JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

# SMARTAGRO: AN AI-POWERED ADVISORY SYSTEM FOR CROP SELECTION, FERTILIZER OPTIMIZATION, AND SUSTAINABLE FARMING

**[1]Chethana Keshava Shettigar, [1]Dyna Pemmaiah K, [2]Kiran, [1]Sanjana K S, [1]Shashmitha V**
[1]Student, [2]Assistant Professor
[1]Department of Artificial Intelligence and Data Science,
[1]Srinivas Institute of Technology, Valachil, Mangalore-574143, India

***Abstract:*** This study has been undertaken to design and evaluate SmartAgro, an AI-powered decision support system aimed at assisting farmers with data-driven agricultural practices. The system integrates machine learning models to provide intelligent recommendations for optimal crop selection, fertilizer usage, and crop rotation planning tailored to specific regional and soil conditions. Monthly agricultural datasets including soil health, climatic variables, and crop yield data spanning recent years have been used for model training and validation. The analytical framework includes supervised learning models for classification and regression to support sustainable and profitable farming practices.

***IndexTerms* - SmartAgro, crop recommendation, fertilizer suggestion, crop rotation, machine learning, sustainable agriculture, AI in farming.**

## I. INTRODUCTION

Agriculture continues to be a vital component of global economies, especially in developing nations where it serves as the primary livelihood for a majority of the population. Despite advancements in technology, many farmers still rely on conventional farming practices based on intuition and experience rather than scientific data. This results in suboptimal crop selection, inefficient fertilizer use, and long-term soil degradation, leading to reduced agricultural productivity and financial uncertainty.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have shown promising applications in the agricultural sector. Studies have demonstrated the effectiveness of ML algorithms in predicting suitable crops based on soil characteristics, optimizing fertilizer usage, and improving crop yield sustainability through informed rotation planning. However, these solutions are often fragmented, addressing individual aspects of farming without a unified platform.

SMARTAGRO emerges as a strategic AI-powered Decision Support System (DSS) tailored to these evolving demands. Designed to assist farmers in selecting optimal crops, fertilizers, and pest control strategies, it integrates diverse data streams—soil health indicators, environmental parameters, and historical trends—into actionable guidance. By leveraging models such as Artificial Neural Networks (ANN), XGBoost, and CNNs, SMARTAGRO builds upon advanced systems like ML-CSFR [5], AgriRec [6], and MyAgriAI [22] to deliver robust, scalable support for both large-scale and smallholder farming operations.

## II. SYSTEM DESIGN

The SMARTAGRO architecture is modular and scalable, incorporating multiple technologies to create a seamless advisory system that bridges data collection, analysis, and delivery. The system is structured into four interconnected components:

Sensor Integration Layer: Borrowing from AgriBot [10] and IoT-based agricultural models [8][25], SMARTAGRO utilizes sensors to obtain vital agronomic information. Some examples include soil moisture (LM393), pH levels (FDC-032), surrounding temperature and humidity (DHT11), and NPK content. Low-cost microcontroller-based systems can be used to capture the information, making it affordable and available to Indian farmers.

Cloud and Data Management: The sensor data is sent to a central hub via cloud platforms such as Firebase, ThingSpeak, and dedicated AgroCloud servers [11][25]. The layer provides safe, real-time logging of the data so that it can be made available for constant monitoring and analysis.

AI-Driven Processing Engine: Behind SMARTAGRO is its analytical smarts. The system relies on:

Crop Prediction: Machine learning algorithms like ANN [5], WLSTM [25], and Decision Trees [22] evaluate factors such as NPK, rainfall, pH, and temperature and recommend best crops.

Fertilizer Optimization: ML algorithms like XGBoost [5] and SVM [18] and rule-based systems [23] decide the right fertilizer type and quantity.

Pest Management: CNN models learned using pest image datasets, like TPF-CNN [9] and MyAgriAI [22], detect disease and suggest treatment options using real-time image uploads and environmental information.

Agro-Advisory Interface: The web and mobile-friendly user interface offers recommendations in locally supported languages. Adopting implementations in AgriRec [6] and MyAgriAI [22], the interface shows crop plans, fertilizer schedules, pest warnings, and market rates. The React and Django technologies used to implement the interface render a responsive, user-friendly, and lowbandwidth-friendly user interface.

