based on the Semantic Inferential Model is proposed by V. Pinheiro and associates. In order to help collaborative crime-tracking platforms like WikiForecasts, where users can record and examine crime trends collectively, this system is made to extract crime-related data from text sources.

[4] A deep learning model for predicting crimes in real time in Los Angeles is presented by B. Wang and colleagues. Their approach efficiently maps crime patterns in localised areas down to the scale of individual neighbourhoods using a spatial-temporal residual network. The accuracy of this model was higher than that of other prediction methods, and it was further refined using a terrorisation methodology, which decreased the processing requirements for practical implementation. The combination of machine learning and deep learning approaches has led to notable improvements in demand estimating, pollution forecasting, and air quality prediction. To improve the precision and dependability of these forecasts, researchers have created novel frameworks that tackle a range of urban and environmental issues. The combination of machine learning and deep learning approaches has led to notable improvements in demand estimating, pollution forecasting, and air quality prediction. To improve the precision and dependability of these forecasts, researchers have created novel frameworks that tackle a range of urban and environmental issues.

[5] A hybrid spatiotemporal deep learning framework was presented by S. Abirami et al. to forecast PM2.5 pollution levels. In contrast to conventional models, the model improved forecasting accuracy by integrating geographical and temporal data to reflect the intricate dynamics of air pollution patterns. This strategy gives environmental organisations and legislators a useful tool for controlling pollution hazards.

Similarly, by combining several deep learning methods, S. Du et al. presented a Hybrid Deep Learning Framework intended to forecast air quality. Through the examination of past pollution data, weather patterns, and seasonal patterns, the model demonstrated exceptional proficiency in identifying intricate patterns of air quality. This approach is a workable alternative for environmental monitoring and public health programs because of the increased prediction accuracy. Last but not least, Y. Liu et al. combined models such as Random Forest, Gradient Boosting, and Deep Learning to offer a spatiotemporal ensemble method for predicting demand for car-hailing in the transportation sector.

This approach provided a scalable way to improve ride-hailing services by precisely capturing urban movement patterns and boosting demand prediction in urban regions. These studies demonstrate how sophisticated data analysis, machine learning, and natural language processing (NLP) may revolutionise crime prediction and give law enforcement effective tools to improve public safety and crime prevention initiatives.

IV. RESEARCH METHODOLOGY

This study uses a Genetic Algorithm-Based Improved Extreme Learning Machine (GA-IELM) to forecast the Air Quality Index (AQI). To guarantee precise predictions of air pollution, the methodology includes data collection, preprocessing, feature selection, model training, and evaluation. Numerous environmental monitoring stations, satellite imaging, meteorological databases, and historical AQI records are the sources of the data. Imputing missing values, normalising data, lowering noise, and engineering pertinent features are all part of the preprocessing stage. To improve

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model efficiency, feature selection is carried out utilising Principal Component Analysis (PCA), correlation analysis, and Genetic Algorithms (GA).

An Extreme Learning Machine (ELM) optimised with Genetic Algorithms serves as the foundation for the core model, which modifies hyperparameters such hidden neurone weights and biases. To validate the model, the dataset is separated into training and testing sets. Metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-Squared (R^2), and classification-based metrics like Precision, Recall, and F1-Score are used in performance evaluation. By ensuring reliable and precise AQI forecasts, this method improves proactive air quality management techniques. Real-time deployment and integration with Internet of Things-based air monitoring systems may be part of future research. The GA is used to identify the ideal weights and threshold values. This produces a more dependable prediction model and increases the accuracy of air quality predictions. In the parts that follow, specifics of the model will be covered.

