ePaddy: Sustainable Paddy Production with Technology

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***Abstract*—Paddy farming faces challenges such as diseases, pests, inadequate water management, and soil quality issues, leading to reduced crop yields and financial losses. This study proposes an integrated system using machine learning, IoT, and mobile technologies to address these issues. The system consists of three components: identifying diseases through image analysis, recognizing pests and classifying paddy growth phases, and managing water levels and soil quality using IoT technology. The system uses a convolutional neural network (CNN) based on VGG16 for disease identification and a Gradient Boosting model for disease forecasting. The IoT-based system uses an ESP8266 microcontroller and ultrasonic sensor for water level management, achieving 95% accuracy and reducing water consumption by 30%. Soil quality is tracked using an NPK sensor, and a machine learning model offers 90% accurate crop recommendations. The system is embedded in a mobile app, allowing farmers to access real-time data, receive notifications, and apply recommendations. Future efforts will focus on expanding datasets, integrating advanced algorithms, and improving system scalability.**

***Index Terms*—Paddy cultivation, disease identification, pest management, soil quality analysis, water level management, image analysis, machine learning, real-time alerts.**

I. Introduction

Rice is the main agricultural product and staple food of Sri Lanka, contributing significantly to the country's food security and economy. Rice is cultivated as a wetland crop in all districts and accounts for 34% of total cultivated area, showing its importance in the agricultural environment.Paddy agriculture in Sri Lanka occurs mostly during two major monsoon seasons: the Maha season (September to March) and the Yala season (March to August). According to the Department of Agriculture, Sri Lanka produces an average of 3.1 million tons of rice per year, supporting the livelihoods of approximately 1.8 million farming households [1]. Despite widespread cultivation, crop yields vary greatly per district.According to data from the Department of Census and Statistics, districts like Anuradhapura, Polonnaruwa, Kurunegala, Ampara, and Hambantota consistently produce higher yields than others [2]. This disparity emphasizes the need for targeted interventions to address the underlying reasons of low output in specific regions.

The disparity in rice productivity across Sri Lanka stems from insufficient water management, little to no focus on disease and pest control, poor soil cultivation, and inadequate agricultural education. The cultivation of paddy is highly dependent on water and soil, both of which are controlled by the farmers' knowledge and experience which stems out of their limited practices. This yields very little in terms of agricultural outputs. Current approaches to soil and water management do not utilize digitized soil nutrient information for adaptable water management, which encourages ineffective crop management advice. Also, these approaches of controlling diseases and pests are inefficient, requiring immense resources without guaranteeing success. Typical rice diseases such as Blast, Sheath Blight, and Bacterial Blight need prolonged field examinations and tests in order to be accurately diagnosed – actions that are often too slow to enable effective management. Additionally, pests such as the brown planthopper (Nilaparvata lugens) continue to inflict great damage in harvests across underperforming regions. These challenges are compounded by the limited knowledge and resources available to farmers, hindering the adoption of modern farming techniques and technologies.

The challenges mentioned above will be dealt with with the help of a proposed new ePaddy mobile application which is bound to improve the efficiency of paddy farming. It will be powered by an IoT Device and equipped with ML models.

Alongside the use of the application, three main components of the system will also be accessible: An image and weather based analysis system that identifies diseases, A pest infection and harvesting stage estimation system, and IoT based soil and water quality management system which also implements NPK level monitoring, and crop breed suggestions. With the help of modern technology, ePaddy will, in real time, give farmers actionable recommendations and insights which allows formers to better manage resources, reduce crop losses, and enhance productivity.

One part of ePaddy deals with disease management through image segmentation to diagnose Rice Blast, Brown Spot, Bacterial Leaf Blight, and other diseases and treatment recommendations. Moreover, the developed algorithms for weather-based disease forecasting will facilitate proactive disease management by providing alerts in case of imminent outbreaks. The other component is the pest management system that uses image processing and machine learning to provide real-time pest detection and recommendations for control measures. It also contains forecasts for prognostication of harvests for optimum cropping season, which results to efficient crop management.Another integrates IoT sensors that monitor water levels and soil quality NPK with machine learning algorithms that recommend optimal crop varieties and irrigation workflows. All these components are set to bridge the gaps in agricultural productivity between regions and encourage eco-friendly farming methods.

