Web-Based AI Model as a Decision Support System to Enhance Precision Farming for Smart Agriculture: Special Reference to Paddy Crop in the Wet Zone of Sri Lanka

Panditharathne D. L. D.[1*] and Herath H.M.Badra S.[2]

[1]Faculty of Graduate Studies: University of Sri Jayewardenepura, Sri Lanka

[2]Department of Geography: Faculty of Humanities and Social Sciences, University of Sri Jayewardenepura, Sri Lanka

*lakshani.edu92@gmail.com (*Corresponding author's email only)

ABSTRACT

Precision farming leveraged advanced technologies to enhance agricultural productivity and sustainability by overcoming the limitations of traditional methods of nutrient assessment, which often lacked accuracy and efficiency. This study focused on the application of a web-based AI model as a decision support system to identify major nutrient deficiencies in paddy crop within the wet zone of Sri Lanka. The main objective was to apply an AI-driven tool that could accurately diagnose nitrogen (N), phosphorus (P), and potassium (K) deficiencies, thereby enabling timely and precise nutrient management. The methodology adopted in this study integrated deficiency data and machine learning algorithms to accurately detect nutrient deficiencies. Field data collection, model training, and validation were key components of the methodology. The model's efficacy was evaluated through field trials and accuracy assessments. The findings demonstrated the viability of real-time nutrient deficiency identification, leading to more precise and timely interventions. The display of results on the web map was implemented using Java and Spring Boot for the backend, JavaScript for the frontend, and MongoDB for the database. By integrating real-time web GIS capabilities, the study facilitated the immediate visualization of AI-generated insights on a web map, enhancing accessibility and usability for agricultural stakeholders who are ready to adopt precision farming for smart agriculture. The research also explored strategies to integrate this decision support system into farmers' practices especially on nutrient management, aiming to improve their decision-making processes and overall crop yield. The successful implementation of the proposed system held significant potential for advancing precision farming practices, ultimately contributing to increased agricultural productivity and sustainability in the wet zone region and it can be applied to other agroecological regions in the country.

Keywords: AI model, decision support system, nutrient deficiencies, paddy crop, precision farming

1 Introduction

The cultivation of paddy is a crucial component of Sri Lanka's agricultural landscape, especially in the wet zone, where it sustains the local population and makes a substantial contribution to the national economy (Abeysekera et al., 2017). Rice cultivated in these paddy fields is a fundamental component of Sri Lankan cuisine and plays a crucial role in ensuring the country's food security (Bishwajit et al., 2013). An essential factor for the success of paddy farming is the efficient use of fertilizers, which supply the necessary nutrients for optimal plant development (Shrestha et al., 2020). The nutrients nitrogen, phosphorus, and potassium are of utmost importance in enhancing agricultural productivity (Jiaying et al., 2022).

Achieving optimal yields in paddy cultivation requires the precise application of fertilizers at the appropriate periods (Fairhurst et al., 2007). Misapplication or insufficient use of fertilizer can result in a substantial decrease in agricultural productivity and the manifestation of noticeable signs of insufficiency, such as inhibited development and discolored foliage (Bang et al., 2020). Hence, it is imperative for farmers to expeditiously identify and resolve deficiencies in fertilizers to sustain the welfare and productivity of their crops (Shah & Wu, 2019). Nevertheless, conventional approaches to evaluating nutrient insufficiencies require a significant amount of time, effort, and financial resources. These procedures include gathering soil and plant samples for laboratory analysis (Barbedo, 2019). Standard methods postpone the detection and resolution of nutrient problems, therefore diminishing agricultural productivity and causing economic volatility.

For farmers to overcome these issues, they need more effective techniques for monitoring nutrient levels and making well-informed decisions (Hedley, 2014). Smart agriculture technologies, such as Artificial Intelligence (AI) and Geographic Information Systems (GIS), when integrated, provide a promising answer (Said Mohamed et al., 2021). Modern techniques offer precise and up-to-date data on nutritional insufficiencies, allowing farmers to promptly and precisely intervene (Monteiro et al., 2021). These technologies can be utilized by farmers to improve crop productivity, enhance their decision-making processes, and ensure economic stability (None Olawale Adisa et al., 2024).

Aiming to manage nutrient shortages in paddy crops within Sri Lanka's wet zone, this research examined the implementation of web-based AI models and GIS technologies. There has been very little research on using smart agricultural techniques in paddy cultivation in Sri

Lanka, even though agricultural technology has advanced significantly worldwide. The objective of this effort was to create a comprehensive framework that integrates these sophisticated technologies, therefore establishing a model for agricultural innovation and providing feasible solutions that may be applied in comparable situations globally. The findings of this study can greatly enhance agricultural methods, make a valuable contribution to food security, and stimulate economic growth in Sri Lanka and other regions.

1.1 Objectives

1.1.1 Main objective

To apply a Web-based AI model as a decision support system to enhance precision farming for smart agriculture with special reference to the identification of nutrient deficiencies in paddy crop of the wet zone in Sri Lanka

1.1.2 Specific objectives

1. To enhance a Web-based AI model to identify nutrient deficiencies in paddy crop in the wet zone.
2. To evaluate the model for the viability of the decision support system
3. To propose strategies to enhance farmers' decision-making using a Web-based AI model

2 Literature Review

Rice (Oryza sativa) is a highly adaptable cereal crop from the Poaceae family that thrives in warm and water-abundant landscapes. It is a staple food for more than half of the world population, especially in Asia. The crop is grown in many environments, such as flooded paddies and dry upland fields, and consists of two primary subspecies: Japonica and Indica. Roots, stems, leaves, and panicles make up the plant's structure. The height of the plant ranges from 0.4 to 5 meters based on the type and growing conditions (Roy, 2013). According to Richmond et al. (2018), the growth of rice can be broken down into three distinct phases: the vegetative phase, the reproductive phase, and the grain filling and ripening phase. Each of these phases is affected by environmental factors such as temperature and the availability of water, which in turn affects the yield and quality of the rice.

