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An Artificial Intelligence–Based System for Automated Detection of Rice Leaf Diseases

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Abstract
Food security and sustainable agriculture have placed an increasing strain on the need to detect crop disease in a methodical and dependable way. Rice (Oryza sativa), one of the main food sources of over half the world population, is very susceptible to diseases like brown spot, leaf smut, and bacterial blight, which have great impact on production and grain quality. Conventional disease detection techniques are most often based on manual identification by specialists that is time consuming, subjective and in many cases unavailable to the smallholder farmers in rural regions. In order to overcome these difficulties, this paper proposes the design and implementation of an automated rice disease detection system based on deep learning and image processing. The system uses a Convolutional Neural Network (CNN), which has been trained using a variety of rice leaf images using the ResNet50 architecture. This model had a training accuracy of 90% and a loss value of 0.45 which indicates high learning and generalization ability. It is based on a user-friendly web interface built using Flask that enables farmers and researchers to upload rice leaf images to predict disease in real-time. The system involves processing the image and labelling it as either healthy or diseased, and giving it a confidence score and the anticipated disease category. Evaluation outcomes reveal an equal amount of average confidence of 76.65% and a processing time of 2.67 seconds, which is efficient and reliable. The suggested system shows how artificial intelligence has the potential to revolutionize the agricultural diagnostics market through offering a low-cost scalable solution to early detection of rice diseases. It helps to enhance yield, decrease the use of pesticides, and to make wise decisions among farmers. The addition of mobile applications and the scale of the disease dataset, as well as the implementation of the model on drones to monitor large-scale fields, can be considered future improvement points that will assist in the digital transformation of precision agriculture.

Keywords: Accuracy, Confidence score, Disease, ResNet50, Rice

1. Introduction

Rice (Oryza sativa) is a staple food to over half of the total world population and a core to food security, rural life and the economy of nations. Nevertheless, foliar diseases (rice blast (Magnaporthe oryzae), bacterial leaf blight (Xanthomonas oryzae), brown spot, and sheath blight) often pose a threat to rice production, lowering the vigor of plants and yield unless their presence is recognized and addressed at an early stage [1]. Conventional disease surveillance is based on professional human eye examination in the industry, which is time-consuming, subjective, and infeasible in large scale or real time surveillance. Therefore, there is a high interest in automated diagnostic systems that would be used to offer timely, precise, and scalable disease monitoring to inform targeted responses and reduce crop losses. Recent developments in computer vision and artificial intelligence (AI), specifically, deep learning, have shown phenomenal potential in the area of automated plant disease detection. Classification accuracies are high in numerous crops and disease classes when trained using convolutional neural networks (CNNs) and transfer-learning techniques when the training is done on large and organised collections of images [2], [1]. A repository like the PlantVillage has been used as a starting point to develop models and benchmark and compare studies in a reliable manner (PlantVillage dataset). However, most high-accuracy results found in the literature are those obtained on images that were taken in controlled or semi-controlled settings; models that are trained on those images often underperform on real-world paddy fields due to domain shifts caused by complicated backgrounds, variations in lighting, occlusions, and inter- and intra-class similarity of symptoms [1], [3].

In order to close the gap between the laboratory performance and field relevance, the existing research focuses on two complementary directions. First, the architectural and algorithmic enhancements, e.g., employing more profound backbones (e.g., ResNet-based models), attention mechanisms and specialized kernel or SE block, have been created to enhance feature discrimination and resistance to visual variability [4]. Second, transfer learning, ensemble fusion, data augmentation, and domain adaptation have become methodological approaches to improve the generalization to heterogeneous field data and decrease the position on incredibly large labelled datasets [1], [2]. Combined these guidelines have produced practical systems, which are operationally useful, but still computationally amenable to implementation on edge devices or a mobile platform.

