SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I7P136

Volume 12 Issue 7, 459-471, July 2025

Original Article

Precision Agriculture: Machine Learning based Weather Prediction – A Comparative Study of Adaboost and Modified Adaboost Algorithm

A. Lavanya[1], B. Swapna[2]

[1,2]*Department of Electronics and Communication Engineering, Dr. M.G.R. Educational and Research Institute, Chennai, Tamilnadu, India.*

[1]*Corresponding Author : lavanyajishnu@gmail.com*

Received: 19 May 2025 Revised: 20 June 2025 Accepted: 20 July 2025 Published: 31 July 2025

Abstract *- Optimal crop growth through irrigation is achieved through the intelligent use of ensemble algorithms in predictive modelling, which depend on the massive amounts of information gathered and transmitted by various electronic devices and sensors pertaining to the crop's environment, well-being, and soil quality. Existing system: In traditional farming practices, the monitoring of environmental factors and soil conditions is often manual, resulting in delayed responses to potential issues, such as nutrient imbalances, water stress, or suboptimal climatic conditions. The delayed response in decision-making can result in decreased crop yield, inefficient resource use, and increased production costs. Many farmers rely on intuition or historical data, which do not account for the dynamic changes in the farm environment. As a result, there is an urgent need for systems that can offer real-time, data-driven insights into key environmental factors that influence crop health. Proposed system: This study presents an innovative framework of ML aimed at optimizing environmental management through continuous surveillance of essential weather parameters like temperature, air pressure, wind speed, and humidity to predict the future temperature with the Internet of Things. The objective of this article is to present the prediction of weather parameters through Adaboost and Modified Adaboost models, and to compare their performance indicators. Weather prediction with a modified Adaboost technique achieves an accuracy of 94%. By integrating these technologies, farmers can improve their farms' output and sustainability. They will also receive helpful information and be able to make informed decisions about irrigation and fertilization.*

Keywords *- Machine Learning (ML), Weather prediction, Precision agriculture, Crop health, Adaboost and Modified Adaboost models.*

1. Introduction

Edible and non-edible products are produced through various agricultural activities, including crop and livestock production, aquaculture, and forestry. When people learned to raise domesticated animals, it led to food surpluses that allowed them to settle down in cities, which paved the way for sedentary human civilization. Heatwaves, droughts, and other extreme weather events have a devastating effect on agriculture. These disasters cause crop failures, lower yields, and interruptions in farming cycles, affecting food security and people's ability to make a living.

A better understanding of the weather is crucial for public safety since it allows for prompt planning and evacuation in severe weather occurrences such as cyclones, heat waves, and floods. Consequently, applications that provide data-driven insights into critical environmental parameters impacting crop health in real-time are urgently required. The spatial and temporal variability in environmental conditions further increases the complexity of farming environments. For instance, soil moisture levels and temperature can vary significantly across a single farm, and these variations directly affect crop growth. IoT sensors offer the ability to monitor these factors in real time. Still, the challenge is integrating this large volume of data into a cohesive system that can provide accurate predictions and actionable recommendations. Without an integrated solution, farmers are likely to either under- or overapply resources like water or fertilizers, leading to inefficient practices and uneven crop performance. The Decision Support System integrated into this framework provides dynamic recommendations for weather monitoring for irrigation scheduling, nutrient management, and pest control measures. With the help of an AR dashboard, which provides easy-to-understand data visualizations, farmers can make data-driven decisions while working the land. Along with accuracy in weather monitoring, measures like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are used to appraise the performance of machine learning frameworks. The outcomes prove that the system is capable of enhancing crop management methods, increasing output, and guaranteeing the sustainable utilization of agricultural resources.

Agriculturally, they aid in optimizing crop management, resource utilization, and loss mitigation due to weather-related catastrophes. Weather prediction aids producers in making well-informed decisions regarding planting, irrigation, and harvesting, thereby maximizing crop management, reducing risks, increasing yields, and improving resource efficiency (Adinarayana, S., et al., 2024). Artificial intelligence and machine learning in agricultural surveillance systems can significantly enhance crop yield prediction, insect detection, and soil health diagnosis (Kowalska, A., et al., 2023). Artificial intelligence (AI) systems may do things like predict weather patterns, evaluate the health of crops, and identify problems like pests, illnesses, or inadequate irrigation because of unpredictable weather conditions. In numerous disciplines, extensive research has been conducted to improve rainfall prediction, including statistical forecasting, operational hydrology, environmental machine learning, and weather data mining (Xu, T., et al, 2021). An essential principle of data mining is Knowledge Discovery in Databases (KDD). The primary emphasis of modern scholars is on discovering patterns in time series data. Meteorologists analyze data from previous hours, days, weeks, months, and years to forecast future rainfall (Shu, X., et al., 2023)..

Weather forecasting is taken to the next level with AdaBoost. This ensemble ML technique merges numerous "weak" predictors (such as decision trees) into a single, more robust predictor by zeroing in on misclassified occurrences and giving forecast weights (Nti, I.K., et al, 2023).. It improves both accuracy and generalizability. The standard AdaBoost implementation bases the weight update on the error rate. Altering AdaBoost means recalculating alpha or including a regularization term. Alternatively, the combinations used for the weaker students will be changed. One alternative is to use a different base estimator. For example, switching from decision trees to SVMs is our learning system's backbone. Although theoretically feasible, SVMs are not frequently employed with AdaBoost due to their great learning capabilities. AdaBoost is an excellent tool for various machine learning problems due to its ensemble technique, which has benefits such as high accuracy, resilience to noisy input, and low implementation complexity.

1.1. Objective of the Article

- The proposed system uniquely integrates AI and recent information from diverse sources, including meteorological parameters and agricultural monitoring, with the help of IoT. This comprehensive approach ensures that decision-making is based on a holistic understanding of environmental conditions from a smart weather monitoring node.
- Unlike traditional methods that rely on static resource allocation based on historical data, this system employs an advanced ML Ensemble algorithm of AdaBoost and a modified AdaBoost algorithm to predict the values accurately, considering real-time factors including humidity, wind speed and direction, temperature, and pressure to make precise weather predictions.
- Both algorithms are performed, and their performance metrics are compared. The modified Adaboost algorithm predicts the weather with more accuracy than the standard Adaboost algorithm. Incorporating ML to create an AI-driven irrigation system that uses weather predictions and data from Internet of Things sensors (soil moisture, temperature, and humidity) to determine when crops need to be watered most effectively.

Here is the article's structure. Section 2 outlines the relevant work that improves local weather forecasts using research methodologies and cutting-edge breakthroughs in computational intelligence for growing internet-enabled devices. The methodology's framework is labelled in Section 3, and the outcomes of Adaboost and modified Adaboost projected values are shown in Section 4. Section 5 of the paper gives a synopsis of the findings and their possible applications moving forward.

2. Literature Survey

Researchers found that Intelligent Farming is made possible by nimble AI and the Internet of Things, including a reasonably priced cognitive weather station. The research introduced a cheap, agile framework for cognitive monitoring in smart farming powered by AI and built on the Internet of Things. Constantly monitoring a wide range of agricultural metrics, the hybrid Multi-Agent and completely containerized system includes pressure, humidity, and temperature to supply consumers with up-to-the-minute weather reports and predictions powered by artificial intelligence (Faid, A et al, 2021)

Issa, A. A. et al. 2024 suggested Farming in the Digital Age: Smart Agriculture with AI and IoT. The present article gives a thorough overview of the developments in digital agriculture management, focusing on how sensors, machine learning, the Internet of Things (IoT), and machine learning have improved farming efficiency and output. The essay discusses 5G networks and innovative agricultural solutions. They explored how these networks affect rural data transport and communication. This essay examines how AI and the IoT may transform farming, enhance food security, and promote sustainable development.