For optimal growth, rice necessitates sixteen vital elements. The basic macronutrients include Nitrogen (N), Phosphorus (P), and Potassium (K), while the secondary macronutrients include Magnesium (Mg), Calcium (Ca), and Sulphur (S). Additional essential micronutrients include

Zinc (Zn), Iron (Fe), Manganese (Mn), Copper (Cu), Boron (B), Molybdenum (Mo), and Chlorine (Cl). There is a correlation between deficiencies in these nutrients, particularly nitrogen, phosphorus, and potassium, and visible changes in leaf color and morphology, which in turn can affect crop health and yield (Latte et al., 2017; Nayak et al., 2023). To prevent yield loss, timely on-field diagnosis is necessary due to nutrient deficiencies, which are frequently made worse by pests, pathogens, and environmental stressors (Sharma et al., 2023; Sethy et al., 2020).

Table 1: Nitrogen(N) Deficiency Symptoms

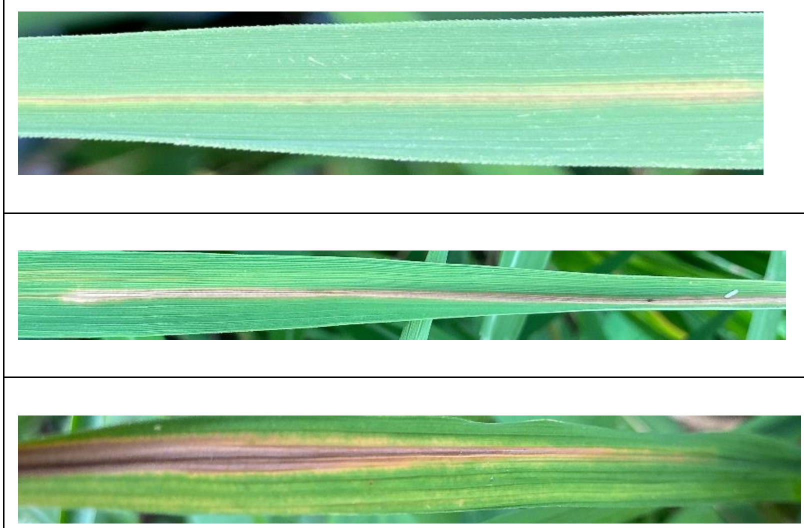

Table 2: Potassium(K) Deficiency Symptoms



Table 3: Phosphorus(P) Deficiency Symptoms

In recent years, mobile applications have developed into essential tools for smallholder farmers, effectively connecting traditional methods with current technology. The widespread utilization of smartphones and internet connectivity has revolutionized these devices from simple communication devices into versatile platforms with the potential to increase agricultural productivity (Kamal & Aziz Bablu, 2023). There have been a variety of applications that have been developed to support time management, fitness tracking, and agricultural productivity (Cosmin Alexandru Teodorescu et al., 2023; Athirah et al., 2020). These applications have been made possible by the evolution from 2G and 3G networks to advanced smartphones equipped with high-resolution cameras and sensors. In modern agriculture, these mobile technologies have become indispensable, assisting crop management and operational effectiveness (Aletdinova, 2021).

Web GIS has become a potent instrument in modern agriculture, facilitating the gathering, analysis, and dissemination of spatial data. The incorporation of Geographic Information Systems (GIS) with web technologies has fundamentally transformed the acquisition and application of spatial information, therefore enabling enhanced estimation of crop production, examination of soil, and identification of erosion (Ghosh & Kumpatla, 2022; S Oliazadeh et al., 2021). Transitioning from desktop GIS to web-based systems enables effortless data exchange with many stakeholders such as farmers, researchers, and academics (Jayasinghe & Machida, 2008). As a complement to IoT, Web GIS offers extensive cartography and analytical capabilities that facilitate remote monitoring and well-informed decision-making, hence promoting sustainable agriculture practices (Dhanaraju et al., 2022; Mathenge et al., 2022).

Artificial Intelligence (AI) has transformed agriculture by replicating human intelligence using sophisticated algorithms and models. By combining with current technologies to handle vast datasets and optimize decision-making, AI improves efficiency and precision in agriculture (Alatawi et al., 2022). Artificial intelligence (AI) applications enhance the accuracy of crop production predictions, as well as the management of pests and diseases, leading to higher productivity and lower expenses (Sydoruk, 2023). AI can help find diseases quickly using computer vision, which means that treatments can be made more timely. It can also help identify pests and nutrient deficiencies (González-Rodríguez et al., 2024).

By improving plant health monitoring and nutrient deficiencies identification, the IoT has a major impact on the current agricultural sector. Intelligent agriculture utilizes Internet of Things (IoT) technology to offer immediate and accurate information that exceeds conventional offline datasets, allowing for accurate field forecasts and enhanced crop quality and quantity (Anushree & R. Hari Krishna, 2018; Senapaty et al., 2023). The integration of IoT sensors, mobile devices, and cloud computing enables a smooth flow of data updates and remote monitoring, therefore simplifying the process for farmers to obtain and utilize this information via mobile applications. Dholu & Ghodinde, (2018) used a production monitoring system that allows for real-time, remote surveillance of environmental indicators, expanding agricultural efficiency and uniformity, to show how successful the Internet of Things can be in the field of agriculture.

3 Methodology

3.1 Study Area

This study was carried out in the wet zone of Sri Lanka, an area distinguished by abundant rainfall and fertile soil, rendering it an essential site for the growth of paddy. The wet zone extends over the southwestern region of the island and has many important districts with significant paddy cultivation. The selection of this region was based on its importance in rice cultivation and the varied agro-ecological factors that impact the availability of nutrients and the health of growing crops. The successful application of the AI-based decision support system for precision farming was highly dependent on the region's regular rainfall patterns and distinctive climatic variables. Data gathering concentrated on several paddy fields in this region to ensure thorough analysis and the transferability of models to diverse agro-ecological environments.

