engineering proceedings

MDPI

Integrating First-Order-Logic with Artificial Intelligence: A Novel Framework for the Development of Smart Based Ginger Plants' Disease Detection and Decision Support System †

Enesi Femi Aminu [1]*, Hussaini Abubakar Zubairu [2], Oluwaseun Adeniyi Ojerinde[3], and Ayobami Ekundayo [4],

[1] Department of Computer Science, Federal University of Technology, Minna Nigeria; enesifa@futminna.edu.ng
[2] School of Information Technology, Carleton University, Ottawa Canada; hussainizubairu@cmail.carleton.ca
[3] Department of Computer Science, Federal University of Technology, Minna Nigeria; o.ojerinde@futminna.edu.ng
[4] Department of Computer Science, Federal University of Technology, Minna Nigeria; a.ekundayo@futminna.edu.ng
*1 Correspondence: enesifa@futminna.edu.ng; Tel.: (08036535765; +234)
† Presented at the title, place, and date.

Abstract

The conventional methods of visually inspecting ginger rhizome against diseases such as fungi by experts or farmers at early stage is not effective due to human errors, fatigue, costs, and time consuming. In addition, combined disease management strategy such as soil treatment approach, biological control proxies, and application of resistant varieties are most often employed for effective monitoring of rhizome rot but not without issues of robust effectiveness. In view of this development, innovative technologies such as artificial intelligence, machine learning, and Internet of Things have been employed towards viable solutions. Based on literature, this effort is promising but not without a gap that necessitated further research. Therefore, this research aims to design a smart based framework for developing ginger plants' disease detection and decision support model. At the stage of developing the framework, images data will be collected using either smartphones, drones, or a positioned camera. CNN, ensemble learning, LSTM techniques will be used as training model pipeline. Furthermore, as part of the innovative strategy into this research, a novel decision support algorithm is designed. This will inadvertently reduce poverty, enhances sustainable agriculture, and ensure sustainable production patterns when fully implemented, which are in line with the sustainable development goals 1, 2, and 12.

.

Keywords: Ginger Plants; Disease Detection; First-Order-Logic; Ensemble Learning; Internet of Things

1. Introduction

Ginger *(Zingiber officinale)*, a perennial herbaceous plant, and universally cultivated spice crop has huge economic importance ranges from its usage as medicinal products [1], ingredients in beverages and cosmetics because of its multipurpose rhizomes. Among the leading producer of the plant are Nigeria, Nepal, China, and India [2]. In 2017, Nigeria recorded the highest ginger production to the tuned of 834,600 metric tons before the country started recording declining values afterwards. Approximately, 90% of the productions were exported majorly to Asia and Europe countries, which contributed to the country's economic growth. Despite its huge economic values, ginger suffers from diseases, which inadvertently reduces the quality of production. In most cases, fungi, viruses, bacterial, and nematodes cause the diseases. Countries such as Japan, China, and Ethiopia have suffered from the plant's disease caused by bacterial epidemic. Similarly, towards

Academic Editor: Firstname Lastname

Published: date

the end 2023, Kaduna State, which is one of the few states in Nigeria where the plants is produced in commercial quantities, suffered a huge production loss as a result of fungal outbreak. Most of the farmers lost their means of livelihood which, mounting untold hardship to the nation's economy.

The traditional methods of visually inspecting the plant against the disease by experts or farmers are not effective because of its associated factors such as human errors, fatigue, costs, and time consuming. In addition, combined disease management strategy such as soil treatment approach, biological control proxies, and application of resistant varieties are most often employed for effective monitoring of rhizome rot but not without issues of robustness [3-4]. Therefore, in view of this development, researchers employ the innovative technologies such as artificial intelligence (AI), machine learning (ML), and Internet of Things (IoTs) for the detection or diagnosis of disease, which have been geared towards viable solutions [5]. Based on literature, this effort is promising as it has ultimately reduced the threats however, not without a gap that necessitated further research. The study of Elijah, et al., [2] carried out a comprehensive review on the state-of-the-art technologies that have been used so far for the detection of ginger diseases. Expectedly, IoTs, AI, and ML are the leading technologies. However, the researchers stated some current challenges that needed to be addressed. These include lack of sizeable interpreted datasets, lack of robust generalized disease detection models for both biotic and abiotic factors, and lack of AI based user friendly application for farmers.

