**J**ournal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 16, Issue. 1: 2025
ISSN : **1906-9685**


# GENETIC ALGORITHM-BASED IMPROVED EXTREME LEARNING MACHINE FORECASTING OF AIR QUALITY INDEX

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**Abstract:** One of the most significant environmental issues facing society and the general public has always been air quality. The investigation of future air quality trends from a macro viewpoint benefits from the use of machine learning techniques for Air Quality Index (AQI) prediction. It is difficult to get a satisfactory prediction result when utilizing a single machine learning model to forecast air quality under different AQI fluctuation patterns. A genetic algorithm-based enhanced extreme learning machine (GA-KELM) prediction approach is improved to successfully solve this issue. In order to generate the kernel matrix, which takes the role of the hidden layer's output matrix, a kernel approach is first presented. A genetic algorithm is then used to optimize the number of hidden nodes and layers of the kernel limit learning machine in order to solve the problem of the conventional limit learning machine, which is that the number of hidden nodes and the random generation of thresholds and weights cause the network learning ability to deteriorate. The fitness function is defined by the weights, the thresholds, and the root mean square error. Lastly, the model's output weights are calculated using the least squares approach. Through an iterative optimization process, genetic algorithms may identify the best solution in the search space and progressively enhance the model's performance. The optimized kernel extreme learning machine is used to predict air quality (SO2, NO2, PM10, CO, O3, PM2.5 concentration, and AQI) using comparative experiments based on CMAQ (Community Multiscale Air Quality), SVM (Support Vector Machines), and

DBN-BP (Deep Belief Networks with Back-Propagation) in order to validate the predictive ability of GA-KELM. This is done using the basic data of a long-term air quality forecast that was collected at a monitoring point in a Chinese city. The findings demonstrate that the suggested model produces more accurate predictions and trains more quickly. In order to maximize feature weight in both forward and backward directions, we have experimented with the BI-LSTM algorithm.

***Index terms*** *- Air Quality Index (AQI), Genetic Algorithm (GA), Kernel Extreme Learning Machine (KELM), Machine Learning, BI-LSTM, CMAQ, SVM, DBN-BP, Air Quality Prediction..*

## 1. INTRODUCTION

One of the most common environmental issues of the twenty-first century is air pollution. Air pollution is becoming worse due to the fast urbanization and industrialization, which has a significant impact on our health and living conditions. According to Li et al., China's ambient air pollution makes outdoor physical exercise 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 tiny particles (such 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 very 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 may 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.

## 2. LITERATURE SURVEY

### 2.1 Variational Bayesian Network with Information Interpretability Filtering for Air Quality Forecasting:

[Mathematics | Free Full-Text | Variational Bayesian Network with Information Interpretability Filtering for Air Quality Forecasting (mdpi.com)]

**ABSTRACT:** People's health is greatly impacted by air quality, and anticipating air quality may help with sustainable development and government planning decisions. On the other hand, because multi-step forecasting is complicated and nonlinear owing to both temporal and geographical dimensions, it is difficult to do so properly. Deep models are now the main techniques used for air quality forecasting because of their capacity to represent significant nonlinearities. Uninterpretability forecasting, however, renders judgements riskier due to the absence of mechanism-based analysis, particularly when the government is making decisions. In order to anticipate PM2.5, this research suggests an interpretable variational Bayesian deep learning model with information self-screening.

In order to capture as much useful information as possible, an interpretable multivariate data screening framework for PM2.5 forecasting was first developed based on variables associated with PM2.5 concentration, such as temperature, humidity, wind speed, geographical distribution, etc. Second, to maximize the choice of input variables, the self-screening layer was inserted into the deep learning network. In order to overcome the complicated distribution of PM2.5 and accomplish precise multi-step forecasting, a variational Bayesian gated recurrent unit (GRU) network was built after the screening layer was implanted. The effectiveness of the suggested strategy, which uses deep learning technology to assess numerous parameters for PM2.5 forecasting, is confirmed using PM2.5 data from Beijing, China.

