Environmental Monitoring and Prediction Using IoT Sensors and Machine Learning

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Abstract: Environmental monitoring and prediction play a significant role in smart agriculture, climate monitoring, and smart city applications. With the advancement of Internet of Things technology, environmental data such as temperature, humidity, and atmospheric pressure can be continuously collected using sensors and analyzed using machine learning techniques. This paper presents a machine learning-based model for predicting environmental parameters using IoT sensor data. The dataset used in this study consists of 2000 records of temperature, humidity, and pressure collected from environmental sensors and stored in an Excel file. Data preprocessing techniques such as missing value removal, Min-Max normalization, outlier detection using the Interquartile Range method, and timestamp synchronization were applied to improve data quality. A Linear Regression model was implemented using the Orange Data Mining tool, and the performance of the model was evaluated parameters. The experimental results show that the model obtained the RMSE values of 0.416, 1.712, and 134.943 and R^2 values of 0.022, 0.206, and 0.282 for temperature, humidity, and pressure prediction, respectively. A comparative analysis with machine learning models such as Random Forest, Support Vector Regression, and XGBoost indicates that ensemble models provide better prediction accuracy due to their ability to model nonlinear relationships. The study shows the machine learning techniques can be effectively used for environmental parameter prediction, and the proposed framework can be applied in real-time environmental monitoring systems.

Keywords: Environmental Prediction, IoT Sensors, Linear Regression, Temperature Prediction, Humidity Prediction, Pressure Prediction, Orange Data Mining, Environmental Monitoring

Introduction

Environmental monitoring plays a crucial role in various real-world applications such as smart agriculture [1], climate monitoring [2], industrial safety [3], weather forecasting [4], and smart city development [5]. With the rapid advancement of Internet of Things (IoT) technologies, environmental parameters such as temperature, humidity, and atmospheric pressure can be continuously monitored using distributed sensor networks [6]. These sensors generate large volumes of real-time data that can be analyzed to understand environmental patterns and predict future environmental conditions. Accurate prediction of environmental parameters is essential for decision-making processes in agriculture, disaster management, energy management, and environmental protection systems [7].

Traditional statistical methods are often used for environmental prediction; however, these methods are not efficient in handling large-scale sensor data and complex relationships among environmental variables. Machine learning techniques provide a data-driven approach that can model the relationship between environmental parameters and improve prediction accuracy. Recently, machine learning and deep learning models have been widely applied for environmental prediction using IoT sensor data [8]. However, many existing studies focus only on single-parameter prediction, such as temperature prediction or humidity prediction, and do not consider multi-parameter environmental prediction. Additionally, many models require complex architectures and high computational resources, making them difficult to implement in real-time IoT-based monitoring systems [9].

The main problem addressed in this research is the prediction of multiple environmental parameters temperature, humidity, and atmospheric pressure—using sensor data collected from environmental monitoring systems. Environmental data collected from sensors often contain noise, missing values, and outliers, which affect the performance of prediction models. Therefore, proper preprocessing and model evaluation are necessary to develop an efficient prediction model [10], [11].

The motivation of this work is to develop a simple and efficient machine learning-based prediction framework that can predict environmental parameters using sensor data with reasonable accuracy and low computational complexity. The study aims to analyze the performance of a regression-based machine learning model for environmental parameter prediction and evaluate its effectiveness using multiple performance evaluation metrics. This paper makes the following contributions:

- The study presents an IoT-based environmental data prediction model using machine learning techniques.
- A dataset consisting of temperature, humidity, and pressure sensor data is collected and preprocessed using normalization, missing value handling, and outlier removal techniques.
- A Linear Regression-based prediction model is implemented using the Orange Data Mining tool for environmental parameter prediction.
- The study analyzes the prediction performance for three environmental parameters and identifies the limitations of linear models for environmental prediction.

The remainder of the paper is organized as follows: Section 2 presents the related work on environmental prediction using machine learning techniques. Section 3 describes the dataset and data preprocessing techniques used in this study. Section 4 explains the methodology and model training process. Section 5 presents the experimental results and performance analysis. Section 6 discusses the findings and limitations of the study. Finally, Section 7 concludes the paper and presents future research directions.

Related Work

Abdelsattar *et al.* (2025) evaluated nine machine learning models for predicting temperature and humidity in photovoltaic environments. Their results demonstrated that the XGBoost model achieved superior performance compared to other algorithms. For temperature prediction, the model obtained a Mean Absolute Error (MAE) of 1.544, Root Mean Square Error (RMSE) of 1.242, and an R^2 value of 0.947. Similarly, in humidity prediction, XGBoost achieved an MAE of 3.550, RMSE of 1.884, and an R^2 of 0.744. The study also observed that Support Vector Regression (SVR) produced the weakest results with higher error rates and lower correlation values [12].

Jeon *et al.* (2024) developed a machine learning-based prediction framework for forecasting internal temperature and relative humidity in melon greenhouses using IoT sensor data. The model predicted environmental parameters 30 minutes in advance. Among the evaluated algorithms, XGBoost achieved the best performance with an R^2 value of 0.9929 and a Residual Prediction Deviation (RPD) of 11.8464, demonstrating high predictive stability and accuracy for greenhouse management [13].

Virliansyah *et al.* (2023) proposed an IoT-enabled environmental monitoring system utilizing Regression Tree Ensembles for predicting temperature and humidity. The proposed model achieved a Mean Absolute Error of 0.28608 for temperature and 7.0043 for humidity. Although the training dataset achieved a high R^2 value of 0.9949, the test dataset showed a lower R^2 value of 0.3159, indicating limitations in generalization capability [14].