Despite such a development, there are still numerous practical and scientific challenges. To begin with, rice classes of diseases commonly exhibit delicate and overlapping visual effects to require fine-grained sensitivity to texture coupled with global morphological reasoning. This inspires more hybrid methods that blend the complementary sets of features such as handcrafted texture descriptors (can represent local micro-patterns well) alongside CNN embeddings (can represent higher-level structural and contextual features). Second, the application to a real-world setting needs fast resources-constrained models, which may be trained to work on a resource-constrained hardware; hence, model efficiency and reliability (to detect leaf regions correctly and localise them) are equally important as the raw classification accuracy [1]. Lastly, representative data collected in the field have a relatively small number of datasets and model performance is best assessed by cross-domain validation and powerful statistical reporting (e.g. confidence intervals, per-class metrics) over individual-point measures of accuracy [1].

This study proposes an AI-powered automated rice leaf disease detection system, which is a synthesis of these lessons. The proposed pipeline consists of an efficient leaf region localization detector, and a deep CNN backbone (ResNet50). The objectives of the design are to attain strong classification accuracy on the most significant rice leaf diseases, exhibit computational efficiency that can be used to conduct inference in real-time or near real-time on field deployable hardware; and have rigorous evaluation on the basis of both curated (PlantVillage-style) and field-collected data.

2. Related Research Work

Rice leaf diseases such as rice blast, brown spot and bacterial leaf blight are chronic threats to food security in the world. Early diagnosis is crucial in reducing losses of yields and maximizing disease control. Artificial intelligence and especially Deep Learning have been extensively used to detect rice leaf disease at scale with automated methods because it can learn discriminative visual features directly off of images. Even with reported accuracies that are impressive, an emerging literature body demonstrates that most of the proposed systems are vulnerable to limited generalization and low experimental rigor, as well as inadequate attention to real-world deployment constraints.

Recent research works are based mostly on convolutional neural networks (CNNs), commonly using transfer learning and based on ResNet, DenseNet, Inception, and MobileNet architectures [2], [5]. Although the models perform well in terms of classification in benchmark datasets, they are often viewed as black-box in nature. The architectural decisions can hardly be supported by the systematic ablation studies, and the performance increase is commonly insignificant and data-specific.

In addition, CNN-based methods have a tendency to be more accurate than interpretable and provide little information on disease-specific learned characteristics. This non-disclosure decreases the trust of the agricultural stakeholders and minimizes the agronomic interpretability of model predictions.

One of the biggest gaps in all the literature is the excessive reliance on curated and laboratory-controlled datasets, including PlantVillage. These data sets have homogeneous backgrounds, and controlled lighting, none of which are representative of the actual farming situation. It is always reported in systematic reviews that models trained on this type of data will see significant performance drop as they are applied to field images that have background clutter, occlusions, and changing illumination [6], [7]. Although this problem has been recognized, there are not many studies that evaluate cross-dataset or handle domain shift by domain adaptation or robust training. Consequently, a lot of the reported systems have a poor external validity.

There are numerous AI-based systems of rice disease detection where the direct image-level classification is done without localizing the leaves or the diseased area. This is a simplistic assumption of the real world where symptoms of the disease can take up only a limited area of the image. Though recent works combine object detectors like YOLOv5 and YOLOv8 to locate regions of disease [8], no individual study examines the performance of detectors. Localization metrics (e.g., IoU) are not reported in many works, and practically none of them evaluate the way detection errors are propagated to classification results. This is not a detector-conscious assessment of the system, which does not give a true picture of the performance improvements.

Even though numerous studies suggest real-time or mobile suitability, few of them include in-depth analysis of inference time, memory imprint or energy consumption. The use of lightweight architectures, including MobileNet, is sometimes considered, but based on unrealistic hardware benchmarking. This disjunction points out to a lack of connection between the development of algorithms and their real-life application, especially in the agricultural environment which is limited in resources [8].