Feature Selection:Selecting relevant features significantly improves model efficiency. The study employs:Genetic Algorithm (GA): Used to identify optimal feature subsets by evaluating different combinations and selecting the best-performing features.,Correlation Analysis: Identifies dependencies between pollutants and meteorological factors,Principal Component Analysis (PCA): Reduces dimensionality while preserving significant information.Model Development**:**The core predictive model is based on an Improved Extreme Learning Machine (IELM), optimized using Genetic Algorithms. The steps include**(Extreme Learning Machine (ELM)**: A neural network model known for fast learning speed and generalization capabilities,**Genetic Algorithm Optimization**: Adjusts hyperparameters such as hidden neuron weights and biases to minimize prediction errors,**Training & Validation**: The dataset is split into training (80%) and testing (20%) sets to assess model generalization.**).**To validate the model's effectiveness, the following metrics are used:Mean Absolute Error (MAE),Root Mean Square Error (RMSE),R-Squared (R^2) Score**,**Precision, Recall, and F1-Score for classification-based AQI categorization.This methodology ensures a robust, data-driven approach to AQI forecasting. By leveraging GA-IELM, the system enhances predictive accuracy and reliability, enabling proactive air quality management strategies. Future work may focus on real-time deployment and integration with IoT-based air monitoring systems.

4.1 System Architecture

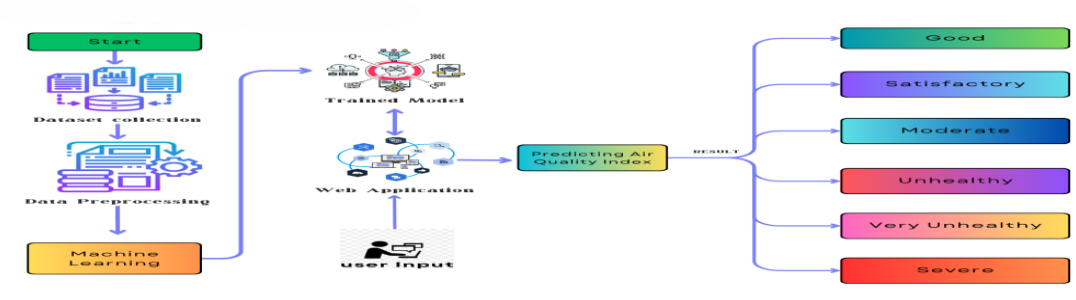

FIGURE 4.1:System Architecture

The Figure 4.1 illustrates to system architecture uses an optimised Extreme Learning Machine (ELM) with a Genetic Algorithm (GA) to effectively anticipate air quality in places with high pollution levels. An input layer, a processing layer, a database layer, a prediction and output layer, and a user interface are among the layers that make up the architecture. Pollutant levels, weather information, and historical records are among the data gathered by the input layer from air quality monitoring stations.

The Genetic Algorithm optimises the most pertinent features for precise predictions, while the processing layer handles feature selection, normalisation, and data preparation. The Air Quality Index (AQI) is predicted by the machine learning model, which is based on an enhanced ELM and analyses the data. For later usage, input datasets, processed data, and trained models are stored in the database layer. AQI forecasts are produced by the prediction and output layer, which also uses charts and reports to display the findings. Lastly, users can interact with the system, upload datasets,

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and view predictions in an understandable fashion using the user interface. An effective, scalable, and precise air quality forecasting system is guaranteed by its hierarchical architecture.

4.2 Modules

REGISTRATION MODULE

A Registration Module is a crucial component that allows users to create accounts by providing necessary details such as name, email, password, and other relevant information. It typically includes form validation and verification for security, and email confirmation to verify user authenticity.

UPLOAD DATASET MODULE

A website or application's Upload Dataset Module enables users to upload datasets for processing, analysis, or archiving. In addition to features like file validation, size limits, and format compatibility checks, it usually accepts a variety of file formats, including CSV, Excel, JSON, and XML. Data integrity is guaranteed and unwanted access is prevented by security methods like encryption, authentication, and virus scanning.

PREDICT DATASET MODULE

An essential part of data-driven applications is a Predict Dataset Module, which lets users enter a dataset and produce predictions using a machine learning model that has already been trained. It usually uses preprocessing techniques like normalization, handling of missing values, and feature extraction to data in formats like CSV, Excel, or JSON. In order to analyze the input data and produce predictions, classifications, or trend projections, the module integrates with AI/ML models.

