AI-Powered Precision Agriculture for Paddy Cultivation Enhancement

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***Abstract*-Although paddy cultivation is essential to preserving the world's food supply, yield projections, variety selection, disease control, and weed control present obstacles to the best possible yield. This study presents RiceGenie, a four-part AI-powered system that facilitates the best possible paddy farming decision-making. The Crop Yield anticipate Model uses machine learning to analyze soil and agroclimatology variables to accurately anticipate yields. The Paddy Variety Forecast Model uses machine learning to recommend the optimal rice variety based on environmental variables in several Sri Lankan regions. The Pest and Disease Detector uses Convolutional Neural Networks (CNNs) to automate the detection of major diseases affecting paddy with treatment advice to improve the health of the plants. Computer vision with the aid of machine learning is applied by the Weed Detection and Weed Management Model to identify and classify the weeds to support sustainable management of the latter. The research combines extensive datasets of the Rice Research and Development Institute (RRDI) - Batalagoda with the Department of Census and Statistics of Sri Lanka to provide a comprehensive data-driven approach. RiceGenie combines domain knowledge with AI to provide a robust decision support system that increases the productivity, efficiency, and sustainability of paddy farming in Sri Lanka.**

Keywords-Paddy Disease Detection, Machine Learning, Paddy Variety Prediction, AI in Agriculture, Paddy Yield Prediction, Weed Detection, Paddy Yield Prediction, Sri Lanka Agriculture

I. INTRODUCTION

Accurate crop yield prediction is of paramount value to modern farming by enabling farmers and other concerned persons to plan the deployment of resources, supply chain management, and strategies to improve the food supply base. Traditional approaches to yield estimation are normally time-consuming, subjective estimates by experts with the potential to contain error [1]. With increasing amounts of historical agro-statistics at disposal, the field of agrotechnology is experiencing the arrival of innovative approaches with the support of machine learning algorithms to build predictor models that are insensitive to a range of agro-environmental conditions. In this work, the research will build a predictor of the yield of the paddy crop in Sri Lanka with the support of historical data and a range of agro-environmental conditions.

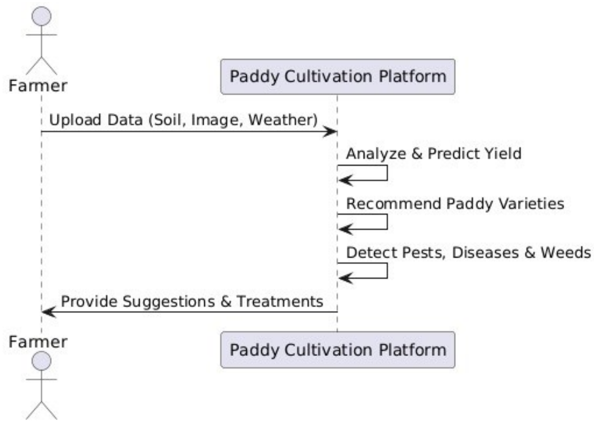

Fig1. Overall system diagram

Rice is a major component of the diet of well over a majority of the entire world's population, and maximizing the yield is central to food security. Yet the wrong choice of rice variety can translate to disappointing harvests, higher expenditures, and susceptibility to climatic change. Traditional approaches to choice are farmer experiential with broad-brush advice that is perhaps not optimal for a location. Farmers have no rational and systematic means of determining the best-suited paddy variety at the current time since current methodologies are mostly time-consuming, subjective, and manually oriented. It is the purpose of this work to introduce a machine learning-enabled approach to forecast the best-suited paddy variety considering environmental conditions, climatic conditions, and historical yield data. The major contributions are the compilation of a complete database of the union of rice variety information, soil, climatic conditions, and determinants of yield; the deployment of a machine learning-enabled solution to recommend a range of rice varieties; and a performance gain compared to traditional heuristics. The final purpose is to introduce a user-accessible choice-making support system to improve farming productivity and the practice of precision farming.

Paddy cultivation is important to the issue of food security, especially among nations like Sri Lanka where the major cereal is rice [2]. Paddy is also very vulnerable to diseases that can significantly compromise the yield if they are not properly managed. Accurate identification of diseases is very important to the sustenance of sustainable farming. New technologies have made automated disease recognition possible with the aid of AI and image processing that can inform the farmer to intervene promptly.

