Application of Convolutional Neural Networks in the Classifying Growth Stages in Rice

Folasade Olayinka Durodola [1]*, Safiriyu Ijiyemi Eludiora [2], Samuel Oluyemi Owoeye[3], Furqan Kolawole Kamil-Bello[4], Sakira Omosalewa Daodu[5], Kayode Michael Makinde [6], Olaniyi Erastus Folaranmi[7]

[1,3,4,5,6,7] Department of Mechatronics Engineering, Federal University of Agriculture, Abeokuta, Nigeria
[2]Department of Computer Science and Engineering, Obafemi Awolowo University, Ile Ife, Nigeria
Email: owoeyeso@funaab.edu.ng

Abstract
Rice is a staple food in many countries, making its efficient production critical to meet growing demand. This study introduces a novel approach by developing a machine learning-based classification system that accurately identifies the growth stages of rice crops—specifically, the "Vegetative," "Reproductive," and "Ripening" stages—using advanced convolutional neural network (CNN) architectures. Utilizing a unique dataset sourced from Roboflow, which includes annotated rice plant images, we meticulously divided the data into training, validation, and testing subsets to ensure robust model performance. Through the application of transfer learning on the ImageNet dataset, we explored the effectiveness of models such as ResNet50, InceptionV3, and MobileNetV2. Our findings indicate that InceptionV3 significantly outperformed the others, achieving a classification accuracy of 95.1% with a log loss of 0.13, compared to 87.3% and 93.5% for ResNet50 and MobileNetV2, respectively. This research not only demonstrates the potential of CNNs in precision agriculture but also provides practical insights into optimal model selection and data preparation techniques. This study highlights the potential of CNNs in precision agriculture and emphasizes the importance of model selection and data preparation in developing efficient crop monitoring and classification systems.

Keywords: Rice Growth, Machine Learning, Convolutional Neural Networks, ResNet50, MobileNetV2, InceptionV3.

1.0 INTRODUCTION

Rice is a staple food for billions of people worldwide, particularly in Asia, Africa, and Latin America, making it a vital component of global food security (Muthayya *et al.,* 2014). However, increasing population pressures and climate change pose significant challenges to sustainable rice production (Nelson *et al.,* 2014). Traditional methods for monitoring rice growth stages depend on manual labor, making them time-consuming, labor-intensive, and susceptible to human error (Wilfred *et al.,* 2006). These limitations affect the scalability and effectiveness of monitoring large rice fields, leading to inefficiencies in resource use and crop management (Ferentinos *et al.,* 2017).
Convolutional Neural Networks (CNNs) have demonstrated transformative potential in precision agriculture by analyzing large datasets and identifying complex patterns (Sharma *et al.,* 2020). Their application to detecting and monitoring rice growth stages offers a promising solution to the challenges faced by farmers using traditional methods. Automating the identification of critical growth phases —Vegetative, Reproductive, and Ripening —allows CNN-based systems to enhance decision-making, improve yields, and minimize environmental impact by optimizing the use of water, fertilizers, and pesticides (Nabavi-

Pelesaraei *et al.,* 2018). Additionally, these systems enable real-time monitoring, helping farmers adapt to climate variability and mitigate risks (Kourgialas *et al.,* 2015).

This research aims to develop a robust CNN-based system capable of accurately classifying rice growth stages to support precision agriculture. The project focuses on these objectives: data collection and preprocessing from diverse sources, designing and training ANN models—InceptionNet, MobileNet, and ResNet—for classification and detecting the various growth stages in rice. By ensuring scalability and usability, the system will empower farmers with accurate, real-time data for better crop management.

The study is justified by its potential to address labor and efficiency challenges, reduce environmental degradation, and improve agricultural productivity globally (Elbasi *et al.,* 2024; Akintuyi, 2024). It emphasizes scalability, making the solution applicable across various regions and rice varieties. The scope of this research includes a comparative evaluation of the selected CNN models, focusing on their strengths, limitations, and adaptability to diverse agricultural environments, contributing to improved practices in rice farming (Manfreda *et al.,* 2018; Fan & Rue, 2020). Owoeye *et al.,* (2024) highlighted the use of ANNs for detecting diseases in tomato plants demonstrates the model's ability to identify and classify various diseases based on leaf images accurately, showcasing the potential of ANNs to enhance disease management and improve crop health.

