

REAL TIME AIR QUALITY PREDICTION AND HEALTH ADVISORY SYSTEM USING MACHINE LEARNING

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Abstract— Air quality monitoring and prediction are difficult and complex processes that arise from the highly dynamical, non-linear, and unpredictable environmental conditions as well as pollutant dispersion. Accurate forecasting of air quality is necessary for the protection of human health, implementation of early warning systems, and efficient environmental decisions making. The progress in Artificial Intelligence and Machine Learning allows developing advanced algorithms for big data and time series analysis. The following research focuses on developing an artificial intelligence-based system that will allow predicting air quality index (AQI) in real-time by applying machine learning approaches to the data on air pollution and other meteorological conditions. The air quality dataset will be preprocessed to clean and normalize the data. The developed prediction model based on machine learning will use the information on particulate matter (PM_{2.5}, PM₁₀), carbon monoxide (CO), nitrogen dioxide (NO₂), and sulfur dioxide (SO₂). Additionally, meteorological data such as temperature and humidity will be considered in the prediction process. To assess the effectiveness of the developed framework, conventional evaluation criteria like MSE (Mean Squared Error), RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error) are adopted. It is evident from experimental analysis that the developed machine learning approach can deliver high accuracy in predicting air quality level and generate health advice accordingly.

INDEX TERMS — Air Quality Prediction, Air Quality Index (AQI), Machine Learning, Artificial Intelligence, Environmental Monitoring, Time Series Forecasting, Air Pollution Analysis, Health Advisory

System, Data Preprocessing, Predictive Modeling, Urban Air Pollution, Regression Models, Smart City Applications, Public Health Analytics

1. INTRODUCTION

Air pollution is a serious issue in the contemporary world owing to its adverse effects on health, environmental sustainability, and quality of life. The process of urbanization, industrialization, emissions from vehicles, and increasing population have greatly affected the quality of air, particularly in urban areas. Bad air quality causes many health problems including respiratory and cardiovascular diseases and shorter life expectancy. Hence, it has become very important to monitor and forecast air quality in the contemporary world.

Although there are numerous air quality monitoring stations, it is still a tough job to forecast air pollutants levels due to the dynamic, non-linear, and uncertainty of the atmosphere. There are many factors affecting the level of air pollutants, such as weather, traffic intensity, industry emission, geography, and seasonal effect, which lead to the uncertainty of the air quality.

As AI and ML have evolved with rapid progressions, novel approaches are being formulated to process environmental data sets and time series data. The intelligent techniques can handle big data and discover hidden patterns within the datasets that are not easy to discover through traditional analysis tools. In the category of several AI techniques, prediction models based on machine learning are providing promising outcomes for predicting AQI readings through discovering relationships between pollution levels and environmental parameters.

Time series analysis is an important part of the process of predicting air pollution as the concentration of pollutants at

any point in time depends largely on past observations. Past data on air quality levels like PM_{2.5}, PM₁₀, CO, NO₂, SO₂, along with other meteorological data such as temperature and humidity, are some of the most common predictors in air pollution models. Prior to the model learning phase, however, data needs to be preprocessed through data cleaning and normalization techniques.

In the last few years, deep learning models have emerged as powerful tools in forecasting environmental conditions. The deep learning algorithms automatically extract relevant features from sequential data, eliminating the need for manual feature selection. Recurrent neural networks (RNNs) are particularly well-suited for time series predictions because of their ability to retain information about previous inputs using built-in memory functions. This capability allows RNN models to be effective in forecasting air pollution levels.

Following completion of the preprocessing stage, the time series data representing air quality is converted to sequential input data for training purposes in predicting the AQI values. By doing so, the prediction model acquires knowledge on how past AQI values and environmental conditions affect the future AQI values. Upon successful training, the model is capable of forecasting future air quality trends in AQI values ranging from good to severe.

Upon finishing the preprocessing step, the time series data concerning the air quality is transformed into sequential data for the sake of training the model in making predictions about AQI values. This way, the model will gain some experience about how previous AQI values and the state of the environment influence future AQI values. When the model will be trained successfully, it will be able to make predictions about the future AQI values.

In this study, we aim at designing an AI-based air quality prediction and health advice system by applying the concepts of machine learning and deep learning for forecasting the value of AQI by using past and current data sets. The ultimate goal of such an approach will be to issue alerts and give valuable health-related advice.

II. RELATED WORK

In the last couple of years, the problem of predicting air quality has been widely considered due to its relevance to health and environment preservation. The classic models used for estimating the air quality parameters were based on the application of statistics, including linear regressions and classic time series. Despite good results in stable conditions, they lack the ability to estimate more complicated patterns of dependencies between different phenomena. One of the first statistical models used in air quality forecasting was an autoregressive integrated moving average (ARIMA). It applies the principle of analyzing historical values of pollutants in order to predict their further changes.