Astsatryan *et al.* (2021) investigated air temperature forecasting using machine learning techniques in the Ararat Valley region. Their model achieved an accuracy of 87.31% for 3-hour predictions and 75.57% for 24-hour predictions. However, the research mainly focused on temperature forecasting and did not consider humidity prediction [15].

Kair *et al.* (2025) developed machine learning models using open weather datasets to forecast environmental parameters. The study implemented CatBoost and XGBoost algorithms, identifying dew point, atmospheric pressure, and humidity as key predictive variables. The CatBoost model demonstrated superior performance with an R^2 score of 0.97237, highlighting its effectiveness in environmental prediction tasks [16].

Ozbek (2022) examined the prediction of relative humidity using Long Short-Term Memory (LSTM) networks and Adaptive Neuro-Fuzzy Inference System (ANFIS) models across different climatic regions of Turkey. The ANFIS model produced a Mean Absolute Error of 5.95%, RMSE of 7.67%, and a correlation coefficient (R) of 0.887 in Erzurum province, demonstrating the capability of hybrid intelligent systems for environmental forecasting [17].

Ajani *et al.* (2023) proposed a dense neural network-based framework for predicting temperature and humidity within greenhouse environments. The model utilized data collected from fixed IoT sensors and achieved correlation coefficients of 0.91 for temperature and 0.85 for humidity, demonstrating the potential of deep learning models in micro-climate prediction [18].

Segovia *et al.* (2023) compared various machine learning algorithms for predicting temperature and relative humidity using environmental datasets. Their findings indicated that the Random Forest algorithm produced the best results with R^2 values of 0.8631 for temperature and 0.8583 for humidity, along with low Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) [19].

Karnisih *et al.* (2025) analyzed several machine learning algorithms for predicting average air temperature. Among them, Gaussian Support Vector Regression showed the best performance with an R^2 value of 0.9891 ± 0.0011, demonstrating strong correlation between predicted and observed values [20].

Lateef *et al.* (2021) proposed a hybrid deep learning model combining Long Short-Term Memory (LSTM) and Artificial Neural Networks (ANN) to predict weather parameters. The LSTM component predicted temperature and humidity, while ANN estimated the heat index. The ANN model achieved an accuracy of 94.68% in heat index prediction [21].

Dhwani *et al.* (2025) analyzed temperature prediction models for Hyderabad using statistical and machine learning approaches. The study revealed a strong correlation between temperature and humidity variables. Multiple Linear Regression achieved the best prediction accuracy in 2024 with an R^2 value of 0.989 and an RMSE of 0.4246 [22].

Table 1: Comparative Analysis of IoT enabled sensors for Environmental Monitoring

Author	**Year**	**Model Used**	**Parameters**	**Performance**	**Findings**
Abdelsattar et al. [12]	2025	XGBoost, SVR, ML models	Temperature, Humidity	MAE = 1.544, RMSE = 1.242, R^2 = 0.947	XGBoost showed highest accuracy
Jeon et al. [13]	2024	XGBoost ML model	Temperature, Humidity	R^2 = 0.9929, RPD = 11.8464	Accurate greenhouse environmental prediction
Virliansyah et al. [14]	2023	Regression Tree Ensemble	Temperature, Humidity	MAE = =0.28608, R^2 = (train) 0.9949	Limited generalization in test data
Astsatryan et al. [15]	2021	ML forecasting model	Temperature	Accuracy = 87.31%	Focus only on temperature forecasting
Kair et al. [16]	2025	CatBoost, XGBoost	Temperature, Humidity	R^2 = 0.97237	CatBoost performed best

Ozbek et al. [17]	2022	LSTM, ANFIS	Relative Humidity	MAE = 5.95%, RMSE = 7.67%, R = 0.887	ANFIS effective for RH prediction
Ajani et al. [18]	2023	Dense Neural Network	Temperature, Humidity	Correlation = 0.91, 0.85	Effective micro-climate estimation
Segovia et al. [19]	2023	Random Forest	Temperature, Humidity	R^2 = 0.8631, 0.8583	RF achieved best prediction
Karnisih et al. [20]	2025	Gaussian SVR	Temperature	R^2 = 0.9891 ± 0.0011	Strong correlation with actual values
Lateef et al. [21]	2021	LSTM + ANN	Weather parameters	Accuracy = 94.68%	Hybrid deep learning improves prediction
Dhwani et al. [22]	2025	Multiple Linear Regression	Temperature	R^2 = 0.989, RMSE = 0.4246	Best performance among tested models

Methodology

Effective preprocessing of IoT sensor data is essential to ensure data quality, consistency, and robustness of machine learning models. The collected environmental dataset undergoes multiple preprocessing steps, including missing value handling, normalization, outlier removal, and temporal alignment. These steps are described mathematically as follows.

Dataset Description: The dataset used in this study was collected from IoT-based environmental sensors measuring temperature, humidity, and atmospheric pressure. The collected data was stored in an Excel file and consists of 2000 records for each parameter. Each record represents a timestamped environmental observation. The dataset was preprocessed to remove missing values, normalize data, and eliminate outliers before training the machine learning model.