The authors introduced a LoRaWAN-based Internet of Things device that uses unsupervised machine learning and anomaly detection to provide control and monitoring solutions for smart farming. An innovative LoRaWAN-based Internet of Things (IoT) device control and monitoring solution, including performance evaluation parameters, experimental setup, and dataset, is presented. This research examined Isolation Forest's ability to detect temperature and humidity anomalies. The study revealed that both linear regression and random forest predictors of temperature change are accurate. This technology boosts precision agriculture, smart farming efficiency, production, and sustainability (Fahaad Alumfareh, M., 2024)

Precise crop monitoring and management utilizing AI and IoT was documented by Sharma et al. 2024. Innovative methods, for instance, agroBots, inspection by satellite, and high-throughput phenotyping, are covered in this overview. By automating processes like sorting, harvesting, and weed detection, these technologies drastically cut down on labor expenses and their adverse effects on the environment. For more informed judgments about fertilization, irrigation, and pest management, high-throughput phenotyping gathers data on plant attributes using robotics, spectral imaging, and remote sensing. DGPS and remote sensing provide accurate, real-time data to evaluate soil quality and track crop health.

Integrative methods in contemporary agriculture, such as the Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence (AI), were suggested by Delfani et al. (2024) for disease forecasting in the context of climate change. This article discusses the technical background, validation testing, developments, and significance of high-quality, publicly available data in crop disease forecasting models. It also explores the challenges and potential solutions for open-source, easily understandable AI models. The agricultural community can enhance these models by pooling its data in a novel research effort.

A study by Rahaman, M., et al. (2024) proposed using privacy-centric AI along with IoT technology to monitor and regulate country farms smartly. This project offers a comprehensive framework for intelligent remote farming surveillance that preserves privacy through computational intelligence and the web.

Susmitha, P., et al. (2014) discovered the creation and establishment of an atmospheric surveillance and control system. Collecting data on temporal dynamics is crucial because monitoring the weather is critical to human survival. Certain risks necessitate weather monitoring. The objective of this embedded system project is to track industry-specific weather conditions. The surveillance system featured an LPC1768 central processing unit (ARM9), as well as sensors for gas, humidity, and temperature, all in a single setup. Through Serial Communication, the microcontroller transmits sensor data to LABVIEW, which then stores the data in an Excel spreadsheet and, through the GSM module, sends SMS messages to our phones. The system is powered by small-form-factor circuits derived from the LPC1768 (ARM9) microprocessor. Embedded C applications can be written using the Keiluvision4 IDE. Microcontroller code is loaded over the JTAG interface.

Almalki, F. A. et al. 2021 proposed a low-cost platform for an environmentally innovative agricultural surveillance system utilizing uncrewed aerial vehicles and the World Wide Web of Things. This experimental study met the criteria for automated, real-time monitoring of environmental factors using both above-ground and below-ground sensors. According to empirical results, the novel combination of Internet of Things (IoT) sensors with drones enables the application and suggestion of both automated and human-made activities. Because of these astute moves, precision agriculture can significantly increase crop output while decreasing the usage of natural resources.

Improving agricultural circumstances through the use of internet-enabled devices was suggested by Doshi, J., et al. (2019). A multi-channel alert system is recommended for farmers to enhance crop yield. This alert system enables contemporary farmers to monitor their harvests. If farmers have access to real-time weather reports, they may be able to increase agricultural yields while reducing fertilizer and water usage.

As an example of an AI-based real-time weather forecast with optimal agricultural resources, Pierre, N., et al. (2023) presented the idea. This project aimed to develop an AI and IoT system that analyzes, manages, and schedules fertigation and irrigation using real-time weather and agricultural data. The system will also allow farmers to connect with their farms through smartphones or computers, which will help them optimize their energy and water resources.

Data collected in real-time from weather sensors, including pressure, temperature, humidity, and wind speed, is analysed using a Fuzzy Inference System (FIS) to forecast the rainfall rate for the next 24 hours in the agricultural area. Javaid, M., et al. (2023) uncovered the possible uses of predictive modelling in farming. This study identified and analyzed articles about AI in agriculture that were relevant to the topic. This paper aims to examine AI and its potential uses in agriculture. This presentation aimed to introduce the audience to AI and its numerous applications in agriculture, specifically focusing on the features that AI is presently monitoring.

Applying machine learning techniques for weather prediction in crop production was proposed by Kumari, S., et al. (2024). This study aimed to increase crop productivity using a machine-learning model for weather prediction. The survey of humidity, wind speed, direction, precipitation, and temperature uses various meteorological sources. Data outliers and missing values are removed during preprocessing, and essential information is extracted during feature engineering. Researchers trained and assessed prediction models using ensemble approaches, decision trees, and regression models.

A study conducted by Banerjee, S., et al. in 2023 debuted crop prediction using machine learning techniques applied to weather data broken down into regions. Predicting the weather before planting crops is helpful for farmers. In recent technological developments, machine learning can help with everyday issues. A machine may mimic human behavior and learn from its own experiences and other forms of data using this technique. Modern agriculture is a subfield of AI that uses various algorithms to forecast crop yields using weather records. It is a boon to farmers, who can use those forecasts to their advantage.

Researchers Das, S.K., 2024 discussed Innovation in Agronomy: The Internet of Things (IoT) and Artificial Intelligence (AI) for local weather forecasting. Researching weather prediction tasks that benefit agriculture using AI-ML and IoT techniques is an essential part of this study's contribution to the area.

It also incorporates real-time, high-resolution meteorological data provided by IoT technology, a significant advancement. Additionally, the article delved into important knowledge gaps, such as the substantial challenges farmers, especially those in rural regions, face when trying to incorporate AI into their weather forecasting and agricultural practices. These challenges include a lack of clear solutions and digital literacy. Further empirical studies are upgraded to improve the present designs and tackle these shortcomings.

Kamatchi, S. B., et al (2019) improve crop production using a recommender system based on weather forecasts. According to this study, combining Case-Based Reasoning (CBR) with other systems enhances system success and enables the prediction of the optimal crop to plant based on weather conditions.

Researchers applied collaborative filtering and case-based reasoning in their innovative hybrid system. The model's hybrid recommender system examined data collected at the district level to generate weather predictions and crop recommendations tailored to each district's unique agricultural pattern. Building on related work, my proposed research focuses on environmental monitoring and weather prediction.

3. Methodology

The needs of farming activities were considered when building an artificial intelligence-based answer for farmers. This solution was created with a human development perspective in mind. Thunderstorms, heatwaves, heavy rainfall, fog, and other severe weather phenomena have been better predicted by the India Meteorological Department (IMD) by 40-50% over the last five years, according to modern Indian meteorology.

Predicting severe weather occurrences has become significantly easier for the IMD, with an accuracy boost of 40-50% over the last several years. The accuracy for severe rainfall events remains below 80%, indicating a gap in the forecasting system that could lead to catastrophes. Here, prediction is planned with the ensemble technique of the Adaboost classifier because it is a powerful tool for classification and regression issues that is straightforward to deploy and achieves high accuracy.

As shown in Figure 1, the server with machine learning collects raw weather data from online sources for prediction. Environmental parameters, such as temperature, pressure, wind speed, and humidity, are considered to predict the weather in a particular location.

Real-time data were collected in an Excel file for historical data collection. This article demonstrates the AdaBoost technique with an alteration of weight assignment to enhance accuracy. The boosting technique achieves more accuracy in modifying the weight than Adaboost. Here, the proposed ML ensemble technique, Adaboost, and its modified version with a learning rate of 1.5 have been performed, and the results are compared with predicted parameters.

