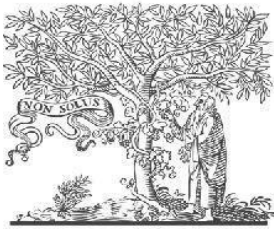


COPY RIGHT



ELSEVIER

SSRN

2024 IJIEMR. Personal use of this material is permitted. Permission from IJIEMR must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. No Reprint should be done to this paper; all copy right is authenticated to Paper Authors

IJIEMR Transactions, online available on 8th Aug 2024. Link

<https://ijiemr.org/downloads.php?vol=Volume-13&issue=issue08>

DOI: 10.48047/IJIEMR/V13/ISSUE 08/1

Title A Comprehensive Approach to Real-time Data Monitoring, Predictive Analytics and Automation

Volume 13, ISSUE 08, Pages: 01 - 09

Paper Authors

Anees Fatima, V. Archana Reddy, Shaik Gousiya Begum, D Anusha, Ch. Shwetha, Mohammed Muzeebuddin, Md Nazeer



USE THIS BARCODE TO ACCESS YOUR ONLINE PAPER

To Secure Your Paper as Per **UGC Guidelines** We Are Providing A Electronic Bar code

A Comprehensive Approach to Real-time Data Monitoring, Predictive Analytics, and Automation

Anees Fatima¹, V. Archana Reddy², Shaik Gousiya Begum³, D Anusha⁴, Ch. Shwetha⁵, Mohammed Muzeebuddin⁶, Md Nazeer⁷

^{1,2,3,4,5,6}Vidya Jyothi Institute of Technology, Hyderabad, India.

aneesit@vjit.ac.in, vareddy.cse@gmail.com, gousiyaai@vjit.ac.in

anushaaa21995@gmail.com, swethach1317@gmail.com, mujeebmtech07@gmail.com
nazeer8584@gmail.com

Abstract

This study presents an innovative IoT-based solution to modernize traditional farming practices through cost-effective, real-time agricultural and weather data monitoring. The study adopts a comprehensive data collection approach, utilizing advanced algorithms for weather forecasting, plant disease and pest detection, and recommendations for fertilizers and crops. The proposed study employs Wi-Fi, cellular access, and long-distance communication to automate key tasks such as irrigation, pest control, and inventory management, significantly enhancing operational efficiency. By optimizing soil nutrient levels and leveraging machine learning and image processing, focusing on nitrogen, phosphorus, and potassium. Proposed a hybrid XG-Boost algorithm integrating LSTM, ARIMA, Ridge Regression, ResNet-50, SVM, Random Forest, Extreme Gradient Boosting, and MobileNetV3. Obtained results demonstrate the effectiveness of this approach, delivering accurate weather forecasts, precise crop and fertilizer recommendations, and reliable pest and disease detection. The obtained result is useful and envisions a sustainable IoT solution that democratizes the benefits of smart agriculture, bridging the gap between traditional and modern practices for a more efficient, sustainable, and accessible future. Notably, the hybrid XG-Boost model achieves a 99.24% accuracy rate in crop yield prediction, surpassing the existing Crop Yield Prediction Algorithm and RNN.

Keywords — Smart Agriculture, IoT, Predictive Analytics, Machine Learning, Real-time Data Monitoring.

Introduction

Smart agriculture is essential for several reasons, driven by the challenges and opportunities facing modern farming and the broader agricultural sector. Traditional farming methods, while foundational, face challenges in today's dynamic world due to the lack of real-time monitoring and efficient operations, leading to lower productivity and

increased wastage. To address these issues, we propose an IoT-based solution utilizing Wi-Fi, cellular access, and long-distance communication methods for real-time monitoring of agricultural data and weather conditions. Our system automates critical tasks such as irrigation optimization, pest control, livestock monitoring, and field management. We maintain optimal soil