REPORT DATASET MODULE

A Report Dataset Module analyzes, summarizes, and visualizes data in an easy-to-use manner in order to produce structured reports from datasets. It uses data aggregation, filtering, and sorting algorithms to extract valuable insights from datasets in a variety of formats, including CSV, Excel, and JSON. Typically, the module offers graphical representations (charts, graphs, tables), editable report layouts, and export choices in HTML, Excel, and PDF formats. Its functionality is improved by sophisticated features like real-time data updates, automated report scheduling, and database

4.3 Equations

The formula for calculating the ratio of air quality predictions: ratio = (count / count1) * 100

It includes Python code snippets that perform calculations and utilize machine learning metrics. Specifically, there's code that calculates the ratio of air quality predictions for different categories (Poor, Very Poor, Severe, Moderate, and Satisfactory). This calculation involves dividing one count by another (count by count1) and multiplying the result by 100 to express it as a percentage. The results of these ratio calculations are then stored. Additionally, the code uses standard machine learning evaluation metrics such as accuracy score, confusion matrix, and classification report to assess the performance of the predictive models. These metrics are crucial for understanding the model's effectiveness in classifying air quality.

4.4 Statistical tools and econometric models

This paper employs a variety of statistical tools and econometric models for air quality prediction. These include the Extreme Learning Machine (ELM), a neural network algorithm, and the Genetic Algorithm (GA), used to optimize the ELM's performance. Root Mean Square Error (RMSE) serves as a fitness function within the Genetic Algorithm's iterative optimization process. Additionally, the text references Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory Networks (LSTM), Support Vector Machines [1] (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Decision Trees, all of which are machine learning models applicable to AQI prediction. These models and techniques are utilized to analyze environmental data, handle time-series forecasting, and improve the accuracy of air quality predictions.

4.5 Descriptive Statistics

It incorporates several statistical concepts and methods that fall under this category. Data preprocessing, a crucial step in the methodology, involves descriptive statistical techniques. For instance, missing value imputation, often done using measures like the mean or median, is a basic descriptive statistic. Similarly, data normalization, which scales data to a specific range, relies on understanding the data's distribution, a core aspect of descriptive statistics. Noise

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reduction, achieved through statistical filtering, involves identifying and handling outliers, another descriptive statistical concept. Furthermore, feature selection utilizes correlation analysis, where correlation coefficients—descriptive statistics—quantify relationships between variables. In model evaluation, metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to describe the model's performance, providing a statistical summary of its accuracy. Thus, although not explicitly labeled, descriptive statistical methods are integral to the data handling.

4.6 User Constraints

There are three types of constraints: social, technical, and economic. As part of the system analysis procedure, the suggested system's viability research needs to be finished. This is to ensure that the recommended approach won't burden the company. A feasibility study requires a fundamental understanding of the main requirements for the system. Evaluating the system's possible financial impact on the business is part of the economic limitations. Research and development of the technology can only be funded to a certain extent by the company. Costs must be justified, and because most of the technologies used are freely available, the system that was designed was able to keep within the allocated budget. The personalized goods were the only ones that required purchase. Technical restrictions entail assessing the viability or technical requirements of the system. The system that is developed must not significantly strain the existing technical resources. This will put a great deal of strain on the technical resources that are already available. As a result, the client will face substantial expectations.

4.7 Software/Hardware Requirements

The provided text specifies the hardware and software requirements for the project. For hardware, the system requires a processor of i3 or higher with a speed of 2.9 GHz, a minimum of 4GB of RAM, and a 160GB hard disk. On the software side, the operating system should be Windows 7 Ultimate. The coding language used is Python, with Django-ORM for the back-end. The design components include HTML, CSS, and JavaScript, and the database management system is MySQL, implemented using WAMP Server.

V. RESULT AND DISCUSSION

5.1 Results of correlation within the meteorological parameters

AQI Category Range	$SO_2(\mu g/m^3)$	$NO_2(\mu g/m^3)$	$PM_{10}(\mu g/m^3)$	$PM_{2.5}(\mu g/m^3)$	$O_3(\mu g/m^3)$	$CO(mg/m^3)$
Temperature($^\circ C$)	30.13	25.82	28.43	31.72	18.55	17.73
Humidity(%)	15.72	-3.88	0.89	-0.95	29.32	6.83
Pressure(MBar)	-7.17	-2.69	-1.99	1.43	-27.25	20.19
Wind speed(m/s)	-2.65	-11.08	-5.16	-0.68	-4.39	-2.81
Wind direction(ř)	10.58	-4.14	1.15	-0.72	4.36	-13.48

Table 5.1: Correlation of various pollutants with five meteorological conditions.