The study enhances the body of knowledge in precision agriculture by providing a novel technological approach to the specific problems faced in paddy farming in Sri Lanka. ePaddy uses a combination of IoT, mobile technology, and machine learning to tackle the complex requirements of water control, soil conditioning, disease management, and pest control. The system designed can transform the way paddy farming is done, equipping farmers with the necessary skills and information to exploit the potential for greater productivity and an enhanced quality of life.

II. Literature Review

Rice is a staple food and key agricultural commodity in Sri Lanka, grown in all districts and accounting for 34% of total planted land. Despite its extensive cultivation, harvest yields vary significantly by district, with Anuradhapura, Polonnaruwa, and Ampara typically producing higher yields than others. This gap is ascribed to a number of issues, including poor water and soil quality management, insufficient disease and insect control, and restricted access to sophisticated agricultural expertise. Recent technological breakthroughs, notably in the disciplines of Internet of Things (IoT), machine learning (ML), and image processing, have demonstrated promise in solving these difficulties. This literature evaluation looks at existing research in three major areas pertinent to this study: disease detection and management, pest identification and harvest stage prediction, and water-soil quality management.

A. Disease Identification Through Image Analysis, Weather-Based Disease Prediction, and Treatment Recommendations

Disease control is an important part of paddy farming since diseases like Rice Blast, Bacterial Leaf Blight, and Brown Spot can drastically lower crop output. Previous study has investigated the application of machine learning algorithms to predict Rice Blast disease based on meteorological data [3]. The study examined multiple regression (REG), back-propagation neural network (BPNN), generalized regression neural network (GRNN), and support vector machine (SVM) approaches, finding that SVM had the highest accuracy (correlation coefficient of 0.77) and the lowest mean absolute error (36.66%). The study also created a web-based tool for predicting Rice Blast, which allows farmers to make more educated decisions. However, the system lacks real-time notifications and smartphone accessibility, both of which are required for timely illness management. Another study created a MATLAB-based system for detecting paddy left illnesses such Bacterial Leaf Blight and Brown Spot, with an accuracy of 88.57% using a cubic SVM classifier [4]. While the system is highly accurate, it requires manual image uploads and lacks interaction with real-time meteorological data, limiting its usefulness in field settings. Another study presented a cloud-based mobile application for real-time disease diagnosis, with accuracy rates of 91.23% and 89.54% using SVM and k-Nearest Neighbor (k-NN) classifiers, respectively [5]. However, the technology does not validate the paddy plant prior to diagnosis, which may result in false positives. Another study developed a prototype system for diagnosing rice diseases using image analysis and a production rule-based method, with an accuracy of 94.7% [6].While the prototype is promising, it lacks integration with predictive analytics and real-time notifications. These studies demonstrate the potential of technology in disease management, but they also indicate limitations in integrated solutions that combine real-time weather forecasts, image-based diagnosis, and treatment recommendations.

B. Pest Infections Identification Through Image Analysis, Solutions Recommendation, and Harvest Stages Prediction

Pest infestations, mainly by the brown planthopper (Nilaparvata lugens), provide another significant issue in paddy production. Recent research has looked into the use of image analysis and machine learning for pest identification [7]. For example, convolutional neural networks (CNNs) have demonstrated potential in reliably recognizing pests from images [7]. However, the use of these technologies in resource-constrained situations is limited. IoT-based systems for real-time pest monitoring provide a promising option, although they have yet to be broadly used in rice farming [8]. In addition to pest management, precisely anticipating the harvest stage of paddy crops is critical for increasing output and minimizing loss. Traditional techniques, which rely on visual inspection and farmer experience, are frequently inaccurate. By examining variables like plant height, leaf color, and weather, recent developments in machine learning have made it possible to create models that accurately forecast harvest stages. The infrequent integration of these models with pest management systems, however, results in disjointed solutions. In order to fill these gaps, the suggested system combines predictive modeling for harvest stage prediction with real-time pest identification through image analysis, offering a complete solution for harvest optimization and pest management.