**2.2 Spatiotemporal air quality forecasting and health risk assessment over smart city of NEOM:**

Spatiotemporal air quality forecasting and health risk assessment over smart city of NEOM - ScienceDirect

**ABSTRACT:** To give early warnings concerning dangerous atmospheric compounds, it is crucial to model and forecast air pollution concentrations. However, forecasting air quality is extremely challenging due to dynamic process uncertainty and incomplete knowledge of chemical components and emissions sources. In NEOM City, Saudi Arabia, this study suggested a unique deep-learning technique to extract high degrees of abstraction from data and capture spatiotemporal variables at hourly and daily time intervals. The suggested approach combined convolutional long short-term memory (ConvLSTM) with a residual network (ResNet). A ResNet model enhanced the ConvLSTM approach to mitigate feature information loss by thoroughly extracting spatial features from pollution and meteorological data. In order to measure the risk sensitivity of PM10 and PM2.5 in five districts of NEOM City, a health risk assessment was then proposed. In comparison to current state-of-the-art models, the results showed that the suggested approach with efficient feature extraction may significantly maximise the accuracy of spatiotemporal air quality forecasts. MASE's PM2.5 and PM10 scores for the upcoming hour prediction tasks were 13.57 and 9.13, respectively. The suggested approach offers a practical way to enhance air pollution concentration forecast while being transferable to different parts of the world.

**2.3 Development and evaluation of an advanced National Air Quality Forecasting Capability using the NOAA Global Forecast System version 16:**

(PDF) Development and evaluation of an advanced National Air Quality Forecasting Capability using the NOAA Global Forecast System version 16 (researchgate.net)

**ABSTRACT:** NOAA's Global Forecast System (GFS) and limited-area models for regional weather and air quality applications employ a novel dynamical core called the Finite-Volume Cubed-Sphere (FV3), which was created at both NASA and NOAA. In addition, NOAA has updated the operational FV3GFS to version 16 (GFSv16), which incorporates several important developmental improvements to the model design, data assimilation, and underlying model physics, especially for weather feedback from atmospheric composition. In order to create a more sophisticated version of the National Air Quality Forecasting Capability (NAQFC) that will continue to safeguard ecosystem and human health in the United States, we combine the GFSv16 with the Community

Multiscale Air Quality (CMAQ) model concurrently with the GFSv16 upgrade. The creation of the FV3GFSv16 coupling using a "state-of-the-art" CMAQ model version 5.3.1 is described here. The groundbreaking NOAA-EPA Atmosphere–Chemistry Coupler (NACC), which was a key component of the next operational NAQFC system (i.e., NACC-CMAQ) on July 20, 2021, is what enables the GFS–CMAQ coupling. Among NACC-CMAQ's scientific innovations are satellite-based data collection technology to enhance land cover and soil properties, as well as inline wildfire smoke and dust forecasts that are essential for estimating fine particulate matter (PM2.5) concentrations during dangerous events that impact ecosystems, human health, and society. In comparison to the former operational NAQFC, where evaluation of NACC-CMAQ reveals generally improved near-surface ozone and PM2.5 predictions and diurnal patterns, the GFS-driven NACC-CMAQ model has significantly different meteorological and chemical predictions. Both of these predictions are extended to a 72-hour (3-day) forecast with this system.

