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Air Quality Index Prediction Using An Enhanced Extreme Learning Machine Based On Genetic Algorithms

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Abstract *– Security of human wellbeing and heading of ecological arrangement rely basically upon air quality prediction. Precise expectation of air quality changes is quite difficult for the vast majority traditional single-model frameworks. This work answers with areas of strength for a framework utilizing state of the art machine learning draws near. We examine many models like "support Vector Relapse (SVR), Genetic Algorithm-Enhanced Extreme Learning Machine (GA-KELM), and Deep Belief Network with Back-Propagation (DBN-BP)" from a near perspective. To further develop expectation precision considerably more, we likewise recommend including a deep learning design called "bidirectional long short-term memory (BiLSTM)". Through broad trial and error and assessment, we show that BiLSTM displays lower "Root Mean Square Error (RMSE) and Mean Squared Error (MSE)" values, so astounding current models. In addition, we expand the presentation of BiLSTM by adding GA-KELM, accordingly further developing its prescient powers considerably more. Aside from giving better accuracy in air quality expectation, the recommended half and half model assists with directing general wellbeing efforts and contamination control approaches through informed choices. This study emphasizes the need to explore approaches to conceptually address important biological issues in air quality monitoring and the potential improvement of machine learning outcomes.*

Index Terms — *Time series, air quality forecasting, machine learning, extreme learning machine, genetic algorithm.*

I. INTRODUCTION

Ascending as a significant worldwide issue in the twenty-first 100 years, air contamination is disturbed by quick industrialization and urbanization [1]. Declining air quality influences general wellbeing as well as the climate [2]. Li et al's. concentrates on feature the wellbeing dangers associated with open air actual practice within the sight of surrounding air contamination, particularly in regions like China that are quick seeing modern advancement [3]. As in numerous different countries, China estimates air quality utilizing rules characterized in the "Chinese Encompassing Air Quality Principles, including sulfur dioxide (SO2), nitrogen dioxide (NO2), particulate matter with sizes under 10 microns (PM10), and 2.5 microns (PM2.5), ozone (O3), and carbon monoxide (CO [4])".These pollutants have obviously unfortunate results for human wellbeing [5]. With long haul openness to contaminations like PM2.5 and traffic-related emanations connected to more prominent frequency of cellular breakdown in the lungs, coronary illness, and different sicknesses, the Worldwide Energy Organization assesses that air contamination causes roughly 6.5 million unexpected losses every year [6]. Thus, creating productive designs for air quality gauge turns out to be progressively significant since natural security drives rely upon it [7].Expectation of air quality generally relies upon data accumulated from checking stations spread over significant urban areas [8]. These destinations guide figure models and proposition sagacious examination of contamination levels. Offering the ability to naturally learn highlights at a few degrees of deliberation [9], machine learning algorithms have become more compelling instruments for assessing such information. In any case, there are hardships like the shortage of careful datasets and the trouble displaying a few pollutants simultaneously [10].New investigations have taken a gander at multiple ways of meeting these hardships. Utilizing information from six air pollutants, "Wu Q. et al. proposed an ideal half breed model for day to day Air Quality Index (AQI)" expectation [11]. Customary brain network calculations do, nonetheless, regularly stumble into issues including slow learning, aversion to neighborhood minima, and troublesome preparation methods [12]. In view of the summed up converse grid hypothesis and with a solitary secret layer feedforward brain organization, Huang et al. introduced the "extreme learning machine (ELM)" way to deal with beat these limitations [13]. As for boundary choice, preparing time, and expectation precision the ELM calculation has shown preferable execution in AQI expectation over traditional brain networks [14]. The ELM calculation's dependence on haphazardly picked boundaries for buried layer hubs presents hardships to expectation exactness regardless of whether its proficiency [15].In this regard, this work endeavors to tackle the disadvantages of current air quality expectation models by recommending a new strategy consolidating further developed boundary enhancement methods with the advantages of AI calculations. We present explicitly a crossover model consolidating the "Genetic Algorithm-Enhanced Extreme Learning Machine (GA-KELM) engineering with the Bidirectional Long Transient Memory (BiLSTM)" design. Utilizing the prescient powers of BiLSTM and hereditary calculation enhancement of model boundaries, this mix looks to build the exactness and versatility of air quality projections [16].This work presents another mixture model that addresses the requirements of current strategies, hence supporting the nonstop endeavors to further develop air quality conjecture methods. Joining BiLSTM with GA-KELM will assist us with giving more precise and reliable figures, thusly empowering informed choices for general wellbeing the executives and natural insurance.