The modified Adaboost algorithm yields more accurate predictions than the original Adaboost algorithm. The server with machine learning will be incorporated into the Decision Support System (DSS) to achieve automated irrigation and crop monitoring for smart agriculture.

The DSS receives real-time data from IoT sensors in the farm field to predict the weather and inform farmers on how to perform according to the environment. This article demonstrates the successful implementation of ML technology in predicting weather, as shown below.

3.1. Adaboost Algorithm Flow Chart

The Adaboost algorithm flow chart is shown in Figure 2. The first input step involves fetching a large dataset, and the algorithm then creates the first base learner. This learner is initially a decision stump or a weak learner trained on the entire dataset with equal weights. It is a classification challenge because the target column is binary.

Before anything else, these data points will be given weights. Everything starts with an equal weight. Then, a repetition loop for T-weak learners takes place there. The method of determining the error rate (TE) after training is by the weights of the misclassified data points. The mistake rate is used to evaluate the performance of a weak learner, such as the decision stump.

The stump's impact on the final model directly relates to its performance. Revising the masses of samples as AdaBoost raises the weights of the incorrectly classified cases and lowers them for the true ones. At this point, the algorithm is prepared to tackle the more difficult problems in the subsequent round. For the following round, use the revised weights to create a new dataset.

If there are a lot of misclassified cases, the algorithm will prioritize the ones with the highest weights. The next step is to repeat the process as many times as necessary to train additional weak learners and update the weights until the required number of iterations has been reached. This method enables AdaBoost to construct a robust classifier by focusing on challenging data points, thereby improving the model's performance over time. The modified Adaboost criteria are that the learning rate is increased to 1.5, and the alpha value is also set to 0.5.

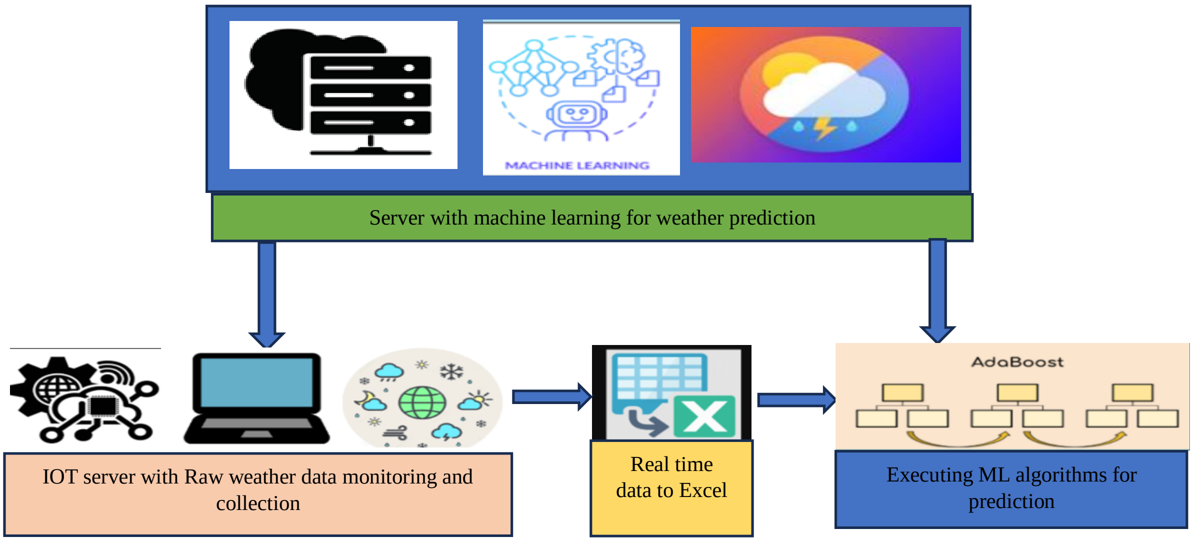

Fig. 1 Server with Machine Learning (weather prediction)

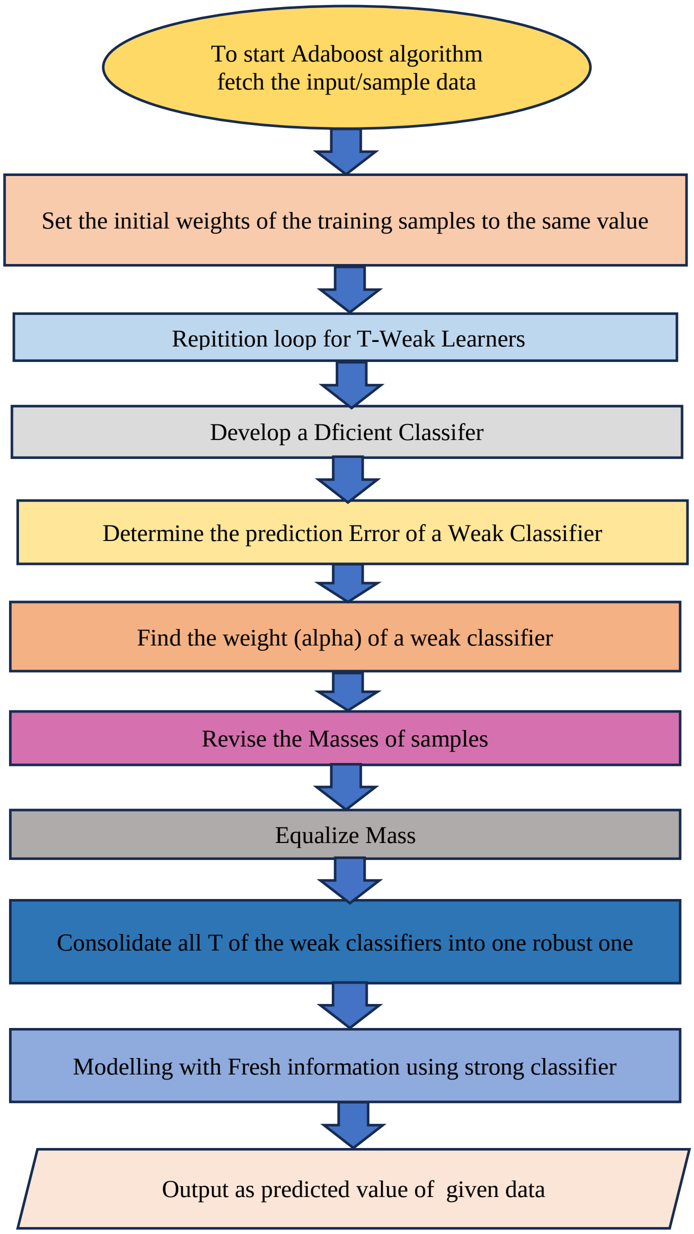

Fig. 2 Adaboost algorithm flowchart

3.2. Implementation

Python packages such as scikit-learn, pandas, and NumPy are required for the machine learning aspects of implementing the AdaBoost algorithm for weather prediction. The AdaBoost technique for classification tasks is available in sklearn. Ensemble.AdaBoostClassifier module. It is well-suited for predicting weather conditions, such as the range of possible temperatures or the presence or absence of rain. Separate the weather data into training and testing sets using sklearn.model_selection.train_test_split. Then, a test can be done on the model's accuracy with new data. sklearn. The metrics package provides metrics to measure the performance of your AdaBoost model, including MAE, RMSE, R-Square, Training time, and accuracy. Python's numpy library includes numpy.ndarray, which is excellent for doing calculations and feature scaling efficiently on data. For data visualization and model performance, optional libraries include Matplotlib and Seaborn. The Plotly platform is terrific for creating dynamic data visualizations.