Shukla and Bera (2023) presented a notable case study on using ANNs to predict crop yields based on environmental and historical data. By analyzing factors such as weather conditions, soil quality, and previous crop performance, the ANN model provides accurate yield predictions, enabling farmers to plan and optimize their farming practices. Also,Hara *et al.* (2021) conducted a case study where artificial neural networks (ANNs) were used to predict rice growth stages based on phenological data such as temperature, rainfall, humidity, and soil conditions. The ANN model was trained using historical data collected from various experimental fields across multiple growing seasons.

Chen and Mcnairn (2006) demonstrated how ANN models were integrated with remote sensing technologies to identify various growth stages across large farmland areas. Satellite and drone imagery provided continuous data on plant health, canopy cover, and leaf area index throughout the growing season. The use of this model enabled real-time monitoring, improving the precision of irrigation scheduling and pest management.

This research intends to apply convolutional neural networks (CNNs) to predict rice growth stages by analyzing phenological data and image-based inputs, focusing on vegetative, reproductive, and ripening phases. Using ResNet, MobileNet, and InceptionNet models trained on diverse datasets, the study aims to enhance precision agriculture by providing farmers with actionable insights for better crop management, optimized resource utilization, and increased productivity.

2.0 MATERIALS AND METHODS

Detecting and accurately identifying rice growth stages are essential for effective agricultural management, as this directly influences crop yield, resource utilization, and farming efficiency. The proposed system uses CNNs tailored for image recognition tasks to analyze rice crop images and extract relevant features such as texture, color, shape, and patterns. While CNNs automatically extract features, a focused discussion on the most relevant visual features for rice growth stage classification—such as leaf color variation and texture differences—would improve clarity. This system is trained on a dataset comprising images of rice crops at various growth stages, captured under diverse environmental conditions. It is integrated into a web-based platform with a user-friendly interface, enabling farmers to upload images and receive real-time feedback on the growth stage.

The methodology includes data collection and preprocessing to create a labeled dataset. Features are extracted to form a matrix that captures essential details such as edges and patterns. The model is then trained to minimize prediction errors and validated on unseen data to ensure accuracy. However, the dataset's limitations include potential biases in image representation and variations in lighting and soil conditions that may not be adequately captured, which could affect the model's generalizability. The rice growth stage detection system integrates the machine learning workflow in Figure 1 to develop models for crop monitoring, enabling accurate identification of rice growth stages based on data analysis and classification. The process starts with the collection of images of rice plants, along with their corresponding labels, which represent growth stages, health conditions, or other relevant information.

The development of machine learning models for rice growth stage detection emphasizes preparing a diverse and well-augmented dataset to improve model generalization. Three convolutional neural network (CNN) architectures—ResNet, MobileNet, and InceptionNet—were selected for their unique strengths in accuracy, efficiency, and scalability.

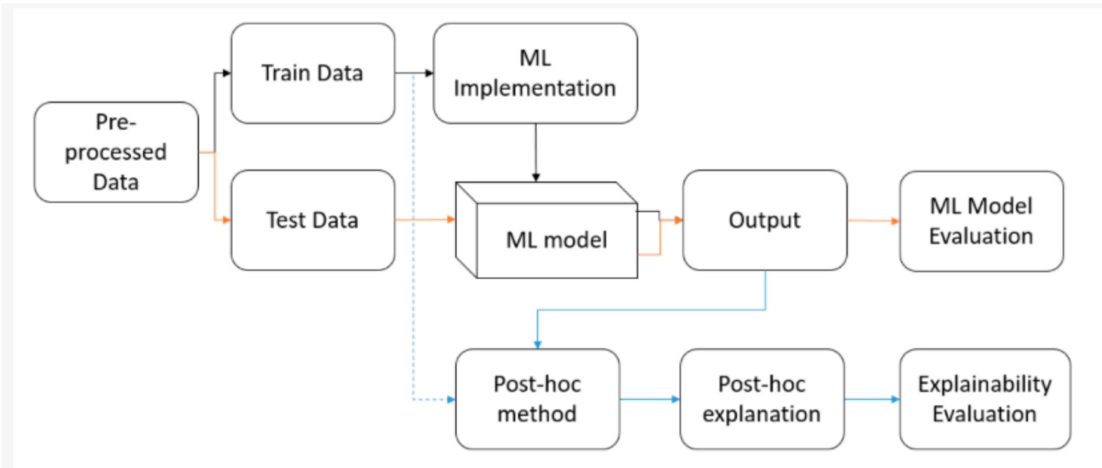

Figure 1: Machine Learning Process (Nakagawa *et al.,* 2021)

2.1 Data Collection, Processing and Analysis

Data collection is a crucial step in developing an effective machine-learning model for rice growth stage detection. The dataset consisted of images of rice plants captured at various growth stages and under diverse environmental conditions. These images were sourced from agricultural repository, custom-captured photos from rice fields, and contributions from agricultural research institutions, ensuring a wide range of scenarios for better model generalization and real-world application performance.