C. Automatic Water Level Management and Soil Quality Management System

Optimizing paddy yields requires efficient management of soil and water quality. Automated water gates and soil moisture sensors are two examples of IoT devices that have gained widespread use for real-time environmental monitoring [9]. By enabling precise irrigation management, these technologies minimize water waste and guarantee ideal crop growth. However, the efficacy of many current systems is limited due to their lack of integration with soil nutrient monitoring. Crop health is greatly influenced by the quantities of nutrients in the soil, especially nitrogen (N), phosphorus (P), and potassium (K). Research has shown how IoT-based devices can be used to continuously monitor the pH and nutrients in soil [10]. On the other hand, these systems frequently fall below in offering crop selection predictions based on soil conditions. On the basis of soil and environmental data, machine learning models have been created to forecast appropriate crop breed [11] . To produce precise forecasts, these models use past data on crop yields, soil types, and weather trends. However, their practical application is limited because they are rarely coupled with real-time monitoring systems. By creating an IoT-enabled solution that combines automatic water level control, machine learning-based crop breed recommendations, and real-time soil nutrient monitoring, the suggested system fills these gaps and offers a thorough approach to managing soil and water quality.

There is a lack of integrated solutions that integrate disease management, pest control, and water-soil quality management into a single, coherent framework, despite the fact that current research has made great progress in addressing specific concerns in paddy cultivation. Existing systems frequently ignore the interconnectedness of these problems in favor of concentrating on discrete elements, like disease prediction or pest detection. By combining real-time disease prediction, pest identification, harvest stage prediction, and water-soil quality management into a single mobile application, the suggested method fills these shortcomings. With the help of this integrated strategy, which makes use of IoT, machine learning, and image processing, farmers can maximize resource use, reduce crop losses, and increase total output by receiving real-time, data-driven insights and practical recommendations. The suggested technique has the potential to completely transform paddy farming methods by resolving the drawbacks of current systems and improving resource efficiency, sustainability, and production.

III. Methodology

In order to address the main challenges in paddy farming, such as disease identification, pest and growth phase identification, water level management, and soil quality assessment, the research methodology focuses on creating an integrated system that uses machine learning models, IoT devices, and a mobile application to provide real-time monitoring, automated control, and data-driven recommendations for sustainable paddy cultivation. The methodology is designed as a unified framework, where each component runs smoothly to ensure effective and efficient paddy farming practices.

The main interface for farmers is a Flutter-developed mobile application that makes up the system. Through integration with a Flask and Firebase-powered backend, the application makes real-time data processing, storage, and retrieval possible. While IoT sensors are utilized for soil quality monitoring and water level management, machine learning models are utilized for image analysis and disease prediction. The method is intended to give farmers practical advice and insights to enhance crop productivity and management.