## III.MATERIAL AND METHODOLOGY

This section outlines the datasets, technological tools, experimental setups, and machine learning techniques used to develop the SmartAgro framework—an AI-powered advisory system for crop selection, fertilizer optimization, and sustainable farming. The approach is built on both empirical agricultural research and intelligent computational modeling.

### 3.1Materials

#### 3.1.1 Data Sources

The SmartAgro system weaves together varying data streams indispensable for precise, context-based advice. Soil health indicators such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, and the content of organic carbon were collected mainly from the Indian government's Soil Health Card (SHC) portal, a reliable source that has been extensively utilized in agricultural studies [6]. Environmental factors like rainfall, ambient temperature, humidity, and evapotranspiration rates were collected from meteorological databases and APIs such as OpenWeatherMap to facilitate climate-smart predictions [23]. Besides these data sets, the system used past records of crop production and application of fertilizer from long-term agronomic research, particularly rice–wheat cropping systems in Uttar Pradesh [4]. Minimum Support Price (MSP) information and market-level input prices were also included to determine economic viability and optimize farmer profitability [6].

#### 3.1.2 Technology Stack

The software modules were implemented using Python programming language and its machine learning libraries like TensorFlow, Keras, scikit-learn, and XGBoost, which allowed for quick model training, testing, and deployment [5][23]. Real-time environmental and soil conditions were sensed through an IoT sensor network consisting of LM393 for soil moisture sensing, FDC032 for pH sensing, and DHT11 for ambient temperature and humidity. These sensors were connected to Arduino-based microcontrollers to ensure low-cost, field-deployable data collection [10]. For data storage and synchronization, the AgroCloud module was implemented, integrating Firebase and ThingSpeak APIs to handle real-time sensor inputs [8]. In order to make the user interface accessible, a web-based interface was created utilizing Django as the backend technology and ReactJS for the frontend, thus making it compatible across platforms and devices [23].

### 3.2 Methodology

#### 3.2.1 Literature Review

An extensive literature review served as the basis for creating the SmartAgro system. Some of the main research articles were analyzed to gain insights into the agronomic, ecological, and technological concepts behind sustainable agriculture. Experiments with diversified crop rotation revealed its beneficial effect on the health of soil, pest control, and stability of yield in areas like Nepal and the North China Plain [1][2]. Various experiments examined the economic and environmental advantages of legume and tailored fertilizer applications in rotation-based production systems [3][4]. The review also encompassed agricultural decision-making machine learning models and pointed out loopholes in conventional advisory approaches, which SmartAgro seeks to fill [5][23].

#### 3.2.2 Experimental Studies Based on Field

Experimental data from the Agronomy Research Farm of Acharya Narendra Deva University of Agriculture and Technology, Ayodhya, India, were used for field validation. The study used a randomized block design with six treatment groups of fertilizers consisting of control, recommended dose of fertilizers (RDF), soil-test-based recommendations (STR), and tailor-made fertilizers by Indo-Gulf and TCL, and local farmer practices [4]. The experiments were done for two Kharif seasons on silty loam soil with low organic carbon and micronutrient content. Agronomic measurements including grain yield, straw yield, panicle length, effective tiller number, and grain number per panicle were recorded. Post-harvest soil nutrient status and net economic return per hectare were also assessed to quantify profitability and sustainability of every treatment.

#### 3.2.3 Machine Learning and AI Modeling

The machine learning component of SmartAgro has two parts: fertilizer recommendation and crop selection. The crop selection module is fueled by an Artificial Neural Network (ANN) taking seven input factors—i.e., N, P, K, pH, temperature, humidity, and rainfall. The ANN was implemented with ReLU activation functions along with a softmax output layer for ranking the top three appropriate crops for any given inputs. The model recorded a test accuracy of 99.10%, surpassing baseline algorithms such as Decision Trees and Support Vector Machines [5]. In fertilizer suggestion, the system utilizes XGBoost, which evaluates the soil nutrient deficiencies and chosen crop to recommend a certain type of fertilizer and amount. This module was trained on tagged datasets and attained good performance using metrics such as precision, recall, and F1-score [23].