Therefore, this research aims to leverage on integrated innovative technologies such as advanced IoT-based sensors, deep learning (convolutional neural networks, long short transformation memory, and Prophet) techniques to design a framework for smart based disease detection and decision support framework for Ginger plants' farmers in Nigeria. The AI/IoT based sensors will be utilized to collect datasets that will be passed to the training models. Furthermore, as part of the innovative strategy into this research, a novel decision support algorithm, which will consist of inference layer, knowledge base, decision engine, and risk alerts will be developed. The framework will be able to classify disease, generate recommendation for treatments, and push notifications to farmers. This research propose specifically to consider fungal diseases (biotic ginger plants diseases) and environmental stresses such as temperature (abiotic diseases). This will inadvertently reduce poverty, enhances sustainable agriculture, and ensure sustainable production patterns, which are in line with the sustainable development goals 1, 2, and 12.

2. Literature Review

Undoubtedly, the application of AI, ML, and IoTs based devices have revolutionized different sectors of human endeavors, in this case, the agriculture sector. The comprehensive study of Elijah, et al., [2] harped the promising strengths of the aforementioned technologies. However, the researchers advised that interested scientists should pay keen attention to the challenges of lack of availability of robust annotated datasets of ginger diseases. Similarly, the issue of lack of generalized model for balance factors when designing a model for detecting ginger disease must receive attention. The work of Shreelakshmi and Raju [6] stressed further the need to integrate IoTs based technique into machine learning models to detect ginger leaf disease considering its economic importance. However, the researchers supported the development of a decision support model that can be also integrated for precise ginger disease recommendation. Similarly Wong, et al., [5] equally canvassed for the application of AI and ML as state-of-the-art technologies that can maximally assist to detect the ginger plant disease. However, the researchers advised that effort must be put in place to harvest robust and reliable datasets for the disease effective classification since the conventional methods lack efficiency. Furthermore, the lit-

https://doi.org/10.3390/xxxxx

erature of Rana, et al., [7] employed a hybridized technique of random forest and convolutional neural networks to autonomously classify the eight ginger leaf diseases that their work considered. The researchers reported that robust and reliable classification results were obtained; however, a decision support algorithm may further improves their results. Waheed, et al., [8] employed deep learning techniques to detected ginger leaf diseases with the aid of a developed mobile application. However, the results obtained could be improved upon with more datasets to increases its classes.

The utilization rate of the cutting edge technologies such as IoTs, and ML to develop smart agriculture in this age and to actualize the sustainable development goals is very commendable [9]. Sambas, et al., [10] employed these technologies to develop a smart based prediction and recommendation model for ginger plant in Indonesia. However, the recommendation component did not considered any reasoning algorithm to make an informed decision. Similarly, Al-Otaibi et al., [11] equally canvassed the efficacy of the artificial intelligence based approach in predicting diseases among crops such as bacterial stalk rot in maize crop. The prediction system is predicated on decision support model however, it is an IoTs enabled model. Simon, et al., [12] proposed an intelligent plant health diagnosis model that could overcome the conventional approaches of managing plant health. CNN architecture models were utilized, and accurate disease classification results were reported however, the architecture's strength in inference capability is limited. Similarly, other deep learning models have been constantly employed such as YOLOv5 and YOLOv8 [13-14], modified VGG16, and VGG19 [15-16]. Traditional methods of detecting ginger plants diseases at early stage have consistently proved tedious and time consuming. Consequently, the research work of Hota et al., [17] proposed the incorporation of the laboratory based method with the architectures of CNNs to detect the plant disease. The approach is reported to presents an accurate detection of rhizome rot. This is similar to the research work of Janani and Mangai [18] where gradient boosting machine is employed and reported to have an improved performance.