nutrient levels by integrating Machine Learning and image processing (N, P, K). We aim to enhance traditional agriculture's efficiency and make these advancements accessible to a broader farming community, potentially transforming the agricultural landscape. The integration of machine learning methods in precision agriculture has been widely explored, focusing on crop production forecasting, nitrogen status estimation, and climate variability management [1][2]. These studies emphasize sustainable development, particularly through deep reinforcement learning models for agricultural production prediction focusing on sustainable farming techniques [3]. Agricultural yield prediction has been extensively examined using machine learning methods and multi-layered, multi-farm datasets for grain crop production forecasting [4-6]. Recurrent neural networks (RNNs) have proven effective in enhancing crop yield projections. Through accurate disease diagnosis, deep learning techniques have been employed to mitigate crop losses. At the same time, drone technology has been utilized to detect leaf diseases in agricultural applications and address challenges related to weed categorization [4][5][6]. Research on plant diseases has delved into deep learning methods for disease classification and the development of drone-enabled leaf disease detection systems [7][8]. In precision agriculture, machine learning applications extend to disease detection, crop production prediction, weather forecasting, and IoT-based pest management systems [9]. Drone technology for detecting leaf diseases is particularly emphasized, showcasing the benefits of combining machine learning-

based disease diagnostics, recommendation systems for fertilizer application, and predictive models for disease outbreaks [10-12]. The literature also explores complex topics such as big data analytics and AI-driven smart weather data management for precision agriculture. This includes deep learning techniques for road weather detection with attention mechanisms. An all-encompassing strategy is employed to promote innovative and sustainable precision agriculture practices. This strategy combines soil analysis, machine learning-based crop recommendations, and a thorough investigation of deep learning-based pest identification and detection methods.

Methodology

A collaborative learning technique, XGBoost, is based on gradient boosting and decision trees. The XGBoost model is trained on the dataset used in this study to extract features and generate significant features. The XGBoost algorithm was applied, with stated parameters for the learning rate, maximum depth, and objective. The data was successfully gathered using the XGBoost model to reveal intricate patterns and connections, and it facilitates the discovery of nonlinear correlations and interactions between the unprocessed input characteristics. The goal function is regularization for generalization, shrinkage, and column subsampling to minimize overfitting, and gradient tree boosting for additive training are the three major components of XGBoost. This performance-boosting approach sequentially combines the outputs of weak learners. Regression trees are used for classification, and the gradient

boosting method is used for integration. The first step in evaluating various model performances to predict the weather is the publicly available data set <https://data.telangana.gov.in/dataset/telangana-weather-data-2023-2024>. For plant disease and pest detection, a diverse image dataset enhances model robustness by capturing a wide range of plant diseases and pests. The data set is publicly available from the Kaggle website, and its links are <https://www.kaggle.com/datasets/nirmalsankalana/crop-pest-and-disease-detection>; <https://www.kaggle.com/datasets/mathumithram/rice-pest-detection> <https://www.kaggle.com/datasets/dev523/leaf-disease-detection-dataset>

In fertilizer and crop recommendation, real-time data on soil conditions and nutrient levels are gathered through IoT sensors deployed in agricultural settings and then carefully preprocessed to facilitate accurate model development. This comprehensive approach to data collection prioritizes quality, diversity, and relevance, establishing a solid empirical foundation for subsequent stages, including machine learning model development and context-aware crop and fertilizer recommendations. Diverse image dataset for plant disease and pest detection undergoes detailed preprocessing, including cleaning and normalization techniques. To enhance model robustness, the detailed process of data preprocessing is shown in Figure 1. Figure 2 shows the proposed architecture of Enhanced Smart Agriculture for disease detection, Fertilizer Recommendation, Weather

Forecast, Crop Recommendation, and Pest Detection.