II. LITERATURE SURVEY

Worldwide, air contamination has turned into a significant ecological and general wellbeing concern requiring exhaustive examination to distinguish its sources, results, and moderating procedures. With an eye toward the use of machine learning approaches for air quality expectation, we assess significant examination on air contamination observing, determining, and control in this writing study. Accentuating the need of handling air quality issues at the territorial level, Li et al. (2019) underlined air contamination as an overall concern requiring neighborhood arrangements [1]. From this vantage point, restricted air quality observing and figure frameworks become significantly more significant in directing centered measures. To survey the effect of air contamination the executive's strategies in China, "Han et al. (2018) introduced a Bayesian Long Short-Term Memory (LSTM)" model, consequently featuring the worth of modern factual techniques for information investigation of air quality [2]. Their exploration underscores how well LSTM models could gauge what strategy changes would mean for air quality outcomes.Bai et al. (2018) examined a few displaying procedures and information sources applied in air quality expectation [3] along with a rundown of air contamination estimates. Their investigation underscores the trouble of air quality expectation and the need of including numerous information sources, including ground-level checking information, meteorological information, and satellite perceptions. Utilizing inertial sensor information of air penmanship, Ding and Xue (2019) recommended a deep learning approach for essayist ID, after which they demonstrated the adaptability of deep learning methods to sensor information requirements for a number of purposes [4]. Researching the change of outside air proportion in cooling frameworks for arriving at wanted indoor air quality and greatest energy reserve funds, Cheng et al. (2019) [5] found Their exploration stresses the need of boosting ventilation procedures to protect indoor air quality and lessen energy utilization. Exhibiting the importance of LSTM models in air quality estimating, "Chaudhary et al. (2018) made a period series-based LSTM model" to expect air contamination focuses in eminent Indian urban communities [6]. Their work adds to the rising corpus of material on information driven techniques for air quality expectation.In light of publicly supported and cloud-based air quality pointers, Chen et al. (2018) recommended a metropolitan medical services enormous information framework featuring the potential outcomes of publicly supporting information for checking metropolitan air quality [7]. Their examination stresses how new innovation could assist with expanding the degree of general wellbeing observing and air quality control. Joining "convolutional neural networks (CNNs) and LSTM networks [8]", "Du et al. (2021) exhibited a deep air quality guaging framework utilizing a half breed deep learning method". Their examinations show that mixture deep learning calculations catch complex spatiotemporal examples in air quality information rather successfully.The writing audit calls attention to for the most part the developing interest in utilizing ML strategies for the executives, guaging, and air quality checking. In order to expand the accuracy and reliability of air quality forecasting, research has taken a gander at several approaches including LSTM models, deep learning algorithms, and cross breed ML algorithms

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III. METHODOLOGY

A. Proposed work

With an eye toward explicitly PM2.5 level forecast, the proposed work tries to consolidate “Genetic Algorithm (GA)with Extreme Learning Machine (ELM)”to further develop air quality expectation. To boost the decision of stowed away hubs and layers inside the ELM model, GA will be utilized, in this manner improving the learning limit and expectation accuracy of the model. The ELM model can powerfully change its design to all the more likely catch the mind boggling relationships inborn in air quality information by utilizing GA’s [14] ability to look for best arrangements inside a preset pursuit space. Utilizing execution measures including “Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)”, near study will be finished against traditional methodologies such “Support Vector Machines (SVM)” [16]. The recommended technique expects to give a more dependable and exact air quality expectation framework, in this manner empowering exhaustive investigations of contamination levels and their potential consequences for the climate and general wellbeing.

B. System Architecture

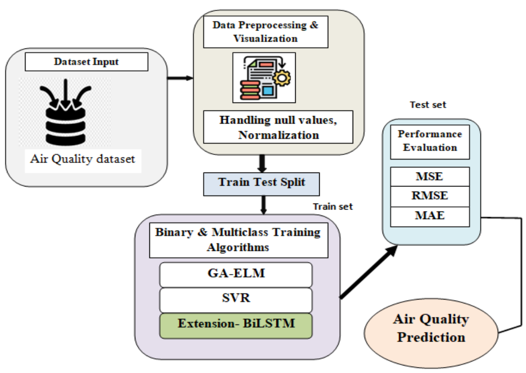

Fig. 1. Proposed Architecture

Fig. 1 shows The system architecture for air quality prediction encompasses several key components to effectively process, train, and evaluate predictive models.