4. Results and Discussion

The historical data, derived from Chennai's weather data from 2009 to 2024, is sourced from Kaggle and historic weather data. The Chennai Weather Dataset has a Comprehensive Record of Climate Variations from 2009 to 2024. Here, we have taken a comprehensive dataset that shows the weather patterns in Chennai, India, from 2009-09-09 to 2024-07-29. A wealth of weather data is available for analysis, comprising 6,488 distinct entries. Standout characteristics of data are time-sensitive. Nearly 25,000 data points are available in the historical weather data. A timestamp that includes the day, month, and year. Varying temperature, surface pressure, wind speed, and humidity are parameters. Overall, 26,000 data points have been taken as input data for the modeling. Changing the learning rate, utilizing various base learners, or altering the weight update rule are common modifications to AdaBoost. One alternative is to include a regularization term in the weights to avoid overfitting.

Next, a data set is split for training at the rate of 80 percent and testing at the rate of 20 percent. AdaBoost is an ML ensemble model that uses shallow trees as single-level "stumps" to generate a series of weighted decision trees. Every tree learns from the full dataset, but some have adaptive sample weights that prioritize instances incorrectly classified in the past. Train the Adaboost and modify the Adaboost models. The performance evaluation has been completed, and the values mentioned in Tables 1 and 2 are for season-wise predictions, while Table 3 provides month-wise predictions, accompanied by respective graphs. These graphs are shown in Figures 3(a), 3(b), 3(c), and 3(d) for season-wise predictions and Figures 4(a), 4(b), 4(c), and 4(d) for month-wise predictions. Day-wise predictions are shown in Table 4, with the respective graphs presented in Figures 5(a), 5(b,) 5(c), and 5(d).

4.1. Weather Parameters Predictions Season-Wise

Weather parameters have been predicted for the twelve months as prescribed, including months 1 and 2 for winter, months 3, 4, and 5 for spring, months 6 and 8 for summer, and months 9, 10, and 11 for autumn. Weather Parameters predictions are season-wise, as shown in Tables 1 and 2, and corresponding graphs in 3a, 3b, 3c, and 3d.

Table 1. Weather parameters predictions season-wise

Season	AdaBoost Temperature°C	Modified_AdaBoost Temperature°C	AdaBoost Humidity $g.m^{-3}$	Modified_AdaBoost Humidity $g.m^{-3}$
Summer	29.31058	30.01595	88.53721	84.32383
Winter	28.58638	27.35704	86.2847	83.86158
Autumn	29.02642	29.80777	88.53721	84.14164
Spring	30.52046	30.32	88.53859	87.33566

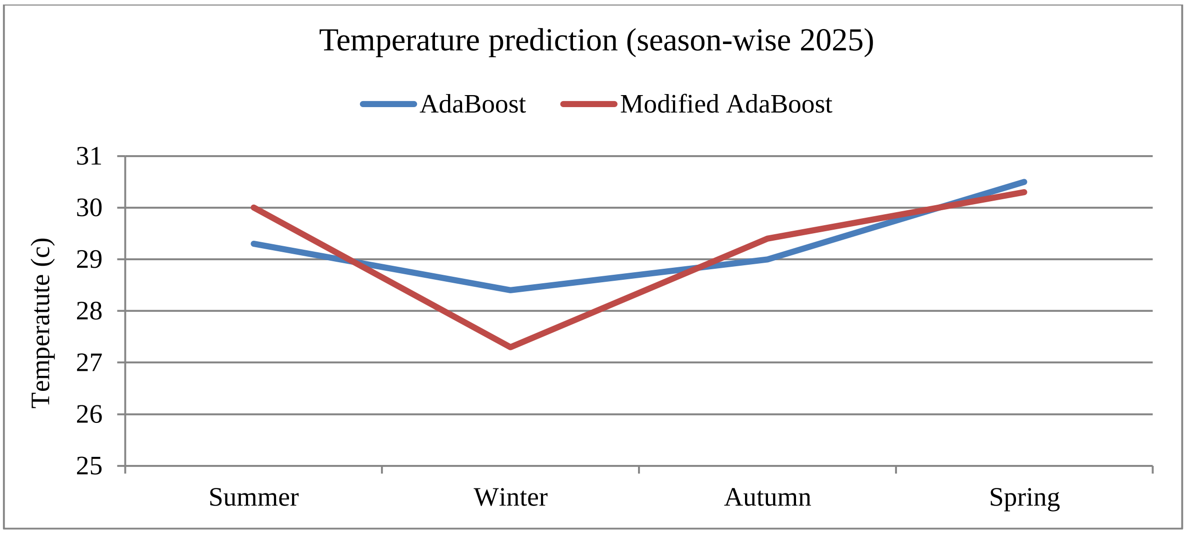

Fig. 3(a). Temperature prediction season-wise

Table 2. Weather parameters predictions season-wise

Season	AdaBoost Wind speed m/s	Modified_AdaBoost Wind speed m/s	AdaBoost Pressure bar	Modified_AdaBoost Pressure bar
Summer	12.47233	13.25593	1008.057	1004.558
Winter	13.73194	13.25593	1012.162	1012.003
Autumn	14.84173	14.32589	1008.784	1009.411
Spring	14.90017	14.30567	1009.028	1010.113