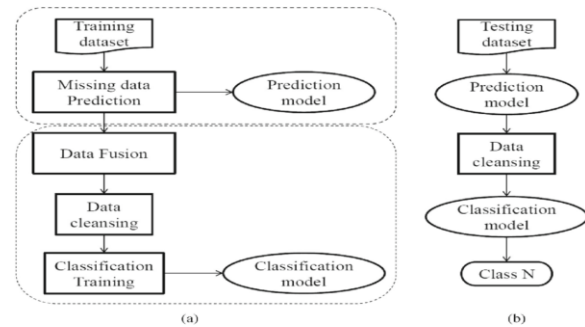


Fig. 1: Data Preprocessing Framework

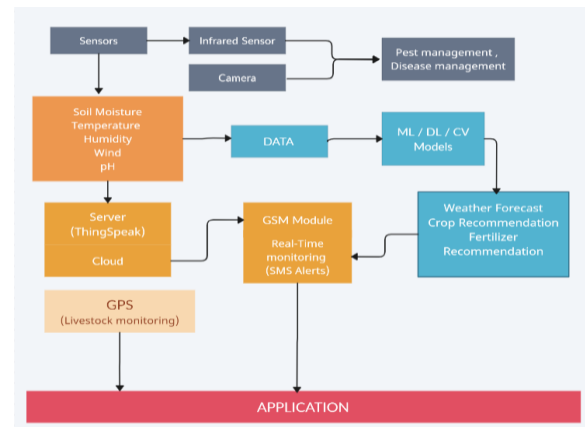


Fig. 2 Architecture of Enhanced Smart Agriculture

Disease Detection

The importance of the agricultural sector in supplying food and its significant contribution to growing economies and populations is emphasized. It is noted that plant diseases can lead to substantial losses in food production and threaten species diversity. This study highlights the potential benefits of early disease diagnosis through accurate and automatic detection techniques in improving food quality and reducing economic losses. This study uses advanced computer techniques, specifically deep learning with pre-trained models like CNN, ResNet-50, and VGG-16, to identify plant diseases effectively. [13][14] These models are fine-tuned using a manual dataset with

over 4,000 images of various plant diseases. This research is essential for improving food production and protecting plants from diseases.

Fertilizer Recommendation

To recommend the appropriate fertilizer for affected leaves based on severity levels, this proposed system utilizes input parameters like nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, moisture, soil type, temperature, humidity, soil pH, and the intended crop. The process begins by creating datasets through IoT sensors designed to monitor agricultural data. After analyzing the dataset, various preprocessing stages are employed. Following this, models like SVM and Random Forest classifier algorithms are trained using the processed data [15][16]. These input parameters can be manually entered or retrieved from sensors. Admin can categorize and store fertilizers based on disease severity levels, with recommended measurements tailored to the severity of the identified plant diseases. This approach provides a practical and data-driven solution for efficient fertilizer recommendations in agriculture. Among all the algorithms, Random Forest produced better results with an accuracy of 98.67%.

Weather Forecast

Weather conditions significantly influence pest prevalence, water availability, and fertilizer requirements in agriculture. Farmers rely on weather forecasts to decide crop cultivation and planting times. Precision irrigation and soil solarization are tailored to specific meteorological conditions. While short-range forecasts (1-7 days) are commonly used, medium-range (up to a month), long-range (up to a year), and hazardous weather forecasts also play crucial roles in planning field activities. Local meteorological forecasts help farmers prepare for severe weather events,

minimizing potential harm to crops and stored seeds. Different algorithms, including Ridge Regression, LSTM, and ARIMA, are used in the proposed system. [17-20] To distinguish regular approaches, these algorithms are integrated with a backtesting algorithm, which results in a better forecast than other approaches; results are shown in Table 1.

Crop Recommendation

The type of soil, climate, rainfall, temperature, and altitude in an area all influence which crops are best suited for cultivation. For instance, sandy soils are not ideal for water-dependent crops, while clay soils are unsuitable for those needing good drainage. Considering these factors, the proposed system uses SVM, Random Forest, and XGBoost, trained on data retrieved from the field sensors. [21-23] The Results of these algorithms are tabulated in Table 2.