The system architecture for air quality prediction encompasses several key components to effectively process, train, and evaluate predictive models Gate-level design of integrated circuits, detailed security systems (including watermarking and stenography), Internet and Personal Computer design, in general will not be accepted.Powerful handling, preparing, and assessment of prescient models rely upon various essential components in the plan of the framework for air quality expectation.The framework begins by consuming air quality datasets including relevant data including geographic data, meteorological information, and contamination fixations.Perception and information handling: Dealing with invalid qualities, normalizing, and include designing assistance to set up the information for displaying. Strategies of envisioning assist one with grasping information appropriations and connections. Preparing and testing sets split the dataset so that model preparation and evaluation might be worked with. This ensures that the summing up limit of the model is assessed on inconspicuous information, thus directing its exhibition.Paired and Multi-Class Preparing Calculations: The framework joins “bidirectional long short-term memory (BiLSTM) networks, Support Vector Regression (SVR), and Genetic Algorithm-Enhanced Extreme Learning Machine (GA-ELM)”[14]. These calculations find the basic examples and connections between's feedback elements and air quality results through the preparation information.Model execution is evaluated as to measures such “Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE)”. Through these actions, the distinctions among expected and real air quality qualities are measured, hence offering data on the constancy and accuracy of the models. When prepared, the models are applied to

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give forecasts on natural information, subsequently assessing air quality boundaries including contamination fixations or Air Quality Index (AQI) values. Surveying present and future air quality circumstances relies upon these gauges, which likewise help to direct astute choices on general wellbeing efforts and contamination control.Utilizing ML calculations and execution assessment strategies to deliver exact and trustworthy estimates, the framework engineering offers a total system for air quality prediction by and large

C. Data Set

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	AQI_Bucket
0	Ahmedabad	2015-01-01	0.0	0.0	0.92	18.22	17.15	0.0	0.92	27.64	133.36	0.00	0.02	0.00	0.0	0
1	Ahmedabad	2015-01-02	0.0	0.0	0.97	15.69	16.46	0.0	0.97	24.55	34.06	3.68	5.50	3.77	0.0	0
2	Ahmedabad	2015-01-03	0.0	0.0	17.40	19.30	29.70	0.0	17.40	29.07	30.70	6.80	16.40	2.25	0.0	0
3	Ahmedabad	2015-01-04	0.0	0.0	1.70	18.48	17.97	0.0	1.70	18.59	36.08	4.43	10.14	1.00	0.0	0
4	Ahmedabad	2015-01-05	0.0	0.0	22.10	21.42	37.76	0.0	22.10	39.33	39.31	7.01	18.89	2.78	0.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
497	Ahmedabad	2016-05-12	0.0	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0
498	Ahmedabad	2016-05-13	0.0	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0
499	Ahmedabad	2016-05-14	0.0	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0
500	Ahmedabad	2016-05-15	0.0	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0
501	Ahmedabad	2016-05-16	0.0	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.00	0.00	0.0	0

Fig. 2. Data set

Fig.2 shows air quality data set and Estimating numerous toxins including "sulfur dioxide (SO2), nitrogen dioxide (NO2), particulate matter with breadths under 10 microns (PM10), 2.5 microns (PM2.5)[17],[20][21],ozone (O3), and carbon monoxide (CO)", the air quality dataset Each perception comprises of contamination levels along with matching timestamps and geological directions. Moreover included could be meteorological information including "temperature, humidity, wind speed, and air pressure". This dataset helps concentrate on the impacts of contamination on general wellbeing and the climate by permitting examination of air quality patterns over the long haul and across a few regions.

Data Processing

Viable information control and preprocessing tasks are achieved utilizing the Pandas DataFrame. To prepared the dataset for model preparation, this covers normalizing, tending to missing qualities, and erasing undesired sections.

Assuming any missing qualities exist, they are taken care of by strategies including ascription or end. This ensures the nature of the information and assists with staying away from biases in next examinations. Typically somewhere in the range of 0 and 1, mathematical elements are standardized to a standard scale to ensure consistency and keep away from highlights with higher scales from controlling the model preparation process.