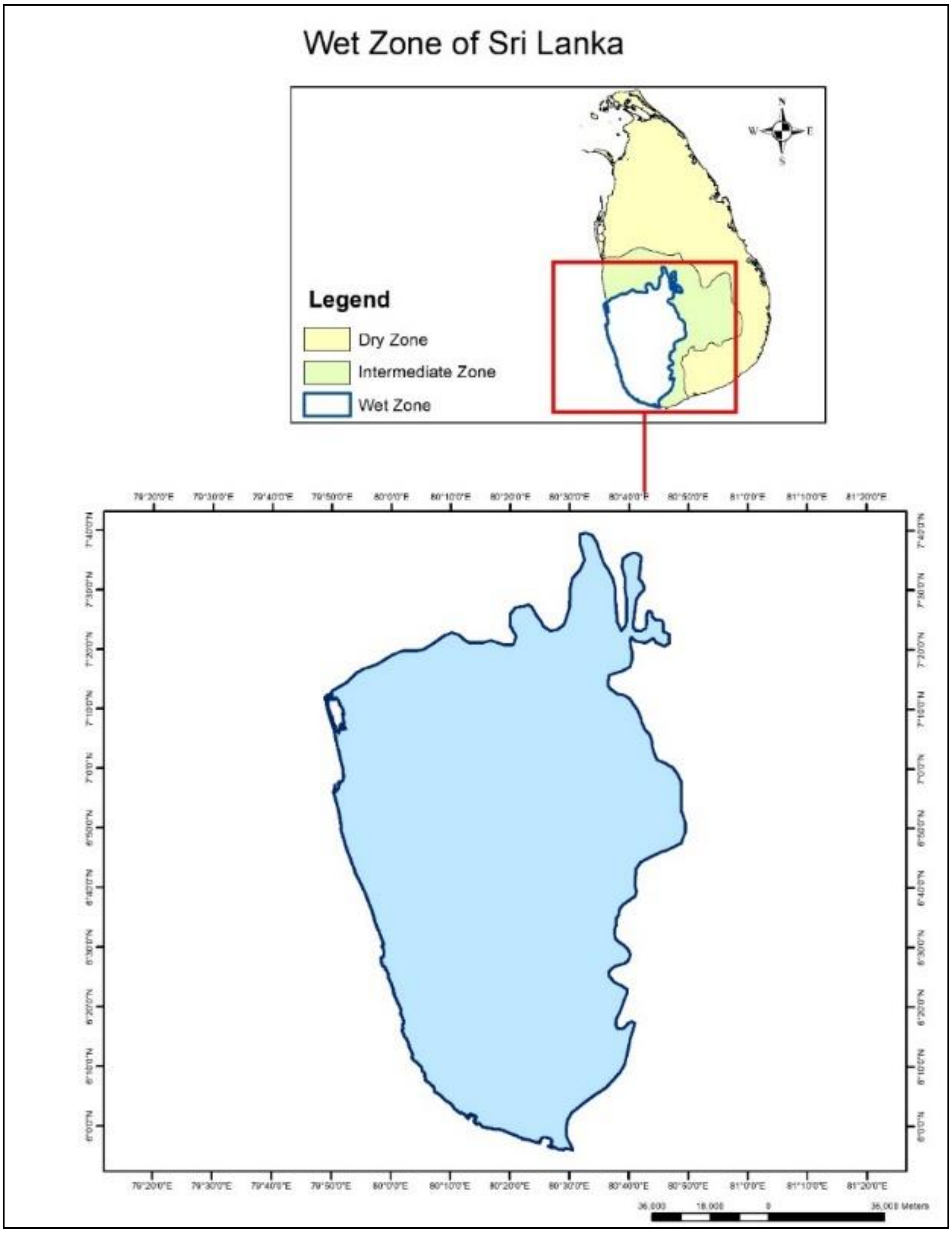

Figure 1: Study area map of Wet zone in Sri Lanka

A comprehensive summary of the system architect was provided by the flow diagram that was supplied. This system established cutting-edge technology such as Artificial Intelligence (AI), the Internet of Things (IoT), and Web Geographic Information Systems (GIS) to provide real-time insights into the presence of nutrients in the soil. As a result, it enabled farmers to make decisions based on the data they collected.

