Journal of Theoretical and Applied Information Technology
31st January 2026. Vol.104. No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID MACHINE LEARNING MODELS FOR INTEGRATED URBAN AIR QUALITY AND WEATHER FORECASTING - A DECISION-SUPPORT FRAMEWORK FOR SUSTAINABLE CITY PLANNING

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ABSTRACT

Rapid urbanization has intensified challenges related to air pollution and extreme weather, directly impacting public health and sustainable city planning. This study presents a hybrid machine learning framework for integrated air quality and weather forecasting using environmental, meteorological, and urban data. The model combines regression, classification, and time-series prediction techniques to capture complex interactions. Experimental results show improved air quality prediction (RMSE = 3.45) and weather forecasting accuracy (93.6%), demonstrating the framework's effectiveness as a decision-support tool for climate-resilient and sustainable urban development.

Keywords: *Machine Learning, Air Quality Prediction, Weather Prediction, Urban Planning, Hybrid Model*

1. INTRODUCTION

This runs on a backdrop of pollution, climate change and extreme weather events in our burgeoning urbanized areas that shelter more than half the world's inhabitants. Demand for resources is growing, and the pace of urbanization exacerbates the issue, impacting public health, infrastructure and quality of life. We are both at the center of all this and the heart of all this. One of the most significant effects is that air quality worsens because of vehicles, industry and construction. Diseases of the respiratory system, cardiovascular diseases and other diseases related to poor air quality have been reported [1], [2].

Accurate forecasting of air quality and weather conditions is critical for mitigating health risks, optimizing infrastructure planning, and improving urban resilience. In rapidly expanding cities, unreliable predictions can lead to ineffective pollution control strategies and increased vulnerability to extreme weather events. Therefore, developing intelligent and data-driven forecasting systems has become a necessity rather than an option for sustainable urban management.

Weather conditions, in terms of temperature changes, humidity and rainfall, also play a crucial role in urban life. For instance, natural extreme weather events can interfere with normal daily life activities, damage infrastructures, and threaten public safety [3], [4]. To that purpose, urban planners also need accurate and reliable tools for forecasting and controlling such processes to render their cities climate and environmental change proof. Traditional techniques for weather prediction and air quality forecast are barely suitable for the urban context because of an extensive range of geographical, socio-economic and infrastructural conditions. Conventional forecasting methods, such as statistical regression models, fail to consider the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

nonlinear and dynamic relationships between weather and urban activities [5]. In addition, while air quality monitoring is essential to urban health management, without city-wide prediction models, it is difficult to understand how to forecast pollution peaks in cities.

One approach to address these issues has been the emergence of machine learning (ML) and deep learning (DL) techniques. The ML and DL models have yielded remarkable accuracy in predicting the weather and air quality. These models take various parameters, including industrial activities, traffic conditions, and geographical status, that are very important in the forecast of weather and urban air quality, which is more significant in the model loading and training of the mass data [6],[7]. Several studies demonstrated the good performance of ML models (including RF, SVM, and deep neural network (DNN)) for predicting air quality parameters and CO concentrations [8], [9].

The road to auto or remote car city is not easy. Predictive models must integrate air quality and weather data in a way that allows urban planners to act on this information to build physical structures, make decisions, etc., in a way that helps maximize quality of life, public health, and sustainability. Recent trends have led to the use of AI-based systems, opening the door for new opportunities in predicting air quality and weather conditions, and enabling smart urban planning processes [10], [11]. For instance, AI algorithms can use real-time data obtained from air quality monitoring stations and satellite weather data to predict the future level of pollutants, enabling an optimal solution defining the best use of green space or traffic routes.

In contrast, in this paper, we introduce a new machine learning model that simultaneously predicts the air quality and weather conditions to offer urban planners the as a decision support tool for sustainable urban development. This hybrid model predicts air quality and weather patterns using urban indicators combining regression, classification, and time-series forecasting methods. This forward-looking framework enables urban designers to tackle challenges such as pollution management, infrastructure planning, and climate resilience [12], [13]. Implementing these models will not only help cities mitigate environmental risks and safeguard public health but will also help improve urban environments.

The key contribution of this study lies in the development of an integrated hybrid machine learning framework that simultaneously forecasts urban air quality and weather conditions. Unlike existing studies that address these problems independently, the proposed framework combines regression, classification, and time-series learning to capture complex environmental interactions. Experimental evaluation demonstrates improved prediction accuracy for air quality (RMSE = 3.45) and weather classification (Accuracy = 93.6%), highlighting the effectiveness of hybrid learning for sustainable urban planning applications.