Pest Detection

Detecting and managing insect pests that harm crops is crucial for successful farming. Traditional methods for pest detection are often slow and inefficient. The study uses a dataset of pest images from public sources, field observations, and online resources. The dataset includes diverse images of pests in different environments, resolutions, and angles. Images are standardized for pest size and visibility under various angles to test the detection algorithms. 1309 images were created, with 1178 for training and 131 for validation and testing. The images are annotated using free software called Labeling. The goal is to enhance the diversity and complexity of the dataset, and the images are resized for a balance between performance and computational efficiency in model training. As a result, these images are trained with Mobile Net [24], which results in better accuracy compared to other existing

approaches, and results have been shown in Fig. 2 and Fig. 3.

Model Evaluation

A suite of appropriate evaluation metrics was deployed to assess our diverse range of models employed across various agricultural services. For weather forecasting, including LSTM, ARIMA, and Ridge Regression models, performance was evaluated using metrics such as Mean Absolute Error (MAE), ensuring the models' ability to provide accurate weather predictions. In the context of crop and fertilizer recommendation, models including K-Nearest Neighbors (KNN), Linear Regression, and XGBoost were evaluated using the Confusion Matrix. This enabled the assessment of the models' precision in classifying crops and recommending suitable fertilizer types.

Pest Detection

The MobileNetV3 model with underlying architecture has been tested on a dataset of 3773 rice pest and disease images, achieving an accuracy of 92.3% and a mAP@ 0.5. The proposed MobileNet-CA model is a high-performance and lightweight solution for detecting rice and other crop pest, providing accurate and timely results for farmers and researchers [25].



Fig. 2 Training and Validation Accuracy



Fig. 3 Training and Validation loss

Leaf Disease Detection Results

The Resnet model with underlying architecture has been tested on a dataset of 1256 Leaf disease images, achieving an accuracy of 95.7% and a mAP@ 0.42. The following graph shows the accuracy and loss of training data over the epochs for the Resnet algorithm [26].

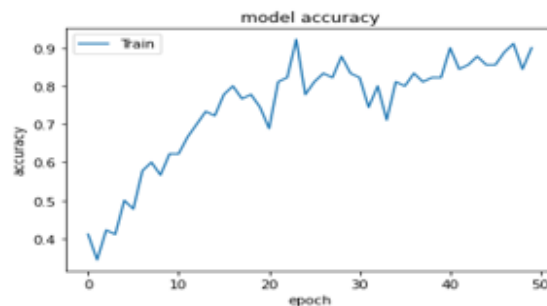


Fig. Model Accuracy

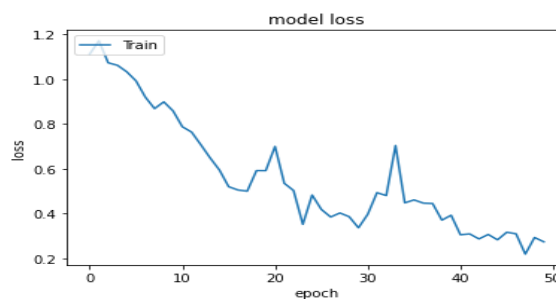
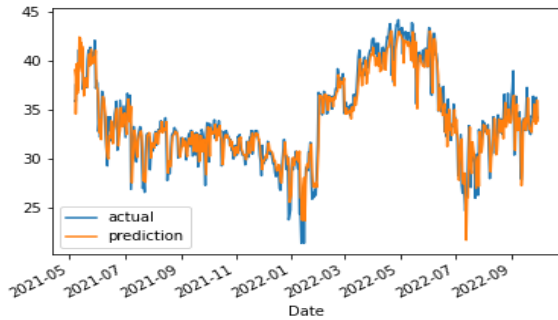