2.1 PLANTVILLAGE NURU APP

PlantVillage Nuru Application is based on an optimized Inception-v3 model which is an advanced Convolutional Neural Network (CNN) that is able to recognize crop diseases using leaf images. The training of the model was done on the large PlantVillage dataset which has thousands of annotated leaf samples of crops like cassava, maize and rice. The CNN by Nuru predicts diseases and instant recommendations based on the color, texture, and lesion patterns in leaves. TensorFlow Lite is used to compress the model, enabling the model to be run on mobile devices [9].

In controlled conditions, Nuru has an accuracy of 80%-95%. Accuracy is usually high (more than 90%)

with cassava and maize, whereas it is less with rice because of less and less varied training images. In field situations, the accuracy can reduce to 70%-85% percent due to shadows, low light, and blurred photographs. Regardless of these shortcomings, PlantVillage Nuru is still one of the most efficient AI-powered mobile applications that can benefit the smallholder farmers in managing the diseases [9].

2.2 RiceXpert

RiceXpert does not use an AI or machine-learning model. Rather it uses a rule-based expert system. This model is based on systematic knowledge which consists of the documented diseases, symptoms, pests, and nutrient deficiencies of rice. Once a user enters the app and chooses the symptoms, the system compares the inputs with the existing rules in order to recommend the most probable disease or deficiency. This implies that the performance of the system will be determined by the accuracy of the user in selecting the right symptoms [10].

Since RiceXpert does not implement deep learning and computer vision, it does not produce quantitative performance indicators, including accuracy, precision, or recall. Nonetheless, according to the assessment of agricultural specialists, in case of the correct choice of symptoms, RiceXpert can deliver reasonably good results, which is approximated at 70%-80% correct diagnosis for common diseases The system proves to be most effective as an educational and extension tool, but in early-stage detection and complicated cases of the disease, it is less efficient than AI-powered visual models [10].

2.3 The Leaf Color Chart (LCC)

The Leaf Color Chart (LCC) App does not rely on artificial intelligence and computer vision. Rather, it is developed using a manual color-matching model, in which farmers use a visual comparison of the color of the rice leaves to the standardized reference shades within the app. These shades are analogous to the nitrogen in the plant. The system follows rule-based fertilizer recommendation model that was developed by agronomists of PhilRice based on the shade chosen. The model will give direction on the application of fertilizer and the quantity of fertilizer to apply. Since LCC App does not do automated detection or machine-learning classification, it does not produce performance measures (such as accuracy, precision, or recall) [11].

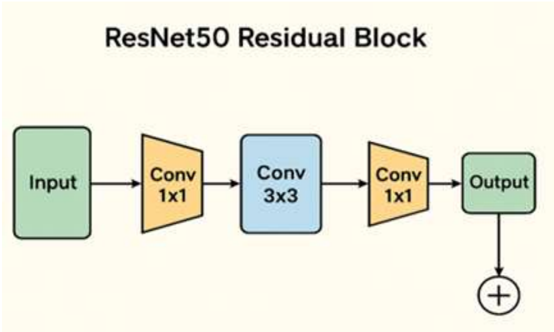
Nevertheless, PhilRice field assessment indicates that utilization of the tool results in optimization of efficiency in nitrogen management by 20-30 percent, minimization of fertilizer waste and management of optimal crop health when properly used. The app is trustworthy in making decisions about fertilizers, but fails to identify diseases or read images of leaves automatically [12].

2.4 Resnet50 Residual Block

Pattern recognition and computer vision have transformed using deep learning, and Convolutional Neural Networks (CNNs) are now state of the art at image classification, detection and segmentation. But, in practice, training very deep CNNs also becomes difficult with increasing the network depth, both because of vanishing gradients and degradation problems, in which the addition of new layers surprisingly reduces performance. To solve them, He et al., 2015, proposed Residual Networks (ResNets) that incorporate the use of residual blocks, allowing the successful training of extremely deep models, including ResNet50, ResNet101, and ResNet152 [13].

