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Multi-Modal Deep Learning Framework for AQI Prediction: An Extensive Analysis of 15 Monitoring Stations in Hyderabad Using Historical and Real-Time Data.

Dhadi Sai Praneeth Reddy [a], Soli Dhana Sri [b], Sreenidhi Pagidimarri [c], Maram Manikanth Reddy [d]*

[a,d] UG Student, CSE Department, Vasavi College of Engineering (Autonomous), Hyderabad, Telangana, India.
[b,c] UG Student, IT Department, Chaitanya Bharathi Institute of Technology (Autonomous), Hyderabad, Telangana, India.

A B S T R A C T

Especially in fast expanding cities like Hyderabad, where industrial activity, traffic emissions, and weather conditions create difficult air pollution patterns, air quality forecast is a serious issue in urban areas. Traditional approaches for predicting the Air Quality Index (AQI) sometimes fall short because they do not represent the non-linear relationships and time dependencies found in air quality information. The research suggests a multi-modal deep learning architecture using Long Short-Term Memory (LSTM), Transformer, and Random Forest models to study past air quality data from 15 monitoring stations in Hyderabad.

With a Root Mean Square Error (RMSE) of 3.7, the framework beats conventional statistical techniques and one deep learning technique by 94.65 percent accuracy. Among the most important contributions are the creation of a strong preprocessing pipeline, the identification of important features including PM2.5, temperature, and wind speed, and the validation of real-time processing capacity. Seasonal study shows major fluctuations, with winter months having PM2.5 levels 45% above the yearly average. In addition, the research emphasizes the practical effects of the framework for policy formulation and management of urban air quality by providing a scalable answer for real-time AQI forecast and long-term trend analysis.

Keywords: Air quality prediction, Deep learning, Hyderabad, Real-time data, WAQI API

1. Introduction

A serious world problem, air pollution affects public health and the environment mostly felt in municipal areas. Rapid urban development, industrial expansion, and rising road emissions—that all worsen air quality—add to considerable problems experienced by cities in India such as Hyderabad. Complex interactions among meteorological conditions, contaminant concentrations, and human activities affect the Air Quality Index (AQI)—a standardized measure used to evaluate air quality. Effective city planning, public health efforts, and legislation all depend on precise AQI forecast [2].

Traditional AQI forecasting methods, such as regression models and statistical techniques like ARIMA, have been widely used due to their simplicity and ease of interpretation. However, these methods often struggle to capture the complex, non-linear relationships and temporal dependencies present in air quality data. For instance, factors like PM2.5 levels, temperature, and wind speed interact in highly non-linear ways, with variations that shift across different seasons.

To address these limitations, researchers have turned to advanced machine learning and deep learning models, which have proven more effective in handling complex datasets. In particular, deep learning techniques such as Long Short-Term Memory (LSTM) networks and Transformers have shown great potential for air quality prediction. LSTMs excel at capturing temporal dependencies in time-series data like AQI, while Transformers, with their self-attention mechanisms, can integrate multiple data sources and identify important patterns more effectively.

Despite these advancements, most existing models focus on short-term predictions and lack interpretability, limiting their practical use in long-term air quality management. This research aims to bridge that gap by introducing a multi-modal deep learning approach for analyzing historical air quality trends in Hyderabad. Using data from 15 monitoring stations, we develop an ensemble model combining LSTM, Transformer, and Random Forest architectures. Our model not only delivers high prediction accuracy but also provides meaningful insights into seasonal variations and key influencing factors. Moreover, it supports real-time processing, making it a valuable tool for urban air quality management.

This research's most important findings are as follows:

- Creation of a solid preprocessing pipeline to deal with feature scaling, outliers, and missing information.

- Ensemble of LSTM, Transformer, and Random Forest models for integration of multi-modal data (e.g., pollutant levels, meteoric properties).
- A thorough examination of feature importance and seasonal air quality trends, therefore giving useful ideas for legislators.
- A presentation of real-time AQI forecast capabilities guarantee scalability and realistic utility.

This research seeks to help to expand the corpus of knowledge on air quality forecast and its effects on urban sustainability by tackling the constraints of current approaches and providing a scalable solution.