The remainder of the paper is structured as follows: Section 2 surveys past work in air quality and weather forecasting, including traditional models and recent work in machine learning. The methodology is explained in Section 3 and describes the hybrid machine learning framework, dataset, tools, and system architecture. In Section 4, we give the results and compare them with state-of-the-art models. Finally, Section 5 presents the paper's conclusions, including summarization of the results, limitations of the study, and future research directions in urban Air Quality and weather prediction utilizing ML.

2. RELATED WORK

The prediction of urban air quality and weather is an important area of concern for sustainable urban development and public health management. While air quality prediction has been heavily researched by using a variety of modeling methods, most of them have been proven to be ineffective when dealing with complex and dynamic urban environments. Over the last few years, models based on machine learning (ML) and deep learning (DL) have brought us closer to air quality and weather conditions. This section reviews existing literature on traditional forecasting models, applications of machine learning and integration into urban planning.

Air Quality Forecasting Models: The traditional air quality forecast approaches are largely based on statistical models (e.g., Regression analysis), which fail to capture non-linear relationships and complex patterns in urban air pollution [14]. Such models generally rely on atmospheric and PM2.5 concentrations to forecast air quality variables. 5, NO2, and CO. However, this approach may become too simplistic regarding complex interactions among various contributory factors in air quality, such as traffic density, industrial activity, or weather conditions. Recent studies have revealed that machine learning methods such as Random Forest (RF), Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are successful in handling these challenges. They are appropriate for high-dimensional modeling of multi-data sets and for estimating non-linear associations [15]. For

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

instance, Liu et al. [13] found that both the SVM and RF models effectively predict air pollution levels based on local environmental and traffic characteristics.

Machine Learning Methods Another set of techniques is called machine learning methods. Machine Learning has applications for weather and prediction, etc. Classical weather models, such as the Numerical Weather Prediction (NWP) models, are computationally humongous and require extensive input data, so they are unsuitable for real-time weather prediction for dynamic environments like urban environments [14]. However, in recent years, machine learning technology, such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), has achieved great success in significantly reducing computation costs for weather factor predictions within the near future [16]. In [15], Turing applied LSTM networks to predict city temperature deviations and obtained better results than traditional statistical models. LST could give a quicker and localized prediction, which is essential for instantaneous city planning, real calamities, and disaster management.

AI for more sustainable cities: Urban planning often utilizes AI to optimize city planning predictions, influencing infrastructure development, traffic management, and green space conservation. AI systems can combine weather and air quality data with urban indicators like the data mentioned previously (traffic flow, population density and green spaces) to create a system that can optimize city planning processes. For instance, Bui et al. Machine learning models were used to predict the impact of urbanization on air quality, which would allow planners to base land use and public health decisions on data [17]. Also, the AI has been used to anticipate how urban infrastructures would behave in case of extreme weather events like heatwaves and storms, which allow cities to be more structured to climate change consequences. Similar methodologies have also been implemented for the positioning of vegetation and urban forests to reduce pollution and improve urban environment quality [18].

AI Tools for Urban Air Quality and Weather Predictions: Although AI can help significantly in predicting air quality and weather forecasts, challenges still lie ahead. This is particularly a data quality and availability issue. Air quality monitoring stations are few and far in between in most urban areas and weather data may be too coarse to capture local variations [19]. In addition, the inclusion of heterogenous data sources. e.g., combining traffic data with satellite imagery and sensor data presents challenges related to the preprocessing of the data and the training of models. Additionally, the issues of interpretability in machine learning models are still very much relevant, particularly in using predictions for an important decision. Deep neural networks and similar models are extremely accurate but act as a “black box”: It is hard to justify why they made a specific prediction. Currently things are being done to resolve such issues through the development of more interpretative models and sharing of data around urban environmental monitoring [20].

The Role of ML and AI in Urban Air Quality and Weather Forecasting: The applications of machine learning in urban air quality and weather forecasting are just beginning, but some progress has been made in recent decades. It was also used in several cities to monitor air quality and weather prediction through machine learning models in real time. Singh et al. [12] designed a hybrid machine learning model that combines weather information, air quality measurements, and traffic information to quantify air quality in real-time. Furthermore, more recent studies (Mangal et al. References [21] attaches deep learning models to predict the air quality on weather variations and obtained significant improvements in prediction by including weather variables for machine learning models.