Weed infestations are a serious issue in farming that leads to economic loss and famine. It is imperative that they are detected at the beginning and managed well to contain their impact to a bare minimum. Conventional techniques of detecting weeds are labor-intensive and time-consuming. New technologies of image processing and AI have the potential to provide solutions to automate the identification of weeds. The present research aims to develop a robust image-based plant/weed detection system to improve the quality of farming and farming output.

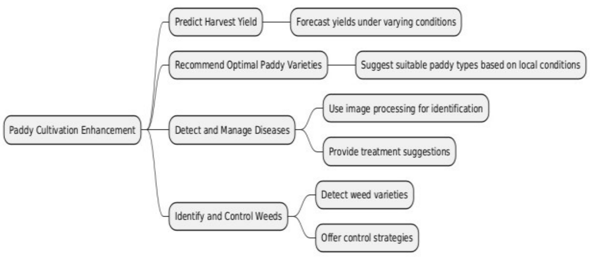

Fig 2. Mind map of the system

II. LITERATURE REVIEW

Numerous research studies have investigated the use of machine learning in agricultural yield prediction, showcasing its capacity to handle enormous datasets and uncover intricate connections between crop productivity and environmental parameters. Depending on the availability of data and preprocessing methods, previous studies have used models like Decision Trees, Support Vector Machines, and Deep Learning to forecast yields, with differing degrees of success. When working with high-dimensional agricultural datasets, ensemble approaches—in particular, Random Forest and Gradient Boosting—have demonstrated encouraging outcomes. There hasn't been much research done in Sri Lanka on utilizing historical data to estimate paddy yields by location. To increase model accuracy and application, this study expands on earlier research by integrating a wide range of agro-climatic and soil-related data.

Research on paddy variety selection is regional and lacks a generalized learning approach or learning device, whereas studies on seed broadcasting rates by At362 and At307 at 100 kg/ha and 75 kg/ha, respectively, show that they increase yield without compromising cost and disease risk [5]. In addition to this, research on farmers' traditional rice cultivation is demonstrated to indicate its profitability and customer preference among the health-oriented segment of society with the priority of authenticity of the seed with marketing restrictions [6]. In addition to this, participatory research in the district of Hambantota demonstrated to indicate that traditional types of rice are salinity-tolerant with sustainable solutions for small farmers with the effect of climatic change [7]. These results are demonstrated to indicate the need for a shared AI-driven approach that integrates multi-source information on climatic, soil, and yield components to support farmers with evidence-based choice of the best paddy variety while encouraging the sustainable practice of rice farming.

Traditional techniques like chemical testing and manual inspection, which were labor-intensive and prone to mistakes, were the mainstay of early paddy disease detection research [3]. Convolutional Neural Networks (CNNs), which analyze picture datasets, have shown great accuracy in classifying plant diseases thanks to developments in deep learning and artificial intelligence [4]. According to studies, CNN-based models can more accurately detect illnesses including sheath blight, brown spot, and bacterial leaf blight. To improve classification performance, research has also looked into several pre-trained deep learning architectures, such as ResNet and VGG. CNNs have greatly enhanced disease identification, but more research is still needed to fully integrate real-time diagnostic capabilities with automated therapy recommendations. The development of a robust AI-powered system capable of real-time disease identification and precise treatment guidance represents a significant advancement in digital agriculture and precision farming.

Several methods for weed detection utilizing image processing and machine learning have been investigated in earlier studies. To differentiate weeds from crops, several studies have concentrated on plant segmentation, feature extraction, and classification algorithms [8]. However, issues like inconsistent environmental circumstances, a dearth of standardized information, and the generalizability of the model continue to exist. This study improves on past work by addressing these limitations and boosting the efficiency of weed detection in large-scale agriculture.