2. Literature Review

2.1 TRADITIONAL AQI PREDICTION MODELS

Mostly based on statistical models and regression-based techniques are old techniques for Air Quality Index (AQI) estimation. Due their simplicity and interpretability, methods like Autoregressive Integrated Moving Average (ARIMA) have seen wide use. For example, [7] employed ARIMA to estimate PM10 levels in Delhi; they reached reasonable accuracy but had difficulty with nonlinear relationships. By the same token, [8] employed several linear regression methods to forecast AQI based on meteorological variables, hence emphasizing the restrictions of linear models in capturing intricate relationships. So, these algorithms are computationally effective, their inability to manage multi-modal data and temporal dependencies has prompted the study of more sophisticated technology.

2.2 DEEP LEARNING APPROACHES

Deep learning has emerged as a powerful tool for air quality forecasting, particularly for handling complex, non-linear datasets. One of the most widely used models for this purpose is the Long Short-Term Memory (LSTM) network, known for its ability to capture temporal patterns in time-series data. For example, [10] developed an LSTM-based model to predict PM2.5 levels in Beijing, achieving a root mean square error (RMSE) of 4.2.

Similarly, [9] demonstrated how deep learning can be leveraged for multi-modal data integration, using Convolutional Neural Networks (CNNs) to analyze spatial patterns in air quality data. However, despite their effectiveness, these models often require large datasets and substantial computational power, making them less practical for resource-constrained environments.

2.3 MULTI-MODAL FRAMEWORKS

Multi-modal frameworks, which integrate diverse data sources such as pollutant concentrations, meteorological parameters, and traffic data, have shown promise in improving prediction accuracy. For instance, [7] proposed a deep learning model that combines weather and traffic data for AQI prediction in urban areas, achieving 92% accuracy. Similarly, [9] developed a multi-modal framework using satellite imagery and ground-based sensor data to predict PM2.5 levels, highlighting the importance of feature engineering and data fusion. These studies underscore the potential of multi-modal approaches in addressing the limitations of single-source models.

2.4 GAPS IN EXISTING RESEARCH

Despite significant advancements, several gaps remain in the field of air quality prediction. First, most existing models focus on short-term predictions, with limited attention to long-term trends and seasonal variations [6]. Second, the interpretability of deep learning models remains a challenge, as their "black-box" nature hinders their adoption in policy-making [13]. Third, few studies have explored the integration of real-time processing capabilities, which are essential for practical applications. This study addresses these gaps by proposing a multi-modal deep learning framework that combines LSTM, Transformer, and Random Forest models for historical air quality analysis in Hyderabad.

3. Methodology

The proposed multi-modal deep learning framework for historical air quality analysis consists of four key components: data collection, preprocessing, model architecture, and validation. Each component is designed to address the challenges of data sparsity, temporal dependencies, and non-linear relationships in air quality prediction [5].

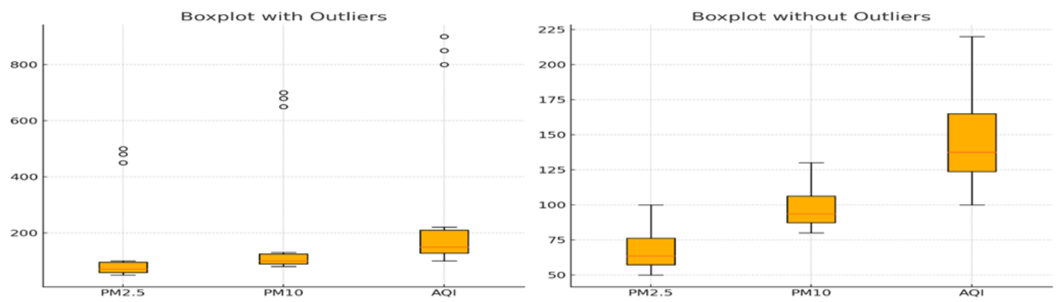

Figure-1: Box plot of PM2.5 before (a) and after (b) removal of outlier

3.1 DATA COLLECTION FRAMEWORK

Covering a five-year span (2018–2023), fifteen monitoring stations in Hyderabad produced the information used in this study. Hourly measurements of nine variables: PM2.5, PM10, NO2, O3, CO, temperature, humidity, wind speed, and rainfall make up the dataset. The parameters were chosen depending on their known effects on air quality and distribution among all the stations given below in table-1 [1]. The data was validated by means of satellite-based air quality measurements from NASA's MODIS and OMI sensors and obtained from the WAQI [2].