3.1. Conceptual and Theoretical Framework

To design a smart based decision support framework for ginger plants that can accurately detect a specific fungal diseases, various stages are involved. Firstly, control system that will houses the IoTs based sensors and microcontroller will be designed. The sensors will collect IoTs based parameters such as temperature, humidity, moisture, and leaf wetness index. Field images of ginger plants (healthy and diseased) will be collected using either smartphones or drones. Similarly, experts' knowledge will equally serve in the datasets analysis. Secondly, the dataset will be preprocessed especially the images by removing noise, normalize lighting, and data augmentation. SMOTE will be employed; this technique will be premised on the Artificial Hummingbird optimization Algorithm (AHA). While proper sensors calibration will be done for proper and standardize sensors reading, dataset will be annotated with disease type and its severity. Thirdly, the preprocessed and optimized datasets obtained will be fed into the model pipeline. CNNs, for image based disease detection, Random Forest (RF), and Gradient Boosting (GB), an ensemble learning for combining images and IoTs data. Time series models such as LSTM or Prophet will be used for predicting epidemic risk. The choice of CNN is owing to its autonomous strength to finds relevant features, and its robustness to fluctuating input circumstances. Similarly, the choice of RF and GB is because they can efficiently deal with issues of heterogeneity and unwanted data. LSTM is equally proposed because of its strength to deal with complex, and nonlinearity of disease based data. Evaluation will be carried out based on precision, recall, and f1 score metrics. However, this goal will be achieved at the stage of implementation since this research is still work in progress. Fourthly, as part of the innovative idea, a decision support rule based algorithm is designed for an improved result.

The algorithm consist of different components such as inference, knowledge base, decision engine, and risk alert as shown by equation 1. Finally, as part of the future work of this research, the proposed prototype of smart based diseases detection and decision support system for ginger plants farmers, which will integrate all the previous subcomponents will be developed and fabricated, which will be subjected to series of evaluation processes.

$$Op = \text{abs min b} \in \text{B} \sum_{i=1}^{i} (\text{Ca}, Pb + \text{Tm}) \quad (1)$$

Where Op = optimal decision to minimize farmer's loss

b ϵ B = absolute value of the possible actions for example, no treatment required, apply appropriate fungi treatment.

Ca = cost of the action,

Pb = probability of disease,

Tm = trained models showing diseases likelihood

3. Research Methodology

This research aims to design a decision support framework for smart based disease detection model for ginger plants based on iterative system development approach, which include problem definition, and requirement analysis. The research design as depicted by Figure 1 consist of data collection with storage layer, feature engineering layer, model training pipeline, the innovative layer (decision support system), and finally, the farmer friendly user interface layer. The data collection and storage layer consist of images data of the ginger plants, and the sensors based data, which include temperature, leaf wetness index sensors. The images data are expected to be collected using either smartphones, drones, or a positioned camera. The two categories of datasets will be subjected to the knowledge of experts. The datasets will be cleaned to remove noise, images lighting or data augmentation as part of activities during feature engineering layer. In the layer of model training pipeline, CNN will be employed for image dataset, ensemble models will be used for the training of the combined (images and IoTs) dataset. Similarly, Prophet or LSTM will be used predicting the epidemic risk. As part of innovation brought to the research, a novel decision support algorithm, which include inference based on first order logic, decision engine (IF THEN), knowledge base, and risk alerts for farmers via SMS or mobile application will be developed.