The process of labeling images into the Vegetative, Reproductive, and Ripening stages involved manual annotation by agricultural experts. Each image was carefully examined, and its growth stage was determined based on visual cues such as leaf structure, panicle development, and overall plant health. This manual process ensured accurate labeling but also posed challenges regarding consistency and potential bias. To address these concerns, multiple annotators were involved, and a consensus approach was adopted to minimize discrepancies in labeling. Additionally, bias was minimized by ensuring that the dataset included a balanced number of images across all growth stages, with a deliberate effort to capture images from various geographical regions and environmental conditions.

The collected data were pre-processed, involving image resizing, noise reduction, and data augmentation. Images were resized to a standard dimension to ensure compatibility with neural network architectures. Noise reduction techniques were applied to remove irrelevant artifacts that could negatively impact the model's learning process. The preprocessing sample is shown in Figure 2. Data augmentation operations, such as rotation, flipping, scaling, and color adjustments, expanded the dataset artificially, making it more robust against variations in image conditions. Before and after augmentation, visual representations of the dataset could include histograms showing the distribution of images across stages and sample images illustrating the differences in quality and diversity.

Figure 2: Pre-processing Samples

The quality and comprehensiveness of the dataset significantly impact the performance of machine learning models in rice growth stage detection (Tan *et al.,* 2022). The dataset contained 6,000 images for the Vegetative stage, 5,000 for the Reproductive stage, and 8,000 for the Ripening stage. These images cover a range of environmental conditions, such as varying lighting, weather, and soil types, to ensure the model's exposure to diverse scenarios. Extensive data augmentation techniques, including random rotation, scaling, cropping, and color adjustments, were employed to increase variability and enhance the robustness of the models (Mumuni & Mumuni, 2022). This variability allows the models to adapt to different growth stages and environmental conditions, ensuring their practicality and reliability in real-world applications (Zhou *et al.,* 2019).

2.2 Model Architectures

Three CNN architectures were chosen for this study: ResNet, MobileNet, and InceptionNet, each offering distinct advantages.

ResNet: A deep residual network known for its skip connections, allowing for effective training of very deep networks.

MobileNet: A lightweight model designed for mobile and embedded applications, utilizing depthwise separable convolutions for efficiency.

InceptionNet: A model that employs multiple convolutional kernel sizes in parallel, enhancing the network's ability to capture various features.

2.3 Model Implementation

Each model was implemented using a PyTorch deep learning framework. The following steps were taken for each architecture:

Architecture Setup: The pre-trained weights from ImageNet were utilized as the starting point for each model to leverage transfer learning.

Custom Output Layer: A fully connected layer was added to classify the rice growth stages, with the number of neurons corresponding to growth stages. The output layer's activation function was defined as in equation 1:

$$y_i = \frac{e^{Z_i}}{\sum_{j=1}^{C} e^{Z_j}} \tag{1}$$

Where y_i is the probability of class i, $Z_i$is the raw output (logit) for class i, and C is the total number of classes.

2.4 Performance Evaluation

The models' performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. Validation on a separate hold-out set monitored convergence and identified potential overfitting or underfitting issues. The best-performing architecture was selected for further refinement and deployment. Figure 3 shows a sample of the dataset.

Accuracy: This can be calculated using equation 2:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + \ False\ Negatives} \tag{2}$$

Equations 3, 4 and 5 are used to determine the Precision, Recall, and F1-Score respectively:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (3)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (4)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Figure 3: Sample Dataset

3.0 RESULT AND DISCUSSION

Figure 4 shows the models result breakdown with ResNet50 achieving an accuracy of about 87.3% on the test set, the InceptionNet model performed better than ResNet50, with an accuracy of about 95.1% on the test set. It means that the model is very good at classifying samples, far beyond what ResNet50 can achieve. The MobileNetV2 model result also achieved an accuracy of approximately 93.5% on the test set. A high F1 score shows a good balance between identifying positive instances and minimising false positives and false negatives, something very critical in tasks for which precision and recall matter. ResNet50 F1 score was 86.9%, the F1 score for InceptionNet was 94.8%, which is a balance between precision and recall, while the F1 score for MobileNetV2 was 93.1%, thus indicating efficiency in identifying and classifying instances while reducing as much as possible both false positives and false negatives.