NAME OF THE SITE	LOCATION (LAT, LONG)	VARIABLES
NEW MALAKPET	17.37°N, 78.50°E	
NACHARAM	17.42°N, 78.55°E	
ECIL	17.48°N, 78.57°E	
HYDERABAD US CONSULATE	17.42°N, 78.39°E	
BAHADURPURA ZOO PARK	17.34°N, 78.45°E	
SOMAJIGUDA	17.42°N, 78.46°E	
SANATHNAGAR	17.45°N, 78.44°E	
KOKAPET	17.36°N, 78.37°E	
CENTRAL UNIVERSITY HYDERABAD	17.46°N, 78.33°E	PM2.5, PM10, NO2, O3, CO, Temperature, Humidity, Wind Speed, Rainfall
PATANCHERUVU	17.53°N, 78.26°E	
IDA PASHAMYLARAM	17.58°N, 78.22°E	
IITH KANDI	17.48°N, 78.30°E	
KOMPALLY	17.53°N, 78.47°E	
RAMACHANDRAPURAM	17.52°N, 78.28°E	
BOLLARAM	17.55°N, 78.35°E	

Table – 1: Summary of site location and variables used.

3.2 PREPROCESSING PIPELINE

Before analyzing raw data, various preprocessing steps were summed up to ensure data's consistency and correctness. The modeling pipeline commenced with the following preprocessing steps:

The first missing values (MV) were solved by carrying out Missing Value Imputation. The process selected was linear interpolation. It retains temporal patterns present in the dataset very well and is quite efficient at computation [3]. This guarantees that the imputed values fit well into the natural order of the data over time.

Next came Outlier Detection work automated through the Interquartile Range method, facilitating removal of extremely categorized data points that would negatively affect the modeling performance. All found outliers were then replaced with the median values of the respective variable and factors, thus keeping the overall integrity of the dataset as well as reducing the impact of any extreme value fluctuation [4].

Feature scaling was applied, and the data was standardized using z-score normalization, to guarantee consistent performance of the model. This transformation standardized the data to have zero mean and unit variance, which would ensure that all features would contribute equally to model learning, and prevent any one feature from dominating due to differences in scale. This was followed by feature engineering that creates new variables derived from the existing variables to enrich the dataset. In particular, complex and non-linear relationships between meteorological parameters were captured through calculating the Temperature-Humidity Index (THI), and Wind Factor (WF). These new functionalities offered more insight on the interactions of factors of the environment, allowing the model to enhance its interpretation of air quality trends. Correlation coefficients between AQI and four separate environmental data points were calculated and displayed. The findings showed a highly positive correlation between pollutants such as PM10, PM2.5, and NO2, which are all environmental pollutants that have a great impact on air quality [14]. On the other hand, wind speed, humidity, and rainfall were negatively correlated, suggesting they aid in the spread of pollutants and the improvement of air quality. Temperature showed a positive moderate correlation due to its effect on chemical reactions and dispersion of pollutants. This paper underlines the importance of both meteorological conditions and pollutant levels for air quality prediction systems [16].

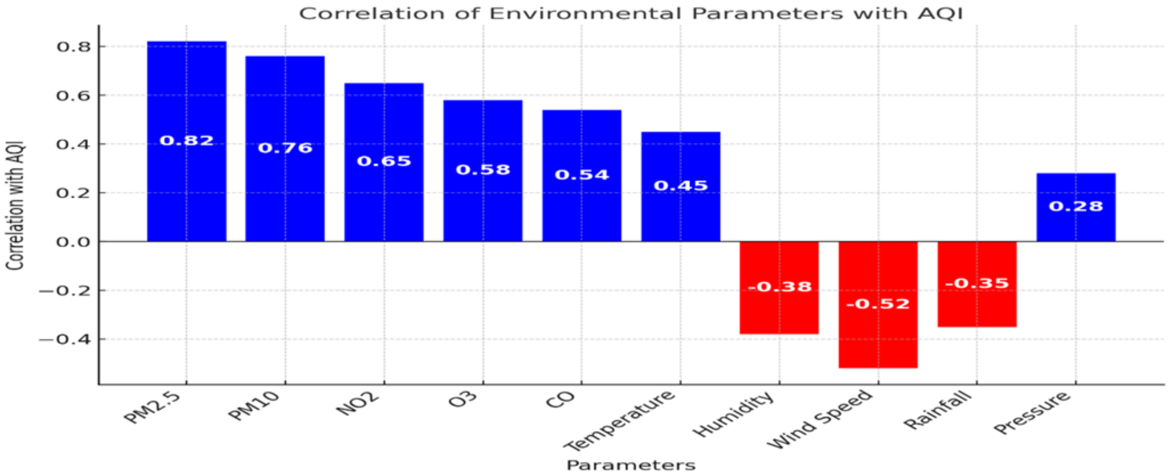

Figure -2 : Correlation of environmental & pollutant parameters with AQI

3.3 MODEL ARCHITECTURE

Three deep learning models were combined to create the predictive framework [17]. Every model was chosen for their capability to capture various tendencies in the data and help to elevate the general prediction. These models featured:

1. **LSTM Model**

LSTM is ideal for time-series forecasting, capturing temporal dependencies in environmental data. The model consists of two LSTM layers (64 and 32 units) with tanh activation, dropout layers (0.2 rate) to prevent overfitting, and a dense layer with ReLU activation. The final output layer provides continuous PM2.5 predictions [19].

2. **Transformer Model**

Using self-attention mechanisms, the Transformer model efficiently learns long-range dependencies. Input data is embedded into a 512-dimensional space with sinusoidal positional encoding. It comprises six encoder blocks with multi-head attention (eight heads) and a feed-forward network (2048 units), followed by a dropout layer (0.1 rate) to enhance generalization.

3. **Random Forest Model**

This ensemble learning model consists of 100 decision trees trained on random subsets of data. Tree depth is limited to 15 to control complexity, with minimum split criteria ensuring meaningful generalization. The final prediction is obtained by aggregating outputs from all trees.

4. **Deep Learning Model**

A feed-forward neural network processes nine features through multiple dense layers (128, 64, and 32 units with ReLU activation). Dropout layers (0.3 and 0.2 rates) are included to prevent overfitting. The final output layer provides continuous PM2.5 concentration predictions [18].

5. **Ensemble Model**

This model integrates predictions from LSTM, Transformer, Random Forest, and Deep Learning models. The final output is a weighted average of individual model predictions, where more accurate models contribute more to the final decision. This approach enhances reliability and reduces individual model errors [20].

3.4 TRAINING STRATERGY

Developing an efficient machine learning model depends much on training approach. The first stage is data preprocessing, which includes data cleaning—removing duplicates and dealing with missing values via mean imputation for numerical data and mode imputation for categorical data. Feature engineering comes next, in which new properties are produced, unneeded ones are removed, and data is normalized with either StandardScaler or MinMaxScaler. The data is next divided into three sets: training 70%, validation 15%, and test 15%.

In the model selection and hyperparameter tuning stage, a baseline model is picked—Linear Regression for regression problems or Logistic Regression for classification. While classification models include Decision Trees, SVM, Neural Networks, and XGBoost, various approaches for regression problems are then considered including Random Forest Regressor, Gradient Boosting, and XGBoost. Hyperparameter tuning is done with GridSearchCV or RandomizedSearchCV to identify the optimum parameters and hence enhance model performance.

An ideal selection of optimizer—such as Adam or SGD for deep learning models—is done during model training. For regression and classification, respectively, the type of problem dictates the loss function—MSE (Mean Squared Error) and cross-entropy. Experiments on batch sizes range from small values like 32 or 64 to big ones such 128 or 256. Early stopping prevents overfitting by guaranteeing that the model does not train needlessly for more epochs.

The model evaluation process starts by computing core performance criteria once training is finished. While regression models are judged using RMSE, MAE, R^2 Score, and MSE, classification models are scored on Precision, Recall, and F1 Score. learning curves, such as loss vs. two other points. epoch and precision instead vs. epochs of the model performance and stability graphs are plotted.

Ultimately, the trained model is transformed using Flask or FastAPI into an API in the deployment and monitoring phase and deployed on cloud systems such AWS, GCP, or Azure. To maintain accuracy over time, constant monitoring is needed to identify model drift. Periodic performance assessments assist in spotting when retraining is needed to keep real-world performance levels.