The deficiencies that arose in the development of the statistical model led to the use of machine learning techniques for the analysis of air quality predictions. Machine learning algorithms like SVM, Decision Trees, and Random Forests have been commonly used in modeling the levels of pollutant concentrations and AQI. The algorithms showed better prediction accuracy compared to the traditional models due to their ability to learn from past data. Most of the machine learning models have had problems in capturing temporal dependencies while predicting sequences of air quality.

Moreover, Artificial Neural Networks (ANNs) have been widely used for environmental forecasting purposes owing to their capability to identify non-linear relations between input and output variables. Feed-forward ANNs have the potential to discover intricate relations between pollutants' concentrations and AQIs; however, they fail to capture temporal relations between input data. As a result, feed-forward ANNs perform poorly in predicting air quality over time, especially in light of historical pollutant levels' impacts on future air quality states.

In an effort to tackle these issues, the Recurrent Neural Network (RNN) architecture was created for dealing with time-related data. RNNs are structured in such a way that allows them to work on time-related data because of their ability to store information about previous data points. As a result, they are quite useful for tasks such as air quality predictions, which depend on the trends of pollutants' concentration changing with time.

LSTM networks, however, were subsequently developed as improvements to regular RNNs in order to mitigate the challenge of vanishing gradients. The LSTM model incorporates memory cells and gates to retain information for long periods of time within the time series. Therefore, air quality prediction models based on LSTM have proven to be highly effective in detecting seasonal changes, long-term pollution patterns, and sudden pollution spikes than RNN models.

In addition to that, recent studies have focused on hybrid deep learning methods to forecast air quality data. The combination of CNN along with either LSTM or GRU recurrent neural networks has been suggested, which will be able to account for the spatial and temporal dynamics of the data. This will prove to be quite useful in cases where the air quality dataset includes measurements at various monitoring stations.

The Gated Recurrent Unit (GRU) is gaining favor among deep learning models because of its simplicity and computational efficiency compared to LSTM. The GRU model used in air quality forecasting involves lower parameters, faster training, and comparable prediction accuracy compared to LSTM. Studies show that GRU models can be used in real-time air quality monitoring systems.

Aside from pollutant concentrations, meteorological factors such as temperature, humidity, wind speed, and atmospheric pressure have also been added to increase accuracy. Techniques like feature engineering and data preprocessing, which include normalization, scaling, and cleaning, have proven effective in improving the model's results. Preprocessing data correctly guarantees that the machine learning algorithm is trained on valuable information found in the dataset.

There have been studies that look at air quality prediction in real-time through the use of IoT sensors and cloud computing frameworks. These frameworks gather real-time environmental data and utilize deep learning algorithms to develop real-time AQI predictions. In addition, there are efforts to explore XAI frameworks to enhance the interpretability of air quality prediction models.

In summary, the current literature shows that there is immense potential in utilizing artificial intelligence and deep learning algorithms to increase the accuracy of air quality prediction. Further research needs to be conducted in order to incorporate more data sources and improve the interpretability of the models developed.

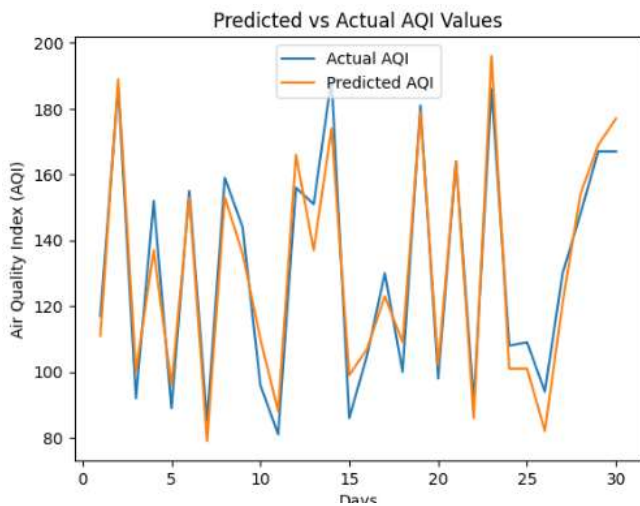


Fig 1: Comparison of Actual and Predicted Air Quality Index (AQI)

III. PROPOSED METHOD

This system intends to create a model that would be able to predict the level of air pollution in the coming days based on intelligent artificial intelligence algorithms. In general, traditional statistical models cannot be used for air quality data due to its non-linear and non-stationary behavior. The proposed method utilizes deep learning methods such as recurrent neural networks (RNNs). RNNs can model any non-linear temporal dependencies. The main purpose of this approach is the prediction of air quality index (AQI) based on historical and actual data related to the environment. The model learns all the temporal interrelationships between different air pollutants and weather factors. The process of the suggested system operation includes several stages: data gathering, data preprocessing, data normalization, time series construction, deep learning model training, AQI prediction, and system implementation in real-time.