Data processing with keras Data frame

The Keras DataFrame enables the assessment of smooth networking and deep learning algorithms, thus enabling complex information systems and model preparation for neural networks

"Handling Missing Values": Missing qualities are dealt with, much as in Pandas, to ensure information culmination and trustworthiness.

Normalization: The Keras DataFrame standardizes mathematical highlights utilizing appropriate scaling techniques. This ensures steady element ranges and helps neural network training join.

E . visualization

Through effective perception draws near, Seaborn and Matplotlib offer significant graphical portrayals that further develop information on air quality insights.

Histograms: Matplotlib's 'hist' and Seaborn's 'histplot' help to show the dissemination of contamination fixations, consequently uncovering patterns and exceptions.

Scatter Plots: Assisting with distinguishing connections, Seaborn's 'scatterplot' and Matplotlib's 'disperse' capabilities show joins between numerous foreign substances or among poisons and meteorological information.

"Line Plots": "Seaborn's 'lineplot' and Matplotlib's" 'plot' capabilities show worldly patterns in contamination focuses across time, in this manner empowering the discovery of occasional changes and long haul patterns.

These visualizations provide valuable insights into air quality dynamics, informing subsequent analysis and model development.

F. Feature Selection

Feature selection is crucial for building effective air quality prediction models. Techniques such as correlation analysis, feature importance ranking, and dimensionality reduction methods like Principal Component Analysis (PCA) are employed. Correlation analysis identifies relationships between pollutants and meteorological variables, aiding in selecting relevant features. Feature importance ranking methods, such as Random Forest feature importances, prioritize influential features for prediction. Additionally, PCA identifies latent variables capturing the majority of data variance, reducing dimensionality while preserving essential information. By selecting the most informative features, feature selection optimizes model performance and computational efficiency in air quality prediction tasks.

G. Training & Testing

Assessing model execution requires breaking out the air quality dataset into preparing and testing subgroups. Generally, an irregular split — say, a 80/20 or 70/30 proportion — is utilized to ensure an adequate number of information for testing and preparing. The prescient models are prepared utilizing the preparation set; the testing set is assigned for surveying model execution and isn't noticeable during preparing. This division ensures objective execution assessment and assesses the speculation limit of the model to new information, so working on the trustworthiness of air quality projections in reasonable circumstances.

H. Algorithms

Genetic Algorithm with Extreme Learning Machine (GA-ELM)": The "Genetic Algorithm with Extreme Learning Machine (GA-ELM)" joins the viable learning system of Extreme Learning Machines (ELMs) with the transformative streamlining powers of Genetic Calculations (GAs). In GA-ELM, the GA changes ELM model boundaries to further develop forecast execution. Commonly surveyed utilizing an approval dataset, the GA iteratively chooses, gets over, and changes people concurring on their wellness, thus developing a populace of conceivable ELM arrangements. The ELM maps input highlights to a higher-layered space utilizing a solitary secret layer with irregular initiation works then utilizes yield weight calculation utilizing the Moore-Penrose pseudoinverse.

Support Vector Regressor (SVR): Support Vector Regressor (SVR) fits a relapse model utilizing primary gamble limiting thought. It looks for the hyperplane amplifying edge that best partitions significant pieces of information. To decrease the misfortune capability, for the most part epsilon-inhumane misfortune, SVR[16] amplifies hyperparameters including piece type and regularization boundary during model preparation. Utilizing its ability to distinguish complex relationships between's feedback ascribes and yield factors, SVR utilizes the learnt hyperplane once prepared to gauge air quality qualities on inconspicuous information.

Bidirectional Long Short-Term Memory (BiLSTM): Bidirectional Long Short-Term Memory (BiLSTM)" expands a brain network plan ready to catch long-range connections in consecutive info. By handling input successions both forward and in reverse, bi-LSTM empowers synchronous catch of past and future setting. Displaying worldly patterns in air quality information, where past and future estimations might influence present air quality levels, is particularly reliant upon this limit. Bi-LSTM models fit for air quality expectation exercises since they have shown productivity in catching complex worldly elements.