### 2.4 Deep Air Quality Forecasting Using Hybrid Deep Learning Framework:

Deep Air Quality Forecasting Using Hybrid Deep Learning Framework | IEEE Journals & Magazine | IEEE Xplore

**ABSTRACT:** One of the main issues with air pollution early warning and control management has been identified as air quality forecasting. In this paper, we present a novel deep learning model for forecasting air quality (mostly PM2.5) that uses a hybrid deep learning architecture to understand the interdependence and spatial-temporal correlation aspects of multivariate air quality related time series data. Bi-directional Long Short-term Memory networks (Bi-LSTM) and one-dimensional Convolutional Neural Networks (1D-CNNs) are the foundational modules of our model because of the dynamic and nonlinear nature of multivariate air quality time series data. In the first, local trend and spatial correlation characteristics are extracted; in the second, spatial-temporal relationships are learnt. Next, we develop a cooperatively hybrid deep learning framework for learning shared representation features of multivariate air quality related time series data, based on one-dimensional CNNs and Bi-LSTM. Using two real-world datasets, we perform comprehensive experimental evaluations, and the findings demonstrate that our model can handle PM2.5 air pollution forecasting with satisfactory accuracy.

### 2.5 Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency:

Multivariate regression analysis of air quality index for Hyderabad city: Forecasting model with hourly frequency (allresearchjournal.com)

**ABSTRACT:** The air quality index (AQI) for Hyderabad, a large Indian metropolis, is described in the current study. NO, NO2, NOx, SO2, ambient temperature, relative humidity, bar pressure, sun radiation, wind direction and speed, benzene, toluene, xylene, PM2.5, and rack temperature are the main parameters taken into account while calculating the AQI. In Hyderabad, the Air Quality Index (AQI) is used to measure and depict the state of the air quality. A multivariate regression model is used to characterise the AQI's change. This study is important for large cities with a variety of activities going on, such as

commercial, residential, and industrial. Both in the short and long term, this model can help with improved forecasting of air quality metrics. The air quality status is divided into five categories—Clean, Moderate, Poor, Bad, and Dangerous—to make the index more useful. Then, using hourly data, long-term air quality indices are computed for Hyderabad, an Indian metropolis that is rapidly growing in terms of many climatologically defined characteristics. Accounting for atmospheric processes, ambient measurements, emissions characterisation, air quality modelling of emissions to ambient concentrations, and characterisation of ecological and human reactions to exposure to ambient pollutants are all included in the application of this formal approach. A new management approach is required to broaden the present accountability practice that links emission reductions with the achievement of air quality as determined by air quality criteria and standards. From a conceptual standpoint, attaining responsibility would set objectives that maximise risk reduction in relation to pollution control.

## 3. METHODOLOGY

**i) Proposed Work:**

The proposed system focuses on addressing air quality prediction challenges by combining Extreme Learning Machine (ELM) with Genetic Algorithm (GA) to create the GA-KLEM model. This hybrid approach optimizes hidden nodes, thresholds, and weights using RMSE as the fitness function, ensuring precise and reliable AQI forecasts. To further enhance the system, the Bidirectional Long Short-Term Memory (BI-LSTM) algorithm is integrated, enabling fine-tuning of feature weights in forward and backward directions, reducing RMSE and MSE significantly compared to other models like DBN, SVR, and GA-KELM.

**ii) System Architecture:**

The system architecture of the proposed GA-KLEM model integrates multiple layers to ensure efficient and accurate Air Quality Index (AQI) prediction. The first layer involves data preprocessing, where raw air quality data (including parameters like SO2, NO2, PM2.5, PM10, CO, and O3) is cleaned and normalized for model input. This data is then passed to the GA-KELM model, where the Genetic Algorithm optimizes the hidden nodes, thresholds, and weights of the Extreme Learning Machine (ELM). RMSE serves as the fitness function, ensuring the best possible configuration for accurate predictions.

Additionally, the architecture includes an extended BI-LSTM module to refine feature weights in both forward and backward directions, further reducing prediction errors. A Flask-based frontend is integrated into the system for user interaction, allowing authenticated users to input data, view predictions, and analyze results. This architecture ensures a seamless workflow from data collection and processing to model prediction and user accessibility, supporting effective air quality management and decision-making.