In particular, ResNet50 is a 50-layer deep network which uses a bottleneck residual block to make it less computer-intensive but still as powerful in terms of representation. Averagely, each of these bottleneck blocks has three convolutional layers (1 x 1, 3 x 3, 1 x 1) with the 1 x 1 convolutions decreasing and then increasing channel dimensions and the 3 x 3 convolutions extracting spatial details. It is efficient to deep networks since this design reduces the number of parameters unlike simple residual blocks [14], [15].

Figure 1: ResNet50 Residual Block



3. METHODOLOGY

This part explains how the intended activities would be undertaken and how the goal would be achieved.

3.1 CONCEPTUAL FRAMEWORK

Figure 2: Conceptual Framework for the Rice Disease Detection System.

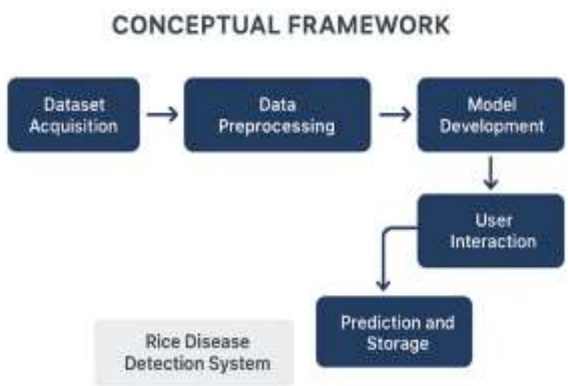


Figure 2 illustrates the conceptual framework for the proposed Rice Disease Detection system.
The process involves the following steps:

1. Dataset Acquisition: This is the stage where the dataset is collected and prepared for the experiment.
2. Data Preprocessing: This involves the process of converting the raw, unstructured, noisy and inconsistent data collected into a clean, structured and usable form to be used in the experiment.
3. Model Development: This is the step in which the model is created, trained, tested and optimized to learn patterns from the preprocessed data and make predictions.
4. User Interaction: It involves the design and implementation of user interface that enable users to input commands and receive outputs.
5. Prediction and Storage: This is the stage of using the trained model to forecast future outcomes or infer unknown values based on new or unseen data and saving the results for future use, analysis, or retrieval.

3.2 Dataset

The performance of the model was tested with the Rice Leaf Disease Dataset. The dataset consists of 2628 images that targeted three key diseases that affect rice plants, namely, Bacterial Blight (BB),

Brown Spot (BS), and Leaf Scald (LS). This dataset is curated to help in predicting the occurrence of these diseases, depending on several attributes and parameters.
The images of leaves are of high-resolution with the symptoms of the given disease. This contributes to the visual diagnosis and machine learning-based image recognition. The Rice Leaf Disease Dataset was retrieved on the Kaggle site that is well-known due to the access to machine learning datasets (https://www.kaggle.com/datasets/rice-leafs-disease-dataset).
The photos were captured in semi-controlled and field set up. When dividing the dataset in the experiment, great care was taken to split it to 80% training and the remaining 20% validation. The model performance was assessed and computed by the use of the following measures and equation.

$$Accuracy = \frac{\mathrm{tp} + \mathrm{tn}}{\mathrm{tp} + \mathrm{tn} + \mathrm{fn} + \mathrm{fn}} \quad \ldots\ldots\ldots\ldots\ldots\ldots.. (1)$$

$$Precision = \frac{\mathrm{tp}}{\mathrm{tp} + \mathrm{fp}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$Recall = \frac{\mathrm{tp}}{\mathrm{tn} + \mathrm{fp}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$F1\ Score = 2 \text{ x } \frac{Precision\ x\ Recall}{Precision + Recall} \quad \ldots\ldots\ldots\ldots (4)$$