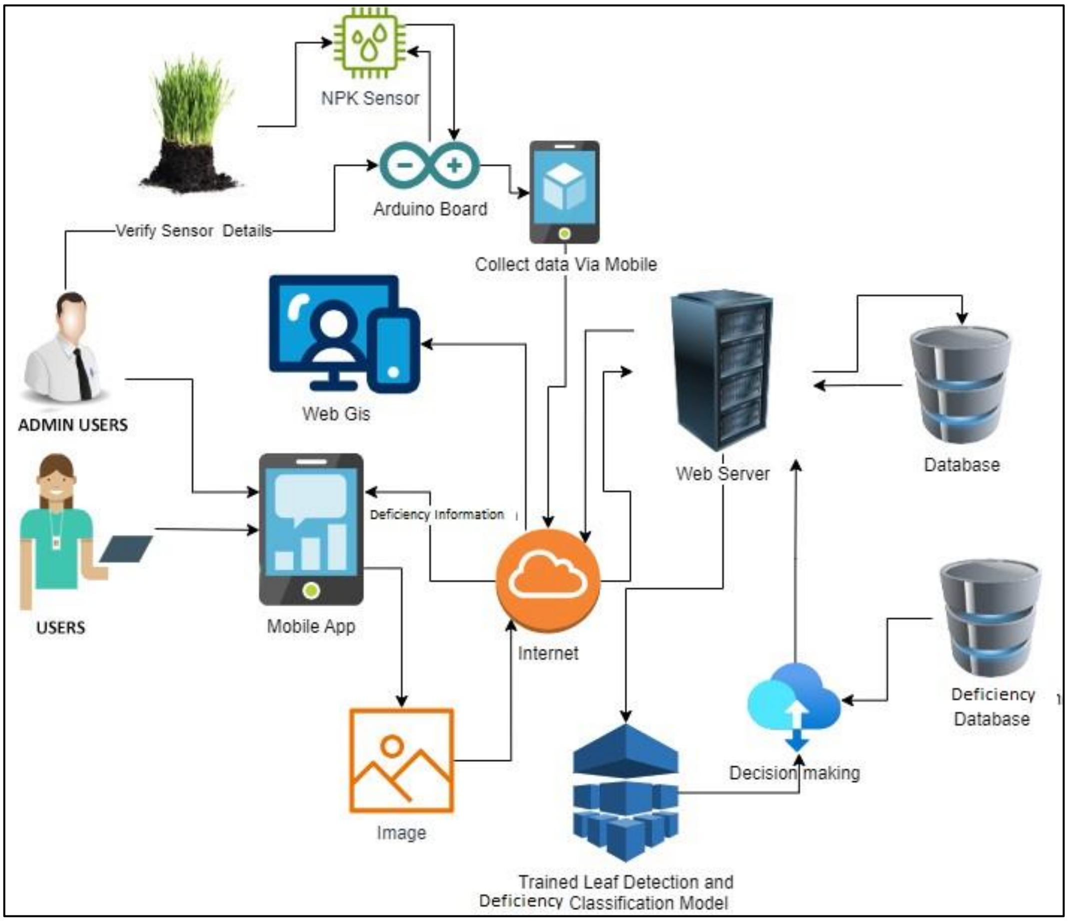

Figure 2: The system architect

3.2 Mobile Application

The mobile application was an essential part of the system's goal to improve precision farming by supporting efficient data gathering and engagement. This was accomplished with the support of the mobile application. The application was crucial in the early phase of the project, during which it was responsible for collecting photos of paddy fields and also for gathering extra data, such as GPS coordinates and observational notes. To train the artificial intelligence model and carry out in-depth analysis, this data-collecting procedure served as the basis. This allowed for the correct diagnosis of nutritional shortages. An intuitive and user-friendly application was designed to ensure that the system could be readily used by those with low technical competence. This was accomplished by ensuring that the application was developed.

The mobile application served also as a platform for providing feedback in real-time, in addition to its feature of collecting data. In addition to providing alerts concerning nutrient shortages, it also supplied management advice based on the analysis performed by the advanced artificial intelligence model. To mitigate the impacts of nutrient shortages before they negatively influence crop health, the feedback process was important in creating the opportunity for early adjustments. The ability of the system to offer quick feedback guaranteed that information on crop conditions was not only communicated on time but also accompanied by activities that could be taken to address any problems that were discovered.

It was developed to increase the system's potential to properly identify and confirm nutritional shortages, and the application was provided with capabilities that were designed to do this. The input of real-time data from the field, including information on the location, photographic proof, and observational details, was made easier due to this facility. By directly receiving this information, the system was able to carry out an in-depth study of the possible deficits in nutrients. In addition, the program enabled the gathering of NPK (nitrogen, phosphorus, and potassium) values through the use of integrated sensors. These sensors offered essential data points that were utilized to validate the observations that were produced through the utilization of image analysis methodology. A rigorous validation procedure for identifying nutrient inadequacies was maintained by the utilization of this dual technique, which included the combination of sensor data and ocular examination.

A key characteristic of the mobile application was its capacity to visually represent data using a deficiency map. This map presented both verified and unverified nutritional deficiencies using distinguishable color codes, providing a clear and readily understandable depiction of nutrient-related problems in various regions. The approach facilitated the identification of areas in need of urgent care by employing visual representations of the geographical distribution of inadequacies. This graphical depiction facilitated focused interventions and improved allocation of resources, hence optimizing the efficacy of nutrition management strategies.

Extensive data management procedures were implemented by the system to guarantee the dependability and integrity of the gathered data. The protocols used different identifying processes, such as non-replicable email addresses and phone numbers, to avoid the duplication of data and ensure precise records. The system ensured that the analysis and subsequent suggestions were based on reliable and precise data by including these protections, hence enhancing the credibility and efficacy of the decision support system.

The mobile application was developed with a well-organized set of processes and strong data processing functionalities to facilitate immediate decision-making. The application design enabled the smooth integration of data gathering, processing, and feedback transmission, thereby establishing a unified set of tools for monitoring and controlling nutritional deficits. The smooth and uninterrupted interaction facilitated the system in quickly producing practical insights, hence facilitating well-informed and prompt decision-making. The program played a crucial role in advancing sustainable and efficient agricultural methods by offering a platform for the identification, validation, and management of nutrient shortages.

Mobile technology integration in the system facilitated the transition from conventional agricultural practices to nowadays precision farming. The incorporation of real-time alerts and customized recommendations in the program enhanced the system's capacity to promptly address nutritional deficiencies, hence maximizing crop health and productivity. The implementation of this proactive and well-informed strategy for nutrient management improved operational efficiency. It facilitated the achievement of the wider sustainability objectives in agriculture by adhering to the concepts of precision farming and intelligent agricultural methodology.

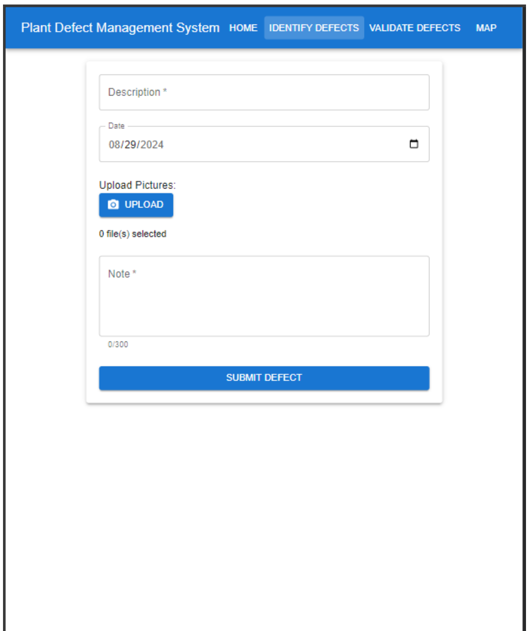

Figure 4: Identify defects using photos

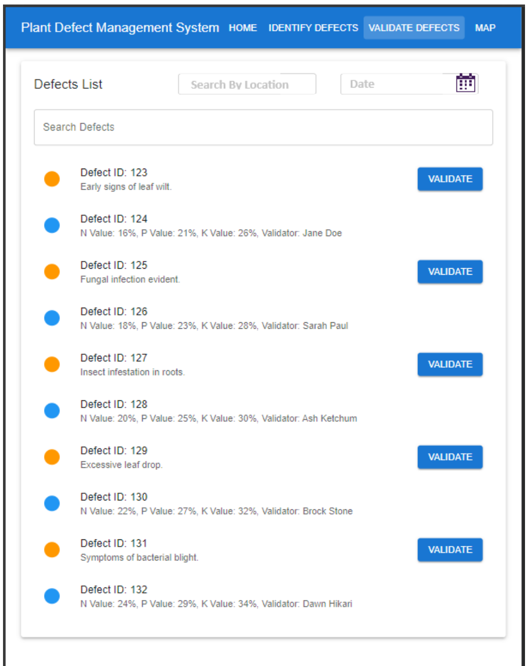

Figure 3: Validate defects using IoT

3.3 Web Server:

An essential function of the centralized web server was to oversee the movement, processing, and storage of data within the system. The system effectively received data sent from the mobile application over the internet, methodically arranged it, and accordingly routed it to suitable destinations such as databases and the AI model. An essential component for processing the gathered data and executing AI algorithms to assess nutrient shortages in paddy crops was the web server. In addition, it enabled the dissemination of feedback derived from the AI analysis, therefore assuring that the system could promptly and precisely react to current agricultural circumstances.