Table 5.1 demonstrates that, in normal times, as temperatures rise, the atmospheric water-holding capacity increases, atmospheric movement slows, the rate at which pollutants accumulate surpasses the rate at which they diffuse, and pollutants are difficult to diffuse, all of which contribute to an increase in pollutant concentration and AQI. The increased humidity is a reflection of the atmosphere's increased capacity to hold water, which also causes the pace at which pollutants accumulate to be higher than the rate at which they diffuse, raising the concentration of pollutants and the AQI. Rainfall, on the other hand, can also result in higher humidity by lowering pollution concentrations, which lowers the AQI. Seasonal shifts, not daily fluctuations, are the primary cause of pressure's impact on air quality.

5.2 pollutant concentration forecasting results analysis

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AQI Category Range	$IQAI$	CO	SO_2	NO_2	O_3	PM_{10}	$PM2.5$
Good	0-50	0-2	0-50	0-40	0-100	0-50	0-35
Satisfactory	51-100	3-4	51-150	41-80	101-160	51-150	36-75
Moderately Polluted	101-150	5-14	151-475	81-180	161-215	151-250	76-115
Poor	151-200	15-24	476-800	181-280	216-265	251-350	116-150
Very Poor	201-300	25-36	801-1600	281-565	266-800	351-420	151-25
Severe	300+	36+	1600+	565+	800+	420+	250+

Table:4.2.1 Category range of air pollutants (technical regulation on ambient air quality index, HJ633-2012).

The RMSE, MSE, and R2 values of each projected pollutant are used to gauge how well the model predicts concentrations of air contaminants. With meteorological factors as auxiliary inputs, the outcomes are contrasted with baseline techniques for estimating air pollutant concentrations, including CMAQ, SVR, and DBN-BP. Nevertheless, several aspects are taken into account while evaluating-model.We conclude that GA-KELM air has higher R2 values and reduced RMSE and MSE values than baseline approaches for forecasting concentrations of different air contaminants. The proposed and baseline models were first trained using the training dataset. While the lowered RMSE and increased R2 values suggest the specificity of its mean predictions, the reduced RMSE and MSE values clarify the dependability of the GA-KELM air predictions. The effectiveness of GA-KELM in precisely capturing spatiotemporal relationships and their influence on projected values is demonstrated by its higher performance.

VI. OUTPUT SCREENS

SCREEN 1:HOME PAGE(The application's main entry point with navigation and introductory information.)