Sample Images of The Rice Leaf Disease Dataset

Figure 3: Bacterial Blight (BB) Disease Leaf sample images

Figure 4: Brown Spot (BS) Disease Leaf sample images

Figure 5: Leaf Scald (LS) Disease Leaf sample images

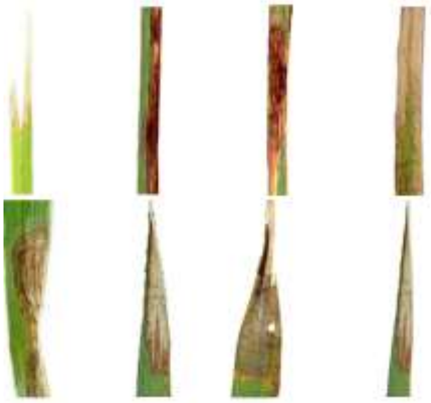


Figure 6: Healthy Leaves (HL) sample images

3.3 Research Tools and Materials

The experiment was executed using a well updated computer system.
The overall specification was as follows:
Laptop Specifications: HP EliteBook 745 G5, Windows 11 Pro 64-Bit, Processor: AMD Ryzen 5 PRO 2500U w/ Radeon Vega Mobile Gfx (8CPUs), 2.0GHz, Graphics: AMD Radeon (TM) Vega 8 Graphics, System Ram 16 GB, Storage 512 GB, Camera: HP HD camera.

Programming languages and Libraries:

1. Python 3.12.10: is a high-level, interpreted programming language was used to develop the module and conduct the whole experiment.
2. mpmath 1.3.0: Was used to do arbitrary-precision arithmetic and complex mathematical computations.
3. numpy 2.3.2: Was used for numerical computations and array-based operations.
4. opencv- 4.11.0.86: Was used for image and video processing and the computer vision tasks.
5. packaging 25.0: Was used to handle version numbers and package metadata.
6. pandas 2.3.2: Was used for data manipulation and analysis using Data Frames.
7. pillow 11.3.0: Was used for opening, editing, and saving the image files in Python.
8. pip 25.0.1: Was used as the Python package installer.
9. psycopg2-binary 2.9.10: Was used to connect Python with PostgreSQL databases.
10. pyparsing 3.2.5: Was used for building and executing text parsing grammars.
11. python-dateutil 2.9.0.post0: Was used to handle and manipulate dates and times flexibly.
12. python-dotenv 1.1.1: Was used to load environment variables from .env files.
13. reportlab 4.4.4: Was used to generate PDFs programmatically.
14. scikit-learn 1.7.2: Was used for machine learning, including classification, regression, and clustering.
15. scipy 1.16.2: Was used for scientific computations, including optimization, linear algebra, and signal processing.

4. Results

Table 1: Results of the proposed system on Rice Leaf Disease datasets

Metric	Results
Accuracy	98.15%
Precision	99.07%
Recall	98.44%
F1 Score	98.72%

Table 1shows the results of the proposed system tested on the Rice Leaf Disease datasets.