IV. EXPERMENT RESULTS

MSE: In measurements, "mean squared error (MSE)" checks factual model mistake. It assesses the normal and noticed values' typical squared distinction. The MSE equivalent zero when a model is without mistake. Its worth ascents as model mistake rises. One more name for the mean squared mistake is the "mean squared deviation, or MSD". The MSE is calculated using equation [1].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - Yi^{\wedge})^2 \qquad (1)$$

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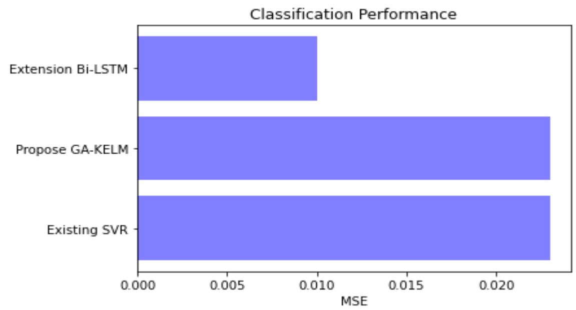

Fig. 3. MSE Comparison Graph

The comparison of the three models' effectiveness for predicting the air quality index in Fig. 3 shows significant variations in mean squared error (MSE). The Extension-BI LSTM model outperforms the other methods with a rough MSE of 0.10, indicating superior accuracy. Both the proposed GA-KELM and the existing SVR provide comparable results with an estimated MSE of 0.23, indicating no discernible improvement over the baseline. According to the comparison, the Extension-BI LSTM model is the most successful of them and demonstrates its ability to predict precise air quality indices.

RMSE: The "root mean square error (RMSE)" checks the typical deviation between the real information and the extended upsides of a factual model. It is, numerically, the residuals' standard deviation. Residuals are the information point distance from the regression line. The RMSE is calculated using equation (2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(yi - yi^\wedge)^2}{N}} \qquad (2)$$

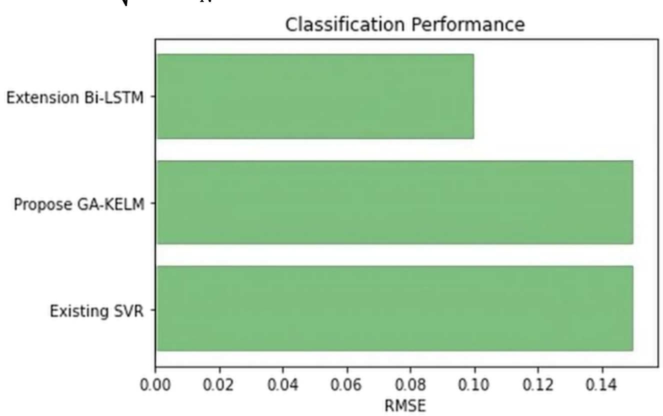

Fig. 4. RMSE Comparison Graph

The classification accuracy of the three models shown in Fig. 4 above for predicting the air quality index was assessed using RMSE as a criterion. The Extension-BI LSTM model performed the best, demonstrating its capacity to successfully detect intricate patterns in the data with an RMSE of roughly 0.10. The RMSE of the proposed GA-KELM model and the existing SVR model, in contrast, was approximately 0.15. While their performance levels were comparable, the Extension-BI LSTM fared better than these two models, demonstrating its superior capacity to predict air quality indices.

MAE The outright error in your estimations is the level of mistake. It is the variety between the "valid" and recorded values. For example, "the scale has an outright error of 90 lbs - 89 lbs = 1 lbs on the off chance that it shows 90 pounds when you realize your genuine weight is 89 pounds". The MAE is calculated using equation (3).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - yi^\wedge| \qquad (3)$$

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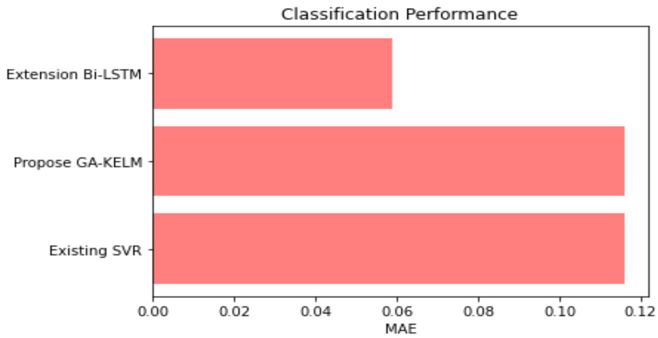