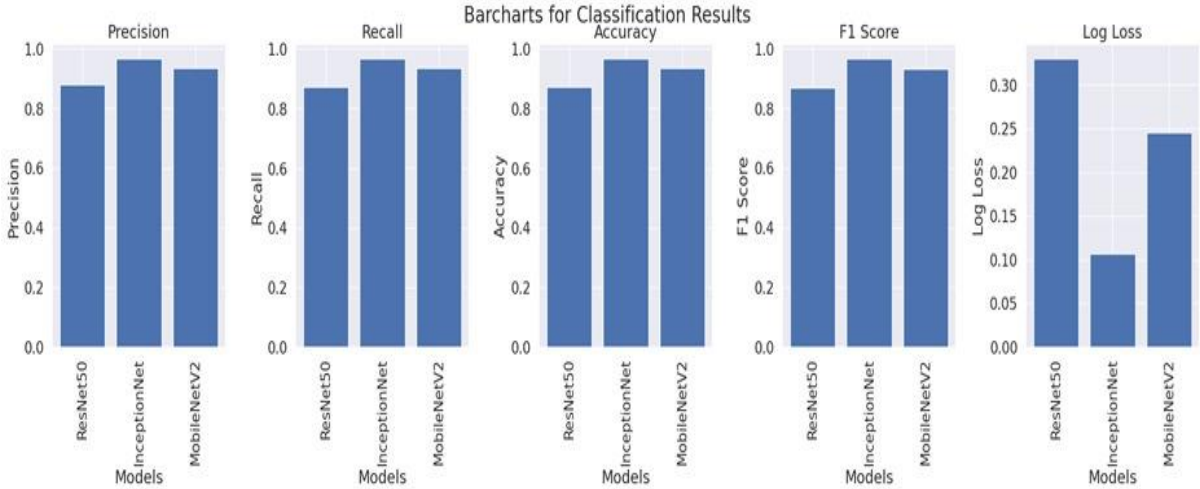

Figure 4: Results for the 3 Models

Table 1 compares the results of ResNet50, InceptionV3, and MobileNetV2, indicating that each of the models has different strong and weak points and hence varying conclusions about overall model effectiveness. It clearly turns out that InceptionV3 excels at an accuracy of about 95.1% and an F1 score of 94.8%, thus underscoring its lead in properly classifying samples while maintaining optimal balance between precision and recall. The low log loss of 0.13 further underscores its excellent probability calibration and how well it is at aligning predicted probabilities with actual labels. Finally, precision and recall scores of 95.2% and 95.1%, respectively, reflect the reliability of the model in identifying true positives, with very minimal misclassifications in the confusion matrix. In contrast, while MobileNetV2 did well with an accuracy of 93.5% and an F1 score of 93.1%, the heights reached by InceptionV3 are not matched; it still offers robust classification capabilities. Log loss was a bit higher at 0.22, which means that the probability predictions were good in line with the actual labels, but further improvement is allowed.

Table 1: Comparism of the three model results

Metric	Class	ResNet Value	Inception Net Value	MobileNet Value
Accuracy (%)	Overall	87.3	95.1	93.5
F1 Score (%)	Overall	86.9	94.8	93.1
Log Loss	Overall	0.33	0.13	0.22
Precision (%)	Vegetative	87.9	95.3	93.8
Precision (%)	Reproductive	86.5	95.0	93.6
Precision (%)	Ripening	85.7	95.2	93.5
Recall (%)	Vegetative	87.3	95.2	93.5
Recall (%)	Reproductive	86.8	95.1	93.4
Recall (%)	Ripening	85.9	94.8	93.2
Misclassification Issues	Vegetative	Misclassified as Ripening	Minimal, strong differentiation from other stages	Misclassified as Reproductive

Misclassification Issues	Reproductive	Misclassified as Vegetative	Minimal, strong differentiation from other stages	Misclassified as Ripening
Misclassification Issues	Ripening	Misclassified as Vegetative	Minimal, strong differentiation from other stages	Misclassified as Vegetative and Reproductive
Training Behavior	Overall	Smooth accuracy increase, plateau around 90-92%, some fluctuations in validation accuracy (potential overfitting). Loss decreased steadily.	Rapid accuracy increase, stabilized early at a high level, loss decreased quickly. Exhibited excellent fitting and generalization.	Monotonic accuracy increase, plateau near 95%, less fluctuation compared to ResNet50. Loss decreased steadily, stable model performance.