Built with scalability as a primary consideration, the web server was designed to efficiently manage substantial amounts of data, therefore meeting the growing requirements of expanding system deployment. Its design facilitated smooth integration and communication among different components, guaranteeing efficient processing and storage of data. The inclusion of this scalability feature guaranteed that the system could sustain operational efficiency even with an increase in the quantity of linked devices and data inputs, therefore establishing a strong and dependable foundation for precision agricultural applications.

3.4 Database:

The database functioned as the central storage for all gathered and manipulated data. It stored inputs, processed data, and maintained historical records. This consolidated storage enabled streamlined data retrieval and facilitated complex queries required for thorough analysis and reporting. In addition, the database included a 'Deficiency Database' that stored the findings of the AI model's study, offering a thorough log of identified nutrient shortages across time.

3.5 AI Model:

An improved and tailored version of the previously created AI model was designed to particularly identify nutrient deficits in paddy crops. The objective of the model was to detect visual symptoms that suggest deficits of nitrogen, phosphorus, and potassium by the analysis of photographs. Initially, the model was trained using a dataset of photos obtained from research institutes and readily accessible sources. The photos underwent hand labeling to get accurate ground truth data, therefore enabling the algorithm to effectively identify patterns related to various nutrient deficits. The implementation of the model was designed to enhance its precision and effectiveness by iteratively retraining and utilizing fresh data inputs. Upon the completion of the training, the AI model was capable of categorizing nutrient deficits in newly uploaded photos via the mobile application. Subsequently, the categories were recorded in the deficient database to facilitate subsequent analysis and decision-making.

3.6 Data Collection and Analysis

The system gathered data mainly using photographed paddy crops that were submitted using the smartphone application. The AI algorithm examined these photos to identify visual indications of nutrient insufficiencies. The trained algorithm, designed to identify patterns related to nitrogen, phosphate, and potassium deficits, examined characteristics such as leaf color, texture, and growth patterns to accurately classify these deficiencies. If a shortfall is detected, the system indicates the location where the image was captured with an orange dot, indicating unconfirmed data.

3.7 Sensor-Based Verification

To enhance the dependability of the AI-generated outcomes, the methodology included a validation procedure utilizing NPK sensors that were linked to an Arduino board. These sensors quantified the precise nutrient concentrations in the soil. Upon comparison of the sensor data with the predictions of the AI model, the data point on the map was designated as confirmed, and the associated dot underwent a transformation from orange to blue.

3.8 Web GIS Visualization:

By integrating a Web GIS platform into the system, data accessibility and usability were improved, therefore providing a robust tool for viewing the spatial distribution of nutritional shortages. By facilitating the detection of patterns across many geographies, this platform facilitated the presentation of both real-time and historical data. The Web GIS included interactive maps that emphasized areas of critical shortage, enabling the investigation and examination of particular sites. The technology enabled focused treatments by providing comprehensive data on the geographical layout of nutritional problems. This measure guaranteed the efficient allocation of resources to regions with the most pronounced nutrient deficiencies, therefore facilitating the implementation of more effective and accurate nutrient management techniques.

4 Results and Discussion

This section outlines the results of implementing and deploying the web-based artificial intelligence model for agricultural precision farming in paddy crops. The primary emphasis is on the role of the AI model in detecting problems related to nutrients, offering practical suggestions, and enhancing the decision-making procedures inside the system. Furthermore, the conversation encompasses the efficacy of the data verification procedure, the user-friendliness of the map-based visualization platform, and the wider consequences for agricultural protocols. By examining both the outcomes and input received from the system, one may identify the strengths and areas needing development. The usage of orange and blue dots to denote varying degrees of data verification is thoroughly elucidated, together with their influence on the engagement with and understanding of data.

4.1 Overview of the Web-Based AI Model Implementation

A web-based artificial intelligence model was developed to detect nutrient shortages in paddy fields by the analysis of photos contributed to the system. By providing visual indicators on a map-based interface that depicted the spatial distribution of nutrient shortages across several fields, it facilitated real-time decision-making. Unverified and confirmed data points were differentiated using two main data visualization categories, characterized by orange and blue dots:

Orange Dots (Unverified Data): These dots indicated data points where photos were uploaded, and the AI model generated results based on the images. However, these results had not yet been verified using sensor data. This category included:

- Identified deficiencies based on AI analysis
- Recommendations derived from AI responses and logical suggestions from a supplementary database
- Notes with additional information provided via the system
- Images, fully accessible through the web app with limited access via the mobile app

Blue Dots (Verified Data): These dots signified data points that had been validated using NPK sensor data in conjunction with AI-generated results. This category included:

- NPK and other sensor values
- Identified deficiencies from AI responses
- Recommendations based on AI-generated results and logical database suggestions
- Notes containing additional data from both system inputs and validators
- Images, fully viewable via the web app, with limited access through the mobile app