With many studies concentrating on employing image processing and machine learning approaches to distinguish weeds from crops, weed detection in agriculture has long been a problem. Conventional weed detection techniques frequently involved human labor, which was labor-intensive, prone to mistakes, and ineffective for large-scale agricultural applications. Initial studies in automated weed detection focused on plant segmentation, feature extraction, and classification algorithms to enhance accuracy [8]. These approaches utilized techniques such as threshold-based segmentation, edge detection, and texture analysis to extract unique visual characteristics of weeds. Nonetheless, despite technological advancements, obstacles such as environmental variability, inconsistent lighting, occlusions, and differences in plant growth stages continue to impede the broader implementation of these methods. To increase accuracy and efficiency, recent developments in weed detection employ deep learning techniques, particularly Convolutional Neural Networks (CNNs). While semantic segmentation methods like U-Net and DeepLabV3+ improve pixel-wise classification in field settings, CNN designs like ResNet, VGG, and MobileNet have demonstrated encouraging results in identifying and detecting weeds. However, issues persist because of the low generalizability of models, geographical variations in weed species, and the absence of uniform information. Many deep learning models struggle in a variety of contexts but perform well in controlled ones. By improving the effectiveness of weed detection for large-scale agriculture, this study overcomes these constraints. To increase generalizability, it uses domain adaptation techniques, sophisticated deep learning models, and real-time image processing. Furthermore, real-time monitoring is made possible by the combination of edge computing, UAV technology, and multispectral imagery. This strategy seeks to minimize manual labor, cut down on the usage of herbicides, and advance sustainable precision farming methods.

TABLE 1. Identifying and Addressing Research Gaps

Reference	Focus Area	Research Gap	How We Address It
[1]	Market trends and rice production analysis	Lacks technological advancements for disease detection and management	Develop a deep learning-based web app for real-time paddy disease detection and treatment recommendations
[2]	Overview of global rice pest and disease management	Does not leverage AI/ML for precise detection and automated recommendations	Utilize CNN-based models to classify diseases and provide treatment suggestions
[3]	Machine vision for detecting rice blast disease	Limited to a single disease; lacks a comprehensive multi-disease detection system	Extend detection of five major paddy diseases and integrate treatment recommendations
[4]	Deep learning for paddy disease detection	Focuses only on detection; lacks treatment recommendations and a farmer-friendly interface	Develop a user-friendly web platform providing both detection and actionable treatment suggestions
[5]	Analyzing the impact of **seed broadcasting rates** on paddy yield and weed control in dry zones of Sri Lanka.	Limited research on the **optimal seed broadcasting rates** for **yield maximization** while minimizing disease risks (e.g., sheath blight).	Integrate **seed rate** as a variable in our model and fine-tune predictions to recommend the best rates for specific **climates and soil types** to optimize yield.
[6]	Investigating the **market demand**, **cultivation constraints**, and **economic feasibility** of traditional paddy varieties across five districts in Sri Lanka.	Lack of a **data-driven** system to predict **the best-suited rice varieties** based on **market demand** and **regional environmental factors**.	Utilize **machine learning** to analyze **historical yield**, **climatic conditions**, and **market trends** to provide accurate **variety recommendations** for different regions.
[7]	Identifying traditional rice varieties for saline conditions through participatory research in Hambantota.	Lack of integration between **local farmer knowledge** and scientific approaches for selecting **saline-resistant** rice varieties.	Incorporate climate-based features like salinity levels and farmer-driven data into our Paddy Variety Prediction Model for region-specific recommendations.
[9]	Paddy yield prediction using weather indices and Random Forest	Focuses on climatic factors; does not consider soil properties, irrigation practices, or pest impact	Expand the model to include variables like soil type, irrigation methods, and pest damage for a holistic prediction approach
[10]	Paddy yield forecasting using ANN with Back-Propagation learning	Limited to ANN and climatic factors; lacks exploration of other machine learning models and additional agronomic variables	Implement a **Random Forest** model incorporating diverse factors such as soil type, irrigation methods, and pest damage for improved prediction accuracy
[11]	Applied regression techniques for rice yield estimation	Limited to a specific province; did not utilize advanced machine learning models	Expand the study to multiple provinces using advanced machine learning techniques like Random Forest and Gradient Boosting
[12]	Rice yield prediction using weather-based machine learning models.	Limited to weather parameters (rainfall, temperature, radiation) and does not incorporate other agro-climatic factors such as soil properties, irrigation, and pest severity.	Incorporates additional key factors such as soil nutrients, fertilizer usage, irrigation type, and pest severity to enhance predictive accuracy. A robust preprocessing pipeline is applied, and multiple machine learning models are evaluated.