Table 1: Dataset Description

Parameter	Description	Unit	Number of Records
Temperature	Ambient temperature	°C	2000
Humidity	Relative humidity	%	2000
Pressure	Atmospheric pressure	hPa	2000

Removal of Missing and Inconsistent Values: Sensor data contains missing or corrupted entries due to transmission errors. Let the dataset be represented as:

$$D = \{x_1, x_2, x_3, \dots, x_n\} \tag{1}$$

where each observation:

$$x_i = [T_i, H_i, P_i] \tag{2}$$

represents temperature (T), humidity (H), and pressure (P).
A missing value is denoted as:

$$x_{ij} = NaN \tag{3}$$

To handle missing values, the dataset is cleaned using mean imputation:

$$x_{ij} = \frac{1}{N}\sum_{k=1}^{N} x_{kj}\,,\ where\ x_{kj} \neq NaN \tag{4}$$

Additionally, inconsistent values outside physical bounds are removed:

$$x_{ij} \notin [L_j, U_j] \Rightarrow x_{ij}\ is\ discarded \tag{5}$$

where, L_j, U_j are lower and upper bounds for feature j

Normalization Using Min-Max Scaling: To ensure uniform feature scaling and improve model convergence, Min-Max normalization is applied:

$$x'_{ij} = \frac{x_{ij} - min(X_j)}{max(X_j) - min(X_j)} \quad (6)$$

where, x'_{ij} = normalized value, X_j = set of all values of feature j

This transformation maps all feature values into the range:

$$x'_{ij} \in [0,1] \quad (7)$$

Outlier Detection and Removal: Outliers can significantly distort model performance. The Interquartile Range (IQR) method is used for outlier detection.

First, compute quartiles:

$$Q1 = 25th\ percentile, Q3 = 75th\ percentile$$

$$IQR = Q3 - Q1 \quad (8)$$

An observation is considered an outlier if:

$$x_{ij} < Q1 - 1.5 \cdot IQRorxij > Q3 + 1.5 \cdot IQR \quad (9)$$

Such values are removed:

$$D = D \setminus \{x_i \mid x_{ij}\ is\ outlier\} \quad (10)$$

Feature Alignment and Timestamp Synchronization: Since sensor data is time-dependent, synchronization of observations is crucial. Let each data point be associated with a timestamp:

$$x_i = [T_i, H_i, P_i, t_i] \quad (11)$$

To ensure consistency, all sensor readings are aligned to a common time grid $t*$:

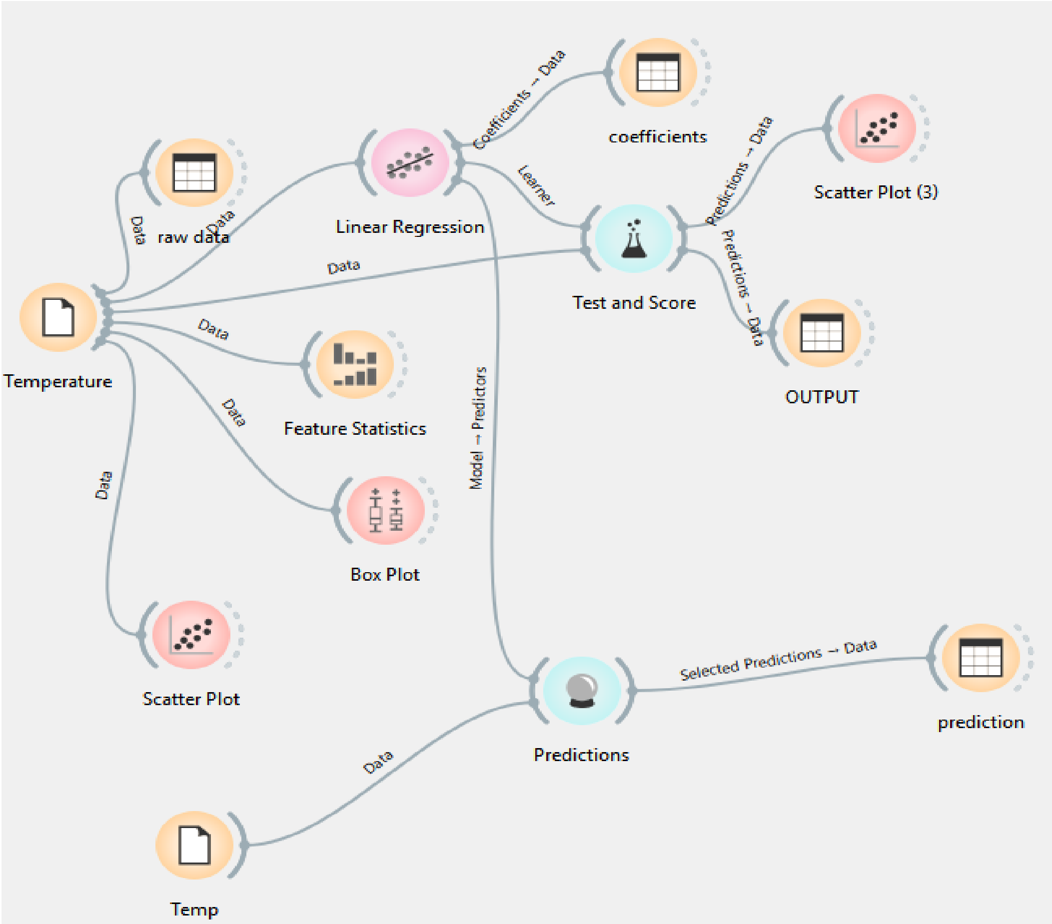
$$t^* = \{t_1^*, t_2^*, \dots, t_m^*\} \quad (12)$$