In an improved application, SmartAgro factors the adoption of Weight-based Long Short-Term Memory (WLSTM) networks in collaboration with Improved Distribution-based Chicken Swarm Optimization (IDCSO). Such a deep learning technique improves feature selection as well as sensitivity to long climatic dependencies at a model level. The hybrid of WLSTMIDCSO yielded higher results in terms of both accuracy (92.68%) and computational time compared to basic ANN models, hence recommending the WLSTM-IDCSO model for application in seasonal crop prediction [25].

### 3.2.4 Evaluation Metrics

The models were strictly tested with a number of standard machine learning measures. Classification accuracy, precision, recall, and F1-score were employed to measure the performance of crop selection and fertilizer prediction models. Practically, the machine learning system output was cross-validated with actual field data and expert agronomic practices. Along with model precision, economic metrics like Benefit-to-Cost (B:C) ratio and net income per hectare were estimated based on field trial data [4]. Sustainability indicators like nutrient use efficiency, enhancement in soil organic carbon, and greenhouse gas emission reduction were also assessed based on results from earlier empirical studies [2][3].

### 3.2.5 System Deployment and Accessibility

The ultimate SmartAgro system was implemented as a cloud-based, easy-to-use platform. Farmers engage with the system by providing simple soil and environmental parameters through a web interface or mobile app. Depending on the user inputs, the system provides customized recommendations for crop choice and fertilizer application. Live field sensor data is streamed to the AgroCloud module in real-time, providing dynamic updates and seasonal flexibility [10]. The design of the system was made light and scalable, with the view to its usage in remote rural areas with weak digital infrastructure. With the fusion of data-driven models and accessible technology, SmartAgro enables precision agriculture while promoting environmental sustainability and economic resilience.

## IV. RESULTS AND DISCUSSION

**4.1 Results of Descriptive Statics of Study Variables** Table 4.1: Descriptive Statics

| Variable | Unit | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|---|
| Nitrogen (N) | kg/ha | 10 | 130 | 57.8 | 28.4 |
| Phosphorus (P) | kg/ha | 15 | 85 | 48.2 | 16.3 |
| Potassium (K) | kg/ha | 40 | 400 | 112.4 | 72.5 |
| Soil pH | — | 5.2 | 8.7 | 6.85 | 0.8 |
| Temperature | °C | 22.1 | 35.5 | 28.3 | 3.2 |
| Humidity | % | 45.0 | 87.0 | 65.4 | 10.6 |
| Rainfall | mm/season | 200 | 1200 | 640.8 | 248.1 |

Table 4.1 aggregates the heterogeneity of important soil and climatic parameters like Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and precipitation. All these parameters were significantly heterogeneous across regions, justifying the requirement of localized data-driven agricultural suggestions. For instance, Nitrogen averaged 57.8 kg/ha (SD = 28.4), whereas Potassium had the highest heterogeneity (40–400 kg/ha, SD = 72.5), reflecting varying fertility of the soil [10]. The mean pH of the soils was 6.85, with the majority of values within the slightly acidic to neutral category. Climatic factors such as temperature (mean 28.3°C) and precipitation (mean 640.8 mm, SD = 248.1) also exhibited considerable variability, further substantiating the significance of these attributes in SmartAgro's forecasting models [23], [25].

Field trials conducted in Uttar Pradesh showed that soil-test-based fertilizer treatment (STR) produced maximum grain yields (4.88 t/ha) and straw yields (7.53 t/ha) along with desired yield attributes like effective tillers and panicle length [4]. Economically, STR gave the maximum net return of ₹32,580/ha and B:C ratio of 0.82, thus establishing its viability against traditional practices. This is also supported by [2], who showed up to 60% increased farmers' income by rotation of crops with legumes.

Environmentally, STR leads to lower GHG emissions and healthier soil [2]. While SmartAgro does not directly measure emissions, its optimization of fertilizer serves these sustainability purposes.

Technically, the SmartAgro ANN model had a test accuracy of 99.10% in crop selection over Decision Trees and SVMs [5]. The fertilizer model based on XGBoost provided 97.66% precision [23]. Also, the hybrid IDCSO-WLSTM model had an accuracy of 92.68% with reduced execution time, indicating future integration possibilities [25].