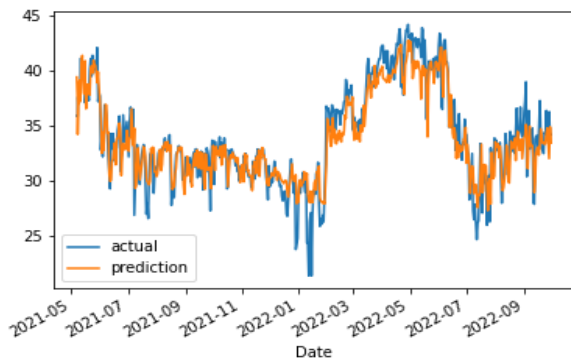
Fig Model loss

Weather Forecasting Model Results

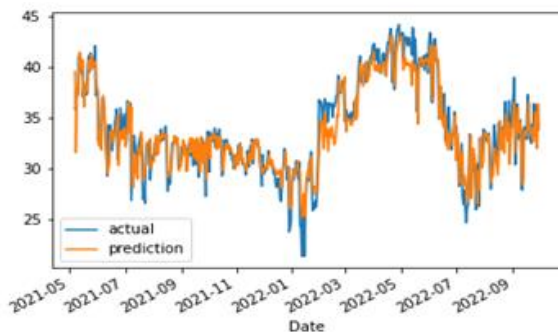
Various algorithms have been used to test the weather forecast data, and the evaluation metric MAE for each algorithm is recorded and tabulated.



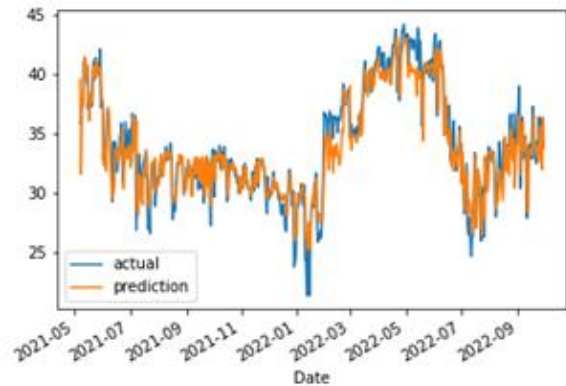
Ridge Regression



Random Forest



XgBoost



Support Vector Regression

Table 1 Comparison of Weather Forecast Results obtained from various Classification models.

| S NO | Algorithm | Mean Absolute Error |
|------|---------------------------------------|---------------------|
| 1 | Ridge Regression + Backtest algorithm | 1.298770 |
| 2 | Random Forest | 1.390408 |
| 3 | XG Boost | 1.345421 |
| 4 | Support Vector Regression | 1.345421 |
| 5 | Neural Network | 1.627084 |
| 6 | LSTM | 1.136421 |
| 7 | ARIMA | 1.342752 |

Fertilizer Recommendation

The type of soil, climate, rainfall, temperature, and altitude in an area all influence which crops are best suited for cultivation. For instance, sandy soils are not ideal for water-dependent crops, while clay soils are unsuitable for those needing good drainage. Considering these factors, the proposed system uses algorithms such as Decision Tree, SVM, Random Forest, and XGBoost, which are trained on data retrieved from the on-field sensors. The Results of these algorithms are tabulated below.

Table 2 Crop Recommendation Results of Various Algorithms

| S No. | Algorithm | F1 Score | Precision | Recall | Accuracy (%) |
|-------|------------------------|----------|-----------|--------|--------------|
| 1 | Random Forest | 0.96 | 0.98 | 0.88 | 99.65 |
| 2 | XG Boost | 0.90 | 0.97 | 0.84 | 98.56 |
| 3 | Naive Bayes Classifier | 0.92 | 0.94 | 0.85 | 96.74 |
| 4 | Support Vector Machine | 0.94 | 0.94 | 0.84 | 95.52 |
| 5 | Decision Tree | 0.89 | 0.89 | 0.79 | 85.94 |