Fig. 5. MAE Comparison Graph

Using Mean Absolute Error (MAE) as the main metric, three models—Extension-Bi BILSTM, Propose GA-KELM, and Existing SVR—were evaluated based on how well they predicted air quality indices (Fig. 5 above). With an MAE of 0.06, the Extension-Bi BILSTM model outperformed the others. This demonstrates how well a bi-directional long short-term memory (Bi-LSTM) model may be used for producing accurate predictions, outperforming the other two models by a significant margin. However, both the existing SVR and our proposed GA-KELM models have an MAE of 0.116, suggesting similar but somewhat lower prediction ability. Although the merging of genetic algorithms (GA) and kernel extreme learning machines (KELM) in the proposed GA-KELM model is encouraging, it did not produce any improvement on the simpler SVR method. These results demonstrate how well-suited systems like BILSTM are for forecasting the air quality index, outperforming more conventional machine learning techniques. Accurate environmental monitoring, public health interventions, and decision-making all depend on timely air quality index estimates. Extension-Bi BILSTM's lower error rate demonstrates its application in dynamic air quality monitoring systems in the real world. Future research might look into adding more pollution and weather[19] data to improve prediction accuracy even further across various geographic areas.

TABLE 1

Performance Evaluation Table

ML Model	MSE	RMSE	MAE
Existing SVR	0.023		0.15
	0.116		
Propose GA-KELM	0.023		0.15
	0.116		
Extension Bi-LSTM	0.010		0.10
	0.06		

The models—Extension-BI LSTM, Proposed GA-KELM, and Existing SVR—were compared in terms of performance using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), as shown in Table 1. With the lowest MSE (0.010), RMSE (0.10), and MAE (0.06), Extension-BI LSTM demonstrated superior accuracy and efficacy in predicting air quality indexes. On the other hand, the current SVR model and the proposed GA-KELM model performed similarly, with an MAE of 0.116, RMSE of 0.15, and MSE of about 0.23. The findings indicate that while GA-KELM and SVR provide comparable accuracy, the Extension-BI LSTM is the best model among the three since it is significantly more accurate across the board.

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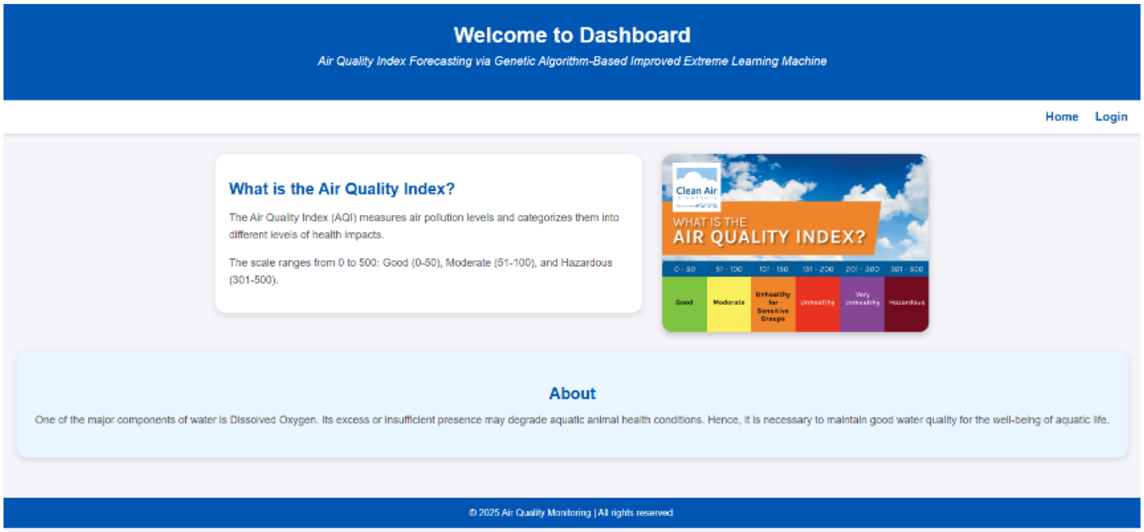

Fig. 6. Home Page

A better Genetic Algorithm-Based Improved Extreme Learning Machine (GA-KELM) for AQI prediction is displayed in Fig. 6 with an easy-to-use interface. The interface categorizes pollution levels into the health-relevant categories in order to describe AQI, a significant measure of air pollution. These bands range from Hazardous (301–500), meaning significant threats to public health, to Good (0–50), meaning having very little impact on health. The image also incorporates a simple but attractive AQI scale to assist users in the interpretation of levels of pollution and their significance on environmental as well as human health. Since it supplies reliable information for forecasting air quality trends and formulating sound decisions, this instrument is most useful for environmentalists, urban planners, and public health authorities. All things considered, Fig. 7 is a comprehensive platform that uses state-of-the-art machine learning to forecast the Air Quality Index while maintaining environmental sustainability. This gadget offers useful data for tracking and enhancing air quality, guaranteeing a more robust ecosystem for all.