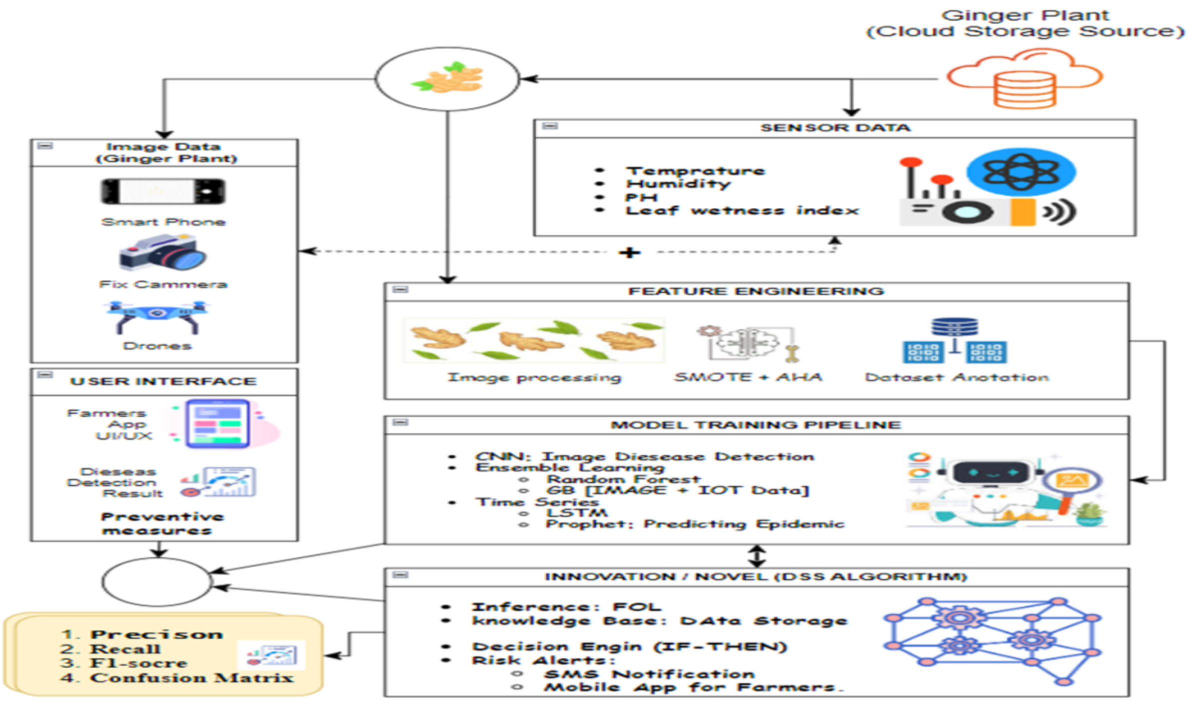

Figure 1: Decision Support Conceptual Framework of the Ginger Plants' Model

Furthermore, Table 1 presents the algorithmic design of the innovative decision support framework for the proposed smart based ginger plants' disease detection model.

Table 1: Algorithmic Representation of the Innovative Decision Support System

Input: Optimized_Data (o_d)
Parameters: Image_Data (i_d) and Sensor_Data (s_d), Optimized_Data (o_d), Convolutional Neural Nrtworks (CNN), Random Forest (RF), Long Short Transformation Memory (LSTM), Synthetic Minority Over-sampling Technique_Artificial Hummingbird optimization Algorithm (SMOTE_AHA), Diseases (d), Fungi (f), Bacterial (b), Virus (v), Treatments (t), Knowledge_Base (k), Soil_Moisture (s), Threshold (z),
Output: Recommendation (r)

1: Input o_d // $o_d = i_d + s_d$ Based on SMOTE_AHA and RF
2: $o_d = 0$ // initialize the optimized image and sensor datasets
3: While $i_d \wedge s_d = o_d$ // setting a condition that the datasets are actually optimized
4:ForAllo_d

5: Apply $$Op = \text{abs min} b \in \mathrm{B} \sum_{i=1}^{i} (\mathrm{Ca}, Pb + \mathrm{Tm}) \quad (1)$$