Table 3 Results Comparison of various Algorithms

| Reference | Algorithm | F1 Score | Precision | Recall | Accuracy (%) | MAE |
|-----------|-----------------|----------|-----------|--------|--------------|------|
| [25] | RNN Model | 0.95 | 0.98 | 0.89 | 98.97 | 0.91 |
| [26] | CYPA | 0.97 | 0.98 | 0.92 | 98.98 | 0.93 |
| | Hybrid XG-Boost | 0.99 | 0.99 | 0.94 | 99.42 | 0.94 |

Conclusion

These research findings demonstrate that Mobile Net is the most accurate for pest detection, ResNet 50 excels in leaf disease detection, and Random Forest offers the best accuracy for fertilizer prediction in providing essential services to farmers. Moreover, The proposed hybrid XG-Boost algorithm was compared with the existing CYPA and RNN models by using various performance metrics such as F1 score, precision, recall, accuracy, and MAE, as shown in Table 5.5. This holistic approach harnesses technology to empower farmers, increase productivity, and promote agricultural sustainability in Telangana.

References

[1] Chlingaryan, A., S. Sukkarieh, and B. Whelan. 2018. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and Electronics in Agriculture* 151:61–69. <https://doi.org/10.1016/j.compag.2018.05.012>

[2] Desa, U. (2016). Transforming our world: The 2030 agenda for sustainable development. Elavarasan, D., and P. M. D.

Vincent. 2020. Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. *IEEE Access* 8:86886–901. <https://doi.org/10.1109/ACCESS.2020.2992480>

[3] Coviello, L., M. Cristoforetti, G. Jurman, and C. Furlanello. 2020. GBCNet: In-field grape berries counting for yield estimation by dilated CNNs. *Applied Sciences* 10 (14):4870. <https://doi.org/10.3390/app10144870>

[4] Hassan E, El-Rashidy N (2022) Review: mask R-CNN models. *Nile J Commun Comput Sci* 3(1):17–27. <https://doi.org/10.21608/njccs.2022.280047>

[5] Talaat FM (2022) Effective deep Q-networks (EDQN) strategy for resource allocation based on optimized reinforcement learning algorithm. *Multimed Tools Appl* 81(17). <https://doi.org/10.1007/s11042-022-13000-0>

[6] M. S. Islam, M. S. Hossain, and M. A. Hossain, “A Comprehensive Study of Plant Disease Detection Using Deep Learning Techniques,” in *Advances in Computer Science and Ubiquitous Computing*, vol. 1253, pp. 399-408, Springer, Cham, 2023,

https://doi.org/10.1007/978-3-031-25088-0_40

[7] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant Disease Detection and Classification by Deep Learning," *Plants*, vol. 8, no. 11, pp. 468, Nov. 2019, <https://doi.org/10.3390/plants8110468>

[8] Drone Technology Enabled Leaf Disease Detection and Analysis system for Agriculture Applications," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), pp. 1-6, Oct. 2021, <https://doi.org/10.1109/ICOSEC51865.2021.9591837>

[9] K. Saranya, P. Uva Dharini, P. Uva Darshni, and S. Monisha, "IoT Based Pest Controlling System for Smart Agriculture," 2019 International Conference on Communication and Electronics Systems (ICCES), 2019, pp. 1-5, <https://doi.org/10.1109/ICCES45898.2019.9002046>

[10] Nawaz MA, Khan T, Mudassar R, Kausar M, Ahmad J. Plant disease detection using internet of thing (IOT). *Int J Adv Comput Sci Appl*. 2020. <https://doi.org/10.14569/IJACSA.2020.0110162>

[11] Zhang, Y., & Zhang, X. (2022). A Research Review of Pest Identification and Detection Based on Deep Learning. In 2022 34th Chinese Control and Decision Conference (CCDC) (pp. 1-6). IEEE <https://doi.org/10.1109/CCDC55256.2022.10034017>

[12] Li, Y., & Li, J. (2020). Insect Pest Detection and Identification Method Based on Deep Learning. In 2020 3rd International Conference on Computer Science and Artificial Intelligence (CSAI 2020) (pp. 1-5).