III. METHODOLOGY

This research follows an evidence-based strategy combining historical records of paddy yields and agro-climatic factors obtained from various districts of Sri Lanka. The dataset created encompasses the most influential factors, such as rain, temperature, relative humidity, hours of sunshine, wind speed, soil category, irrigation type, water source, paddy type, fertilizer use, soil nutrient levels (nitrogen, phosphorus, potassium), pest prevalence, crop season, and district category. A data preprocessing pipeline was applied, and data quality was preserved. All rows with missing values were erased to improve the quality of data. Categorical features were One-Hot encoded while the unchanged group of features was composed of numerics. The data was further split into training (80%) and testing datasets (20%) to enable thorough model evaluation and generalization. To predict paddy yield, three machine learning algorithms were implemented: Random Forest, Gradient Boosting, and Linear Regression. The automated feature extraction pre-processing step was used to ensure that the models were trained on suitable data. Random forest was used as the primary modeling technique because it is highly flexible in considering the interrelationships and interdependencies among all specified agro-climatic factors together. Key performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2), were used to evaluate these models. A feature importance analysis revealed which factors most influenced yield outcomes and provided insights into the main drivers of productivity among paddy types. To enhance the predictive value and usefulness of the proposed model, additional analysis was conducted to test regional differences in paddy yield across different districts. Spatial pattern analysis of vital agro-climatic parameters was carried out to understand localized control over variability in yield. Furthermore, a correlation analysis was performed between the environment and the yield outcomes to identify significant correlations, enabling the strengthening of future prediction models. The findings emphasized that precipitation and soil composition were key drivers of productivity, with some districts being more vulnerable to climatic changes. This study has shown that different regions have distinct agricultural specificities that require both region-specific agricultural plans to be designed and data-powered decision support tools to be employed to enhance yield estimation accuracy. In future studies, building novel ensemble strategies or deep learning approaches can be used to enhance the flexible predictive power concerning climate variability.

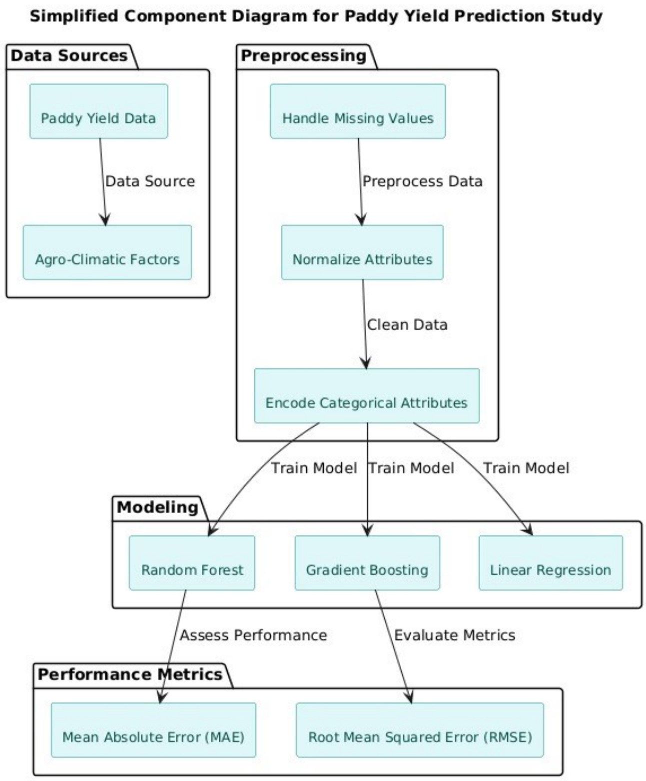

Fig 3. Component diagram for paddy yield prediction system.

This analysis concentrates on the Paddy Variety Prediction Model, the second part of the RiceGenie system that uses machine learning methods to select the most suitable paddy varieties for the different regions in Sri Lanka. This model is developed based on two proprietary datasets. The first one is

"Recommended Rice Varieties in Sri Lanka (1958–2023)" by the Rice Research and Development Institute (RRDI), Department of Agriculture, Bathalagoda, which is a publication from 1958 to 2023 and includes numerous data on paddy varieties such as yield and maturity duration and environmental conditions best suited for them[13]. The second source is a collection of environmental data held by the Department of Census and Statistics of Sri Lanka, such as annual temperature, rainfall, and the agro-climatic conditions of each district. In these datasets, paddy varieties and their environmental conditions were linked through the 'Recommendation' field, thereby forming one integrated dataset. The preprocessing of the data included dealing with missing values, converting ranges of maturity periods into numerical average values, and creating the 'suitability' feature to flag highly productive varieties (where yield > 5.0 t/ha) suggested for certain environmental conditions. Categorical values such as temperature and ranges of rainfall were transformed into a format that could be processed by machine learning algorithms. The dataset was divided into training, validation, and test subsets using an 80:20 ratio to evaluate performance conveniently. Logistic regression was used because it is straightforward and highly interpretable in the case of binary classifications. The model was fitted to classify a rice variety as suitable or not for a specific district based on the yield, maturity period, and the environment. AUC, accuracy, precision score, recall, and F measure were used to assess the performance of the model using 10-fold cross-validation, allowing the model to generalize while reducing the chance of overfitting. Further, the model's predictions were tested against the recommendations to check the applicability of the model. This approach facilitates effective agricultural planning by enhancing productivity through agro-climatic zone-appropriate rice variety selection for Sri Lanka.