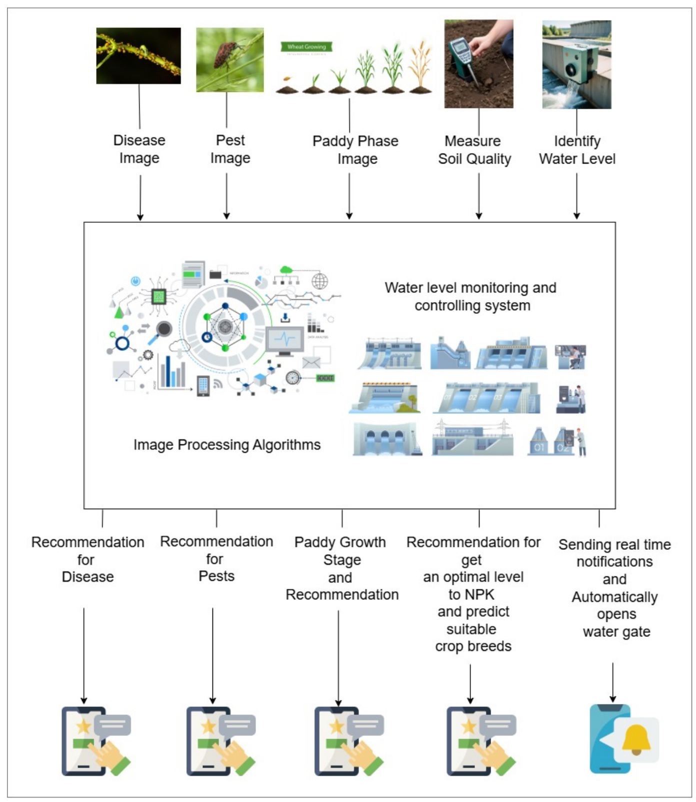

Fig. 1. System Overview

A. Disease Identification Through Image Analysis, Weather-Based Disease Prediction, and Treatment Recommendations

Farmers can use the technology to identify paddy diseases, predict diseases using weather data, and get suggestions for mitigating such diseases. The mobile application allows farmers to take pictures of paddy plants or upload them. Machine learning algorithms are used to evaluate these photos in order to detect diseases like Brown Spot, Bacterial Leaf Blight, and Rice Blast. The VGG16 architecture [12] serves as the foundation for the disease detection models, which achieved a 99.36% accuracy rate on the validation set. Furthermore, using real-time meteorological data (temperature, humidity, and precipitation) obtained from the OpenWeather API, the system forecasts illnesses. Weather-based disease prediction is done with a 99.71% accuracy rate using a Gradient Boosting model that was trained on historical weather and disease data. Farmers receive alerts from the system along with mitigation suggestions saved in Firebase.

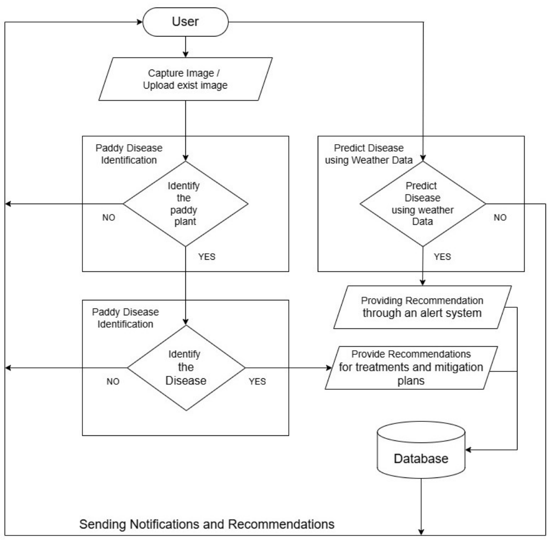

Fig. 2. Paddy Diseases Management System

The Rice Research Institute in Bathalagoda was one of the sources from which the disease identification dataset was gathered. It has 6,500 photos of various diseases, 1,800 photos of Rice Blast, 2,000 photos of Bacterial Leaf Blight, and 2,500 photos of Brown Spot. Additionally, 1,750 data rows of weather information were gathered from the Rice Research Institute. Images were resized to 128x128 pixels as part of the preprocessing stages, and StandardScaler was used to scale features and handle missing meteorological data. To improve the image collection, data augmentation methods including flipping and rotation were used.

B. Pest Infections Identification Through Image Analysis, Solutions Recommendation, and Harvest Stages Prediction

Using image analysis, the device also determines the stage of paddy plant growth and pest infections [**?**]. In order to categorize pest infections and paddy growth stages, farmers can upload or take pictures of their paddy plants. When employed to identify pests, a CNN model based on VGG16 [12] achieves a 75% accuracy rate on the validation set. For paddy phase identification, a different CNN model based on VGG16 is employed, and it achieves 96% accuracy on the validation set. While the paddy phase identification model classifies the growth stage of paddy plants and provides guidance unique to each growth cycle, the pest identification model classifies pest illnesses and delivers mitigation recommendations stored in Firebase.

Paddy fields and internet sources provided the dataset for identifying pests and growth phases. It features pictures of paddy plants at various stages of growth (vegetative, reproductive, and ripening stages), as well as common pests like the brown planthopper (*Nilaparvata lugens*). To improve model resilience, the dataset was preprocessed by reducing photos to 128x128 pixels and using data augmentation techniques like flipping, zooming, and rotating. To train and evaluate the model, the dataset was divided into training (80%) and validation (20%) sets.