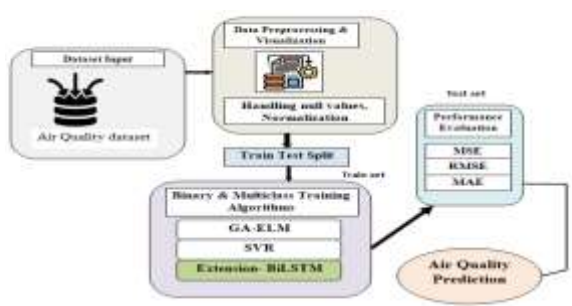


Fig.3.1 System architecture

**iii) MODULES:**

**a) Data Loading:**

- Imports the air quality dataset from the source.
- Ensures the data is ready for further processing and analysis.

**b) Data Processing:**

- Cleans, normalizes, and preprocesses the raw data.
- Extracts relevant features required for model training.

**c) Splitting Data into Train & Test:**

- Divides the dataset into training and testing sets.
- Ensures fair evaluation of the model's performance.

**d) Model Generation:**

- Builds models such as SVR, GA-KELM, DBN-BP, and BI-LSTM.
- Calculates and compares the accuracy of these algorithms.

**e) User Signup & Login:**

- Enables user registration for accessing the system.
- Provides secure login functionality for authenticated access.

**f) User Input:**

- Allows users to input data for air quality prediction.
- Ensures a simple and user-friendly interface for input.

**g) Prediction:**

- Generates the final air quality prediction results.
- Displays accurate AQI values to assist in decision-making.

**iv) ALGORITHMS:**

a) **SVR**: Support Vector Regression (SVR) is a type of machine learning algorithm used for regression analysis. The goal of SVR is to find a function that approximates the relationship between the input variables and a continuous target variable, while minimizing the prediction error.

b) **GA-KELM: GA-KELM (Genetic Algorithm-based Kernel Extreme Learning Machine):** A predictive algorithm for air quality forecasting. It incorporates a kernel method to generate a kernel matrix, replacing the hidden layer output matrix. A genetic algorithm optimizes the number of hidden nodes and layers, considering thresholds, weights, and root mean square error in the fitness function. Output weights are computed using the least squares method, enabling iterative optimization for improved model performance.

c) **DBN-BP(NN with Back-Propagation):** DBN-BP (Deep Belief Networks with Back-

Propagation): A neural network algorithm for air quality prediction. Deep Belief Networks are trained layer-wise, and Back-Propagation fine-tunes the model. It combines unsupervised pre-training with supervised learning, optimizing weights iteratively. This hybrid approach enhances the model's ability to capture complex patterns in air quality data, leading to more accurate predictions.

d) **BiLSTM:** A bidirectional LSTM (BiLSTM) layer is an RNN layer that learns bidirectional long-term dependencies between time steps of time-series or sequence data. These dependencies can be useful when you want the RNN to learn from the complete time series at each time step.