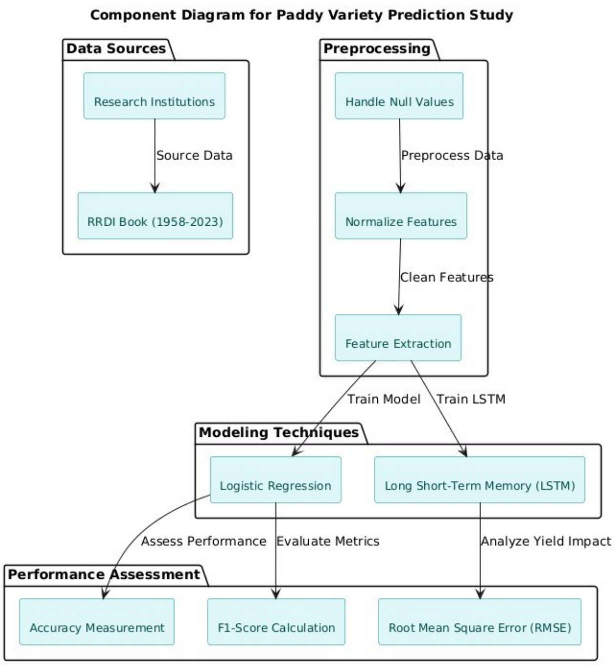

Fig 4. Component diagram for paddy variety prediction system.

This study utilizes the deep learning technique to implement an automatic disease detection system for paddy diseases. This system consists of different stages such as data collection, data cleansing, feature selection, training the convolutional neural network (CNN) model, and treatment recommendation generation. The collected training and testing dataset contains paddy leaf images labeled under five categories: bacterial leaf blight, brown spot, leaf blast, sheath blight, and healthy leaves. These images have been collected from publicly accessible agricultural information systems, research centers, and field surveys. Images were captured under diverse lighting and orientations for augmenting diversity and robustness, thus having a heterogeneous dataset for training the model. Raw images were enhanced through different preprocessing techniques to improve classification accuracy. To achieve input standardization, images were resized to a standard position, and noise reduction such as Gaussian and Median filtering was implemented to improve clarity. Data augmentation methods like rotation, flipping, and enhancement of contrast were also used to step up the variability of the dataset, ensuring that the model is exposed to different views when trying to diagnose the disease. Background segmentation was also implemented to separate the leaf area from the other less important features. So that the model classifier would be able to learn the major image attributes including color distribution, texture, and spatial arrangements. The SoftMax was used on the output layer to predict the probability of each disease class. Cross-entropy with the Adam optimizer was used during model training as a learning loss function. Once recognition was made, a different decision support system recommended control measures based on expert agricultural recommendations for the diseases diagnosed. This included chemical controls, organic alternatives, and prophylaxis so that farmers could properly manage the diseases.

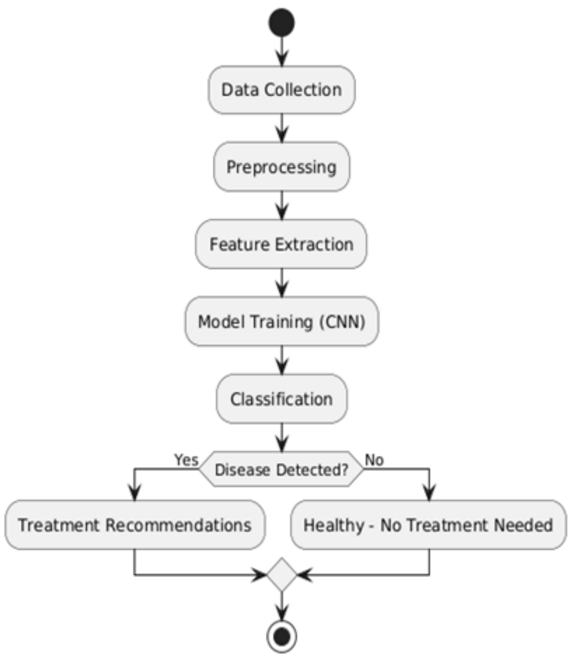

Fig 5. Image processing techniques for disease identification & treatment suggestions.