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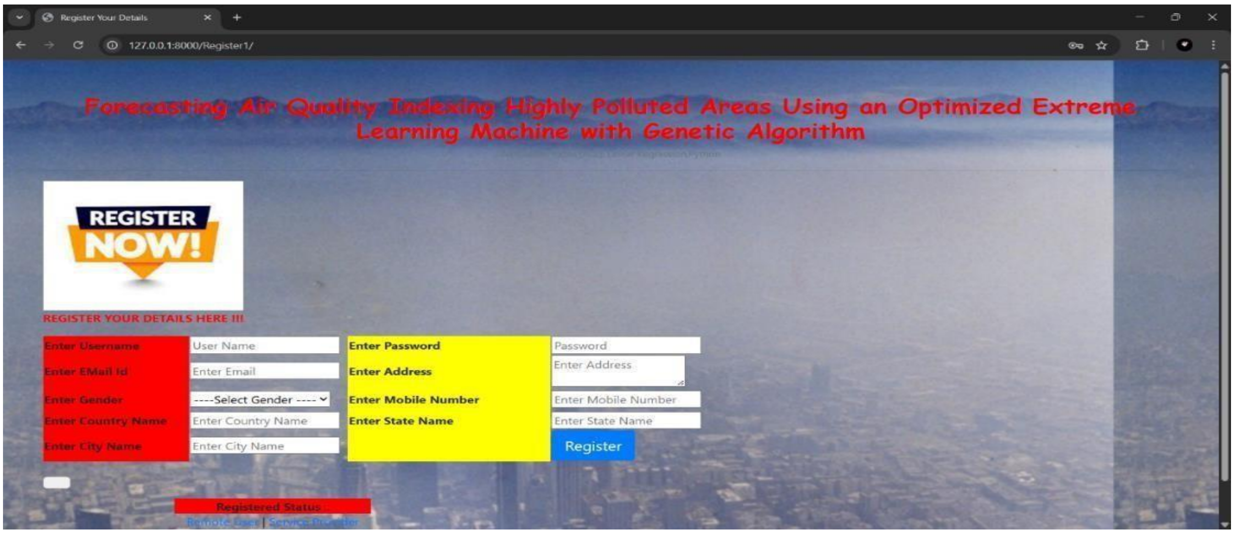
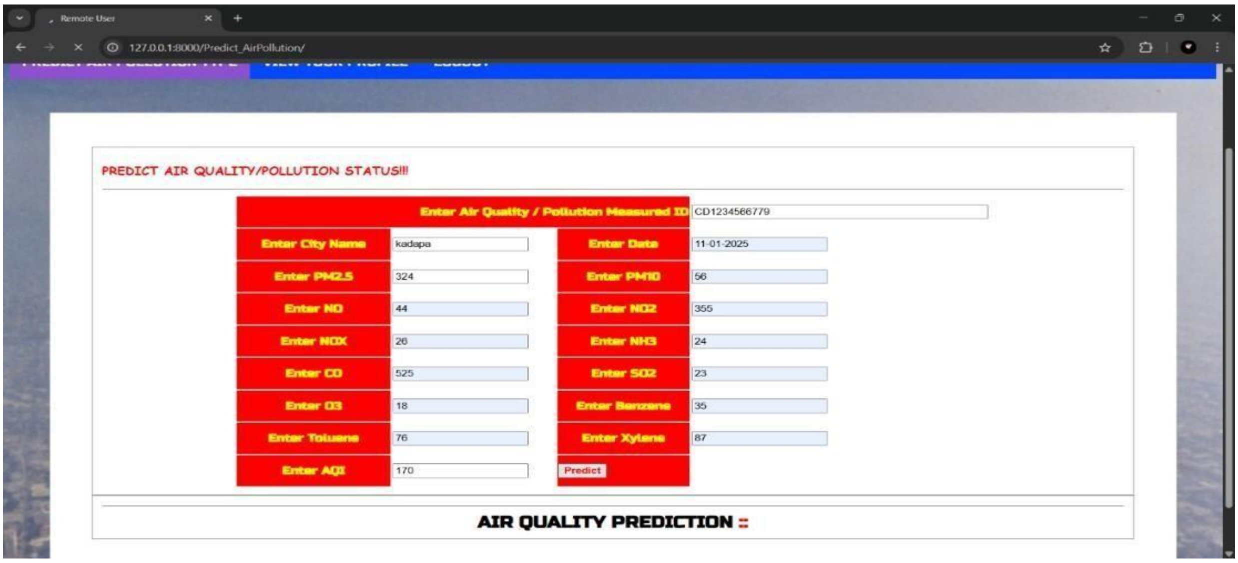
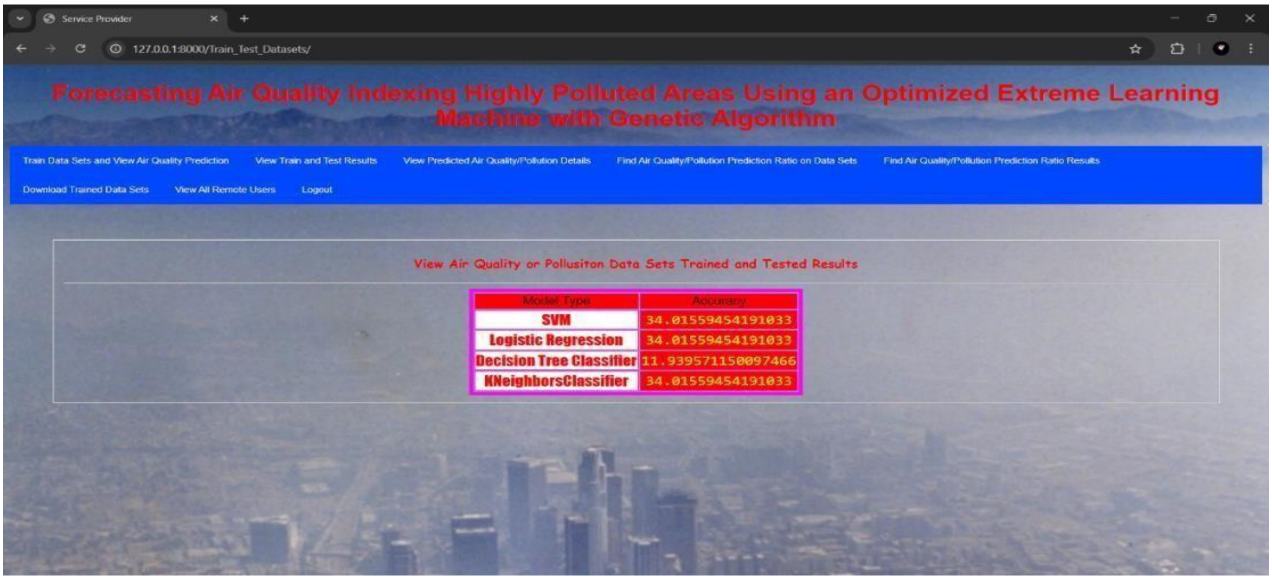