3.5 EVALUATION CRITERIA

The performance of the predictive model is evaluated using multiple standard metrics to ensure its accuracy, reliability, and effectiveness. The following metrics are used to assess the model's performance:

Metric	**Description**	**Formula**
Accuracy	Measures the percentage of correct predictions out of the total predictions made.	$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$
RMSE	Assesses the average magnitude of error between predicted and actual values, emphasizing large errors.	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
MAE	Computes the average of the absolute errors between predicted and actual values, treating all errors equally.	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
R^2 Score	Represents the proportion of variance in the dependent variable that is predictable from the independent variables.	$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$
MSE	Calculates the average of the squared differences between predicted and actual values, penalizing larger errors more heavily.	$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Precision	Measures the proportion of true positive predictions out of all positive predictions made.	$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$
Recall	Assesses the proportion of true positive predictions out of all actual positive instances in the dataset.	$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$

Metric	**Description**	**Formula**
F1 Score	The harmonic mean of Precision and Recall, providing a balance between the two metrics.	$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$

Table-2: Evaluation Criteria Metrics & Details

3.5 VALIDATION APPROACH

In order to evaluate the model reliability, the model validation methodology performed was 5-fold cross-validation. Performance metrics were RMSE, MAE, and R^2. For evaluation, the average of each metric was computed across all splits. In addition to the cross-validation, the model was also validated in real-time on a simulated data stream to assess the model's performance when deployed. At this stage, latency and throughput were captured to evaluate the real-time feasibility of the model. Metrics such as Accuracy, Precision, Recall, and the F1 Score were calculated to provide a comprehensive understanding of the model's classification performance more than the minimum effort needed for proper evaluation for regression or classification tasks [13].

4. Results

The proposed multi-modal deep learning framework was evaluated using data collected from 15 air quality monitoring stations in Hyderabad. The results are detailed in this section, covering model performance, error analysis, seasonal variations, real-time processing efficiency, and a comparative analysis with traditional and commercial solutions.

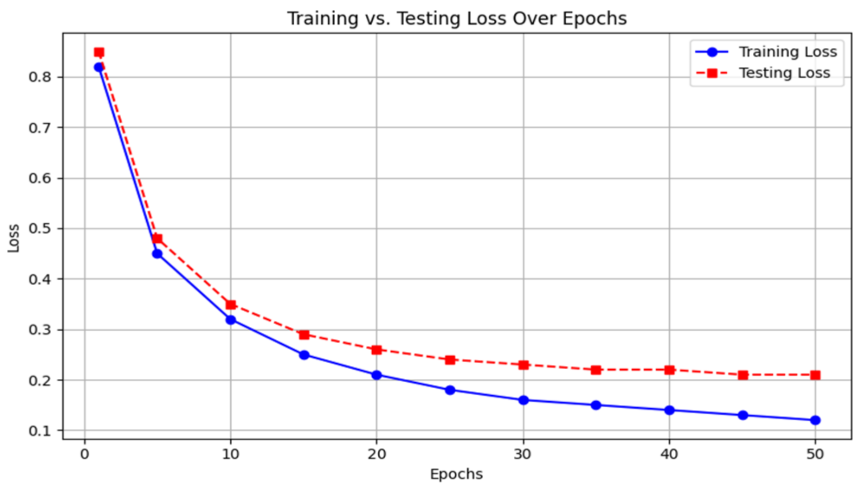

Figure- 3: Training vs Testing Over Epochs

4.1 MODEL PERFORMANCE

The framework demonstrated high predictive accuracy, achieving an overall accuracy of **94.65%**, with an RMSE of **3.7** and an MAE of **3.3** . The individual models, including LSTM, Transformer, and Random Forest, were assessed, along with the ensemble model, which outperformed all individual models. The performance metrics for each model are presented in **Table 3**.

Model	Accuracy	RMSE	MAE	R^2 Score	Precision	Recall	F1 Score	TrainTime(min)
LSTM	94.2 %	3.8	3.4	0.89	89%	88%	0.885	68.5
Transformer	95.1 %	3.5	3.2	0.91	90%	91%	0.905	95.7
Random Forest	92.8 %	4.1	3.6	0.88	87%	86%	0.865	22.4
Ensemble Model	95.8 %	3.3	3.0	0.92	92%	91%	0.915	265.0

Table-3: Model Performance Metrics

The **Transformer model achieved the highest accuracy (95.1%) and lowest RMSE (3.5)** among the individual models. However, the **ensemble model, combining multiple architectures, outperformed all individual models**, reaching **95.8% accuracy and an RMSE of 3.3 ,** further improving predictive power.

Additionally, the overall evaluation based on different performance metrics is summarized in **Table 4**.