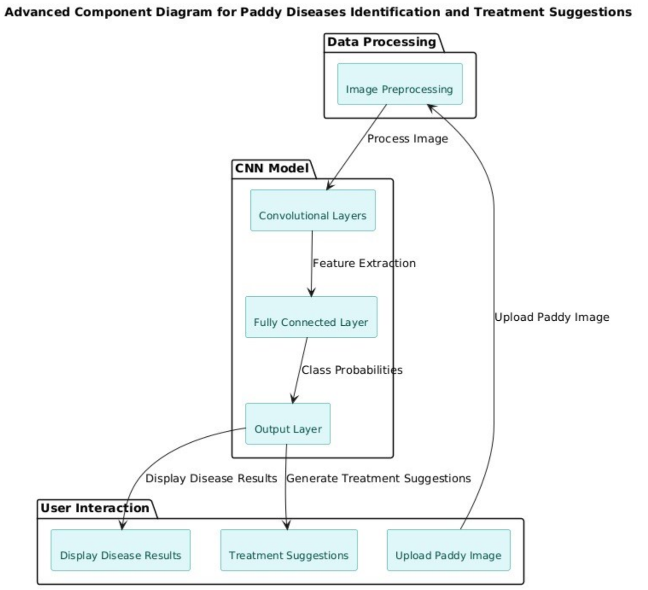

Fig 6. Component diagram for disease detection & treatment suggestion system.

The system involves capturing high-resolution images of agricultural fields using mobile devices and cameras. Pre-processing techniques such as noise reduction and color segmentation are applied to enhance image quality. Machine learning models, including deep learning networks, are trained using labeled datasets to differentiate weeds from crops. Performance evaluation is conducted based on accuracy, precision, and recall metrics to validate the effectiveness of the proposed approach.

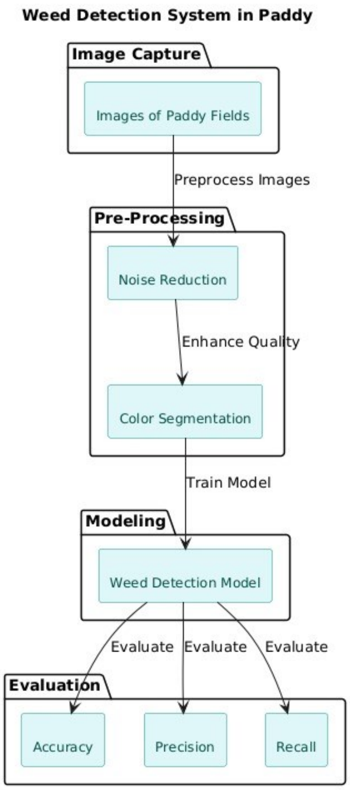

Fig 7. Component diagram for the weed detection system.

IV. Results & Discussion

The Random Forest model outperformed Linear Regression and Gradient Boosting to achieve the highest accuracy, suggesting that ensemble learning methods are a good fit for predicting paddy yield. The most important factors influencing yield variance were temperature, rainfall, soil fertility, and irrigation techniques, according to feature importance analysis. The model's projections corresponded closely with actual yield data, suggesting its promise for real-world applications. However, while interpreting results, one must take into account restrictions like climate anomalies, regional variability, and data availability. For even greater accuracy gains, future studies might investigate deep learning techniques or hybrid models.

TABLE 2. Algorithm Performance Comparison of Yield Prediction Model

Algorithm	MAE	MSE	RMSE	R^2	MAPE	Accuracy	Discussion
I) Random Forest Regressor	510.3	4,755,389.91	2180.69	0.9731	3.49%	96.51%	Best performance for the Prediction.
II) Gradient Boosting Regressor	617.56	5,151,988.03	2270.49	0.9708	4.88%	95.12%	Best performance, risk of slight overfitting.
III) Linear Regression	8505.22	104,963,650.45	10245.21	0.4059	81.04%	18.96%	Poor performance, not suitable for this Prediction.
IV) Support Vector Machine	7450.34	85,620,450.12	9253.85	0.5123	74.89%	25.11%	Very poor performance, unsuitable for this Prediction.