Fig. 7. Sign Page

Fig. 8. Upload Input Data

An input interface for predicting air quality is shown in Fig. 8, where users can input important pollutant concentrations. The five main air pollutants—nitric oxide (NO), ammonia (NH3), carbon monoxide (CO), sulfur dioxide (SO2), and ozone (O3)—are included in the input fields. The numerical representation of each pollutant's concentration allows for accurate and adaptable data entry for forecasting.

These inputs are essential for forecasting the Air Quality Index because they analyze pollutant concentrations and their effects on the environment and human health. For instance, the air quality index is calculated using the following statistics as sample data: 19.2 for NO,27.8 for NH3,33.05 for CO, 19.2 for SO2,and 52.65 for O3.

Air quality monitoring systems depend on this interface because it makes it easier for users to engage with machine learning algorithms that evaluate and predict the air quality index. By enabling real-time pollution data input, it facilitates anticipatory decision-making for environmental management and public health improvement.

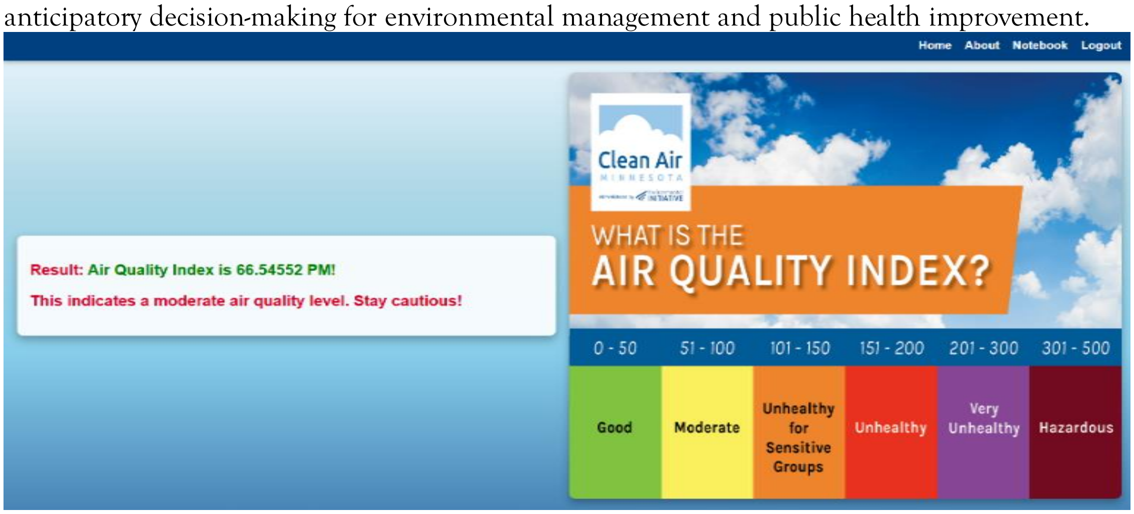

Fig. 9. Result of Air quality Index

Fig. 9 displays a value of 66.54552 PM, which is classified as "Moderate" air quality. This indicates that although the air quality is positive a very small amount of people may experience health issues, especially those who are extremely sensitive to air pollution. In this sense, it suggests being cautious.

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V. CONCLUSION

At last, the joining of "Genetic Algorithm with Extreme Learning Machine (GA-KELM)" and the expansion with "Bidirectional Long Short-Term Memory (BiLSTM)" reflect significant improvements in air quality forecast, so further developing precision and natural administration direction. Utilizing the BiLSTM model inside an easy to use Flask architecture expands the impact of the venture much more by giving both public and scientist commonsense admittance to air quality conjectures. This not just assists individuals with using sound judgment for their wellbeing and prosperity yet in addition elevates proactive moves toward limit the unfortunate results of air contamination on the environmental factors.

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