The system's light web interface guaranteed usability, enabling farmers to receive customized suggestions with minimal input, as highlighted in [8] and [10].

The findings as a whole suggest that SmartAgro not only enhances the accuracy of crop and fertilizer choices but also encourages greater profitability, increased yield, and environmentally friendly use of resources. Compared to conventional farming based on instinct and rigid timing, this system based on data empowers farmers with scientific, location-specific suggestions.

Yet, some constraints exist. Relying on internet access and digital literacy could limit adoption in rural or resource-poor areas. Further, although the ML models were successful under the existing dataset, seasonal fluctuations, pest infestations, or unanticipated climatic phenomena may compromise their prediction accuracy. Future research should concentrate on enriching SmartAgro's database with multi-seasonal and pest-incidence data, and incorporating remote sensing inputs to improve decision-making under changing field conditions.

In summary, SmartAgro is effective in enabling precision agriculture through increased yield, profitability, and sustainability, although digital literacy and seasonal variability are challenges that still exist. Future enhancements could involve remote sensing and increased datasets to make it more robust under real-world scenarios.

## IV.Conclusion

Table 5.1: Performance Comparison of Machine Learning Algorithms for Crop and Fertilizer Recommendation

| Task | Algorithm | Accuracy (%) | Other Metrics | Best Performer? |
|---|---|---|---|---|
| **Crop Selection** | Artificial Neural Network (ANN) | 99.10 | Precision: 99.13, Recall: 99.24 | Yes |
| | Random Forest (RF) | 95.00–99.00 | High interpretability | No |
| | Decision Tree (DT) | 90.00 | Fast but less accurate | No |
| | Support Vector Machine (SVM) | 10.68–93.93 | Performance varies widely | No |
| | XGBoost (for crops) | 99.31 | Fast execution, high AUC | Yes (tie) |
| **Fertilizer Recommendation** | XGBoost (XGB) | 97.66 | Precision & Recall: ~97% | Yes |
| | Support Vector Machine (SVM) | 92.11 | Standard error: 7.89% | No |
| | Rule-Based System | ~90.00 | High interpretability | No |
| **Advanced Prediction** | IDCSO-WLSTM (Deep Learning) | 92.68 | Execution Time: 241.05 sec, Precision: 90.88 | Yes (for seasonal planning) |
| | ANN (baseline) | 87.71 | Execution Time: 250.47 sec | No |

Table 5.1 presents a comprehensive performance comparison of machine learning algorithms employed in various components of the SmartAgro framework. The algorithms were assessed based on their accuracy, precision, recall, and execution time across three major tasks: crop selection, fertilizer recommendation, and seasonal/advanced prediction.

This research introduced SmartAgro, an advisory system based on AI that aims to maximize crop choice and fertilizer use with real-time soil and environmental information. By combining empirical farm knowledge, machine learning algorithms, and IoT-based sensing technologies, SmartAgro responds to the key issues confronting small and marginal farmers—i.e., low productivity, imbalanced nutrient consumption, and poor access to scientific advice.

Field experiments confirmed that fertilizer recommendations based on soil tests performed substantially better than conventional farmer practices in both grain yield and returns. The maximum grain yield of 4.88 t/ha and net profit of ₹32,580/ha was obtained under the STR treatment, underscoring the importance of accurate, data-driven nutrient management [4]. In a similar vein, ANN and XGBoost machine learning models exhibited stellar predictive accuracy in crop and fertilizer suggestions, registering testing accuracies of over 97%, performing better than benchmark models such as Decision Trees and SVMs [5][23].

The incorporation of real-time IoT sensors and cloud analytics into SmartAgro further improves its scalability and usability, especially for resource-poor rural farmers. By providing actionable, field-specific insights through a light-weight web interface, SmartAgro brings advanced agronomic decision-making within reach even without the need for expert intervention.

Beyond productivity and profitability advantages, SmartAgro enables sustainable agriculture through waste reduction of resources, soil health enhancement, and climate resilience—results aligned with international studies on precision farming and crop rotation [2][3].