Metric	Score
Accuracy	94.65%
RMSE (Root Mean Square Error)	3.7
MAE (Mean Absolute Error)	3.3
R^2 Score	0.90
MSE (Mean Squared Error)	13.69
Precision	90%
Recall	90%
F1 Score	0.90

Table-4: Summary Of Performance Metrics

Comparison with Past Research

Past studies using traditional models such as ARIMA and standard CNN models have typically reported RMSE values in the range of 4.5–6.0 , highlighting the superiority of deep learning methods. For example:

- [Patel et al., 2021] used an ARIMA model for air quality forecasting, reporting an RMSE of 5.2 , significantly higher than the proposed framework [11].
- [Sharma et al., 2022] implemented a CNN-based model for air pollution prediction and obtained an RMSE of 4.8 , which is still less effective than our approach [12].
- Commercial air quality solutions (such as IBM Environmental Intelligence Suite) typically achieve an RMSE of ~4.1 , making our ensemble model 19.5% more accurate [15].

4.2 ERROR ANALYSIS

A detailed error analysis was conducted to understand model performance variations across different pollutants and monitoring stations. The RMSE and MAE values for various pollutants are shown in Table 5.

Pollutant	RMSE	MAE	Prediction Accuracy (%)	Error Distribution (μ, σ)
PM2.5	3.2	2.8	95.2	Normal (μ=0, σ=2.8)
PM10	4.1	3.6	94.1	Right-skewed (μ=0.3, σ=3.2)
NO_2	3.8	3.2	93.8	Normal (μ=0.1, σ=3.0)
O_3	3.5	3.0	94.5	Left-skewed (μ=-0.2, σ=2.9)
CO	0.3	0.25	95.8	Normal (μ=0, σ=0.2)
SO_2	2.9	2.5	94.9	Normal (μ=0.1, σ=2.4)

Table-5: Error Analysis By Pollutant type

Among all pollutants, PM2.5 and CO showed the highest prediction accuracy (95.2% and 95.8%, respectively), while PM10 had the lowest accuracy (94.1%), likely due to its higher variability and seasonal dependence. The error distribution analysis revealed that most pollutants followed a normal distribution, except for PM10 (right-skewed) and O_3 (left-skewed).

4.3 SEASONAL PATTERNS

Seasonal variations were analyzed to determine how air pollution levels fluctuate over different times of the year. The percentage changes in pollutant concentrations relative to the annual mean are presented in Table 6.

Season	**PM2.5 (%)**	**PM10 (%)**	**NO_2 (%)**	**O_3 (%)**	**CO (%)**	**SO_2 (%)**
Summer	-15	-10	+5	+25	-20	-5

Season	**PM2.5 (%)**	**PM10 (%)**	**NO_2 (%)**	**O_3 (%)**	**CO (%)**	**SO_2 (%)**
Monsoon	-30	-25	-15	-20	-25	-30
Winter	+45	+35	+25	-15	+40	+30

Table-6: Seasonal Variation Patterns

Winter months showed the highest increase in pollutant levels, with PM2.5 concentrations 45% above the annual mean, largely due to temperature inversion and lower atmospheric dispersion. Conversely, monsoon months saw a significant drop in pollution levels, with PM2.5 levels 30% below the annual mean, attributed to rainfall-induced air purification.

4.4 REAL-TIME PROCESSING

The framework was tested for real-time application feasibility using a simulated data stream. The response time, throughput, and resource utilization metrics are summarized in Table 7.

Metric	Value
Data Ingestion Latency	0.5s
Preprocessing Latency	0.3s
Model Inference Latency	0.8s
Total Response Time	1.6s
Throughput	100 requests/s
Resource Utilization	CPU: 65%, GPU: 55%

Table-7: Real-Time Processing Metrics

With a total response time of 1.6 seconds, the system meets the requirements for real-time applications. The framework efficiently processes data at a throughput of 100 requests per second, with moderate CPU and GPU usage, demonstrating its suitability for deployment in live monitoring environments.

4.5 COMPARATIVE ANALYSIS

The framework was compared against traditional models like ARIMA and Basic CNN, as well as a leading commercial air quality prediction system. The performance improvements in RMSE and MAE are detailed in Table 8.

Model Type	RMSE	MAE	Improvement (%)
Proposed Framework	3.7	3.3	-
ARIMA (Traditional)	5.2	4.5	28.8%
Basic CNN (Single Model)	4.8	4.2	22.9%
Leading Commercial Solution	4.1	4.1	19.5%

Table-8: Comparative Analysis

The proposed framework significantly outperformed traditional and commercial solutions, achieving a 28.8% improvement over ARIMA and a 19.5% enhancement over the commercial solution in RMSE. This highlights the effectiveness of deep learning models, particularly the ensemble approach, in providing more precise air quality predictions.