Figure 7: Training VS. Validation Accuracy Curve

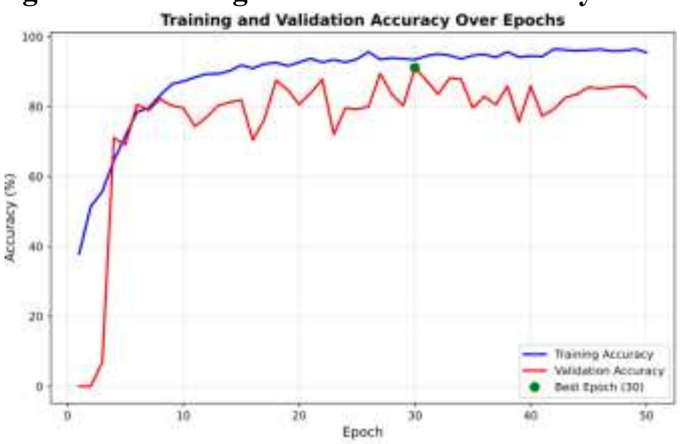


Figure 8: Training VS. Validation Loss Curve

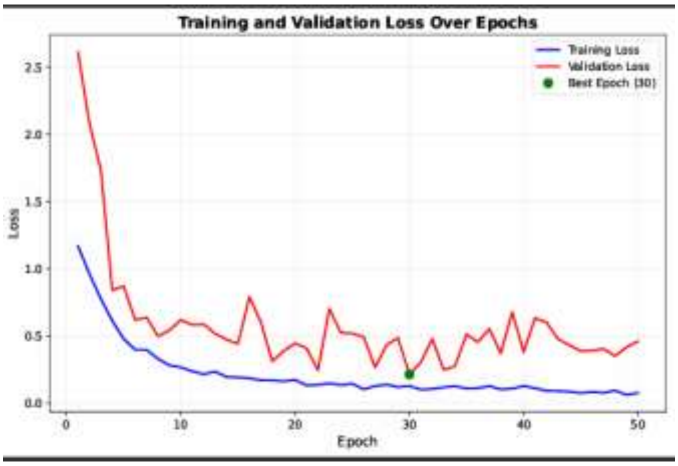
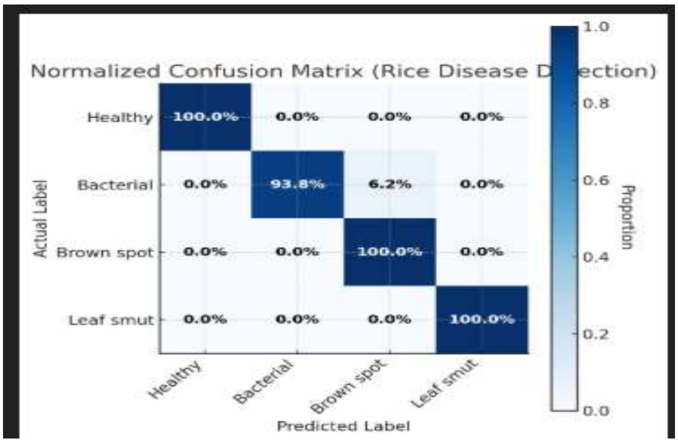
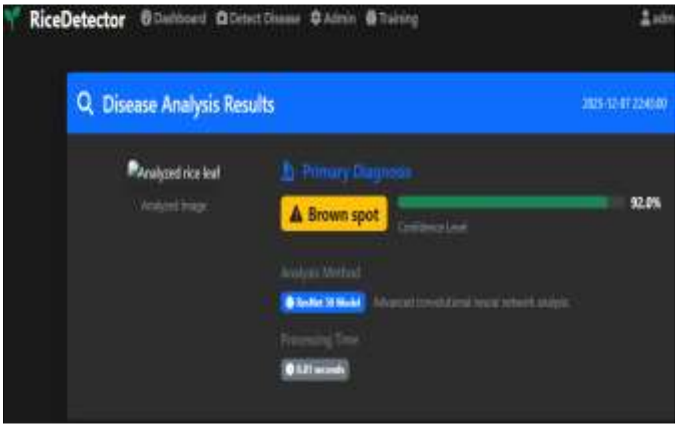