Nonetheless, some limitations remain. The effectiveness of the system depends on regular data inputs and digital access, which might not be equally available everywhere. Future work will involve extending the dataset to cover pest incidence, satellite images, and seasonal anomalies, improving multilingual support and offline capability to boost adoption.

In summary, SmartAgro provides a scalable, promising solution to fill the gap between conventional agriculture and smart agriculture. Its fusion of AI, empirical science, and farmer-oriented design represents a big leap toward making agriculture a datadriven, sustainable, and profitable industry.

### V.Acknowledgment

The authors appreciate the financial support of the Department of Agriculture for offering soil and climate data used in this research. They extend special thanks to the Uttar Pradesh farmers and field officers for their cooperation throughout the data collection and field tests. This research was also facilitated by the Lab at Srinivas Institute of Technology, which offered computational facilities for model training and testing. Genuine gratitude goes to all collaborators and guide who provided useful contributions throughout the project.

### References

[1] Shah, Kabita Kumari, Bindu Modi, Hari Prasad Pandey, Arjun Subedi, Geeta Aryal, Meena Pandey, and Jiban Shrestha. "Diversified Crop Rotation: An Approach for Sustainable Agriculture Production." Advances in Agriculture, vol. 2021, Article ID 8924087, 2021. DOI: https://doi.org/10.1155/2021/8924087.

[2] Yang, X., Xiong, J., Du, T., Ju, X., Gan, Y., Li, S., Xia, L., Shen, Y., Pacenka, S., Steenhuis, T. S., Siddique, K. H. M., Kang, S., & Butterbach-Bahl, K. (2024). *Diversifying crop rotation increases food production, reduces net greenhouse gas emissions and improves soil health*. Nature Communications, 15, 198. https://doi.org/10.1038/s41467-023-44464-9.

[3] Yu, T., Mahe, L., Li, Y., Wei, X., Deng, X., & Zhang, D. (2022). Benefits of crop rotation on climate resilience and its prospects in China. *Agronomy*, 12(2), 436. https://doi.org/10.3390/agronomy12020436.

[4] Kumar, N., Bahadur, R., Yadav, S.K., Singh, S.P., Singh, A., Baheliya, A.K., & Kumar, D. (2024). Productivity and profitability of rice (Oryza sativa) influenced by customized fertilizers under rice-wheat cropping system. *Indian Journal of Agronomy*, 69(1), 11–16. DOI: 10.59797/ija.v69i1.5475.

[5] Bhola, A., & Kumar, P. "ML-CSFR: A Unified Crop Selection and Fertilizer Recommendation Framework Based on Machine Learning." *Scalable Computing: Practice and Experience*, vol. 25, no. 5, 2024, pp. 4411–4427. DOI: 10.12694/scpe.v25i5.2599

[6] Patel, K., & Patel, H.B. "Multi-Criteria Agriculture Recommendation System using Machine Learning for Crop and Fertilizer Prediction." *Current Agriculture Research Journal*, vol. 11, no. 1, 2023, pp. 137–149. DOI: http://dx.doi.org/10.12944/CARJ.11.1.12

[7] Meena, M. S., & Saini, L. S. (2024). *Smart pest management: The role of precision agriculture in modern farming*. In *AgriTech Revolution: Advancing Sustainable Farming (Vol. I)* (ISBN: 978-81-979987-8-2).

[8] Channe, H., Kothari, S., & Kadam, D. (2015). Multidisciplinary model for smart agriculture using Internet-of-Things (IoT), sensors, cloud computing, mobile computing & big-data analysis. *International Journal of Computer Technology & Applications*, *6*(3), 374–382.

[9] Thorat, T., Patle, B. K., & Kashyap, S. K. (2023). Intelligent insecticide and fertilizer recommendation system based on TPF-CNN for smart farming. *Smart Agricultural Technology*, *3*, 100087. https://doi.org/10.1016/j.atech.2023.100087

[10] Krishna Prasath, T., Reddy, S. G., Kaanth, K. K., & Reddy, M. K. (2024). Smart-Agro: Enhancing crop management with Agribot. *Journal of IoT in Social, Mobile, Analytics, and Cloud*, *6*(3), 212–226.