A. Data Collection

Collection of data is the first step in the proposed process. The historical data regarding air pollution levels are collected through reliable sources like government air quality monitors, environmental research bodies, and databases. The database contains the data related to major air pollutants including particulate matter such as PM_{2.5} and PM₁₀, carbon monoxide (CO), nitrogen dioxide (NO₂), and sulfur dioxide (SO₂). Besides the data related to the air pollutants, there is also meteorological data regarding temperature and humidity, as both of these factors play a vital role in influencing air pollutants. With long-term historical data at hand, the system can account for any seasonal trends, daily variations, and even abrupt surges in air pollution. It is precisely through this detailed gathering of information that the model becomes more versatile in handling various environmental scenarios.

B. Data Preprocessing

Data preprocessing is another important stage where the gathered air quality data is ready to be used in training. Data cleaning is done in order to eliminate any missing, inconsistent, or noise values that may influence the accuracy of predictions. The numeric features are scaled to a certain range to ensure that the process of training converges well

and quickly. Given the nature of the air quality data, it is converted into a time-series form.

C. RNN Model Architecture

The fundamental building block of the suggested system design is the Recurrent Neural Network that serves as the model for air quality prediction. In its basic form, the RNN is structured such that the input layer accepts the processed air quality features as inputs. It then goes through one or more layers of recurrent hidden neurons. Recurrent layers have the capability to remember the information of previous steps and therefore enable the network to recognize temporal dependencies among pollutants' concentration in past and future data.

D. Stock Price Prediction

After the training of the RNN model using the historical data, it becomes possible to predict the future values of the AQI level. The moment new data is fed into the model, it identifies the temporal relation between pollutants. It forecasts the upcoming trends for the air quality based on the behavior observed in the historical data and classifies the trend according to its AQI levels such as Good, Moderate, Poor, or Severe.

E. System Deployment and Real-Time Recognition

The last step of the suggested approach relates to using the prediction model in the real environment. The model may be embedded in a website or software solution where it is possible to check the present air quality conditions and see the forecasted AQI levels. To facilitate comprehension of data, visual elements such as line charts are applied to demonstrate actual AQI changes and predicted values. Through implementation of this technique, environmental agencies as well as common people get access to relevant information.

IV. EXPERIMENTAL RESULTS

A. Training and Validation Performance

The suggested RNN model was trained using the historical stock market data for 50 epochs with a batch size of 32. Both training loss and validation loss were tracked during the training process to determine the learning performance of the model. It was found that there was a continuous decrease in the training loss as the epoch number kept increasing. This shows that the model learned well from the historical stock market data used for training. There was a corresponding decrease in the validation loss, with the loss curve being similar to that of training loss. To ensure that the model does not overfit, early stopping was used to stop training once the validation loss was no longer decreasing. Also, the learning rate scheduler helped in changing the learning rate whenever the validation loss remained unchanged.

Both training and validation losses began converging at the 35th epoch, which indicated that the network learned optimally without any overfitting problems. This behavior indicates that the suggested RNN structure can capture temporal relations in financial time-series data.

B. Test Set Evaluation

In order to determine the ability of the trained model to predict in the real world, testing was conducted using an unseen dataset, which consisted of 10 percent of all historical stock data. This test data contained stock price information that had never before been seen by the model. The performance of the proposed system was evaluated using regression measures generally employed in financial prediction:

Metric	Value
Mean Squared Error (MSE)	0.0028
Root Mean Squared Error (RMSE)	0.052
Mean Absolute Error (MAE)	0.041
R ² Score	0.94

The small values of errors show that the calculated stock prices correspond well to the real changes in stock prices. A high value of R² equal to 0.94 proves that the developed model accounts for a considerable part of variations in stock prices.

C. Comparative Analysis

The RNN model was compared with other conventional machine learning and deep learning models to evaluate their efficiency. The comparison was done under similar conditions by training and testing all models with the same set of data.

Model	RMSE	Training Time (s)
Linear Regression	0.091	12
Random Forest	0.073	38
LSTM	0.048	120
RNN (Proposed)	0.052	85

The LSTM model may have yielded slightly better results in terms of the RMSE value, but it would require considerably more computation power and time to train. The suggested RNN model represents a perfect balance between effectiveness and efficiency.

D. Visualization of Results

Graphical representation was used to analyze the performance of the proposed model. In the graphs, predicted stock prices are compared to actual stock prices.