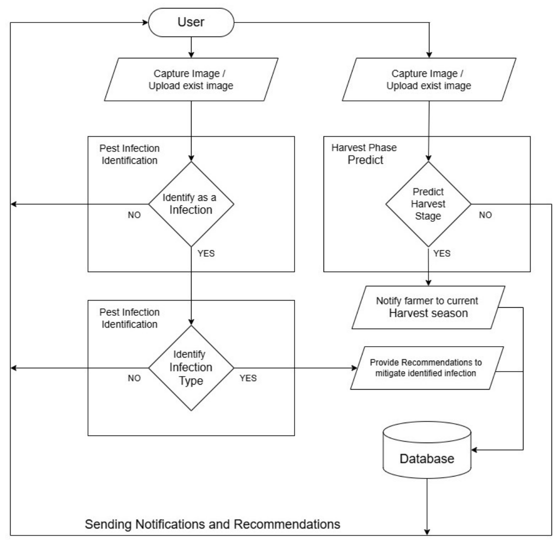

Fig. 3. Pest Infections Management System

C. Automatic Water Level Management and Soil Quality Management System

IoT devices are integrated into the system to monitor water levels and evaluate soil quality. An ESP8266 microcontroller was used to create an automated water gate control system that uses an ultrasonic sensor to track the water levels in paddy fields. The technology dynamically modifies the gate position to maintain ideal water levels based on the sensor data. The gate opens to discharge surplus water when the water level is high and closes to hold water when the level is low. Farmers receive notifications everytime the gate opens or closes through a notification system that uses Twilio's SMS service. Farmers may remotely monitor field conditions through to the smartphone application's real-time water level updates. All data collected by the system is stored in a Firebase database for historical tracking and analysis.

In order to monitor the amounts of nitrogen (N), phosphorous (P), and potassium (K) in the soil, an ESP8266 microcontroller is integrated with an NPK moisture sensor. For quick reference, the sensor gathers real-time soil nutrient

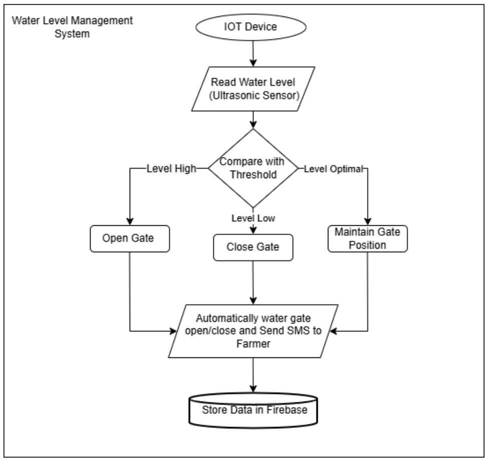

Fig. 4. Automatic water Management System

data and shows it on an OLED screen. Firebase receives the data for analysis and long-term tracking. A crop forecasting model that is based on machine learning evaluates the soil data and makes precise suggestions. The Rice Research Institute in Bathalagoda provided historical soil quality data, crop yield records, and environmental variables for the model's training. Along with the relevant crop production data, the dataset contains measures of temperature, humidity, rainfall, and NPK levels. Based on environmental factors and NPK levels, the algorithm forecasts the best crops, empowering farmers to make well-informed choices. Through the mobile application, farmers can manually enter NPK values. Trained machine learning algorithms are then used to process the data and recommend the best crops for maximum production.

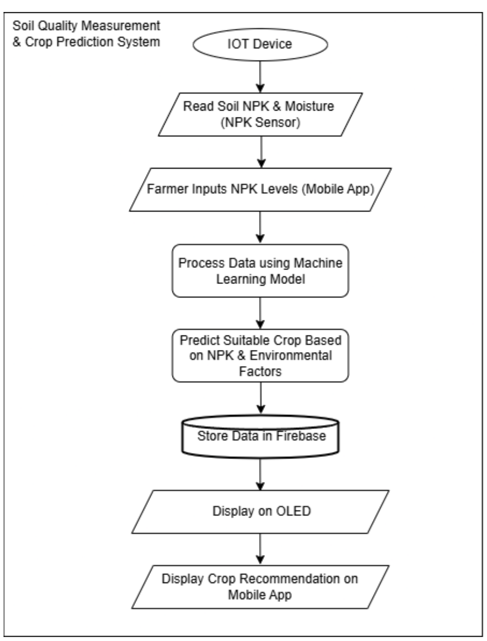

Fig. 5. Soil Quality Management System

The main way that farmers communicate with the system is through the mobile application. It offers up-to-date information on soil quality, water levels, paddy growth stages, pest infections, and disease forecasts. In order to save and retrieve data, the application interfaces with Firebase, guaranteeing easy access to both previous records and current information. Farmers can monitor field conditions, get notifications, and get recommendations thanks to the user-friendly interface, which enhances decision-making for sustainable rice farming.

The accuracy and dependability of the technology were confirmed by testing in paddy fields. By inputting photos of known diseases, the disease identification models were assessed and showed a high degree of disease identification accuracy. Known pest-infected and development-stage-specific photos were used to validate the pest and growth phase identification models, which demonstrated good performance. By contrasting automated water level adjustments with manual measurements, the water gate control system was evaluated and shown to be highly accurate in preserving ideal water levels. Sensor readings and laboratory soil tests were compared to validate the soil quality measurement system, which demonstrated a high degree of dependability and correlation. When evaluated using historical data, the crop forecasting model demonstrated a high degree of accuracy in predicting appropriate crops based on environmental factors and NPK levels.