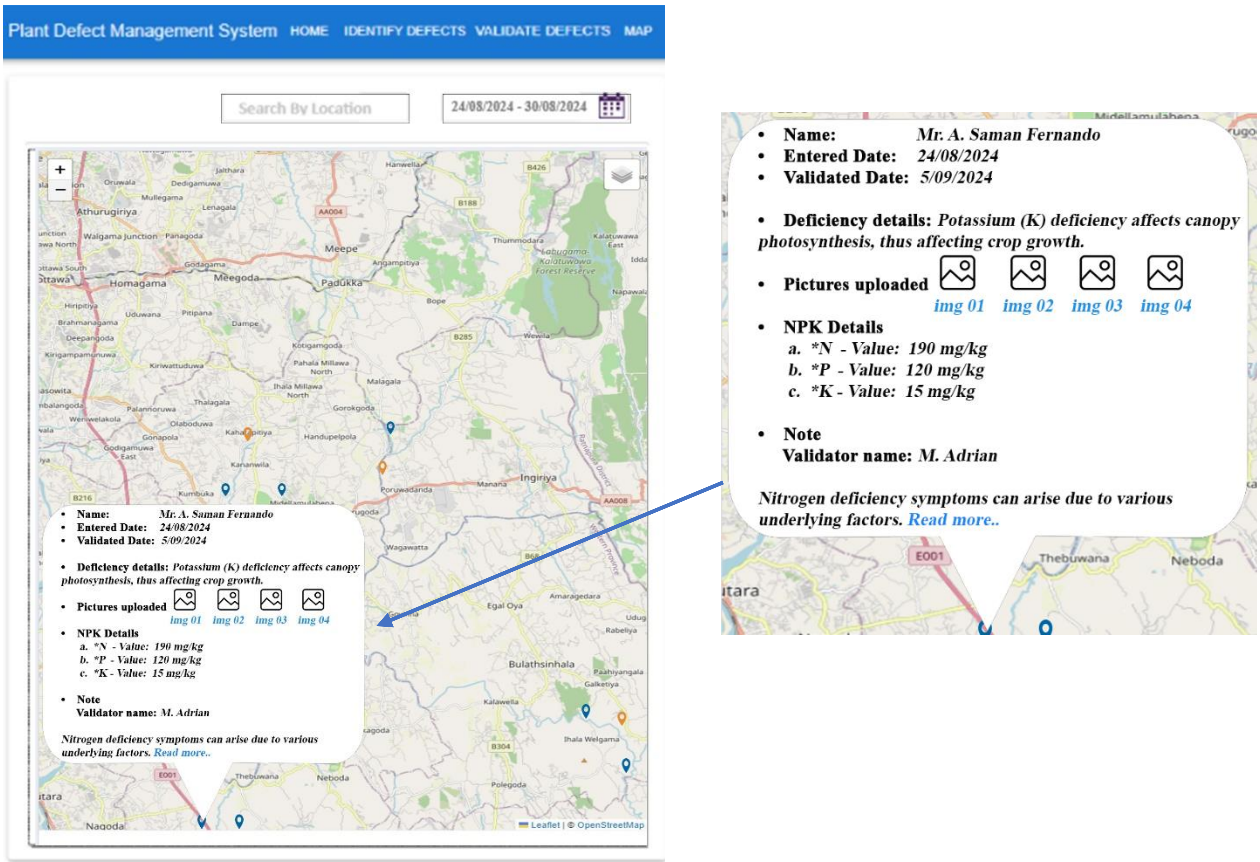

Figure 6: Results map - validated

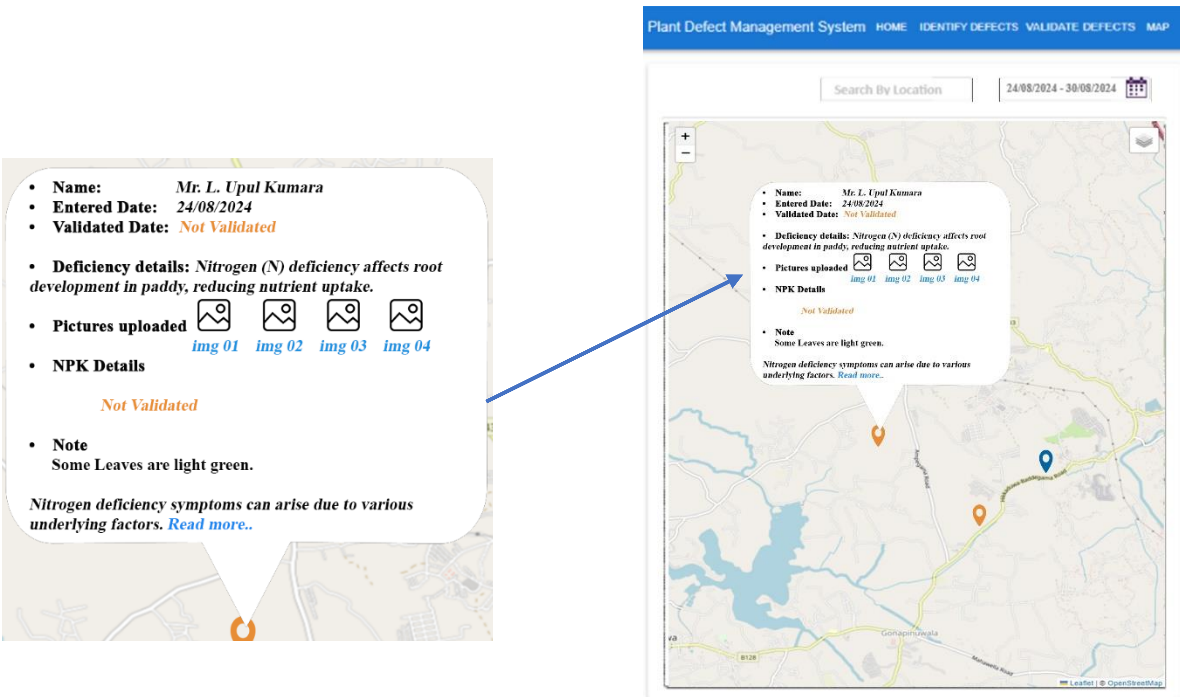

Figure 5: Results map - not validated

4.2 Results of Image-Based Analysis

The artificial intelligence model shown a notable level of precision in identifying nutrients deficits by analyzing the processed photos. In the initial field experiments, the model effectively detected nutrient deficits in more than 85% of the instances. Continual retraining of the model using new data inputs enhanced its capacity to generalize across various environmental circumstances and crop kinds, resulting in this level of accuracy. The consistent accuracy enabled dependable detection of problems in various field situations.

4.3 Results of Sensor-Based Verification

In almost 75% of the instances where sensor validation was carried out, the verification method validated the predictions made by the AI model. 25% of the remaining cases either necessitated additional examination or exposed inconsistencies, frequently attributed to environmental conditions or mistakes during image acquisition. Implementing sensor-based validation greatly improved the system's credibility by proving the accuracy of the AI-generated recommendations with real-world sensor data, therefore offering increased confidence in their reliability.