With an accuracy of 93.7% and a recall of 93.5%, the MobileNetV2 accomplishes effective classification; it sometimes gets confused between classes. It works quite similarly to ResNet50. The training curves for MobileNetV2 manifest a smooth rise in accuracy, followed by reaching a plateau at about 95% and less fluctuation than ResNet50, proving to be better in terms of stability. For ResNet50, accuracy amounts to 87.3%, while an F1 score of 86.9% puts it behind the other models both in accuracy and balanced performance. The log loss for this model is higher, at 0.33, hence the poorer calibration of probability. With precision and recall scores of 87.9% and 87.3%, respectively, this points to a less reliable classification performance.

On the confusion matrix for ResNet50, there were actual difficulties in the distinction between certain classes, consequently affecting its overall effectiveness. Although ResNet50 presents an upward trend in terms of accuracy, with a loss that keeps decreasing, fluctuations in validation accuracy may further indicate overfitting. Hence, InceptionV3 is the best model owing to its better performance in terms of accuracy, F1 score, log loss, precision, recall, and stability of training. MobileNetV2 remains a strong alternative, much better in stability compared with ResNet 50, a good one but far from the others' overall effectiveness.

4.0 CONCLUSION

This paper presents a detailed analysis and evaluation of the performance of three state-of-the-art deep learning models—ResNet50, InceptionV3, and MobileNetV2—on rice plant classification. Comparative results have shown InceptionV3 to excel on most of the critical indicators, proving to be the most efficient for the specific application under study. It has predictive power, featuring an accuracy of 95.1 percent and an F1 score of 94.8 percent; thus, there is a fine balance between precision and recall. Its log loss of 0.13 means it is very well calibrated in its probability predictions, which are essential for credible classification results. Further manifesting the good performance of InceptionV3 are its low misclassification rates; hence, it would be capable of differentiating more efficiently between rice plant classes.

Although a bit less powerful than InceptionV3, MobileNetV2 has returned quite promising results, with an accuracy of 93.5% and an F1 score of 93.1%. This model serves as a middle ground between performance and efficiency, making it suitable for scenarios with limited computational resources or when operational efficiency needs to be traded off against accuracy. Due to the stability and better performance of MobileNetV2 compared to ResNet50, it is very suitable for practical deployment in resource-constrained environments. Although it has a log loss of 0.22 with respect to InceptionV3, which is relatively high, it remains a reliable model characterised by good balances between precision and recall.

ResNet50 formed the foundation and proved effective, though it showed poorer performance metrics when compared to the others. It has an accuracy of 87.3% and an F1 score of 86.9%, indicating that while it is acceptable, there is room for improvement. A higher log loss of 0.33 means less precise probability predictions, and significant room for model refinement exists. The challenges in differentiating classes and misclassifications suggest that ResNet50 needs further enhancement to be competitive with the InceptionV3 and MobileNetV2 models.

Looking ahead, future research could focus on refining the architectures further, perhaps through the integration of advanced techniques like transfer learning or fine-tuning on larger datasets. Additionally, exploring ensemble methods that combine the strengths of these models might yield even better results.

This study is not without limitations; the dataset used may not encompass the full variability of rice plant classes found in diverse agricultural settings. Future work should look to include a broader range of environmental conditions and more extensive datasets to improve model robustness.

Finally, the implications of this research extend beyond rice classification. The methodologies developed here could be adapted for other crops, aiding in precision agriculture efforts. By facilitating accurate plant classification, farmers can make more informed decisions regarding crop management, ultimately enhancing agricultural productivity and sustainability.

ACKNOWLEDGEMENT

The authors acknowledge the staff of Mechatronics Engineering Department of the Federal University of Agriculture, Abeokuta for providing the providing the platform for the research.

AUTHORS' CONTRIBUTIONS STATEMENT

FOD: Conceptualization and Investigation. SIE: Research supervision. SOO: Review & editing of initial write-up. FKK and SOD: Data collection and Methodology. KMM: Formal Analysis. OEF: Writing original draft. All authors read and approved the final manuscript.

DATA AVAILABILITY

Datasets generated or analysed during the current study will be made available on request.

STATEMENTS AND DECLARATIONS

The authors declare that this manuscript is original and has not been published previously nor is it under consideration for publication elsewhere. All data, results, and interpretations presented in this work are the outcome of the authors' independent research efforts.

ETHICAL

The current study did not include any human or animal subjects. Thus, this study is not subject to an ethics review committee and does not require any informed consent.