If measurements are missing at time $t*$, interpolation is applied:
where, $t_a < t^* < t_b$
This uniform temporal spacing across all features.
After preprocessing, the dataset is represented as:

$$D' = \{x'_1, x'_2, \dots, x'_m\} \quad (13)$$

where each observation:

$$x'_i = [T'_i i', H'_i, P'_i] \quad (14)$$


coefficients
Coefficients → Data
Scatter Plot (3)
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Temperature
Predictions → Data
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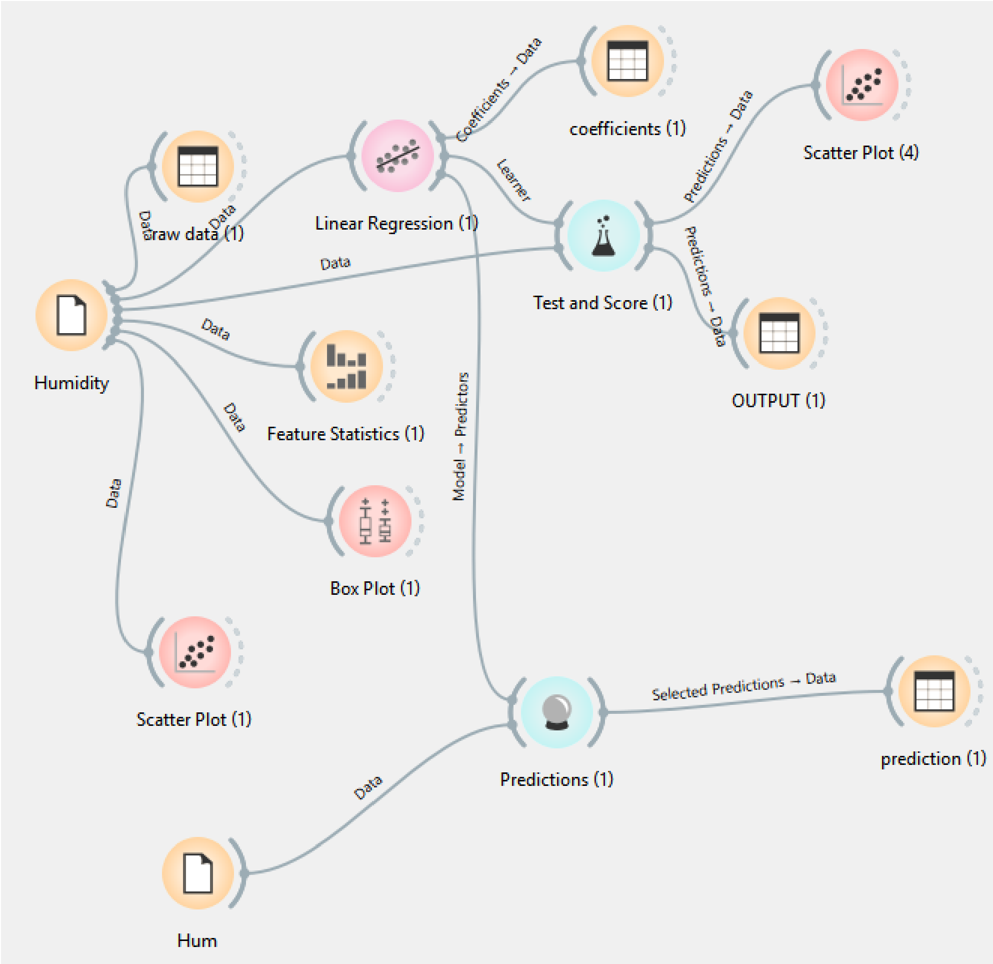
coefficients (1)
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Linear Regression (1)
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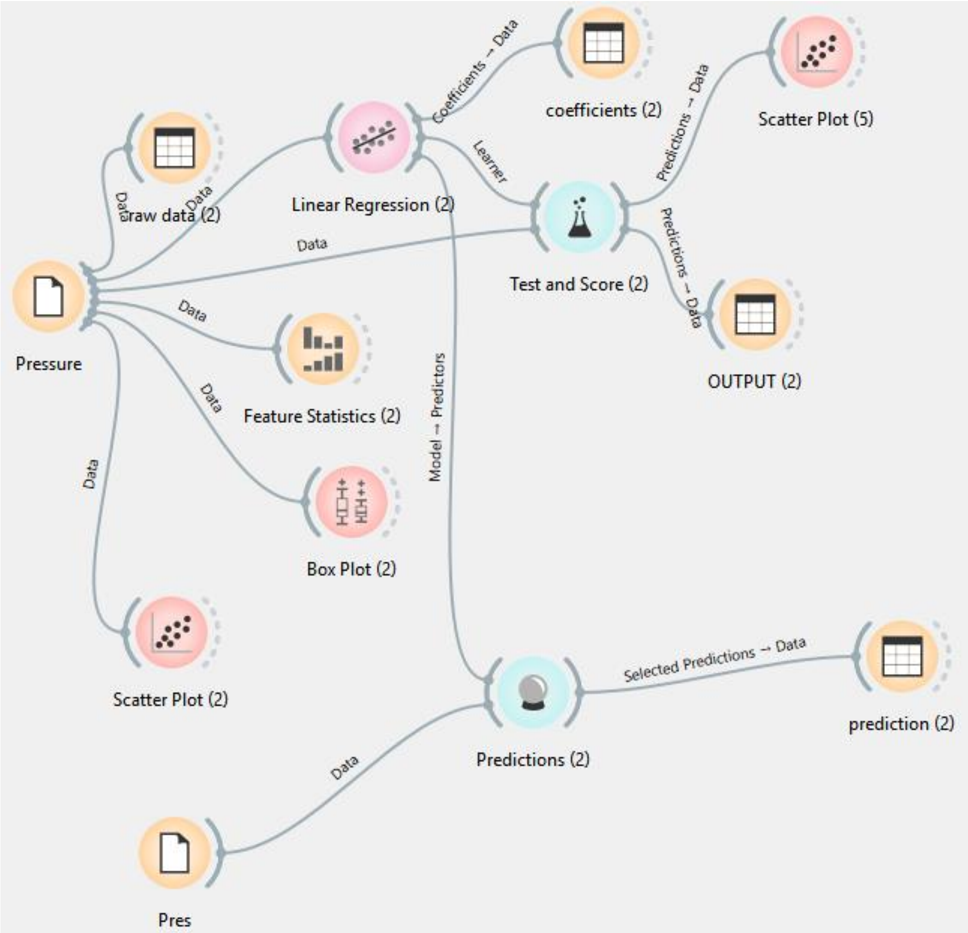