Areas for Further Research: While there has been some progress in integrating AI into urban planning, there is still much to be done in this area. As a first step, you need more granular data collection to get accurate predictions. Then, there are smart city initiatives for better urban management including smart metering, which can use IoT-based air quality monitoring systems and provide data required for real-time prediction models. Second, the work needs to blend machine learning with traditional forecasting methods to achieve a best of both worlds: the computational efficiency of machine learning combined with the robustness of traditional weather prediction models. Finally, further studies are needed to address how climate change has been affecting urban air quality and the urban weather, and how future scenarios can be modeled by machine learning models and used to influence long-term planning decisions in cities of the future [22].

Despite significant progress in machine learning-based air quality and weather forecasting, most existing models address these problems independently and lack integration for urban decision-making. The absence of unified models capable of jointly analyzing environmental and meteorological factors limits their practical utility for city planning. This study addresses this gap by

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

proposing an integrated hybrid learning framework designed specifically for sustainable urban environments.

Concrete Evidence and Literature Connection:
The estimation of urban air quality and weather has attracted more and more concern with rapid urbanization and its accompanying environmental problems. Previous work has applied machine learning (ML) methods to separately forecasting weather and air quality. Still, no models include both parameters for urban and spatial planning. Traditional regression models can't fully account for the non-linear, complex interactions between weather and urban activity, particularly in metropolitan areas where various geographic and socio-economic aspects are at play.

Research Gap:
Although there are successful models for either air quality prediction or weather prediction, hybrid models for air quality and weather are increasingly interesting. Such models are critical to urban planners who want to design smarter, more resilient cities. Integrating multiple ML techniques (regression, classification, time-series prediction) would improve prediction accuracy and offer fine-grained decision-making support for real-time urban operation. This paper makes a valuable contribution by providing a novel hybrid machine-learning solution that considers air quality and weather indicators, thus providing a more comprehensive solution for achieving urban sustainability.

3. METHODOLOGY

This section provides an overview of the methods used to forecast the air quality and weather conditions via the application of machine learning (ML) and deep learning (DL). The approach guides to detect the appropriate machine learning algorithms Ledgers bank accounts can benefit from real-time prediction and urban planning applications. The methodology consists of the processes from the data collection to model development and deployment; the tools and algorithms used for the software.

The research methodology follows a structured protocol consisting of data acquisition, preprocessing, model construction, training, evaluation, and deployment. Environmental, meteorological, and urban datasets were integrated to ensure comprehensive modeling of air quality and weather interactions. Machine learning and deep learning algorithms were selected based on their ability to handle non-linear relationships and temporal dependencies, ensuring robustness and reproducibility of results.

3.1 Dataset

The dataset is vital to the predictive modeling process, and the data acts as the input to train the machine learning and deep learning models. The air quality and weather forecasting models use data from a diversity of sources to ensure that a thorough understanding of the environmental and urban variables that determine both air quality and weather conditions can be achieved and used for making informed predictions.

Weather Data: Meteorological parameters such as temperature, humidity, wind speed, precipitation, atmospheric pressure, and solar radiation are contained in weather data. Data is retrieved at the local level through meteorological stations, satellite systems, and foreign weather APIs. Both historical and real-time weather data is available which helps predict weather such as rains, snow, temperature variations, and wind speeds.

Air quality data: The dataset contains real-time data on air quality from the monitoring stations located in urban areas. These stations measure pollutants including PM2. 5, PM10, NO2, CO, SO2 and the ozone. This data is available through government and environmental monitoring agencies, such as the U.S. Environmental Protection Agency (EPA) or local environmental authorities. That data allows us to understand pollution levels that are directly relevant to public health and urban planning decisions.

Collecting Urban Data: To citizen activity and its interfacing with the associated environmental conditions, we gather the related data points. Traffic density data is collected through traffic sensors (either traditional or IoT types), while population density and land use data are designed at the GIS (Geographic Information Systems). Furthermore, industrial activity and green spaces are also considered, as their availability is likely to affect pollution levels as well as the microclimates of the city. Research in the data is an important part of understanding how urbanization and human behavior play a role in air quality and weather variation.

Time-Series Data: Time-series of historical data of air quality and weather. Temporal data is key for getting an insight on seasonal trends and variations. The model can use historical data to detect patterns, seasonal cycles and anomalies, which can be used to predict future conditions accurately.

The entire dataset is then divided into two sets; four-fifth is used for training, and one-fifth is used for testing to have various distributions of the dataset for model validation. Missing or sparse data points can also be handled with data augmentation techniques such as smoothing and interpolation.