To predict the best rice variety selection based on historical yield data and environmental factors, the study tested several machine learning models, including Random Forest, Gradient Boosting, Logistic Regression, and Support Vector Classifier. Each model was evaluated using accuracy, F1-score, and RMSE metrics; Random Forest and Gradient Boosting showed the highest accuracy, at 100% and 99.65%, respectively, but they also showed signs of overfitting, which may indicate bias in predictions. Logistic Regression, on the other hand, achieved an accuracy of 98.95%, which provided a more balanced performance with better generalizability. The Support Vector Classifier, on the other hand, produced the lowest accuracy at 61.11%, indicating its ineffectiveness for this dataset. Considering the risks of model bias in high-accuracy classifiers, Logistic Regression was chosen as the best model because of its consistent performance under different data conditions, and an LSTM model was used for time-series analysis, which successfully captured climate trends and their effect on rice yield. The results show that choosing the right model is essential for accurate predictions in paddy variety selection; complex models may provide high accuracy, but their potential overfitting highlights the need for careful evaluation. To improve predictive robustness while minimizing bias, future research could investigate hybrid modeling approaches.

TABLE 3. Algorithm Performance Comparison of Paddy Variety Prediction Model

Algorithm	Results				Discussion
	Accuracy (%)	Precision	Recall	F1-Score	
I. Random Forest Classifier	100.00	1.00	1.00	1.00	Perfect accuracy, risk of overfitting.
II. Gradient Boosting Classifier	99.65	1.00	0.99	0.99	High accuracy, slightly better generalization.
III. Logistic Regression	98.95	1.00	0.98	0.99	High accuracy with better interpretability.
IV. Support Vector Classifier	61.11	0.61	0.62	0.61	Poor performance, unsuitable for this task.

The CNN model demonstrated the effectiveness of AI in precision agriculture by successfully identifying the major paddy diseases in Sri Lanka, including bacterial leaf blight, brown spot, healthy, leaf blast, and sheath blight. The study also highlights potential limitations, such as dataset biases and real-world application challenges, which require further refinement. Moreover, incorporating treatment recommendations enhances the practical utility of the system, guiding farmers on proper disease management strategies.

TABLE 4. Algorithm Performance Comparison of Paddy Disease Detection Model

Algorithm	Accuracy	Recall	F1 Score	Discussion
CNN (Custom)	86%	88%	89%	Effective for paddy disease classification
ResNet	72%	75%	73%	Strong feature extraction, high accuracy
VGG	68%	64%	64%	Performs well with paddy disease datasets
EfficientNet	94%	92%	93%	Best accuracy with optimized performance

The results of the experiment show that image processing techniques are effective in accurately identifying and classifying weeds; the system performs well under controlled conditions but struggles with different environmental factors like background noise and lighting; comparisons with conventional weed detection methods show how effective and scalable the suggested method is; the study highlights the need for additional dataset expansion and model optimization for practical implementation.

V. CONCLUSION & FUTURE WORK

This study integrates many agro-climatic and soil-related elements to demonstrate how machine learning may improve the forecast of paddy output. The Random Forest model was the most successful, offering trustworthy approximations that can aid in agricultural decision-making. The results highlight how crucial data-driven strategies are for improving resource management and agricultural productivity. To improve predictive models and increase their applicability in various agricultural locations, more study is required.

Data-driven decision-making in paddy farming is supported by the paddy variety prediction model, which effectively illustrates the efficacy of machine learning in predicting the ideal paddy variety. Future improvements include creating a smartphone application to help farmers obtain predictions and using IoT sensors for real-time data collection.

The five main paddy diseases—bacterial leaf blight, brown spot, healthy leaf blast, and sheath blight—are successfully identified by the established model. High disease classification accuracy was attained by the CNN model, proving AI's usefulness in precision farming. Furthermore, incorporating treatment recommendations improves the system's usefulness in practice by advising farmers on appropriate disease control techniques. The paper also identifies possible drawbacks that require more work, like biases in the dataset and difficulties with real-world applications.

Sustainable agriculture relies heavily on weed control, and automated image processing-based detection offers a workable answer. This study aids in the development of effective weed detection methods that increase accuracy and decrease manual labor. Even though there are still obstacles to overcome, developments in artificial intelligence and computing power are raising the possibility of widespread use of automated weed detection systems in agriculture.

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