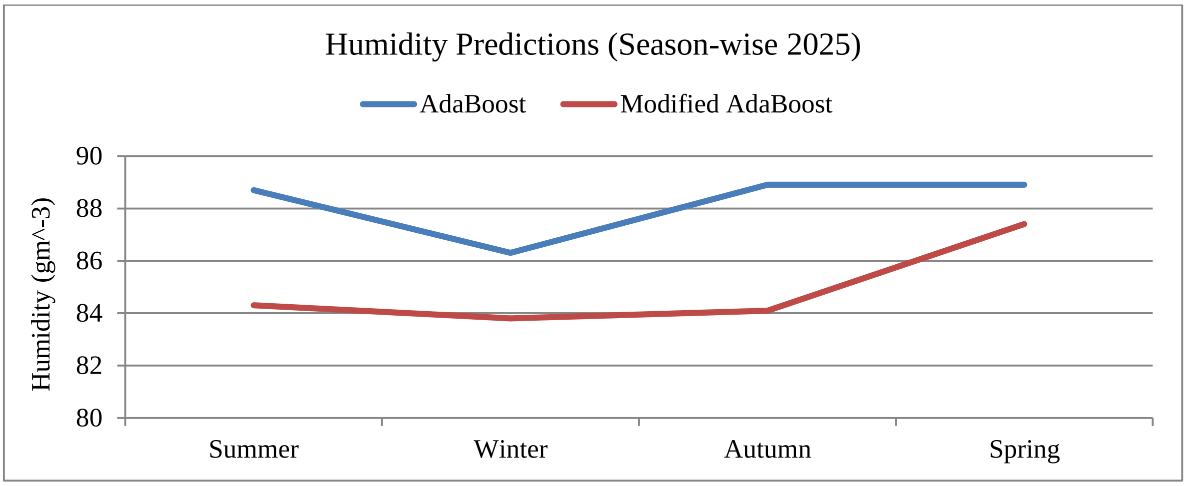

Fig. 3(b) Humidity prediction season-wise

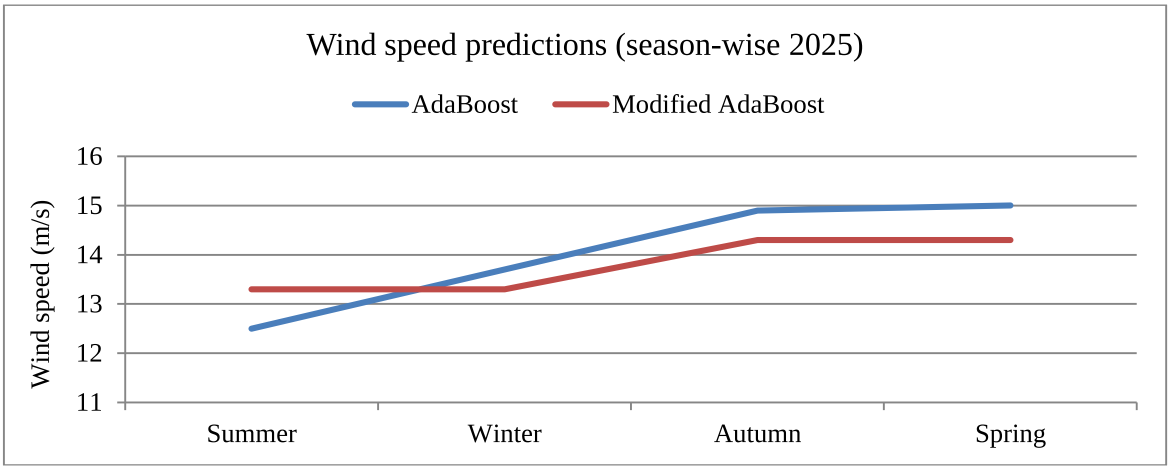

Fig. 3(c) Wind speed prediction season-wise

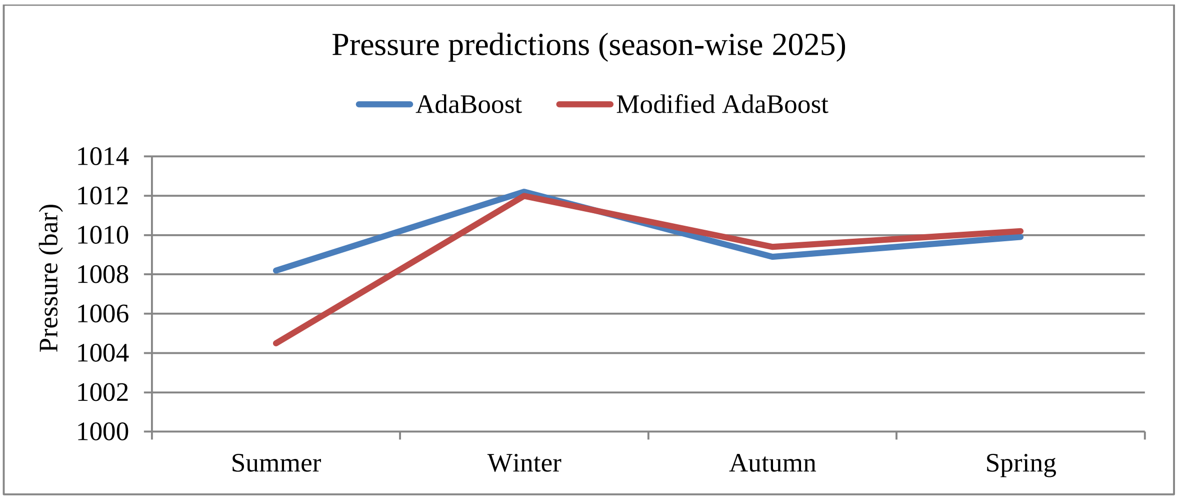

Fig. 3(d) Pressure prediction season-wise

4.2. Weather Parameters Predictions, Month-Wise

Weather parameters have been predicted for the next twelve months, as shown in Table 3, and the corresponding graphs are presented in Figures 4(a), 4(b), 4(c), and 4(d).

Table 3. Weather parameters predictions month-wise

Year	Month	Season	Model	Temperature °C	Humidity %rh	Wind Speed m/s	Pressure bar
2025	1	Winter	AdaBoost	28.58638	86.2847	13.73194	1012.162
2025	1	Winter	Modified_AdaBoost	27.35704	83.86158	13.25593	1012.003
2025	2	Winter	AdaBoost	28.58638	86.2847	13.73194	1012.162
2025	2	Winter	Modified_AdaBoost	27.35704	83.86158	13.25593	1012.003
2025	3	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
2025	3	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
2025	5	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
2025	5	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
2025	6	Summer	AdaBoost	29.31058	88.53721	12.47233	1008.057
2025	6	Summer	Modified_AdaBoost	30.01595	84.32383	13.25593	1004.558
2025	7	Summer	AdaBoost	29.31058	88.53721	12.47233	1008.057
2025	7	Summer	Modified_AdaBoost	30.01595	84.32383	13.25593	1004.558
2025	8	Summer	AdaBoost	29.31058	88.53721	12.47233	1008.057
2025	8	Summer	Modified_AdaBoost	30.01595	84.32383	13.25593	1004.558
2025	9	Autumn	AdaBoost	29.02642	88.53721	14.84173	1008.784
2025	9	Autumn	Modified_AdaBoost	29.80777	84.14164	14.32589	1009.411
2025	10	Autumn	AdaBoost	29.02642	88.53721	14.84173	1008.784
2025	10	Autumn	Modified_AdaBoost	29.80777	84.14164	14.32589	1009.411
2025	11	Autumn	AdaBoost	29.02642	88.53721	14.84173	1008.784
2025	11	Autumn	Modified_AdaBoost	29.80777	84.14164	14.32589	1009.411
2025	12	Winter	AdaBoost	28.58638	86.2847	13.73194	1012.162
2025	12	Winter	Modified_AdaBoost	27.35704	83.86158	13.25593	1012.003