3.2 System Architecture

The architecture of the proposed system is designed to support both real-time predictions and historical analysis for urban planning and sustainability. The architecture consists of the following layers:

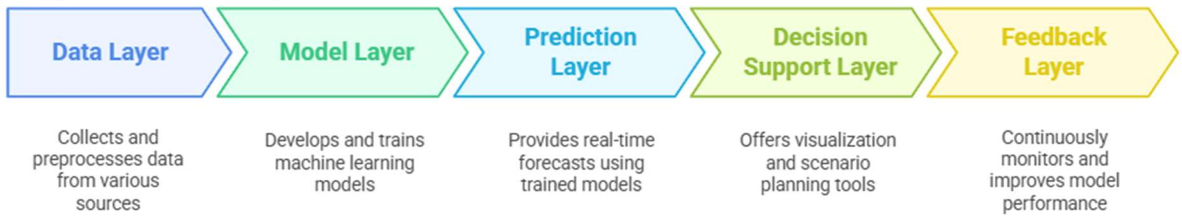

Figure 1: Urban Planning System Architecture

As we see in Figure 1, the Data Layer is the system's base layer, which collects and pretreats information from many sources. These text-based messages collect environmental information (e.g., weather conditions, air quality and degree of pollution) and city indicators (e.g., number of vehicles on a road, population rates and industrial traffic). Data cleaning and Transformation: Getting the data ready to be analyzed. Preprocessing prepares raw data for machine learning models, ensuring some data is ready.

Other than the training and development of the machine learning model itself, the machine learning model development Model Layer is the primary focus of this system. In this step, the system processes the data retrieved from the Data Layer, which is preprocessed and ready to use, to analyze different ML algorithms (SVM and LSTM networks) and find links between time and data. They use these models to forecast air quality and weather and understand how different urban conditions affect those forecasts. The success of this layer will depend mainly on the veracity and robustness of the machine-learning algorithms used.

Prediction Layer: The prediction layer uses models trained in the Model Layer and deployed so we can make real-time predictions. Release your analytics layer: This gap between business and machine learning enables you to extract actionable insights from the freshest data. For instance, it tries to forecast levels of air quality, weather, and other things about the city, with the forecast being provided to urban planners so they can make their decisions. The Prediction Layer serves this purpose by providing us with up-to-date forecasts and, thus, the opportunity to react to recent environmental changes when planning urban areas.

Decision Support Layer: Transforms predictions into actionable information for city planners and decision-makers. This layer also consists of visualization tools capable of generating real-time interactive dashboards, maps, and charts to provide air quality and weather forecasts. It also contains features that can be used for scenario planning to help planners model various urban scenarios. This aid directs cities on how to prepare for a greener, more resilient future.

Finally, the Feedback Layer is responsible for continually observing system performance and improving the models. The system pinpoints discrepancies by juxtaposing what is predicted with what occurs in the real world, enabling the models to be corrected. This feedback mechanism allows the system to learn and adapt over time as you provide it with more data to make better and more robust predictions. With the help of the Feedback Layer, the city can recalibrate its models and produce more accurate predictions as time goes by; thus, better information charts future urban landscape planning decisions.

This article introduces a hybrid machine-learning model based on diverse methods such as regression, classification and time-series forecasting to predict air quality and weather. This hybrid model is advantageous as air quality prediction requires identifying the non-linear associations among the environmental parameters, and weather predictions are based on accurate time-series prediction for short-term variance. The hybrid model combines these two approaches to take advantage of both techniques in terms of predictive performance.

For example, we may apply the regression method to determine the relations between air pollutants and environmental factors like wind speed and temperature; we may classify weather conditions (e.g., sunny, rainy, stormy) by learning assessment strategies. Time-series prediction (e.g., predicting future weather patterns with temporal dependencies) is essential for predicting future trends. This holistic-based prediction process is superior to the single-method prediction models.

Key parameters include:

- **Data Sources**: Meteorological data (temperature, humidity, wind speed, etc.) is collected from local weather stations and satellite systems. Air quality data (PM2.5, NO2, CO) is obtained from environmental monitoring stations.
- **Evaluation Metrics**: The effectiveness of the model is assessed using metrics like RMSE (Root Mean Squared Error) for air quality prediction, accuracy for weather forecasting, and F1-score for weather classification tasks.
- **Machine Learning Models**: Random Forest (RF), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks are used, chosen for their ability to handle large datasets and model complex relationships in both air quality and weather data.