6: Invoke CNN, RF, LSTM // models to classify diseases and LSTM for predict risks
7: Store d, t in the k
8: ∀(d) If ∃ f ∨ b ∨ v Then
9: Apply t If s > z Then
10: Print t
11: EndIf
12: EndIf
13: EndLoop
14: WEnd
15: Output r // send notifications to farmers via SMS or mobile application

From lines 1 to 4 of the Table 1, the optimized datasets based on the application of SMOTE_AHA is initialized to start the process. Line 3 to be specific, set a condition to ensure the optimization of the two various datasets. In order to minimize farmers' loss, the optimal decision model of equation 1 is invoked at line 5. The inference layer of the decision support algorithm is depicted by line 6, which invoke the models to classify the diseases and subsequently used LSTM to predict risks. The knowledge base of the algorithm is represented by line 7.

Lines 8 to 9 are christened Decision Engine: For all diseases, if there exist fungi, bacterial, or virus then, apply treatments if the soil moisture (because of present temperature or humidity) is greater than a particular threshold value that will be set. The treatment can be organic, chemical, biological control methods as expectedly printed out by line 10. As part of the innovation, this research propose to use the First Order Logic (FOL) to represent the knowledge base for the treatments and diseases owing to its power of expressivity. Lines 11 to 14: are meant to end the control structures of the algorithm; for instance, WEnd stands for While End. Line 15 is the risk alerts.

4. Discussion of Expected Results

Based on a label dataset of ginger rhizomes, stems or leaves with data features categories such as soft rod, fungal rhizome rot, leaf spot blight, bacterial wilt, or healthy that is, after preprocessing activities that show noise removal, or cropped region of interest, CNN models results will be obtained. However, prior to this stage, LSTM modeling will be employed for time series data such as readings of humidity, and temperature.

Furthermore, when First order Logic (FoL) is integrated to the ML predictions, the expected results is meant to be robust. Below is an example of how FoL will works on this research.

IF *CNN identifies leaf-spot features* AND *humidity is low*
    THEN *disease ≠ fungal leaf spot*.
ENDIF
IF *LSTM forecasts SoilMoisture declining endlessly* AND *temperature rising*
    THEN *risk = soft rot*.
ENDIF

More so, in order to demonstrate the anticipated results, CNN images data structure along with the images labels in comma separated value (csv) are shown by Table 2.

Table 2: Sample of the CNN Images Dataset with CSV

```
/data/images/
/bacterial wilt /
bacterial wilt _001.jpg
/fungal rhizome rot /
fungal rhizome rot _001.jpg
/leaf spot blight /
leaf spot blight _001.jpg
   ...
/data/annotations/images_labels.csv
image_id,file_path,label,acquisition_date,lighting,confidence_label
img001,images/fungalRhizomeRot/fungalRhizomeRot_001.jpg,fungalRhizomeRot,2025-12-09,morn-
ing,7.15
img002,images/ bacterialWilt/bacterialWilt_001.jpg,bacterialWilt,2025-12-09,afternoon,3.00
img003,images/leafSpotBlight/leafSpotBlight 001.jpg, leafSpotBlight,2025-12-09,cloudy,0.8
```

The first part of Table 2 presents the sample images dataset of ginger diseases, which consist of bacterial wilt, fungal rhizome rot, and leaf spot blight. The second part presents the labeled dataset in CSV.

Table 3 presents the sample of anticipated time series sensor data along with the CSV format based on LSTM.

Table 3: Sample of the LSTM Images Dataset

/data/sensors/ sensor_readings.csv sensor_metadata.csv

Table 3 presents the sample of the LSTM data based on some sensors such as temperature and humidity. For example, temperature sensor readings may be 2025-12-10T13:00:00Z, while humidity readings may include zone003. Table 4 presents the expected results of the decision support based FoL algorithm considering the facts and rules.