[11] Sarma, H. H., Das, B. C., Deka, T., Rahman, S., Medhi, M., & Kakoti, M. (2024). Data-driven agriculture: Software innovations for enhanced soil health, crop nutrients, disease detection, weather forecasting, and fertilizer optimization in agriculture. *Journal of Advances in Biology & Biotechnology*, *27*(8), 878-896.

[12] Prakash, V., Kumar, Y., Singh, A. K., Jeet, P., Ahmed, A., Saurabh, K., Kumari, A., Upadhyaya, A., & Das, A. (2024). Advancing sustainable crop production through agro-advisory services: A review. *Journal of AgriSearch*, *11*(4),

[13] Schut, A.G.T., & Giller, K.E. (2020). Soil-based, field-specific fertilizer recommendations are a pipe-dream. *Geoderma*, 380, 114680. https://doi.org/10.1016/j.geoderma.2020.114680

[14] Maksimovich, K.Y., Kalichkin, V.K., Fedorov, D.S., & Aleschenko, V.V. (2024). Application of Machine Learning Methods for Crop Rotation Selection in Organic Farming System. *E3S Web of Conferences*, 486, 01028. https://doi.org/10.1051/e3sconf/202448601028

[15] Gosai, D., Raval, C., Nayak, R., Jayswal, H., & Patel, A. (2021). Crop Recommendation System Using Machine Learning. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT)*, 7(3), 554–557. https://doi.org/10.32628/CSEIT2173129

[16] Sathya, P., Nijitha, I. I., Karthika, S., & Kavithasri, K. (2024). Crop Recommendation System Using Machine Learning. *International Journal of Novel Research and Development (IJNRD)*, 9(4), 539–543. Retrieved from http://www.ijnrd.org

[17] Deininger, K., et al. (2020). Using Machine Learning to Assess Yield Impacts of Crop Rotation. *World Bank Policy Research Working Paper*, 9306. Retrieved fromhttps://www.worldbank.org.

[18] Manoj Kumar D P, et al. (2021). A Machine Learning Model for Crop and Fertilizer Recommendation. *Nat. Volatiles & Essent. Oils*, 8(5), 10531–10539.

[19] Jamunadevi, K., & Banuroopa, K. (2025). Seasonal Crop Recommendations for High Productivity in India. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT)*, 11(2), 1891– 1896. DOI:10.32628/CSEIT23112552.

[20] Raj L, Raghavendiran M, Gowthaman K S, Kalaivani E. Crop Prithvi and Fertilizer Recommendation System, *International Journal of Advance Research and Innovative Ideas in Education (IJARIIE)*, Vol. 9, Issue 6, 2023, ISSN: 2395-4396, Paper ID: 21910.

[21] Dhruvi Gosai, Chintal Raval, Rikin Nayak, Hardik Jayswal, Axat Patel Crop Recommendation System Using Machine Learning, *International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT)*, Vol. 7, Issue 3, May–June 2021, pp. 554–557, ISSN: 2456-3307.

[22] Dheeraj Gupta, Rushikesh Chougule, Chauhan Aakash, Manish Choudhary, Vaishali Rane. *MyAgriAI – Smart Farming Assistant: An AI-Powered Web-Based Farming Solution*, *International Journal of Research Publication and Reviews (IJRPR)*, Vol. 6, Issue 3, March 2025, pp. 5355–5359, ISSN: 2582-7421.

[23] Christine Musanase, Anthony Vodacek, Damien Hanyurwimfura, Alfred Uwitonze, Innocent Kabandana. *Data-Driven Analysis and Machine Learning-Based Crop and Fertilizer Recommendation System for Revolutionizing Farming Practices, Agriculture (MDPI)*, Vol. 13, No. 11, Article 2141, November 2023.

[24] Kharol Chicaiza, Ricardo X. Paredes, Isaac Mateo Sarzosa, Sang Guun Yoo, Naeun Zang. *Smart Farming Technologies: A Methodological Overview and Analysis*, IEEE Access, Vol. 12, 2024, pp. 164922–164939.

[25] S. Kiruthika, D. Karthika. *IoT-Based Professional Crop Recommendation System Using a Weight-Based Long-Term Memory Approach, Measurement: Sensors (Elsevier)*, Vol. 27, 2023, Article 100722.