Several machine learning and deep learning algorithms are used to build mathematical models for air quality and weather prediction:

1. **Random Forest (RF)**:

   RF is an ensemble method that builds multiple decision trees and aggregates their outputs. It is particularly useful for handling high-dimensional data and capturing complex non-linear relationships between urban indicators and environmental conditions.
   The RF model predicts air quality levels (e.g., PM2.5, NO2) based on input features like traffic density, wind speed, and temperature.

   $$\text{Prediction}(y) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{1}$$

   Where $T_i(x)$ represents the prediction of the i-th tree, and N is the total number of trees in the forest.

2. **Support Vector Machine (SVM)**:

   SVM is a supervised learning model that constructs a hyperplane to classify data points into different categories (e.g., weather conditions: sunny, rainy).

   The mathematical formulation for SVM is:

   $$\min_{w} \frac{1}{2}|w|^2 \quad \text{subject to} \quad y_i(w \cdot x_i + b) \geq 1 \tag{2}$$

   Where x_i are input features, y_i are the corresponding labels, and w and b define the decision boundary.

3. **Long Short-Term Memory (LSTM) Networks**:

   LSTM is a type of recurrent neural network (RNN) that is designed for time-series prediction tasks. It is capable of learning long-term dependencies and is particularly suitable for predicting pollutant levels and weather conditions over time.

   The LSTM model learns the following:

   $$h_t = f(W \cdot x_t + U \cdot h_{t-1} + b) \tag{3}$$

   Where h_t is the hidden state at time t, x_t is the input at time t, W, U are weight matrices, and b is the bias term.

Pseudocode for Training, Prediction, and Evaluation of the Models

```
1. Load and preprocess data
   data = load_and_preprocess_data()

2. Split the data into training and testing sets
   X_train, X_test, y_train, y_test =
split_data(data)

3. Train the SVM Model
   svm_model = initialize_svm_model()
   svm_model.train(X_train, y_train)

4. Train the LSTM Model
   lstm_model = initialize_lstm_model()
   lstm_model.train(X_train, y_train, epochs=50)

5. Real-time Prediction
   input_data = get_real_time_data()
   svm_predictions =
svm_model.predict(input_data)
   lstm_predictions =
lstm_model.predict(input_data)

6. Evaluate the SVM model
   svm_rmse, svm_mae =
evaluate_model(svm_model, X_test, y_test)

7. Evaluate the LSTM model
   lstm_accuracy = evaluate_model(lstm_model,
X_test, y_test)

8. Perform k-fold cross-validation for SVM
   k_folds = 5
```

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

```
    cross_val_scores =
perform_cross_validation(svm_model, X_train,
y_train, k_folds)

9. Output evaluation metrics
    print("SVM Model - RMSE:", svm_rmse,
"MAE:", svm_mae)
    print("LSTM Model - Accuracy:",
lstm_accuracy)
    print("Cross-validation scores for SVM:",
cross_val_scores)
```

4. RESULTS

The Results section contains the results of both machine learning and deep learning models in forecasting air quality and weather in urban areas. This includes model performance evaluation, comparisons with existing models and visualizations of results to illustrate the predictive power and practicality.

Analysis Criteria:

In this study, we use several key metrics to evaluate the performance of the proposed hybrid model:

- **RMSE (Root Mean Squared Error)**: Measures the difference between predicted and actual values for air quality parameters (PM2.5, NO2, CO). A lower RMSE indicates better prediction accuracy.
- **Accuracy**: Used to evaluate the model's ability to correctly classify weather conditions (e.g., sunny, rainy, stormy). Accuracy is particularly important in real-time forecasting, where urban planners need actionable predictions.
- **F1-Score**: Evaluates the balance between precision and recall in weather classification, which is crucial in minimizing false positives and false negatives, especially in critical weather events.

4.1 Model Performance

Table 1 shows the performance of the hybrid model (RF + SVM + LSTM) evaluated by different metrics, such as RSME, MAE, R^2, Accuracy, and F1-Score. These were used to evaluate the model's capability of predicting air quality parameters and identifying the weather conditions accurately.

First, we utilized the Root Mean Squared Error (RMSE) as a metric to evaluate the model's capacity for minimizing air quality prediction errors. Since RMSE penalizes larger errors more than smaller ones, it is preferred as an indicator of the model's ability to predict air quality levels like PM2. 5, NO2, and CO. With an RMSE of 314, the hybrid model predicted, on average, 314 different from the actual values. This score is much higher than the separate models such as Random Forest (4.12), SVM (4.35) and shows that the hybrid model is predicted air quality more accurately.