Figure 7: Validating with IoT

4.4 Accessibility via Web and Mobile Apps

Both mobile applications and web-based applications were developed to be accessible through the system. All of the capabilities, including thorough image viewing and sophisticated data analysis tools, were accessible through the online application, which offered complete access to all of the functions. The mobile application, on the other hand, provided a streamlined user experience that included all of the necessary features. This made it possible to obtain vital information even when working in the field with minimal internet connectivity or technical expertise. This dual-platform approach meant that essential data remained accessible in real-time, independent of location or technical limitations, which supported informed decision-making in a variety of agricultural situations with differing conditions.

4.5 Challenges and Limitations

4.5.1 Technical Challenges

The deployment of the artificial intelligence model and data-driven verification procedure encountered numerous technical obstacles. The accuracy of the system was influenced by the calibration of sensors, fluctuations in environmental conditions, and the quality of photographs obtained by users. To tackle these issues, it was necessary to engage in ongoing surveillance, frequent upgrades, and systematic upkeep of both the artificial intelligence model and the sensor equipment.

4.5.2 Complexities in Diagnosing Nitrogen Deficiencies

Deficiencies of nitrogen in paddy crops are quite difficult to diagnose due to interlapping symptoms. The general symptoms such as yellowing leaves and stunted growth may not specifically be related to nitrogen deficiency since they may arise from other disorders, including water stress and soil health problems. Variations in some environmental parameters include changes in soil pH and temperature, which may affect the availability of nitrogen and hence make the diagnostic process even more complex. Moreover, pest infestations and root injury may assume the appearance of nitrogen deficiency symptoms that would likely lead to misdiagnosis.

4.5.3 Data Quality and Consistency

Verifying the accuracy and uniformity of data was a considerable obstacle, particularly in areas with little infrastructure and technical proficiency. The potential for errors in data collecting techniques and discrepancies in sensor readings presented challenges to the dependability of the AI model's forecasts. Implementing uniform data-collecting procedures and offering enough training to users were essential measures to address these problems.

5. Conclusion

The implementation of the web-based artificial intelligence (AI) model for identifying nutrient shortages in rice crops displayed significant efficacy in the progression of precision farming techniques and the promotion of sustainable agriculture. Through the integration of artificial intelligence with real-time data gathering, map-based visualization, and sensor-based verification, the system offered practical and timely insights that directly influenced the health and productivity of crops. The capacity of the model to detect deficits in nitrogen, phosphate, and potassium enabled focused treatments, therefore enhancing the effectiveness of nutrient management and maximizing the utilization of resources.

Furthermore, the system's interactive characteristics, enabling uninterrupted data updates and immediate feedback, established it as a dependable decision-support tool. Nevertheless, although the system exhibited encouraging outcomes, its sustained effectiveness will rely on further enhancements. Ongoing training in the AI model, including cutting-edge technology, and integrating system feedback will be crucial for improving accuracy and overall performance. The scalability of the system additionally presents significant possibilities for growth, not only to various crops but also to a wide range of agricultural regions globally. Due to its versatility, this technology is a significant asset to the worldwide progress of precision agriculture, facilitating more sustainable and efficient farming methods in many situations.

6. Recommendation

- **Enhance Training Programs**: Develop localized training programs to educate farmers and validators on using the system effectively, interpreting AI-generated recommendations, and handling sensor equipment.
- **Improve Data Quality**: Implement standardized data collecting procedures and allocate resources to enhance the quality of sensors to guarantee consistent and dependable data feeds. Not only did the validated data enhance individual decision-making, but it also aided in wider agricultural planning. Collecting data from several verified sites allowed agricultural organizations and policymakers to analyze regional nutrient patterns, facilitating the development of focused nutrient management programs and support services. Integrating verified data into larger datasets has also enabled exploration and advancement in precision agriculture.
- **Expand the System**: Scale the AI model to cover additional crops and regions, incorporating diverse datasets to improve its accuracy and applicability. By analyzing the output, could identify common issues, adjust recommendation algorithms, and update training datasets. This process of continuous improvement ensured that the system remained relevant and effective in varying agricultural conditions.

- **Integrate Advanced Technologies**: Explore the use of drones and advanced IoT devices for real-time monitoring and data collection, further enhancing the system's capabilities.
- **Promote Collaboration**: Foster partnerships with agricultural organizations, research institutions, and technology providers to support the continuous development and dissemination of the system.
- **Improve Usability and Scalability of the System**: User feedback emphasised that the system's user-friendliness and instinctive design were of paramount importance. The use of a color-coded map interface facilitated farmers in comprehending the condition of their farms and allocating priority to their activities. The system's accessibility through mobile and online applications guaranteed its maximum usability by both field workers and agricultural management. The scalability analyses also encompassed the possibility of extending the AI model to encompass various categories of crops and geographical areas. By integrating a broader array of datasets and conducting training on a more extensive spectrum of nutrient deficiency parameters, the system has the potential to be modified to cater to other agricultural industries. The possible incorporation with sophisticated IoT devices, such as monitoring systems based on drones, offered an additional opportunity for future advancement.

7. References

Abeysekera, W. K. S. M., Arachchige, S. P. G., Ratnasooriya, W. D., Chandrasekharan, N. V., & Bentota, A. P. (2017). Physicochemical and nutritional properties of twenty three traditional rice (Oryza sativa L.) varieties of Sri Lanka. Journal of Coastal Life Medicine, 343–349. https://doi.org/10.12980/jclm.5.2017j7-59

Alatawi, A. A., Alomani, S. M., Alhawiti, N. I., & Ayaz, M. (2022). Plant Disease Detection using AI based VGG-16 Model. International Journal of Advanced Computer Science and Applications, 13(4). https://doi.org/10.14569/ijacsa.2022.0130484

Aletdinova, A. A. (2021). Popular Mobile Applications for Crop Production. IOP Conference Series: Earth and Environmental Science, 666(3), 032036. https://doi.org/10.1088/1755-1315/666/3/032036

Athirah, R. N., Norasma, C. Y. N., & Ismail, M. R. (2020). Development of an Android Application for Smart Farming in Crop Management. IOP Conference Series: Earth and Environmental Science, 540, 012074. https://doi.org/10.1088/1755-1315/540/1/01207

Anushree, M. K., & R. Hari Krishna. (2018). A smart farming system using Arduino based technology. International Journal of Advance Research, Ideas and Innovations in Technology, 4(4), 850–856.