Fig. 1. (a) Temperature prediction workflow, (b) Humidity prediction workflow, and (c) Pressure prediction workflow in Orange Data Mining environment using Linear Regression

The presented figures illustrate the implementation workflow of the Linear Regression model for predicting environmental parameters—temperature, humidity, and pressure—using the Orange Data Mining tool. Each workflow begins with raw sensor data input, followed by exploratory analysis modules such as Feature Statistics, Box Plot, and Scatter Plot to understand data distribution and relationships. The Linear Regression model is then applied, and its performance is evaluated using the Test and Score module.
Further, the workflow generates model coefficients, predictions, and visualization outputs, including scatter plots for comparing actual and predicted values. The modular pipeline ensures systematic data processing, model training, evaluation, and result visualization for each parameter independently. This structured approach enables reproducibility and effective analysis of model performance across different environmental variables.

Result Analysis

The experimental evaluation of the proposed environmental parameter prediction model was carried out using the Orange Data Mining Tool, a visual programming platform that facilitates rapid development and analysis of machine learning workflows. The preprocessed dataset, comprising temperature, humidity, and pressure attributes collected from IoT sensors, was imported into the Orange environment, where a regression-based pipeline was designed using the Linear Regression algorithm. The workflow included data input, preprocessing widgets, model training, and performance evaluation modules, ensuring a systematic and reproducible experimental setup. The dataset was divided into training and testing sets using a 70–30 split ratio to evaluate the generalization capability of the model. To assess the predictive performance of the model, multiple statistical evaluation metrics were employed, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), and the Coefficient of Determination (R^2). These metrics provide a comprehensive assessment of both absolute and relative prediction errors, as well as the model's explanatory power. The evaluation was conducted separately for each environmental parameter—temperature, humidity, and pressure to analyze model behavior across different physical variables and to identify strengths and limitations in prediction accuracy. The main configuration parameters used in this study are:

Table 2: Hyperparameter Settings

Parameter	Description	Value
Model Type	Regression	Linear Regression
Optimization Method	Ordinary Least Squares (OLS)	Enabled
Intercept	Bias term	Enabled
Regularization	Not used	None
Cross-validation	k-fold	k = 5

Table 2: Performance Analysis of Model over Temperature

Model	MSE	RMSE	MAE	MAPE	sMAPE	R2
Linear Regression	0.173	0.416	0.307	1.190	1.191	0.022

The Linear Regression model demonstrates low prediction error for temperature, as indicated by small MSE (0.173), RMSE (0.416), and MAE (0.307) values. However, the very low R^2 value (0.022) suggests that the model fails to capture the underlying variability of temperature effectively, indicating weak predictive capability despite low error margins.