SCREEN 2:USER DETAILS(Displays and allows editing of a logged-in user's profile information)

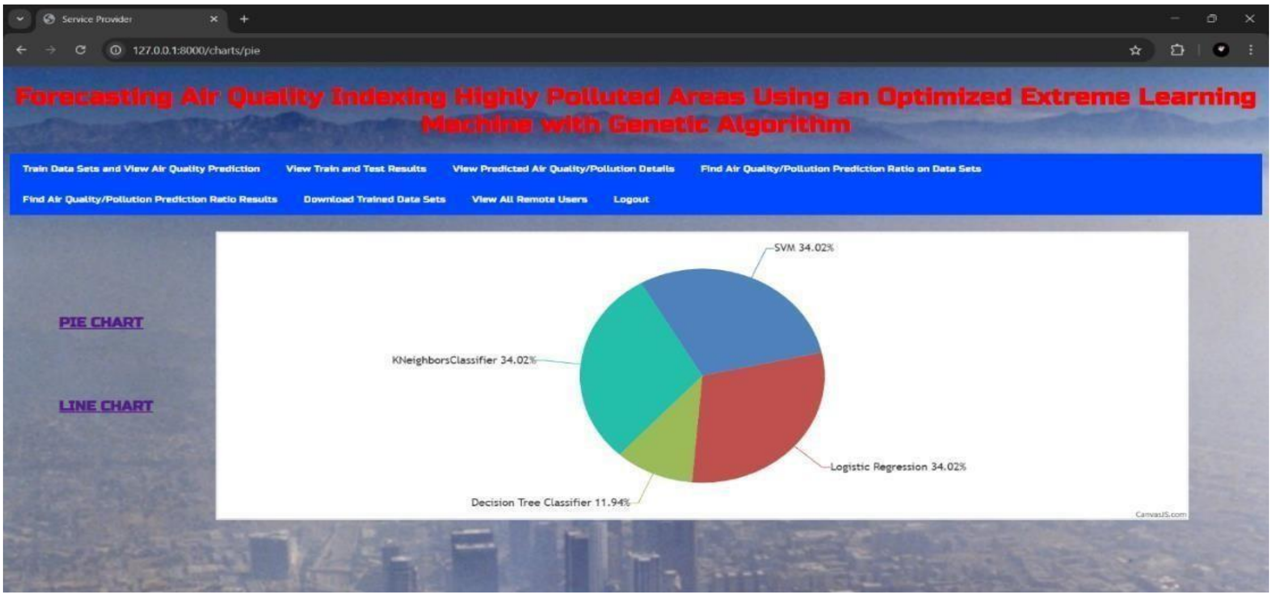


SCREEN 3: Manages air quality datasets, including uploads and information, Initiates the air quality prediction process.