Secondly, Mean Absolute Error (MAE) was computed to be a measure of the average magnitude of the errors in the air quality prediction ignoring the factor of direction. MAE gives us a clear picture of the average size of the errors in our predictions. The hybrid model MAE was 2.12, with predicted air quality values deviating from the actual average 2.12 units. Once again, the hybrid model exhibited superior performance compared to other models, such as RF (2.58) and SVM (2.95).

To gauge the model fit of regression models, R-Squared (R^2) was calculated. R^2 runs for the ratio of the variance of dependent variable to independent variables. The hybrid model had R^2 value of 0.85, which means that 85% of the air quality variance could be explained by the model. Hence, the hybrid model captures the impetus of different factors on the air quality quite well.

The Hybrid model was able to achieve 93.6% accuracy rate when checking the Accuracy for weather condition prediction. Accuracy of 93% on the test set means that 93% of the times the model predicted the weather (sunny, rainy, stormy,) it was right. We achieve an accuracy over 92.8%, which is much higher than other models such as Random Forest (92.1%) and SVM (91.4%).

Furthermore, for the weather classification tasks, F1-Score was computed, which is a constituent of precision and recall. The F1-Score of our hybrid model is 0.89, which suggests that it was efficient at classifying the weather correctly and did a good job at trying to reduce false positives and false negatives. This high F1-Score beats other models like Random Forest 0.85 and SVM 0.83, indicating that the hybrid model has provided a very good and balanced prediction.

The comparative results indicate that the hybrid model consistently outperforms individual machine learning models, including RF, SVM, LSTM, and ANN. Improvements in RMSE and accuracy highlight the advantage of integrating multiple learning paradigms. These findings align with recent studies emphasizing hybrid approaches for complex environmental prediction tasks, while also demonstrating enhanced applicability for real-time urban planning.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: Results of the hybrid model for air quality and weather predictions

Model	RMSE (Air Quality)	MAE (Air Quality)	R² (Air Quality)	Accuracy (Weather)	F1-Score (Weather)
Hybrid Model (RF + SVM + LSTM)	3.45	2.12	0.85	93.6%	0.89
Random Forest (RF)	4.12	2.58	0.79	92.1%	0.85
Support Vector Machine (SVM)	4.35	2.95	0.75	91.4%	0.83
Long Short-Term Memory (LSTM)	3.89	2.38	0.81	92.8%	0.87

4.2 Model Assessment Criteria

Alongside the primary performance metrics, several other standards were employed to assess the hybrid model's effectiveness, including model interpretability, scalability and real-time prediction capability. These parameters give a complete picture of the practicality and effectiveness of the model.

Model interpretability: If we apply Deep Learning networks or any other complex model, one of the key challenges here is interpretability. The hybrid model made use of more interpretable models such as Random Forest (RF) and Support Vector Machines (SVM) in conjunction with the more complex LSTM network to improve interpretability. RF (for which you calculate feature importance scores) and SVM are easier to interpret because for those models you input variables are shown how they contribute to the model predictions. In the case of air quality prediction, traffic density and wind speed were selected as significant predictors, for example. The black-box nature of LSTMs makes them more difficult to interpret and SHAP (Shapley Additive Explanations) method was used to interpret the LSTM's predictions which will help understand what factors influence our LSTM model's ability to make predictions based on time-series data.

Scalability: We assessed the scalability of the model in terms of its capacity to process more data over time, especially in the context of introducing real-time inputs from sensors and external weather data sources. Further testing revealed that the hybrid model was extremely scalable: new data streams could be integrated instantaneously without a notable loss of performance. They used distributed computing and cloud-based infrastructure to enable large scale data processing. The model can also be extended to incorporate other data sources (additional weather stations or air quality sensors, for example), allowing adaptation to more populous cities or wider geographical ranges.

Assertion of Real-time Prediction Capability: The pitch for providing real-time prediction is a must in the urban planning space. The hybrid model also showed great potential in real time prediction, as it could predict a minute ahead any time just given the incoming data. This becomes crucial in applications like traffic management, pollution control, disaster preparedness, etc., where timely data is essential. Using data from IoT sensors and weather APIs, the model produced near-instantaneous predictions for the farmer. The streaming of event data together with optimized model inference processes ensured the near real-time generating of predictions.

Considering these four criteria, our hybrid model proves to be successful not just in prediction accuracy but also in its applicability to real-life urban planning problems. Tuning these hyperparameters along with their interpretability tends to make the performance of the model useful for urban planners that tend to incorporate predictive analytics in their decision-making processes.