[13] S. K. Singh, S. K. Singh, and A. K. Singh, "Disease Prediction using machine learning algorithms," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering

(ICACITE), 2022, pp. 1-5, <https://doi.org/10.1109/ICACITE53722.2022.9823744>

[14] S. K. Singh and S. K. Singh, "Systematic review of deep learning techniques in plant disease detection," *Journal of Crop Science and Biotechnology*, vol. 23, no. 5, pp. 337-346, 2020, <https://doi.org/10.1007/s13198-020-00972->

[15] D. Jayashree, O. Pandithurai, L. Paul Jasmin Rani, Praveena K. Menon, Mahek V. Beria & S. Nithyalakshmi, "Fertilizer Recommendation System Using Machine Learning," in *Disruptive Technologies for Big Data and Cloud Applications*, vol. 905, pp. 709-716, Springer, Singapore, 2022, https://doi.org/10.1007/978-981-19-2177-3_66

[16] S. UshaKiruthika et al., "Fertilizer Recommendation System Using Machine Learning," in *Proceedings of the 2022 International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2022, pp. 1-6, <https://doi.org/10.1109/ICICCS.2022.9610318>

[17] S. Kumar, S. K. Singh, and S. Kumar, "Precision Agriculture Through Weather Forecasting," 2022 International Conference on Digital Transformation and Intelligence (ICDI), 2022, pp. 1-6, <https://doi.org/10.1109/ICDI57181.2022.10007299>

[18] S. M. A. K. Samarakoon, S. A. C. N. Perera, and K. D. G. I. Jayawardena, "A novel approach for weather prediction for agriculture in Sri Lanka using Machine Learning techniques," 2021 International Research Conference on Smart Computing and Systems Engineering (SCSE), 2021, pp. 1-6, <https://doi.org/10.1109/SCSE53661.2021.9568319>

[19] B. Bochenek and Z. Ustrnul, "Machine Learning in Weather Prediction and Climate Analyses—Applications and Perspectives,"

Atmosphere, vol. 13, no. 2, p. 180, 2022,
<https://doi.org/10.3390/atmos13020180>

[20] A. Khan, M. A. Khan, and S. A. Khan, “Deep Learning with Attention Mechanisms for Road Weather Detection,” in Proceedings of the 2021 International Conference on Intelligent Computing and Control Systems (ICICCS), 2021, pp. 1-6, <https://doi.org/10.1109/ICICCS.2021.9610318>

[21] Crop Recommendation System using Machine Learning Algorithms” by S. K. Singh, S. K. Singh, and A. K. Singh, published in the 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 1-5, <https://doi.org/10.1109/ICACITE53722.2022.9823744>

[22] Crop Recommendation System using Machine Learning by S. UshaKiruthika et al., published in the Proceedings of the 2022 International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1-6, <https://doi.org/10.1109/ICICCS.2022.9610318>

[23] Soil Analysis and Crop Recommendation using Machine Learning” by Chouaib El Hachimi et al., published in Agriculture, vol. 13, no. 1, p. 95, 2023, <https://doi.org/10.3390/agriculture13010095>

[24] “Pest Detection and Recognition: An approach using Deep Learning Algorithm” S. S. Kulkarni , <https://doi.org/10.1109/CCIP57447.2022.10058692>

[25] Talaat FM, Ali HA, Saraya MS et al (2022) Effective scheduling algorithm for load balancing in fog environment using CNN and MPSO. Knowl Inf Syst 64:773–797. <https://doi.org/10.1007/s10115-021-01649-2>

[26] Crop yield prediction algorithm (CYPA) in precision agriculture based on IoT techniques and climate changes, Fatma M.

Talaat1, Neural Computing and Applications (2023) 35:17281–17292, Springer, <https://doi.org/10.1007/s00521-023-08619-5>