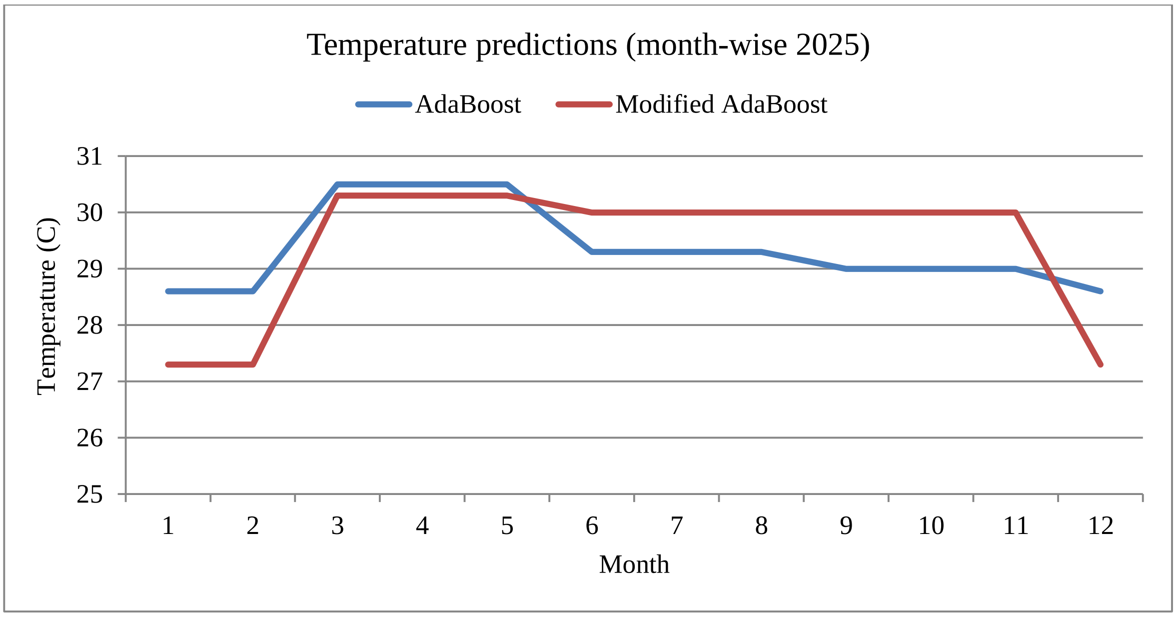

Fig. 4(a) Temperature prediction month-wise

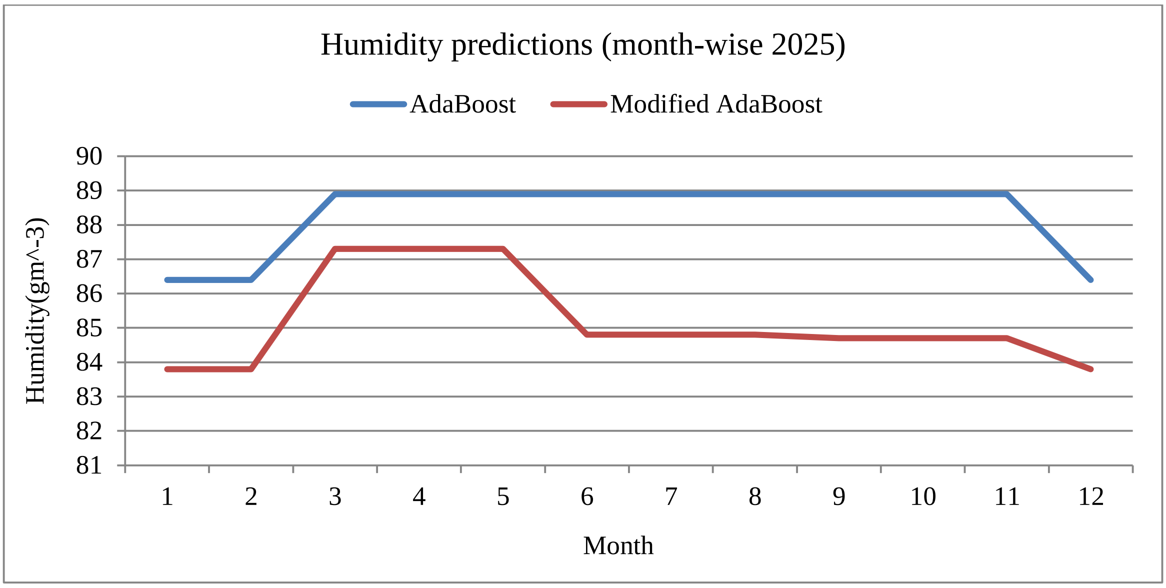

Fig. 4(b) Humidity prediction month-wise

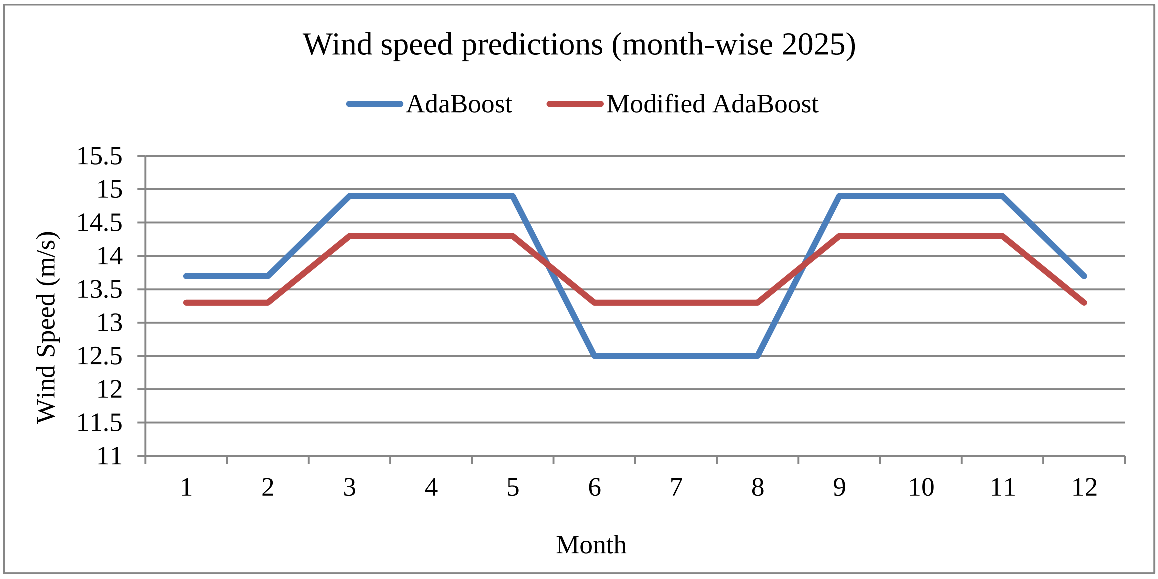

Fig. 4(c) Wind speed prediction month-wise

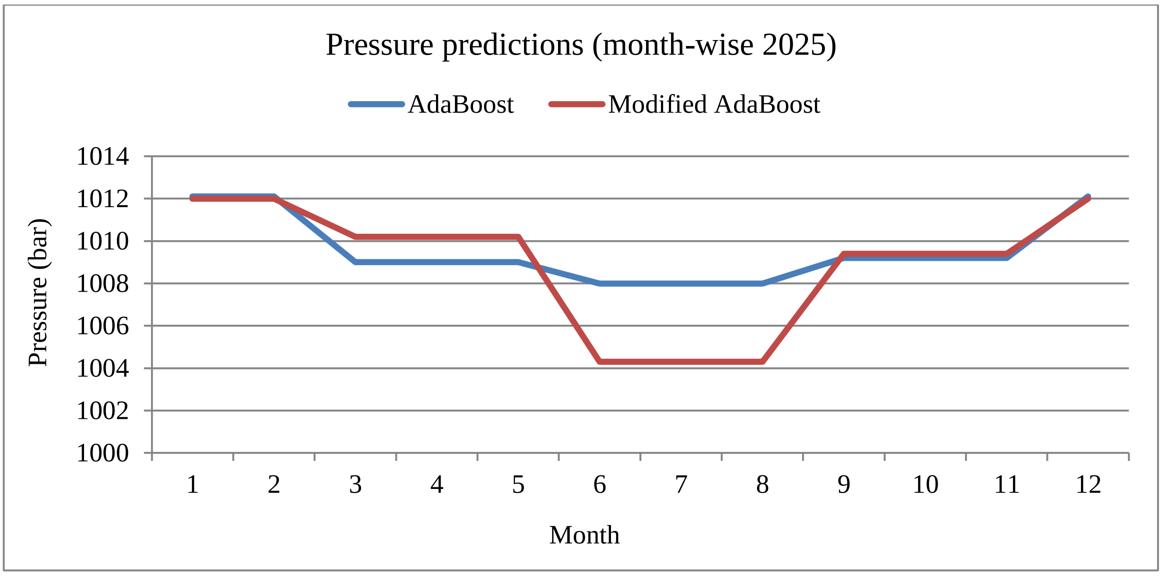

Fig. 4(d) Pressure prediction month-wise

4.3. Weather Parameters Predictions Day-Wise

The day-wise weather parameter prediction is done within 365 days. Here, the sample output is shown in Table 4, and the corresponding graphs are shown in Figures 5(a), 5(b), 5(c), and 5(d).