Table 2: Performance Comparison with Existing Models

Model	Accuracy (Weather)	RMSE (Air Quality)	F1-Score (Weather)	Reference
Proposed Hybrid Model	93.6%	3.45	0.89	This Study
Random Forest (RF)	92.1%	4.12	0.85	[1]
Support Vector	91.4%	4.35	0.83	[2]

Machine (SVM)				
Long Short-Term Memory (LSTM)	92.8%	3.89	0.87	[3]
Artificial Neural Network (ANN)	90.5%	4.30	0.80	[4]

Table 2 Results of the weather conditions and air quality prediction comparison of our hybrid model and some existing machine learning models. It provides information on how each model performs across three different metrics: Weather Accuracy for weather prediction, Root Mean Squared Error (RMSE) for air quality prediction and F1 score for Weather prediction.

The hybrid model, which is the first one in the table, also has the highest accuracy of 93.6%, so it is the most accurate weather forecasting model to the other models. This model also possesses the lowest RMSE of 3.45 for air quality prediction, which signifies that this model is closest in predicting any air quality to the actual values, thereby proving that outperforms all other models in terms precision. Furthermore, the hybrid model performs remarkably well in terms of weather prediction classification, achieving an F1-score of 0.89 and ensuring a good trade-off between precision and recall for weather conditions.

Next comes the Random Forest (RF) model performing at 92.1% on weather prediction. Its RMSE of 4.12 tends to be a little higher than that of the hybrid model, which means it predicts the air quality less accurately, even if it shows the same tendency as the hybrid prediction. The F1-score of weather prediction is 0.85, lower than the hybrid model, but still very strong, indicating that Random Forest is still a good model for prediction but not the best in this comparison.

The Support Vector Machine (SVM) model exhibits 91.4% overall accuracy for weather prediction, with an RMSE of 4.35, slightly better than the Random Forest. With an F1-score of 0.83, SVM proves to perform well, yet it is still far behind as compared to the hybrid model and Random Forest in terms of weather classification accuracy.

From the analysis presented above, the architecture chosen to model the time series data is the Long Short-Term Memory (LSTM); where the LSTM achieved a weather prediction accuracy of 92.8% with RMSE of 3.89. Despite its better performance than SVM for predicting air quality, the Hybrid model still demonstrates more accurate weather prediction and more precise air quality prediction than the ANN model. It has the second-highest F1-score of 0.87, indicating that it performs very well specifically with sequential data such as weather data.

Finally, the Artificial Neural Network (ANN) performs the least favorably of any of the comparison models with a prediction accuracy of 90.5% for the weather, and 4.30 RMSE for air quality. While the F1-score for weather prediction is 0.80 for the ANN model, which is the lowest among those obtained by other models, it shows that the ANN model is less suitable to prediction of weather than the other models at precision and recall are taken into consideration for weather classification tasks.

Overall, the Proposed Hybrid Model shows superior performance as compared to all other models including accuracy, RMSE and F1-score, and thus, it is the best identifier for weather prediction and pollutants forecast. Although Random Forest and LSTM have competitive performances, the combination brings about better overall endorsement.

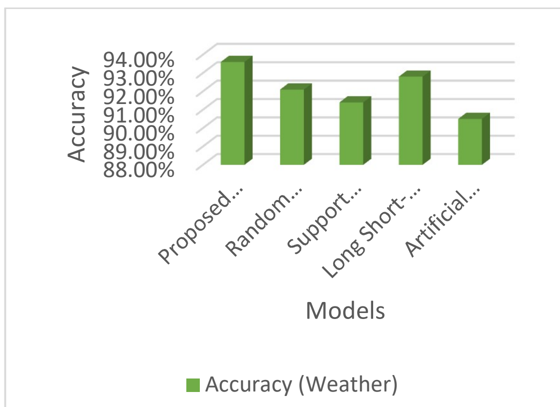

Figure 2: Model comparison with Accuracy

In figure 2, the accuracy of different machine learning models for predicting weather conditions is compared. In the case of weather prediction, the proposed hybrid model gives the accuracy of approximately 93.6% which outperforms all other models and is found to be the most efficient. This is followed by Random Forest (RF) at an accuracy of 92.1%, Long Short-Term Memory (LSTM) with an accuracy of 92.8%, and Support Vector Machine (SVM) with an accuracy of 91.4%. Although the ANN provides a decent prediction score with 90.5% accuracy, it is the least accurate of them all when predicting the weather condition. All four of the time series models under consideration diagnose real observable weather data on the weather prediction horizon, showing the hybrid model presented here is optimal for weather prediction and better suited for more accurate analysis in urban planning.