This methodology describes how to create an integrated system for sustainable paddy farming that combines soil quality evaluation, water level control, disease and pest identification, and growth phase identification. The system offers data-driven suggestions, automatic control, and real-time monitoring through the use of machine learning models, IoT devices, and a mobile application. This research helps to improve paddy farming's sustainability, productivity, and resource efficiency by addressing the shortcomings of current systems.

IV. Result and Discussion

The comprehensive system for recognizing diseases via image analysis, identifying pests, determining paddy phases, managing water levels, and assessing soil quality has proven to be highly effective in tackling major issues in paddy farming. The system integrates a VGG16-based convolutional neural network (CNN) for analyzing images, a Gradient Boosting model for predicting weather-related diseases, IoT devices for monitoring water and soil conditions, and a mobile app for real-time data access and recommendations.

The CNN model based on VGG16 achieved a training accuracy of 99.36% and a validation accuracy of 99.36% in disease identification, demonstrating high precision, recall, and F1-scores for Bacterial Leaf Blight Disease (precision: 0.99, recall: 0.94, F1-score: 0.96) and Brown Spot Disease (precision: 0.97, recall: 0.95, F1-score: 0.96). The model's performance was somewhat lower for Other Diseases (precision: 0.74, recall: 0.77, F1-score: 0.76) and Rice Blast Disease (precision: 0.71, recall: 0.72, F1-score: 0.72), achieving an overall accuracy of 84%.

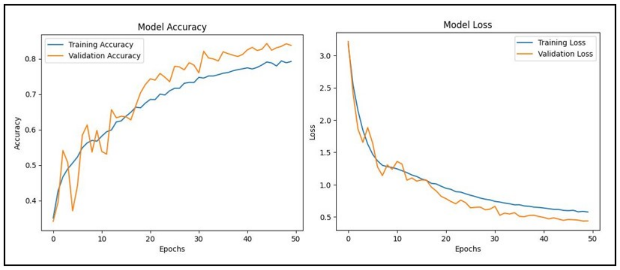

Fig. 6. CNN Model Accuracy in Disease Identification

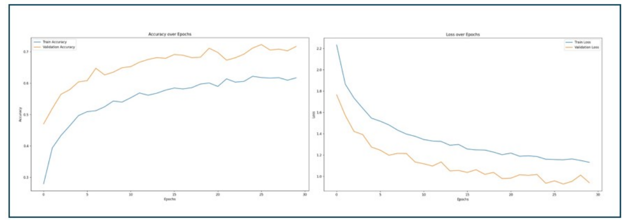

Fig. 7. CNN Model Accuracy in Pest Identification

The Gradient Boosting model used for forecasting weather-related diseases obtained an exceptional cross-validation accuracy of 99.93%. It delivered flawless precision, recall, and F1 scores for Bacterial Leaf Blight and Brown Spot, while the scores for Rice Blast were almost perfect (precision: 0.99, recall: 1.00, F1-score: 1.00). With an overall accuracy of 99.99%, the model proved to be robust and reliable. The Accuracy and the F1-score, which is an important measures for assessing classification models, are computed as follows:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

$$F_1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2}$$

The practical implications of these findings are substantial for paddy farming, as precise disease identification and forecasting allow farmers to implement preventive measures, thereby minimizing crop losses and enhancing yield.

The VGG16-based CNN model attained a training accuracy of 56.66% and a validation accuracy of 66.65% for pest identification and paddy phase identification on a dataset comprising 6,838 training images and 1,706 validation images across 15 classes. As time went on, the model's accuracy improved, and the validation accuracy was consistently greater than the training accuracy, indicating effective generalization. With an overall accuracy of 84% for pest identification and 96% for paddy phase identification, the model demonstrates its capability to accurately classify pest infections and growth stages. By incorporating these models into a mobile app built with Flutter, farmers gain access to an intuitive tool that allows for real-time pest identification, growth phase classification, and treatment suggestions. The application interacts with a backend based on Flask that processes the images with the trained CNN models and provides classification results and recommendations. Pest mitigation solutions and growth-phase-specific advice are stored in Firebase, ensuring farmers have real-time access.