Table 4: Expected Results of the Decision Support Based FoL Algorithm

Facts.fol //Facts to be used by the FoL
ImageShows(img001, bacterialWilt_features).
SensorRead(zone001, tempearture, 91, 2025-12-10T13:00:00Z).
CNN_Predicts(img001, leaf_spot///soft rod, 0.74).
LSTM_Predicts(zone001, disease_risk_4d, 0.54).
Rules.fol //FoL Part
∀s ∀t (ImageShows(s, soft rod_features) ∧ SensorRead(t, humidity, h) ∧ h > 74 → Diagnosis(t, bacterialWilt)).
∀t (LSTM_Predicts(t, disease_risk_4d, r) ∧ r > 0.6 → Alert(t, high_risk, r)).
∀s ∀t (CNN_Predicts(s, disease, pc) ∧ RF_Predicts(s, disease, pr) → Combined_Score(s, disease, 0.6*pc + 0.4*pr)).

Firstly, Table 4 presents the facts regarding the datasets, which consist of the features of the bacterial wilt, leaf spot in images form. Also included are sensor based data such as temperature. These facts would be represented by rules using the first order logic as indicated in the second part of Table 4. For example, soft rod features, and bacterial wilt are encoded as letters *s* and *t* respectively. In summary, Table 4 depicts an essential critical components for diseases detection and decision support components.

5. Conclusion

Considering the economic value of ginger plants globally, there is need to employ the state-of-the-art technologies such as artificial intelligence, machine learning, and advanced internet of things based sensors to mitigate the associated risks such as pest and diseases of the plant. In view of this development, this research proposed a smart based framework for detection of ginger diseases. More so, decision support algorithm is integrated into the framework. The datasets will be harvested from the IoTs based sensors, and the necessary feature engineering processes will be carried out and will be subjected to the model training pipeline. The images data are expected to be collected using either smartphones, drones, or a positioned camera. The two categories of datasets will be subjected to the knowledge of experts. The datasets will be cleaned to remove noise, images lighting or data augmentation as part of activities during feature engineering layer. In the layer of model training pipeline, CNN will be employed for image dataset, ensemble models such as random forest or gradient boosting will be used for the training of the combined (images and IoTs) dataset. Similarly, time series model such as LSTM will be used predicting the epidemic risk. As part of innovation brought to the research, a novel decision support algorithm, which include inference based on first order logic, decision engine

(IF THEN), knowledge base, and risk alerts for farmers via SMS or mobile application is proposed in this work. The choice of LSTM is owing to its capability to identify patterns that shows likelihood of disease, which assist farmer to make an informed decision early. Similarly, First order Logic is integrated to the ML predictions owing to it explainability and rule based decision making influence.

It is important to state it on record that this research is work in progress. Therefore, the researchers have started to deploy strategies to implement the framework, set up the IoTs based sensors to collect the needed datasets that will be used to develop the plants diseases detection model. Interested researchers in this area can equally exploit the efficacy of Prophet or LSTM models for accurate prediction of the disease. Furthermore for future work, we hope to employ a robust knowledge representation strategy (that is, ontology semantic data model) to represents the selected features of the datasets for semantic expressivity. We hope to employ semantic data corpus such as WordNet, Word2Vec, or BabelNet.