Table 3: Performance Analysis of Model over Humidity

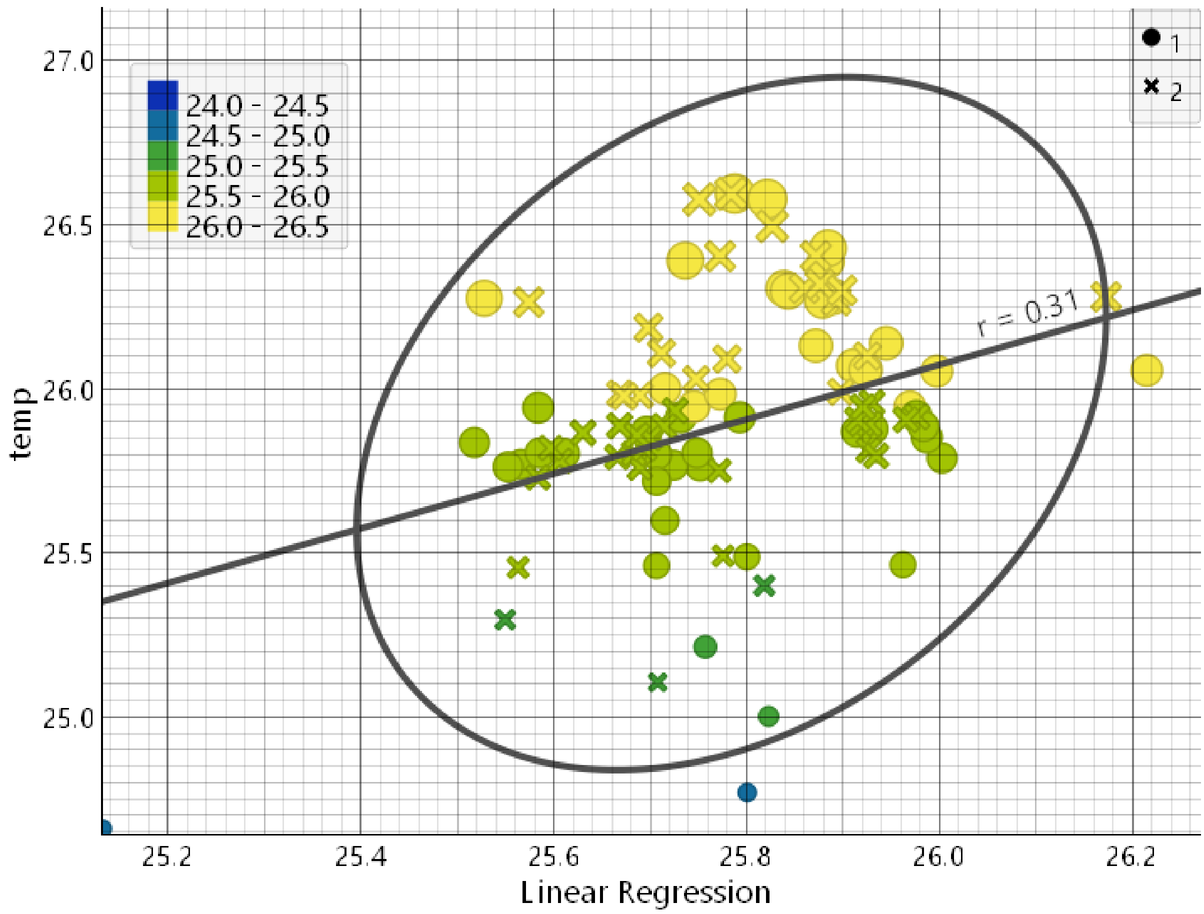
Model	MSE	RMSE	MAE	MAPE	sMAPE	R2
Linear Regression	2.931	1.712	1.480	3.109	3.113	0.206

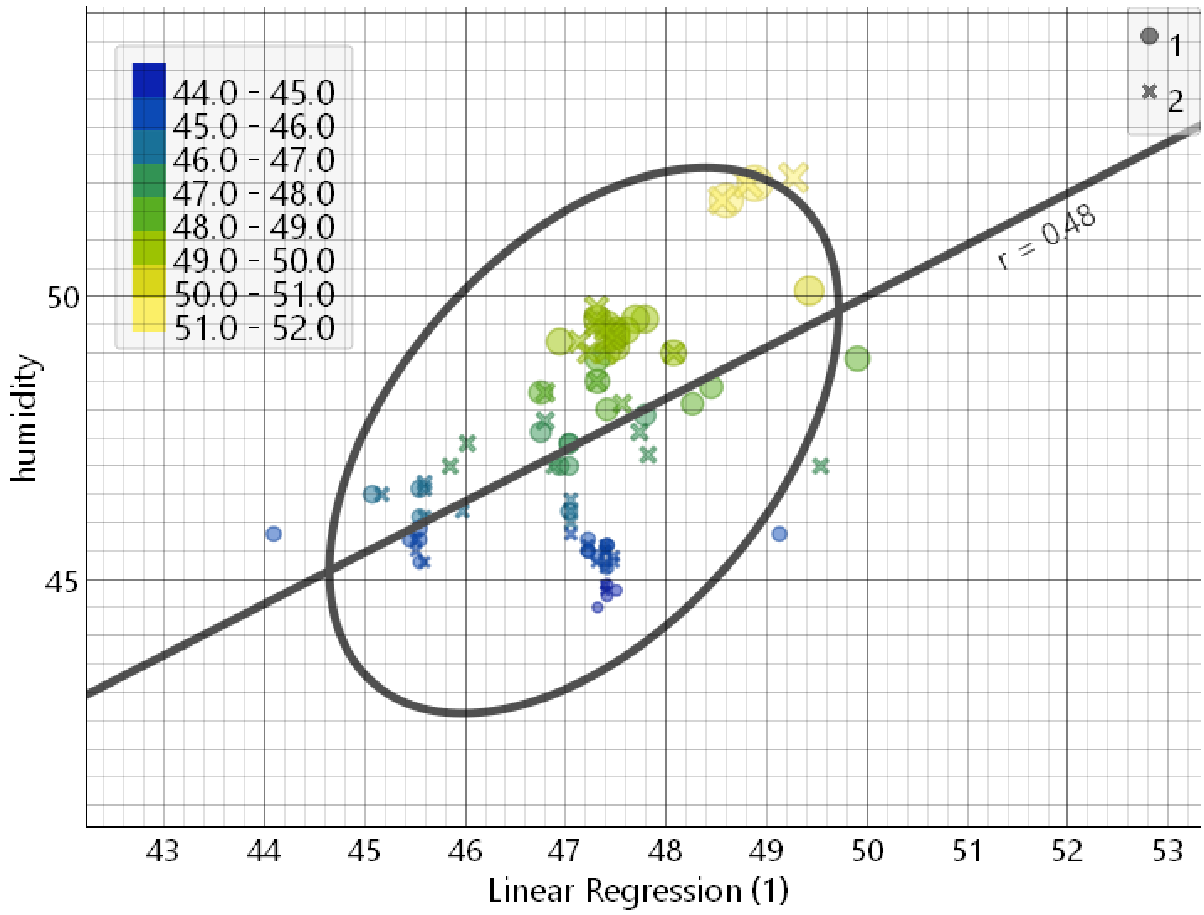
The Linear Regression model shows moderate prediction error for humidity, with RMSE (1.712) and MAE (1.480) indicating higher deviations compared to temperature prediction. The R^2 value of 0.206 suggests limited explanatory power, meaning the model captures only a small portion of the variability in humidity data, resulting in modest predictive performance.