Bang, T. C., Husted, S., Laursen, K. H., Persson, D. P., & Schjoerring, J. K. (2020). The molecular–physiological functions of mineral macronutrients and their consequences for deficiency symptoms in plants. *New Phytologist*, *229*(5), 2446–2469. https://doi.org/10.1111/nph.17074

Barbedo, J. G. A. (2019). Detection of nutrition deficiencies in plants using proximal images and machine learning: A review. *Computers and Electronics in Agriculture*, *162*, 482–492. https://doi.org/10.1016/j.compag.2019.04.035

Bishwajit, G., Sarker, S., Kpoghomou, M.-A., Gao, H., Jun, L., Yin, D., & Ghosh, S. (2013). Self-sufficiency in rice and food security: a South Asian perspective. Agriculture & Food Security, 2(1). https://doi.org/10.1186/2048-7010-2-10

Cosmin Alexandru Teodorescu, Alexandra-Nicoleta Ciucu Durnoi, & Vanesa Mădălina Vargas. (2023). The Rise of the Mobile Internet: Tracing the Evolution of Portable Devices. Sciendo, 17(1), 1645–1654. https://doi.org/10.2478/picbe-2023-0147

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. Agriculture, 12(10), 1745. https://doi.org/10.3390/agriculture12101745

Dholu, M., & Ghodinde, K. A. (2018). Internet of Things (IoT) for Precision Agriculture Application. 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI). https://doi.org/10.1109/icoei.2018.8553720

Fairhurst, T., Witt, C., Buresh, R., & Dobermann, A. (Eds.). (2007). A Practical Guide to Nutrient Management (2nd ed.). Int. Rice Res. Inst.

Ghosh, P., & P. Kumpatla, S. (2022). GIS Applications in Agriculture. Geographic Information System [Working Title]. https://doi.org/10.5772/intechopen.104786

Hedley, C. (2014). The role of precision agriculture for improved nutrient management on farms. Journal of the Science of Food and Agriculture, 95(1), 12–19. https://doi.org/10.1002/jsfa.6734

Jayasinghe, P. K. S. C., & Machida, T. (2008). Web-Based GIS Online Consulting System with Crop-Land Suitability Identification. Agricultural Information Research, 17(1), 13–19. https://doi.org/10.3173/air.17.13

Jiaying, M., Tingting, C., Jie, L., Weimeng, F., Baohua, F., Guangyan, L., Hubo, L., Juncai, L., Zhihai, W., Longxing, T., & Guanfu, F. (2022). Functions of Nitrogen, Phosphorus and Potassium in Energy Status and Their Influences on Rice Growth and Development. Rice Science, 29(2), 166–178. https://doi.org/10.1016/j.rsci.2022.01.005

Kamal, M., & Aziz Bablu, T. (2023). Mobile Applications Empowering Smallholder Farmers: A Review of the Impact on Agricultural Development. ResearchGate.

Latte, M. V., Sushila Shidnal, & Anami, B. S. (2017). Rule based approach to determine nutrient deficiency in paddy leaf images. International Journal of Agricultural Technology, 13(2), 227–245

Mathenge, M., Sonneveld, B. G. J. S., & Broerse, J. E. W. (2022). Application of GIS in Agriculture in Promoting Evidence-Informed Decision Making for Improving Agriculture Sustainability: A Systematic Review. Sustainability, 14(16), 9974. https://doi.org/10.3390/su14169974

Monteiro, A., Santos, S., & Gonçalves, P. (2021). Precision Agriculture for Crop and Livestock Farming—Brief Review. Animals, 11(8), 2345. https://doi.org/10.3390/ani11082345

Nayak, A., Chakraborty, S., & Swain, D. K. (2023). Application of smartphone-image processing and transfer learning for rice disease and nutrient deficiency detection. Smart Agricultural Technology, 4, 100195. https://doi.org/10.1016/j.atech.2023.100195

None Olawale Adisa, None Bamidele Segun Ilugbusi, Adewunmi, O., Franca, O., & Ndubuisi, L. (2024). A comprehensive review of redefining agricultural economics for sustainable development: Overcoming challenges and seizing opportunities in a changing world. World Journal of Advanced Research and Reviews, 21(1), 2329–1241. https://doi.org/10.30574/wjarr.2024.21.1.0322

Richmond, T., Slaton, N. A., Hardke, J. T., Roberts, T. L., & Norman, R. (2018). Rice Aboveground Nitrogen Content, Development, and Yield as Affected by Nitrogen Fertilization and Flood Timing. Agronomy Journal, 110(6), 2626–2640. https://doi.org/10.2134/agronj2018.05.0308

Roy, B. (2013). Breeding, Biotechnology and Seed Production of Field Crops. New India Publishing Agency.

S Oliazadeh, Mahdi Reyahi Khoram, & Mohammad Asad Abbasi. (2021). Design and development of a web GIS for management and performance evaluation of agricultural farms of sahar food industries company (SFIC). Journal of Physics, 1918(4), 042017–042017. https://doi.org/10.1088/1742-6596/1918/4/042017

Said Mohamed, E., Belal, AA., Kotb Abd-Elmabod, S., El-Shirbeny, M. A., Gad, A., & Zahran, M. B. (2021). Smart farming for improving agricultural management. The Egyptian Journal of Remote Sensing and Space Science, 24(3), 971–981. https://doi.org/10.1016/j.ejrs.2021.08.007

Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). Image Processing Techniques for Diagnosing Rice Plant Disease: A Survey. Procedia Computer Science, 167, 516–530. https://doi.org/10.1016/j.procs.2020.03.308

Shah, F., & Wu, W. (2019). Soil and Crop Management Strategies to Ensure Higher Crop Productivity within Sustainable Environments. Sustainability, 11(5), 1485. https://doi.org/10.3390/su11051485

Sharma, M., Kumar, C., Talukdar, J., Singh, T. P., Dhiman, G., & Sharma, A. (2023). Identification of rice leaf diseases and deficiency disorders using a novel DeepBatch technique. Central European Journal of Biology, 18(1). https://doi.org/10.1515/biol-2022-0689

Shrestha, J., Kandel, M., Subedi, S., & Shah, K. K. (2020). Role of nutrients in rice (Oryza sativa L.): A review. Agrica, 9(1), 53. https://doi.org/10.5958/2394-448x.2020.00008.5