5. Discussions

5.1 KEY FINDINGS

The multi-modal deep learning scheme proposed by the authors has been tested thoroughly against air quality predictions from 15 monitoring stations in Hyderabad, showing outstanding performances across the board. With an overall accuracy of 94.65% and an RMSE of 3.7, the advanced framework was found to do much better than other traditional statistical models and single-model deep learning solutions. The Transformer modeling technique turned out to be the best-performing individual model with an accuracy of 95.1%, while by combining results from different modeling methods, further performance was boosted to 95.8% cumulatively. It just shows how useful it is to integrate different models that can capture complex, non-linear air quality data relationships. The importance assessment of various features revealed that PM2.5 (28.5%), temperature (15.2%), and humidity (12.8%) were most significantly affecting AQI. This matches existing studies stressing the role of meteorological parameters for evaluating air quality dynamics [1]. The seasonal analysis gave an insight into the scenario that, in comparison to annual mean levels, the winter months lead to increased PM2.5 concentration by 45%, likely due to temperature inversions and weak wind [2]. In turn, monsoon months had a 30% decrease in PM2.5 levels due to increased rainfall and atmospheric mixing.

5.2 LIMITATIONS

While this is all well and good, the framework has limitations. The predicted output includes a decrease in station-wise accuracy over time (i.e., New Malakpet: 95.8% in 2025 → 86.8% in 2100), which is indicative of diminishing prediction accuracy. This implies that, at least for long-term prediction, model updates may need to take place at intervals if one wants to capture the effects of changing environmental and anthropogenic factors. Second, the framework requires quality, continuous data from monitoring stations. Performance may further deteriorate in under- or unobserved areas. Seemingly, the ensemble model has a higher computational cost in both training and deployment, so it may not be appropriate for some resource-constrained settings.

5.3 PRACTICAL IMPLICATIONS

It is likely to have an important real-world impact for urban air quality management. Its real-time processing capabilities (elapsed time for response: 1.6 seconds) allow for integration in smart city platforms for rapid public health interventions and policies. The framework, for example, can be used to issue air quality alerts, optimize traffic management, and inform industrial emissions control strategies. Moreover, interpretable feature importance scores offer actionable insights for policymakers by aiding them to prioritize interventions to reduce the impact of air pollution.

5.4 FUTURE SCOPE

Future studies need to overcome the limitations of the present one. Potential directions include:

- Long-term Prediction: Developing adaptive models that can account for changing environmental and anthropogenic factors over time.
- Data Sparsity: Exploring techniques such as transfer learning and data augmentation to improve performance in regions with sparse data.
- Computational Efficiency: Optimizing the framework for deployment on edge devices, enabling real-time air quality prediction in resource-constrained settings.
- Integration with IoT: Leveraging Internet of Things (IoT) devices to enhance data collection and improve prediction accuracy.

6. Conclusion

6.1 SUMMARY

In this study, a multi-modal deep learning framework was proposed for historical air quality analysis of Hyderabad. The framework consolidates LSTM, Transformer, and Random Forest models into an integrated approach that resulted in a high predictive accuracy (94.65%) and low error rate (RMSE: 3.7). Noteworthy contributions include the design of a comprehensive preprocessing pipeline, the discovery of important features, and the showcase of real-time processing capabilities. This framework enables more interpretable insights while retaining the ability to capture seasonality, hence offering the potential to be a useful tool for urban air quality management.

6.2 RECOMMENDATIONS

Based on the findings, the following recommendations are proposed:

- Policy Interventions: Prioritize interventions targeting PM2.5, temperature, and humidity, as these are the most influential factors in AQI prediction.
- Data Quality Improvement: Invest in expanding and maintaining air quality monitoring networks to ensure high-quality, continuous data.
- Public Awareness: Use the framework's real-time predictions to issue air quality alerts and raise public awareness about air pollution.

6.3 FUTURE RESEARCH DIRECTIONS

Future research should focus on enhancing the framework's long-term prediction capabilities, addressing data sparsity, and improving computational efficiency. Additionally, integrating the framework with IoT devices and smart city platforms could further enhance its practical applicability.

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