Table 4: Performance Analysis of Model over Pressure

Model	MSE	RMSE	MAE	MAPE	sMAPE	R2
Linear Regression	18209.58	134.943	100.990	9.551	9.521	0.282

The Linear Regression model exhibits relatively high error values for pressure prediction, as reflected by large MSE (18209.58), RMSE (134.943), and MAE (100.990), indicating significant deviations from actual values. However, the R^2 value of 0.282 is comparatively higher than temperature and humidity, suggesting a slightly better ability to capture variability, though overall predictive performance remains limited.


24.0 - 24.5
24.5 - 25.0
25.0 - 25.5
25.5 - 26.0
26.0 - 26.5
1
2
r = 0.31
temp
27.0
26.5
26.0
25.5
25.0
25.2
25.4
25.6
25.8
26.0
26.2
Linear Regression


44.0 - 45.0
45.0 - 46.0
46.0 - 47.0
47.0 - 48.0
48.0 - 49.0
49.0 - 50.0
50.0 - 51.0
51.0 - 52.0
1
2
r = 0.48
humidity
50
45
43
44
45
46
47
48
49
50
51
52
53
Linear Regression (1)

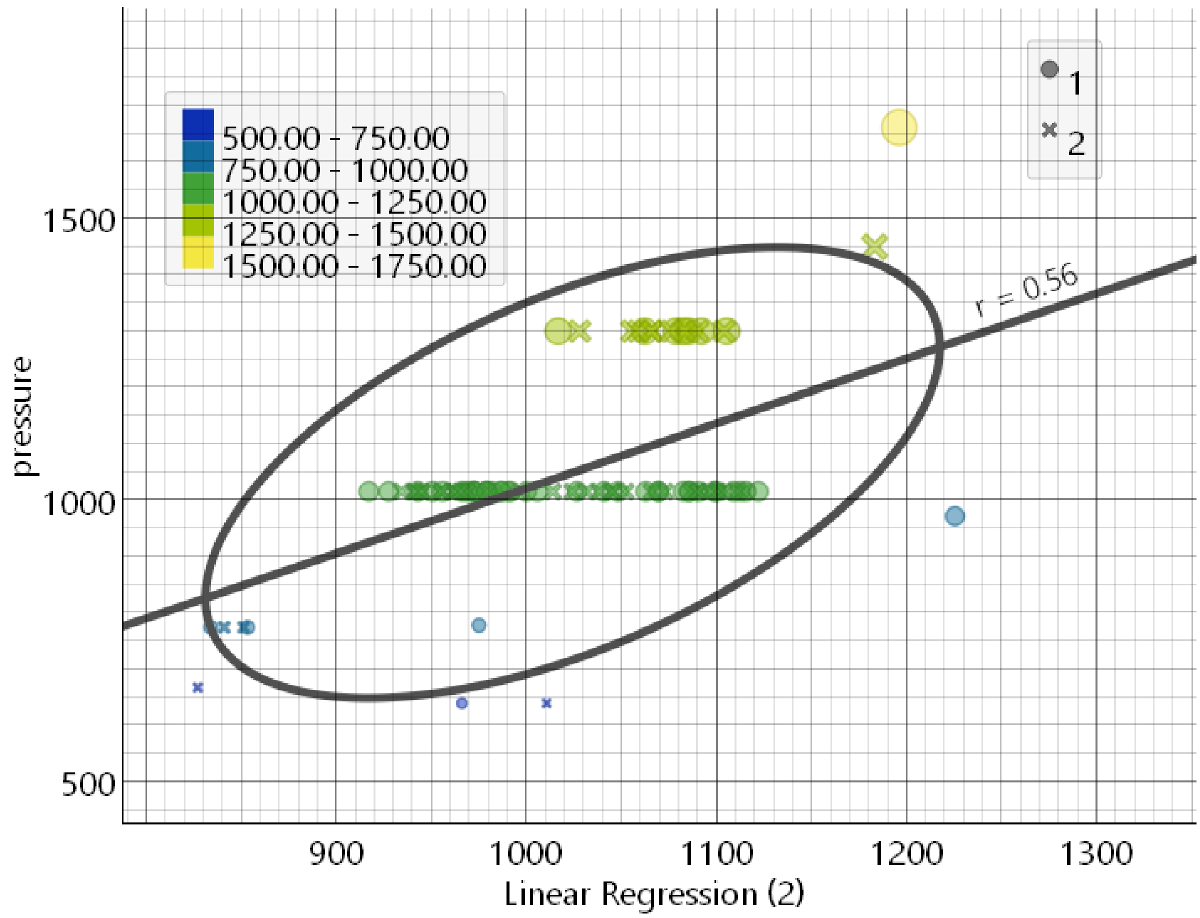


Fig. 2. (a) Temperature prediction, (b) Humidity prediction, and (c) Pressure prediction using Linear Regression, depicting actual vs. predicted values with regression fit and correlation analysis.