Table 4. Weather parameters predictions day-wise

Date	Month	Season	Model	Temperature °C	Humidity %rh	Wind Speed m/s	Pressure bar
17-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
17-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
18-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
18-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
19-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
19-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
20-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
20-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
21-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
21-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113
22-04-2025	4	Spring	AdaBoost	30.52046	88.53859	14.90017	1009.028
22-04-2025	4	Spring	Modified_AdaBoost	30.32	87.33566	14.30567	1010.113

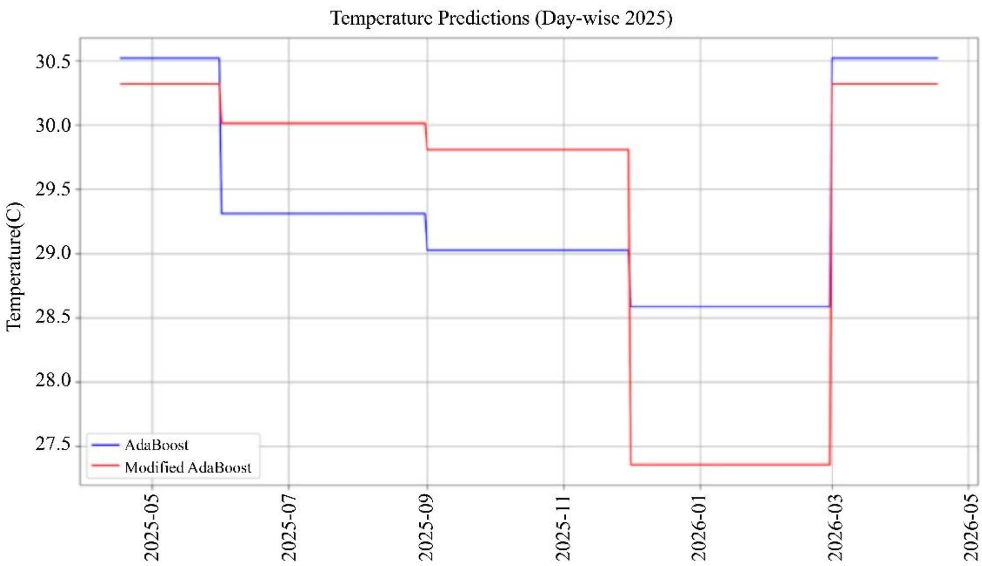

Fig. 5(a) Temperature prediction day-wise

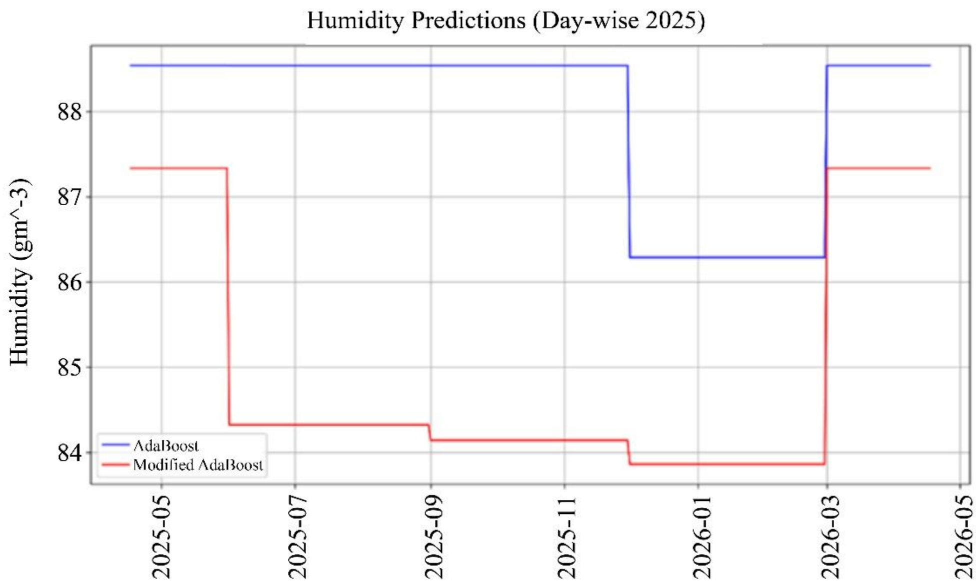

Fig. 5(b) Humidity prediction day-wise

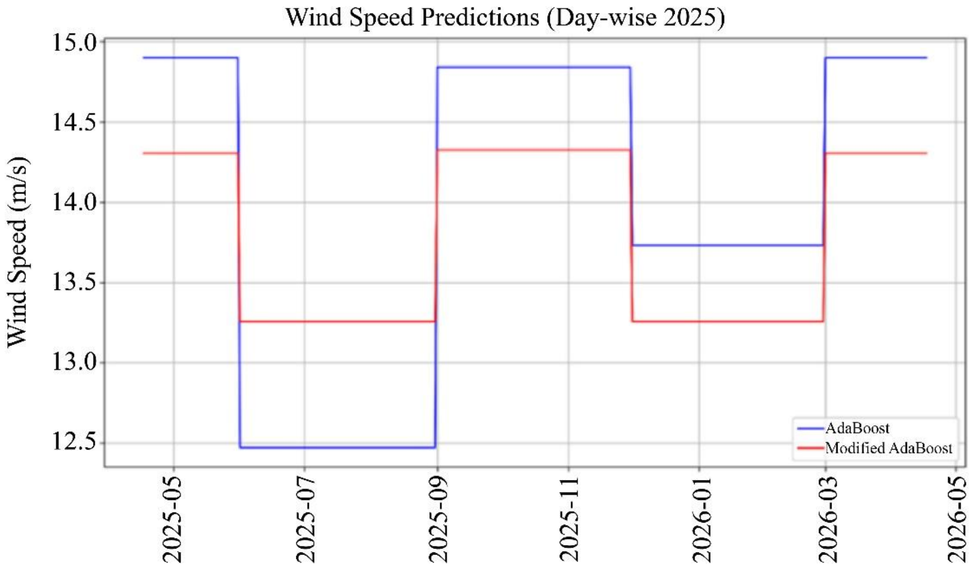

Fig. 5(c) Wind speed prediction day-wise

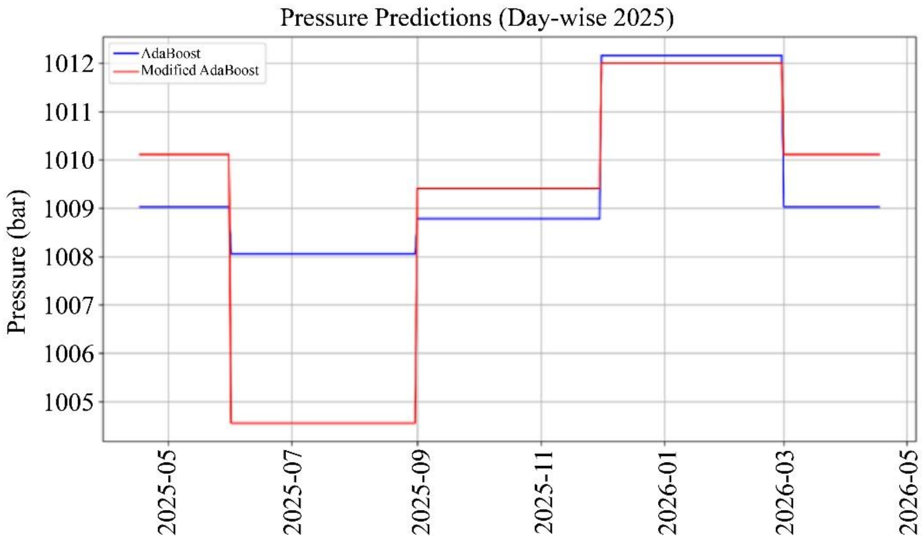

Fig. 5(d) Pressure prediction day-wise

4.4. Metrics of Adaboost and Modified Adaboost Algorithm

The Mean Absolute Error (MAE) is a metric for evaluating regression models that estimates the average magnitude of mistakes without taking their direction into consideration. The Mean Absolute Error (MAE) between the predicted and actual values is calculated. Calculated by averaging the squared discrepancies between the actual and anticipated values, the root-mean-squared (RMSquared) value is the result. The statistical measure of a model's fit to the data is R-squared (R^2), which indicates the percentage of the dependent variable's variance that can be explained by the model. A better fit, where the model explains more of the data's variability, is indicated by an R^2 value that is higher (closer to 1). Training with AdaBoost is typically computationally efficient, particularly when basis learners are shallow decision trees (stumps). However, the time it takes can grow depending on the complexity of the base learners and the number of repeats. The metrics for both models are presented in Tables 5 and 6. The AdaBoost approach compares the model's predictions on a test set to the actual values to verify correctness. Then, it splits the forecasts by the number of correct predictions. The accuracy and false rates of both algorithms are shown in Table 7.