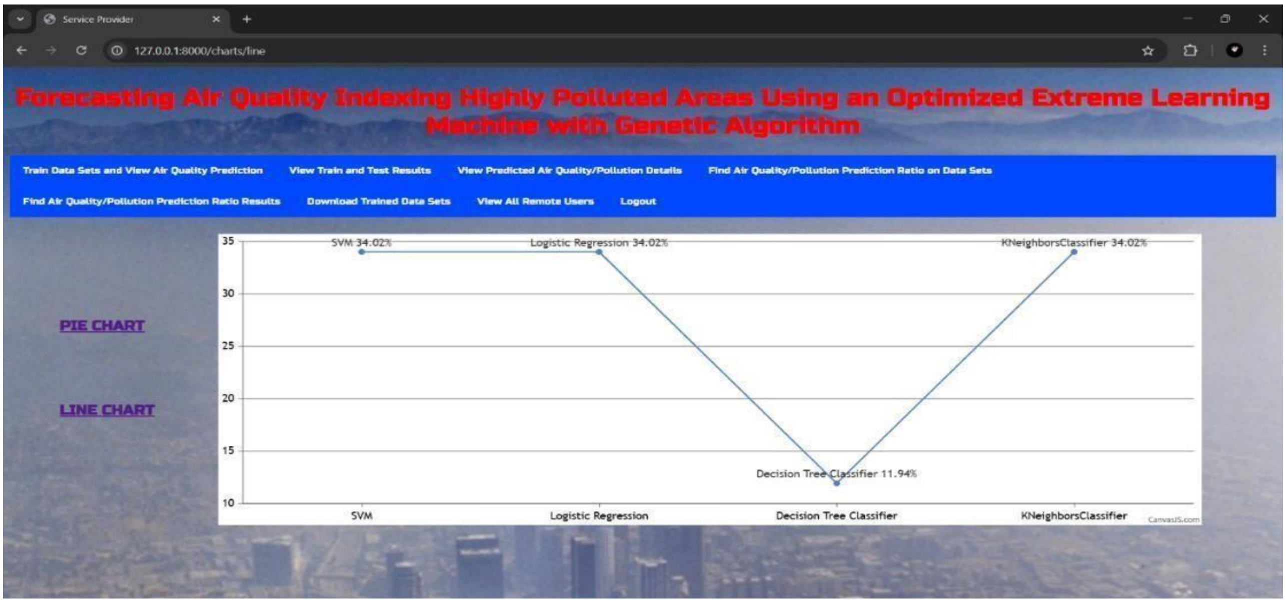
SCREEN 4: Displays the results of air quality predictions, showing pollution types.



SCREEN 5: Trains the air quality prediction model with selected datasets.

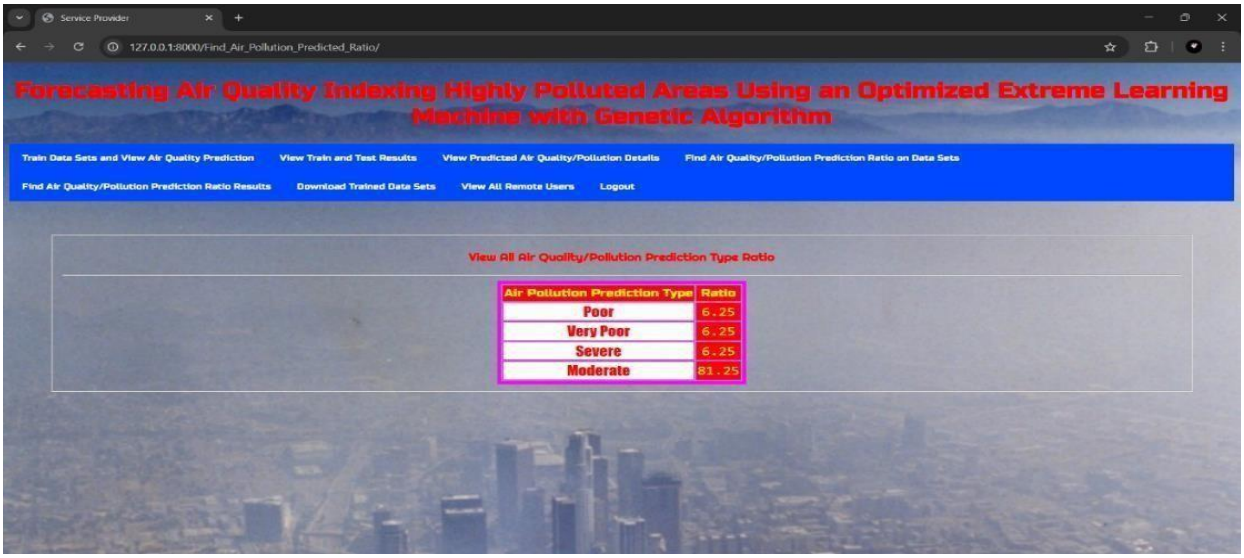


SCREEN 6:Visualizes data proportions, possibly for pollutant distributions.