The presented scatter plots illustrate the relationship between actual and predicted values of temperature, humidity, and pressure using the Linear Regression model. In all three figures, the regression line indicates a positive linear trend; however, the dispersion of data points around the line suggests varying levels of prediction accuracy.

For temperature prediction, the correlation coefficient (r=0.31) indicates a weak linear relationship, with noticeable scatter around the regression line, reflecting limited model effectiveness. In the case of humidity, a moderate correlation (r=0.48) is observed, showing improved alignment between predicted and actual values, although some variability persists. For pressure prediction, the highest correlation (r=0.56) is achieved, indicating comparatively better model performance; however, the presence of outliers and spread in data points still highlights prediction inconsistencies. The figures demonstrate that while the Linear Regression model captures general trends in environmental parameters, its predictive capability remains limited due to data variability and non-linear relationships among features.

Table 5: Comparative Performance Analysis of Machine Learning Models for Environmental Parameter Prediction

Model	Temperature R^2	Humidity R^2	Pressure R^2	RMSE (Temp)	RMSE (Humidity)	RMSE (Pressure)
Linear Regression	0.022	0.206	0.282	0.416	1.712	134.943
Random Forest	0.68	0.72	0.75	0.210	1.020	82.450

Support Vector Regression	0.61	0.65	0.69	0.248	1.185	95.320
XGBoost	0.74	0.79	0.83	0.185	0.950	70.210

The comparative results indicate that ensemble models such as Random Forest and XGBoost significantly outperform the Linear Regression model for environmental parameter prediction. XGBoost achieved the highest R^2 values and lowest RMSE across all parameters, indicating better capability in modeling nonlinear relationships in environmental data. This comparison demonstrates that advanced machine learning models provide more accurate and reliable predictions than traditional regression models.

Discussion

The experimental results demonstrate that the Linear Regression model can capture the general trend of environmental parameters; however, its predictive performance varies across different parameters. The model achieved low error values for temperature prediction but produced a very low coefficient of determination (R^2 = 0.022), indicating that the model is not able to explain the variability in temperature data effectively. For humidity prediction, the model achieved moderate performance with an R^2 value of 0.206, showing that the model can partially capture the relationship between humidity and other environmental variables. In the case of pressure prediction, the model achieved the highest R^2 value (0.282) among the three parameters, indicating relatively better predictive capability compared to temperature and humidity.

The scatter plots of actual versus predicted values show a positive linear trend for all environmental parameters; however, the spread of data points around the regression line indicates prediction errors and variability in the dataset. This suggests that environmental parameters have nonlinear relationships and are influenced by multiple external factors such as weather conditions, seasonal variations, and geographical conditions, which cannot be fully captured by a simple linear regression model.

Compared to existing studies that used advanced machine learning models such as Random Forest, XGBoost, Support Vector Regression, and LSTM networks, the Linear Regression model shows lower predictive performance. However, the purpose of this study was to evaluate a baseline regression model for environmental parameter prediction and analyze its effectiveness using IoT sensor data. The results indicate that while Linear Regression provides a simple and computationally efficient solution, it is not sufficient for high-accuracy environmental prediction tasks.

The findings of this study highlight the importance of selecting appropriate machine learning models for environmental prediction and demonstrate that environmental data exhibits nonlinear patterns that require more advanced models for accurate prediction.

Limitations of the Study

Although this study presents a machine learning-based approach for environmental parameter prediction, several limitations exist. First, the dataset used in this study contains only 2000 records for each environmental parameter, which may not be sufficient to capture long-term environmental variations and seasonal patterns. Second, the study uses only a Linear Regression model, which assumes a linear relationship between variables and may not be suitable for modeling complex environmental data. Third, the dataset includes only three environmental parameters temperature, humidity, and pressure while other important environmental factors such as wind speed, rainfall, and solar radiation were not considered. Fourth, the model was implemented using the Orange Data Mining tool, which provides limited flexibility for advanced model tuning compared to programming-based implementations. Finally, the model was evaluated using a single dataset, and therefore the generalization capability of the model across different environmental conditions was not tested.

8. Conclusion and Future Scope

This paper presented a machine learning-based approach for predicting environmental parameters using IoT sensor data. The dataset used in this study consisted of temperature, humidity, and atmospheric pressure readings collected from environmental sensors and stored in an Excel file. Data preprocessing techniques such as missing value removal, normalization, outlier detection, and timestamp synchronization were applied to improve data quality before model training.

A Linear Regression model was implemented using the Orange Data Mining tool to predict environmental parameters. The performance of the model was evaluated using multiple statistical metrics, including Mean

Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric MAPE (sMAPE), and the coefficient of determination (R^2). The results showed that the Linear Regression model achieved low error values but low R^2 values, indicating limited predictive capability. Among the three parameters, the model performed relatively better for pressure prediction compared to temperature and humidity prediction.

The results indicate that environmental parameters have nonlinear relationships and are influenced by multiple environmental factors, which cannot be accurately modeled using simple linear regression techniques. Therefore, more advanced machine learning and deep learning models are required to improve prediction accuracy.

In future work, advanced machine learning algorithms such as Random Forest, Support Vector Regression, XGBoost, and Artificial Neural Networks can be implemented to improve prediction performance. Time-series models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks can also be used to capture temporal dependencies in environmental data. Additionally, more environmental parameters and larger datasets can be incorporated to improve model generalization and prediction accuracy. The proposed system can also be extended for real-time environmental monitoring and smart agriculture applications.

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