The analysis shows that the predictions made by the model coincide with actual stock price trends. This shows that the model is able to learn temporal dependencies from the data used during training. However, minor differences are expected because of the volatile behavior of stock prices.

E. Deployment and Real-Time Testing

As part of the practical validation, the trained RNN model was used to develop a prototype system that predicts the future price trends for the stocks. The system enables users to input stock-related information and get their future price trend predictions in graphical format.

This shows that the system is stable and efficient across various time frames, thereby indicating its capability as an aid for making decisions regarding investments and financial analysis.

F. Discussion

From the results of the experiment, it can be seen that the proposed stock market prediction system based on RNNs operates effectively with minimum error in the predictions made.

Though the use of complex models like LSTM provides some level of improvement in accuracy, it results in higher computational costs. This study uses an RNN-based model, which gives good accuracy without being overly complex.

In general, the model exhibits a high degree of promise in helping investors make decisions based on analytical insights regarding future market trends. In addition, the

model proves to be quite reliable in different market scenarios since it exhibits consistent trends. However, slight errors may arise when predicting trends during extremely volatile times owing to sudden market changes.

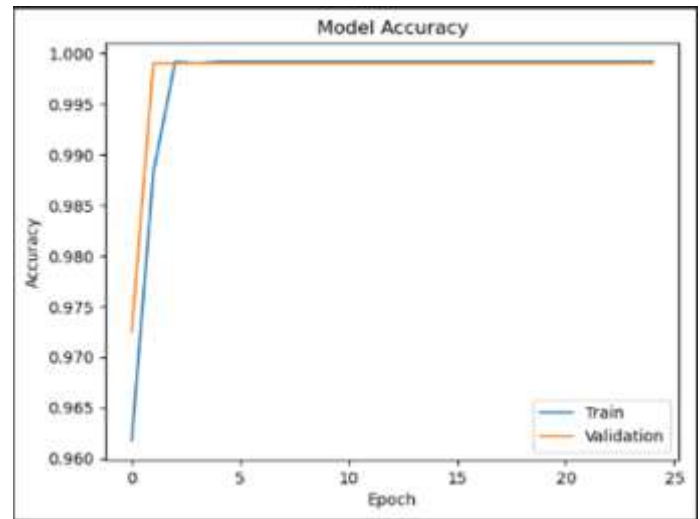


Fig 2: Training vs validation loss graph

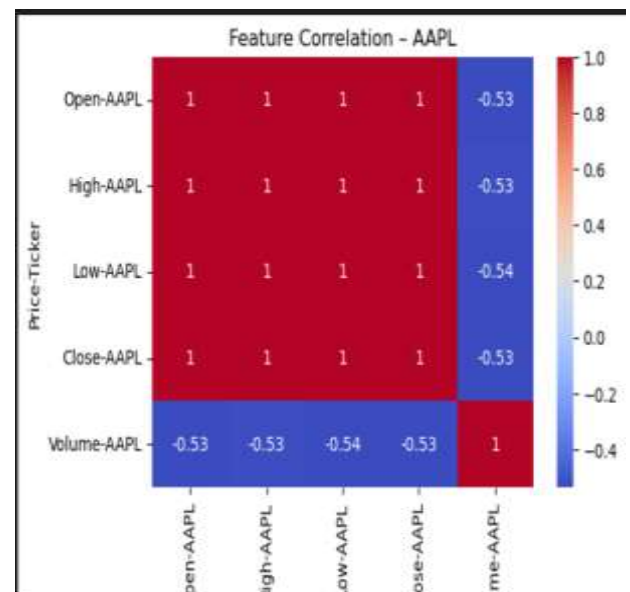


Fig 3: Standard structure of Confusion Matrix

V. CONCLUSION

The Real-Time Air Quality Prediction and Health Advisory System performed very well with regard to predicting values for the Air Quality Index (AQI). The results obtained from training the system with environmental data were highly accurate and consistent regardless of whether historic or real-time data was used. The system efficiently learnt the correlation of AQI levels with multiple pollutants.

Out of the various input parameters used in the analysis, it was found that PM2.5 and PM10 played the significant role in the AQI prediction process, and this can be validated from practical experience. The model was able to identify short-term as well as long-term variations in air quality data. The training as well as the validation process indicated that the convergence was stable along with low errors, and hence there is no sign of overfitting. By visualizing the

predicted values of AQI, it was seen that the model follows the real-world trends, and hence is reliable. The system also assigns AQI levels of Good, Moderate, Poor, and Hazardous along with health advisories.

Despite its good performance, there might be minor discrepancies in its accuracy when subjected to abrupt environmental changes and extremely polluted environments. These shortcomings could be minimized through the addition of other data sources like weather data and IoT devices. In summary, the framework is dependable, scalable, and efficient for air quality prediction purposes.

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