Table 5. Metrics for the Adaboost algorithm's performance

Target	MAE	RMSE	R^2 Score	Training Time (s)
Temperature	1.265938	1.577845	0.744814	2.911027
Humidity	6.660391	7.880355	0.661919	3.106177
Wind Speed	3.758738	4.718315	0.174841	1.652328
Pressure	2.145465	2.696918	0.536688	2.192713

Table 6. Metrics for the modified Adaboost algorithm's performance

Target	MAE	RMSE	R^2 Score	Training Time (s)
Temperature	1.197956	1.493885	0.771249	5.940768
Humidity	6.680387	7.909512	0.659413	6.439621
Wind Speed	3.761094	4.708487	0.178275	6.239073
Pressure	2.083561	2.610958	0.565752	6.188181

Table 7. Accuracy and false rate of models

Model	Accuracy	False rate
Adaboost	87%	13%
Modified Adaboost	94%	6%

5. Conclusion

Developments in artificial intelligence and machine learning are creating new technological possibilities in agriculture. These technologies enable more accurate weather forecasts and environmentally friendly farming practices by continuously monitoring environmental factors, soil conditions, and crop development. Large data sets will be generated quickly due to the increased efficiency and accuracy of weather monitoring. Additionally, modified Adaboost yields better metrics than existing algorithms, including SVM and DT. In addition, weather stations connected to the Internet that update weather reports using real-time data collected by sensors have become crucial resources in various fields, including agriculture, disaster management, and climate research. Potentially actionable early warning of abrupt climate change could be attainable using AI-powered approaches. Connected devices that provide precise weather forecasts in real-time are a step in the right direction. This article investigates how to integrate AI-ML with IoT for weather prediction activities that farmers rely on. Here, the weather prediction is performed using both AdaBoost and a modified version of AdaBoost. The performance metrics of both models are derived and compared. This technology could help develop a local weather forecasting system, providing farmers with access to current local climate data. There would be a lower chance of economic losses, and farmers might complete their agricultural tasks more quickly if this happened. The future work will involve combining this weather monitoring node with smart farming to simplify irrigation and fertilisation processes.

References

[1] Salina Adinarayana et al., *Enhancing Resource Management in Precision Farming through AI-Based Irrigation Optimization*, How Machine Learning is Innovating Today's World: A Concise Technical Guide, pp. 221-251, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Anna Kowalska, and Hadeed Ashraf, “Advances in Deep Learning Algorithms for Agricultural Monitoring and Management,” *Applied Research in Artificial Intelligence and Cloud Computing*, vol. 4, no. 1, pp. 68-88, 2021. [Google Scholar] [Publisher Link]

[3] Tianfang Xu, and Feng Liang, “Machine Learning for Hydrologic Sciences: An Introductory Overview,” *Wiley Interdisciplinary Reviews: Water*, vol. 8, no. 5, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Xiaoling Shu, and Yiwan Ye, “Knowledge Discovery: Methods from Data Mining and Machine Learning,” *Social Science Research*, vol. 110, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Isaac Kofi Nti et al., “A Predictive Analytics Model for Crop Suitability and Productivity with Tree-Based Ensemble Learning,” *Decision Analytics Journal*, vol. 8, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Amine Faid, Mohamed Sadik, and Essaid Sabir, “An Agile AI and IoT-Augmented Smart Farming: A Cost-Effective Cognitive Weather Station,” *Agriculture*, vol. 12, no. 1, pp. 1-31, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Ali Ashoor Issa et al., “Farming in the Digital Age: Smart Agriculture with AI and IoT,” *E3S Web of Conferences*, vol. 477, pp. 1-6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Maram Fahaad Almufareh et al., “An Intelligent LoRaWAN-Based IoT Device for Monitoring and Control Solutions in Smart Farming through Anomaly Detection Integrated with Unsupervised Machine Learning,” *IEEE Access*, vol. 12, pp. 119072-119086, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Kushagra Sharma, and Shiv Kumar Shivandu, “Integrating Artificial Intelligence and Internet of Things (IoT) for Enhanced Crop Monitoring and Management in Precision Agriculture,” *Sensors International*, vol. 5, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Payam Delfani et al., “Integrative Approaches in Modern Agriculture: IoT, ML and AI for Disease Forecasting Amidst Climate Change,” *Precision Agriculture*, vol. 25, no. 5, pp. 2589-2613, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mosiur Rahaman et al., “Privacy-Centric AI and IoT Solutions for Smart Rural Farm Monitoring and Control,” *Sensors*, vol. 24, no. 13, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] P. Susmitha, and G. Sowmyabala, "Design and Implementation of Weather Monitoring and Controlling System," *International Journal of Computer Applications*, vol. 97, no. 3, pp. 19-22, 2014. [CrossRef] [Google Scholar] [Publisher Link]
[13] Faris A. Almalki et al., "A Low-Cost Platform for Environmental Smart Farming Monitoring System Based on IoT and UAVs," *Sustainability*, vol. 13, no. 11, pp. 1-26, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[14] Jash Doshi, Tirthkumar Patel, and Santosh kumar Bharti, "Smart Farming Using IoT, A Solution for Optimally Monitoring Farming Conditions," *Procedia Computer Science*, vol. 160, pp. 746-751, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[15] Nyakuri Jean Pierre et al., "AI Based Real-Time Weather Condition Prediction with Optimized Agricultural Resources," *European Journal of Technology*, vol. 7, no. 2, pp. 36-49, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[16] Mohd Javaid et al., "Understanding the Potential Applications of Artificial Intelligence in Agriculture Sector," *Advanced Agrochem*, vol. 2, no. 1, pp. 15-30, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[17] Shabnam Kumari, and P. Muthulakshmi, "Predicting Weather Conditions using Machine Learning for Improving Crop Production," *AI Applications for Business, Medical, and Agricultural Sustainability*, pp. 267-302, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[18] Saikat Banerjee, Shubha Chakraborty, and Abhoy Chand Mondal, "Machine Learning Based Crop Prediction on Region Wise Weather Data," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 1, pp. 145-153, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[19] Suman Kumar Das, and Pujyasmita Nayak, "Integration of IoT-AI Powered Local Weather Forecasting: A Game-Changer for Agriculture," *arXiv Preprint*, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[20] S. Bangaru Kamatchi, and R. Parvathi, "Improvement of Crop Production Using Recommender System by Weather Forecasts," *Procedia Computer Science*, vol. 165, pp. 724-732, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[21] Chennai 2009-2024 Weather data. [Online]. Available: https://www.kaggle.com/datasets/jkrithika/chennai-2009-2024-weather-data.
[22] Historical Weather API. [Online]. Available: https://open-meteo.com/en/docs/historical-weather-api?hourly=temperature_2m,wind_speed_10m,surface_pressure,relative_humidity_2m&latitude=13.08&longitude=80.27&start_date=2024-01-01&end_date=2025-01-01