## 4. EXPERIMENTAL RESULTS

**Accuracy:** How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

**Precision:** Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

**Recall:** Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

**mAP:** Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

**F1-Score:** A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

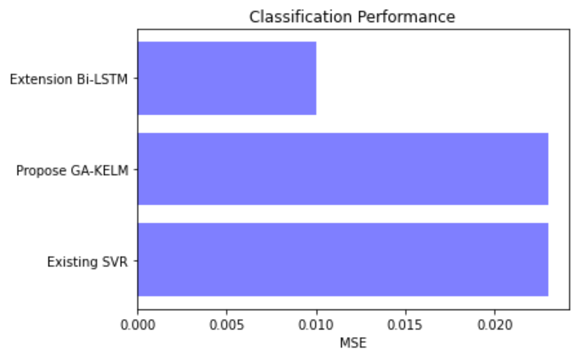


Fig 4.1 MSE Graphs

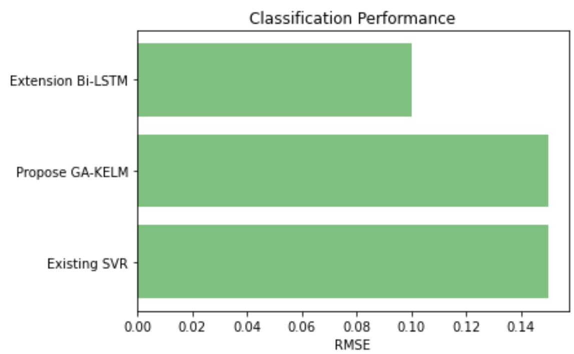


Fig 4.2 RMSE Graphs

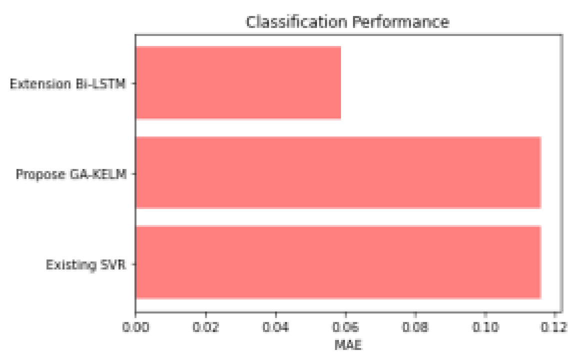


Fig 4.3 MAE Graphs

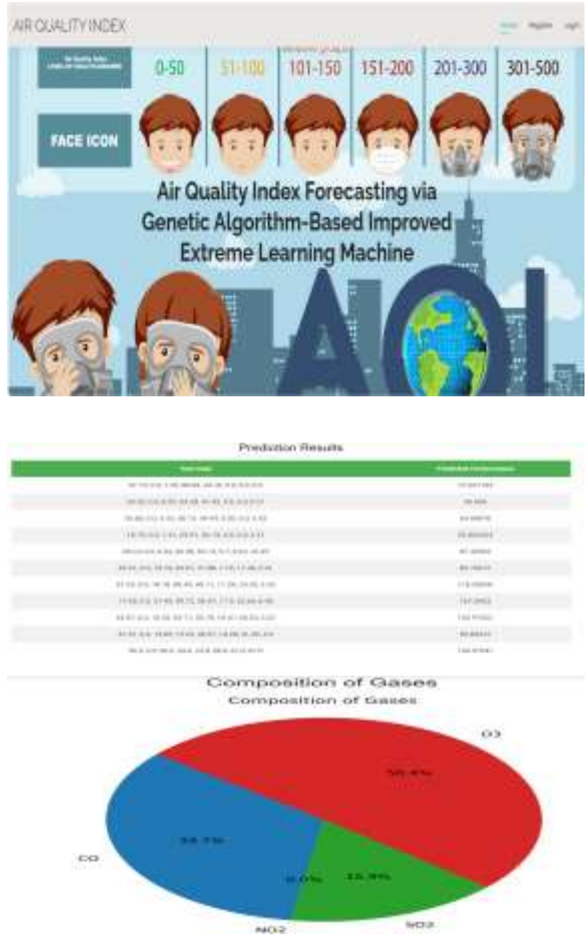


Fig 4.4 results

## 5. CONCLUSION

The proposed GA-KLEM system, enhanced with BI-LSTM, offers a robust solution for accurate air quality prediction by addressing limitations in traditional machine learning models. By optimizing parameters using Genetic Algorithms and refining feature weights with BI-LSTM, the system achieves superior prediction accuracy and reduced error rates. The integration of a user-friendly interface through Flask further facilitates practical usage, enabling governments and environmental agencies to make proactive decisions for pollution management and public health protection.

## 6. FUTURE SCOPE

- The system can be extended to include real-time air quality monitoring and prediction by integrating IoT-based sensors.
- Advanced deep learning models, such as Transformer-based architectures, can be explored to further enhance prediction accuracy.
- The solution can be expanded to predict other environmental factors like water and soil quality.
- The frontend can be enhanced with visualization tools for better user interaction and detailed analytics.
- A mobile application can be developed to provide real-time AQI updates and alerts to end-users.

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