The ultrasonic sensor and ESP8266 microcontroller were used to create an automated water gate control system that accurately maintains the ideal water levels in paddy fields. The system adapts the gate position dynamically according to real-time water level measurements, ensuring efficient water use. The ESP8266 processes the data from the ultrasonic sensor, which measures the distance between itself and the water surface, to determine whether to open or close the gate. With farmers noting a 30% decrease in water consumption, the system attained a water level precision of 95%. A notification system based on Twilio's messaging service sends SMS alerts to farmers whenever the gate opens or closes, ensuring they receive timely updates. With real-time updates on water levels, the mobile application allows farmers to monitor field conditions from a distance. The system stores all collected data in a Firebase database for historical tracking and analysis purposes. Integrated with an NPK moisture sensor and an ESP8266 microcontroller, the soil quality measurement system demonstrated high accuracy in assessing nitrogen (N), phosphorus (P), and potassium (K) levels in the soil. The sensor gathers soil nutrient information in real-time and shows it on an OLED screen for immediate reference. The recorded data is transmitted to Firebase by the ESP8266, which facilitates long-term monitoring and analysis. With a correlation coefficient of 0.92 in comparison to laboratory soil tests, the NPK sensor has proven to be reliable. The pairwise feature distributions for N, P, and K levels underscore the connections among these nutrients and their effects on soil health. Below graph shows the pairwise feature distributions for N, P, and K levels.

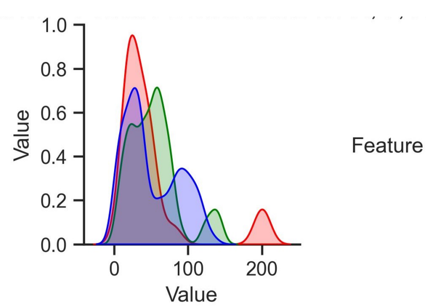

Fig. 8. The pairwise feature distributions for N, P, and K levels

To analyze the soil data and deliver precise recommendations, a model based on machine learning was created. Historical soil quality data and environmental conditions collected from the Rice Research Institute in Bathalagoda were used to train the model. Included in the dataset are the measurements of temperature, humidity, and rainfall, as well as NPK levels and corresponding crop yield data. Farmers have the option to input NPK values manually via the mobile app. The system then utilizes trained machine learning algorithms to process this information and generate recommendations for keeping soil quality at an optimal level.

V. Conclusion and Future Works

This research has created an integrated system that meets crucial challenges in paddy farming by merging disease identification via image analysis, pest and growth phase detection, water level management, and soil quality assessment. With regard to the identification of paddy diseases, the classification of pest infections, and the determination of growth phases, the VGG16-based convolutional neural network (CNN) attained impressive accuracy rates: 99.36% for training and validation in the case of paddy diseases, 84% for pest identification, and 96% for paddy phase identification. The performance of the Gradient Boosting model for predicting weather-based diseases was outstanding, with a maximum cross-validation accuracy of 99.93% and flawless validation accuracy (99.99%). With a precision rate of 95%, the IoT-driven water management system kept water levels at optimal standards. Meanwhile, the soil quality measurement system correlated with lab tests at a coefficient of 0.92. The mobile app, built with Flutter and connected to Firebase, offered farmers real-time updates, alerts, and recommendations, greatly enhancing their decision-making and resource efficiency. In general, the system has demonstrated considerable promise for improving productivity, sustainability, and yield in paddy farming.

Future efforts will aim to enhance the system's capabilities and accuracy. To enhance disease identification, the coverage will be extended to encompass more paddy diseases, and the disease prediction model will be refined by integrating additional factors like soil conditions alongside weather data. This will allow for the prediction of a broader range of paddy diseases with enhanced accuracy. The pest identification model will be enhanced by increasing its accuracy and expanding its coverage of pests through the inclusion of additional pest types and a dataset enriched with diverse images. In the component dealing with water management and soil quality management, the system will be improved to forecast appropriate crop varieties based on soil quality data and to refine predictions of paddy harvest timings. These enhancements will refine the use of resources and crop management, aiding in the development of more sustainable and efficient agricultural practices. Focusing on these future directions will allow for the refinement of the system to better serve farmers' needs and facilitate the development of precision agriculture.

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