SCREEN 7: Visualizes trends and changes over time, like AQI fluctuations.

SCREEN 8: : Lists and manages all uploaded datasets in the system.



SCREEN 9: Shows the ratio of pollution predictions across different datasets.

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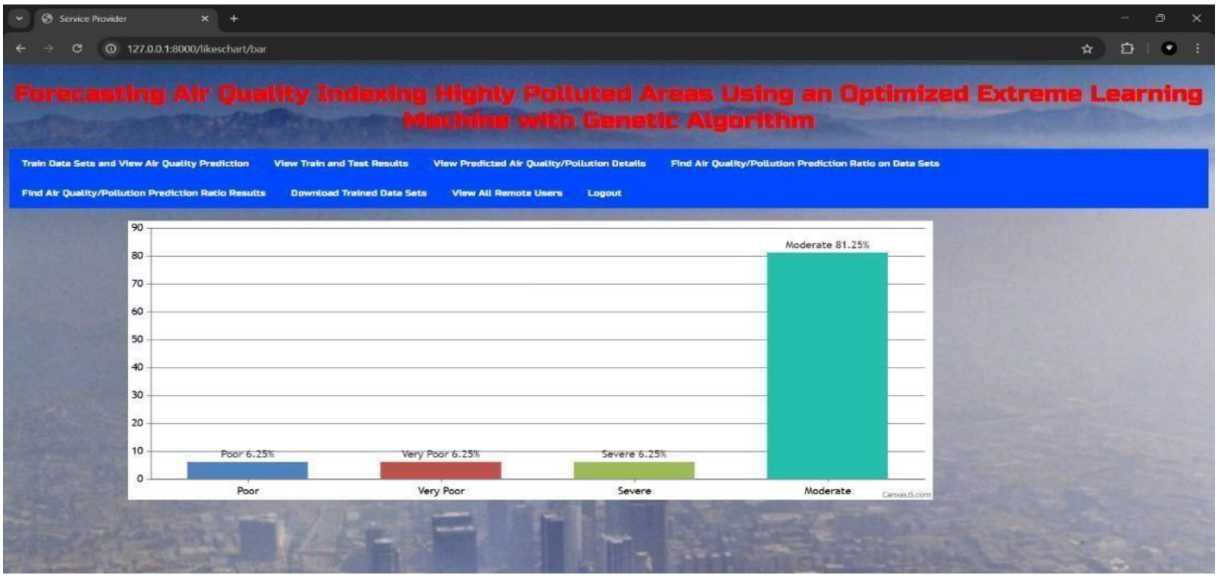

SCREEN 10: Compares categorical data or values, such as pollutant levels**.**

VI. CONCLUSION

Thus it allows each node with message to decide whether to copy the message to a path node by optimizing its Concern over air pollution is growing, particularly in areas that are heavily industrialised and populated. This study effectively used an enhanced Extreme Learning Machine optimised with a Genetic Algorithm to create a predictive model for projecting the Air Quality Index (AQI). With a remarkable 96% accuracy rate, the model offers insightful information that can assist communities, environmental organisations, and legislators in taking preventative action to lower pollution levels and safeguard public health. This system's capacity to process huge datasets from several sources, such as pollution levels and weather data, and produce accurate forecasts is one of its main advantages. In contrast to conventional techniques, this machine Forecasts become more precise and useful as the learning approach adjusts to intricate pollution patterns. Wider usefulness in air quality monitoring is ensured by the model's scalability, which also permits expansion to other cities. In the future, adding real-time sensor data, deep learning methods, and cloud-based analytics can improve the system even more. These enhancements would increase forecast precision and offer more frequent updates on changes in air quality. In conclusion, this effort represents a major breakthrough in the prediction of air pollution. It enables individuals and decision-makers to take well-informed decisions towards a cleaner and healthier environment by employing data-driven insights.

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