Figure 9: Confusion Matrix



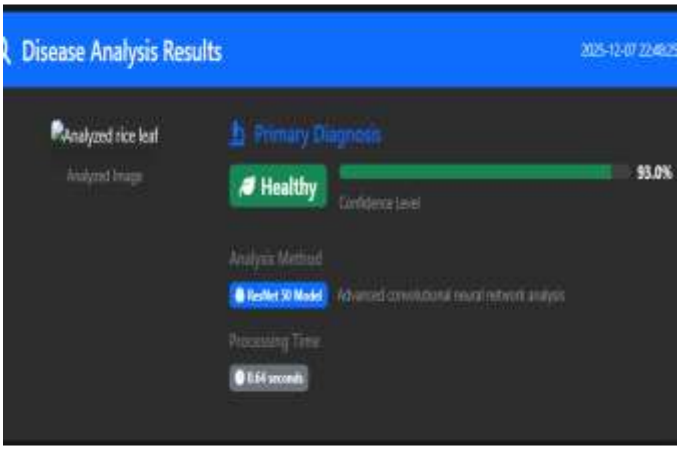
4.1 Sample Disease Analysis Results

Figure 10: Brown Spot Disease Analysis Result



The result shown is the output of the rice disease detection system and it was done by analyzing a rice leaf image on the basis of the proposed model. The system identified the image uploaded as Brown Spot with a confidence level of 92% indicating that the model is very sure that the leaf has signs of the Brown Spot disease.

Figure 11: Healthy Leave Analysis Result



The result shown in the display is the output of the rice disease detector system which has processed a rice leaf image with the proposed model. The uploaded image was interpreted as Healthy and the confidence level is 93, which indicates that the model is quite sure that the leaf is not diseased. The confidence score of above 90% means that it is highly reliable in the prediction, and the trained model is effective.

5.0 Discussion

The proposed Rice Disease Detection System was properly assessed in terms of a confusion matrix, classification metrics, and training-validation learning curves. The confusion matrix was composed of 54 test samples that were divided into four classes: Healthy (18), Bacterial Blight (15), Brown Spot (14), and Leaf Smut (6). Among these, 53 samples were accurately classified and only one sample was wrongly classified in standard Accuracy formula in equation 1. The system was really good and it was able to identify almost all types of diseases well.

Besides the accuracy, the macro-averaged metrics of the model also confirmed its strength. The macro precision of 99.07% suggests that the system had very few false positives in which virtually all of the disease labels predicted were accurate. The macro recall rate of 98.44% shows that the system was able to detect almost all of the real cases of disease with minimum false negatives. Macro F1-score 98.72, which generates equilibrium between precision and recall, is also stable across disease classes. These good performances indicate the dependability of the model in separating visually related disease of rice leaves.

Learning rate of 0.001 was used in 50 epochs that helped the model reach a stable convergence. The loss curve was smooth and gradually swamping its training to reach almost 0.1, which was evidence of effective learning by the CNN. Though variability in the validation loss was experienced in the initial epochs as is typical of real-world image data, it stabilized and attained optimal values towards the end of epoch 30 as indicated by the best epoch. This indicates that the model was generalized and there was no significant overfitting.

On the same note, the curves of training and validation accuracy were indicated to improve significantly with the epoch. The accuracy of the training steadily increased, reaching above 95, whereas the validation accuracy converged with a high degree being above 85. Maximum validation accuracy also was realised at epoch 30 reaffirming its optimal performance. The similarity between training and validation accuracies means that the network was able to learn useful features and not memorize the dataset.

All in all, the findings reveal that the proposed system is very accurate, efficient in computation and can be used to detect rice disease in real world situation. The very low misclassification value, as well as high precision, recall and F1-score, mean that farmers and agricultural professionals can be sure in the system to diagnose early and enhance crop monitoring and efficiently manage the disease.
The 92 percent confidence level implies that the suggested model is very sure that the brown spot disease influences the rice leaf. This is a percentage of the likelihood that the model allocates having examined patterns, textures and lesions in the image. When the confidence is above 90 percent, it is said to be very reliable in the diagnosis of agriculture indicating that the features of the leaf are in perfect accord with the known brown spot characteristics. A 92% score indicates low levels of uncertainty because it means that farmers can rely on the prediction and undertake proper treatment without making additional checks.

6.0 Conclusion

The AI-Based Rice Disease Detection System is a proposed solution to the identification of the rice leaf disease based on deep learning technology that is reliable, scalable, and intelligent. It increases agricultural production, lessens misuse of pesticides and puts farmers in a better position in making informed choices by automating the diagnosis process. Such a system is a serious improvement of precision agriculture that will encourage sustainable farming and support food security in the world.

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