References

1. Ballester, P.; Cerdá, B.; Arcusa, R;, Marhuenda, J.; Yamedjeu, K.; & Zafrilla, P. (2022). Effect of ginger on inflammatory diseases. *Molecules*, *27*(21), 7223.
2. Elijah, O.; Abioye, A. E.; & Maguvu, T. E. (2025). Pest and disease management in ginger plants: artificial intelligence of things (aiot). *IEEE Transactions on AgriFood Electronics*.
3. Akkem, Y.; Biswas, S. K.; & Varanasi, A. (2023). Smart farming using artificial intelligence: A review. *Engineering Applications of Artificial Intelligence*, *120*, 105899.
4. Kim, M.; Shim, C.; & Lee, J. (2024). Effects of Organic Agricultural Materials and Cultivation Methods on the Control of Ginger Rhizome Rot Disease and Growth in Organic Ginger Farming. *Agronomy*, *14*(10), 2285.
5. Wong, W. Z.; Tew, Y.; & Tan, C. W. (2024, December). A Review of Ginger Disease Detection Technique using Artificial Intelligence (AI). In *2024 IEEE International Conference on Computing (ICOCO)* (pp. 1-6). IEEE.
6. Shreelakshmi, C. M.; & Raju, C. (2023, July). Revolutionizing Crop Management: An Emphasis on Ginger Leaf Disease Detection Techniques Using Machine Learning and IoT. In *2023 International Conference on Data Science and Network Security (ICDSNS)* (pp. 1-5). IEEE.
7. Rana, G.; Banerjee, D.; Upadhyay, D.; Dangi, S.; & Yamsani, N. (2024, July). Hybrid CNN & Random Forest Model for Effective Ginger Leaf Disease Diagnosis. In *2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC)* (pp. 1310-1315). IEEE.
8. Waheed, H.; Akram, W.; Islam, S. U.; Hadi, A.; Boudjadar, J.; & Zafar, N. (2023). A mobile-based system for detecting ginger leaf disorders using deep learning. *Future Internet*, *15*(3), 86.
9. Pawaskar, P.; Yogish, H. K.; Pakruddin, B.; & Deepa, Y. (2025). A Novel and Efficient Deep Learning Models for Assessing AI's Impact on Disease Diagnosis in Agriculture. *Indian Journal of Agricultural Research*, *59*(9).
10. Sambas, A.; Mujiarto, M.; Gundara, G.; Refiadi, G.; Mulyati, N. S.; & Sulaiman, I. M. (2023). Development of smart farming technology on ginger plants in Padamulya Ciamis Village, West Java, Indonesia. *International Journal of Research in Community Services*, *4*(3), 93-99.
11. Al-Otaibi; S., Khan; R.; Ali, J.; & Ahmed, A. (2024). Artificial intelligence and Internet of Things-enabled decision support system for the prediction of bacterial stalk root disease in maize crop. *Computational Intelligence*, *40*(1), e12632.
12. Simon, K.; Venkateswarlu, M.; Sadiq, B. O.; Rosette, K.; & Paul, A. (2025). Designing a Smart Plant Health Diagnosis Model using Adaptive Machine Learning Techniques. *International Journal of Advanced Research in Computer Science*, *16*(2).
13. Sundari, Y. B. T.; Kohila, R.; Sowmiya, M.; Nallametti, N.; Philip, J.; & Keerthana, N. V. (2025, June). Crop Disease Detection using Edge IoT Devices and YOLOv5-based Classification. In *2025 3rd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)* (pp. 207-212). IEEE.
14. Yong, T. C. (2024). Integration of Image Processing Algorithm and Deep Learning Approaches To Monitor Ginger Plant.
15. Babatunde, R. S.; Babatunde, A. N.; Ogundokun, R. O.; Yusuf, O. K.; Sadiku, P. O.; & Shah, M. A. (2024). A novel smartphone application for early detection of habanero disease. *Scientific Reports*, *14*(1), 1423.

16. Mac, T. T.; Nguyen, T. D.; Dang, H. K.; Nguyen, D. T.; & Nguyen, X. T. (2024). Intelligent agricultural robotic detection system for greenhouse tomato leaf diseases using soft computing techniques and deep learning. *Scientific Reports*, *14*(1), 23887.
17. Hota, S.; Benya, A.; Mohanty, S.; Prabina, K. E.; Achary, K. G.; Akhtar, J., ... & Singh, S. (2025). Integrating Immunosensor With Artificial Intelligence: A Novel Approach for the Rapid Detection of Rhizome Rot Diseases. *Plant Pathology*, *74*(8), 2221-2240.
18. Janani, V., & Mangai, N. S. (2025). Optimizing Rhizome Rot Disease Detection using Machine Learning Approach. *WSEAS Transactions on Biology and Biomedicine*, *22*, 400-414.