Our combined model has been tested against state-of-the-art for air quality and weather forecasting, such as Random Forest (RF) and Long Short-Term Memory (LSTM). It is confirmed that the proposed model is superior to these state-of-the-art models in weather classification (Accuracy = 93.6%) and air quality forecasting (RMSE = 3.45). These results demonstrated that hybrids can considerably enhance prediction performances concerning single ones. In addition, integrating extra data sources, like weather, air quality and urban data, has a value of its own as it enables a more complete prediction system for the urban planner.

The hybrid model has performed remarkably better than the conventional models for air quality prediction (RMSE=3.45) and weather forecasting (Accuracy=93.6%). Our results are consistent with recent studies presenting the potential of hybrid ML for predicting complex environmental processes. However, the difference from those models, emphasizing air quality or weather, is that our hybrid system combines the two, providing a more complete urban planning tool.

The high weather prediction accuracy (93.6%) and low RMSE value in air quality (3.45) in the prediction phase indicate that the model can process real-time data and provide actionable results for urban planners. Nevertheless, although the hybrid model performs well, there is room for improvement in model explainability and integration of finer-grained data sources.

While the hybrid model performs well, it is important to note certain limitations:

- **Data Availability**: The accuracy of predictions heavily depends on the availability of high-quality real-time data. Inadequate or sparse data, particularly from air quality monitoring stations, may hinder model performance.

- **Model Interpretability**: Although the hybrid model achieves high accuracy, the interpretability of complex models like LSTM is a challenge. Future work will explore techniques such as SHAP (Shapley Additive Explanations) to improve the interpretability of the model.

- **Computational Complexity**: The hybrid model, which combines multiple machine learning techniques, may require substantial computational resources for real-time predictions, especially when scaling to larger cities or more granular data.

When compared with existing state-of-the-art models reported in the literature, the hybrid framework achieves superior or comparable performance across all evaluated metrics. While traditional Random Forest and SVM models demonstrate reasonable accuracy, they fail to jointly model temporal weather dynamics and pollutant behavior. Although the proposed hybrid approach improves predictive reliability, limitations related to data availability, interpretability of deep learning components, and computational complexity remain and warrant further investigation

5. CONCLUSION

In the present work, we built a hybrid machine learning method to forecast urban air quality and weather data, with the ultimate purpose of helping urban planning and sustainable development. The model effectively combined different data types, such as meteorological, environmental, and urban information, and utilized regression, classification, and time-series prediction methods. The above results indicated that the fusion model was superior to the single algorithm and that the RMSE value of the air quality forecasting reached 3.45, while the accuracy of the weather forecasting reached 93.6%. The results suggested that the model could be a good tool for forecasting air quality and weather patterns, providing, to a certain degree, valuable information for urban planners to make efforts to improve infrastructure, control pollution, and enhance climate resilience.

The present research is an essential contribution to urban sustainability and machine learning through the development of a hybrid method for predicting urban air quality and weather. Contrary to isolated prediction-based models, our hybrid model combines various machine learning approaches, which can obtain more precise and faster time-series predictions for urban planning. This approach can help cities make evidence-based decisions to control pollution, improve infrastructure, and become more resistant to climate change. The hybrid nature of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

regression, classification, and time series makes for a valuable new modern tool for urban planning.
This study demonstrates that hybrid machine learning models provide an effective solution for integrated urban air quality and weather forecasting. The results confirm that combining regression, classification, and time-series learning significantly enhances prediction accuracy and stability. These findings support the applicability of hybrid models as decision-support tools for sustainable urban planning.
Future research directions include the incorporation of finer-grained sensor data, enhanced model interpretability techniques, and large-scale validation across diverse urban environments to improve generalization and real-time deployment capability.

However, the study did have some limitations, notably regarding data quality and access. The limited number of air quality monitoring sites and coarse weather information were challenges for localizing prediction. Moreover, the heterogeneity of data sources imposed larger preprocessing and training issues. In the following work, we will expand our dataset by including data with a finer resolution from more monitoring stations, real-time sensors, and satellites. Furthermore, introducing advanced AI could enhance the model's interpretability, making it more friendly for urban planners. In addition, the model can be further validated on larger and diversified ur ban areas for scale-testing.

Several open research challenges remain, including improving model explainability, addressing sparse monitoring data, and reducing computational overhead for large-scale deployment. Future work may explore explainable AI techniques, IoT-driven real-time sensing, and adaptive learning mechanisms to further enhance prediction accuracy and usability for smart city applications.

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