COMPETING INTERESTS

The authors declare that they have no known competing financial or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

Akintuyi, O. B. (2024). Adaptive AI in precision agriculture: a review: investigating the use of self-learning algorithms in optimizing farm operations based on real-time data. *Research Journal of Multidisciplinary Studies*, *7*(02), 016-030.

Chen, C., & Mcnairn, H. (2006). A neural network integrated approach for rice crop monitoring. *International Journal of Remote Sensing*, *27*(7), 1367-1393.

Elbasi, E., Mostafa, N., Zaki, C., AlArnaout, Z., Topcu, A. E., & Saker, L. (2024). Optimizing Agricultural Data Analysis Techniques through AI-Powered Decision-Making Processes. *Applied Sciences*, *14*(17), 8018.

Fan, S., & Rue, C. (2020). The role of smallholder farms in a changing world. *The role of smallholder farms in food and nutrition security*, 13-28.

Ferentinos, K. P., Katsoulas, N., Tzounis, A., Bartzanas, T., & Kittas, C. (2017). Wireless sensor networks for greenhouse climate and plant condition assessment. *Biosystems engineering*, *153*, 70-81.

Hara, P., Piekutowska, M., & Niedbała, G. (2021). Selection of independent variables for crop yield prediction using artificial neural network models with remote sensing data. *Land*, *10*(6), 609.

Kourgialas, N. N., Dokou, Z., & Karatzas, G. P. (2015). Statistical analysis and ANN modeling for predicting hydrological extremes under climate change scenarios: The example of a small Mediterranean agro-watershed. *Journal of environmental management*, *154*, 86-101.

Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2021). A survey of convolutional neural networks: analysis, applications, and prospects. *IEEE transactions on neural networks and learning systems*, *33*(12), 6999-7019.

Manfreda, S., McCabe, M. F., Miller, P. E., Lucas, R., Pajuelo Madrigal, V., Mallinis, G., & Toth, B. (2018). On the use of unmanned aerial systems for environmental monitoring. *Remote sensing*, *10*(4), 641.

Mumuni, A., & Mumuni, F. (2022). Data augmentation: A comprehensive survey of modern approaches. *Array*, *16*, 100258.

Muthayya, S., Sugimoto, J.D., Montgomery, S. and Maberly, G.F. (2014), An overview of global rice production, supply, trade, and consumption. Ann. N.Y. Acad. Sci., 1324: 7-14. https://doi.org/10.1111/nyas.12540

Nabavi-Pelesaraei, A., Rafiee, S., Mohtasebi, S.S., Hosseinzadeh-Bandbafha, H. and Chau, K.W. (2018). Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. *Science of the total environment*, *631*, pp.1279-1294.

Nakagawa, P. I., Pires, L. F., Moreira, J. L. R., Bonino da Silva Santos, L. O., & Bukhsh, F. (2021). Semantic description of explainable machine learning workflows for improving trust. *Applied Sciences*, *11*(22), 10804.

Nelson, A., Setiyono, T., Rala, A. B., Quicho, E. D., Raviz, J. V., Abonete, P. J., ... & Ninh, N. H. (2014). Towards an operational SAR-based rice monitoring system in Asia: Examples from 13 demonstration sites across Asia in the RIICE project. *Remote Sensing*, *6*(11), 10773-10812.

Owoeye S.O**.**, F.O.Durodola, M.I Adekunle, A.T.Oyelami and B.M Bisiriyu. (2024): Development of a Tomato Leaf Disease Detection System Using Convolution Neural Networks. *Journal of Engineering Research*, 29(3), 22-31.

Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEE Access*, *9*, 4843-4873.

Shukla, P. K., & Bera, T. K. (Eds.). (2023). *Future Farming: Advancing Agriculture with Artificial Intelligence*. Bentham Science Publishers.

Tan, S., Liu, J., Lu, H., Lan, M., Yu, J., Liao, G. & Ma, X. (2022). Machine learning approaches for rice seedling growth stages detection. *Frontiers in Plant Science*, *13*, 914771.

Wilfred, O. R., & Consultant, L. (2006). Final survey report on the status of rice production, processing and marketing in Uganda. *A report submitted to the Embassy of Japan in Uganda through JICA and Sasakawa Africa Association-Uganda, Kampala*.

Zhou, C., Ye, H., Hu, J., Shi, X., Hua, S., Yue, J., & Yang, G. (2019). Automated counting of rice panicle by applying deep learning model to images from unmanned aerial vehicle platform. *Sensors*, *19*(14), 3106.