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A Deep Learning-Based Mobile Application for Classifying Rice Crop Diseases in Labo, Camarines Norte

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Abstract— The primary concern of the rice farming community is the early detection of rice crop disease. Rice crop disease can be detected with high accuracy with the availability of advanced digital cameras and smartphones to improved image acquisition modes and deep learning methods such as convolutional neural networks (CNN). This study used a qualitative approach employing focus group discussions with selected farmers and an online meeting with the Department of Agriculture (DOA). Also compared and evaluated different optimizers using several optimization techniques namely Stochastic Gradient Descent with Momentum (SGDM), Root Mean Squared Propagation (RMSProp), Nesterov-accelerated Adaptive Moment Estimation (Nadam), and Adaptive Moment Estimation (Adam) in different dataset partitioned by 80/20%, 60/40%, 50/50%, 40/60%, and 20/80% using cv2 module from OpenCV library. Furthermore, presents the hardware and software to developed a free, easy-to-use and widely accessible mobile application that can efficiently and accurately diagnose 22 types of diseases and a healthy leaf sample. The experiment results show that Nadam optimizer achieve a maximum accuracy of 97.67-100.00% in the 80/20 partition, 88.17-100% in the 60/40 partition, 84.93-100% in the 50/50 partition, 64.67-100% in the 40/60 partition, and 37.03-99.90% in the 20/80 dataset partition. Therefore, the android application “Rice Crop Diseases Classification” can accurately classify rice diseases using Nadam optimizers including healthy rice. Addiditonally, despite employing various dataset partitioning methods, it achieves the highest accuracy from both low and high records using 80 by 20% dataset partitioned.

Keywords- Convolutional neural networks (CNNs), Rice Leaf Diseases, Computer Vision (OpenCV), Neural Network Optimizers

I. INTRODUCTION

The Philippines Department of Agriculture (DOA) in Labo Camarines Norte reported that there are 8,579 framers and fish folks and that 100% of the 2,259 registered rice farmers use pesticides on their land, adding that the pesticides are used to minimize rice crop disease infestations, maintain harvests, and protect crops from diseases. However, pesticide exposure, effects, and risks for both the environment and human health [1], either acute high-level and clinical impactful pesticides exposures may increase the risk of viral infection that causes a painful rash [2]. In addition, (DOA) has stated that to lessen the use of pesticides, on-field diagnosis of rice crop disease is required, emphasizing that it is difficult for inexperienced and young farmers to identify and classify rice crop diseases. Therefore, visual crop disease detection, and laboratory-based analysis methods appear to be time-consuming and labor-intensive; that leads to bias, misconceptions, and errors [3], that may affect the quality and quantity of rice yield [4],[5].

According to the Philippine Statistics Authority (PSA), the total employment in agriculture, forestry, and fishing was 144,651 in 2021, a 4.1 percent increase from 138,977 in 2020. The total workforce consisted of 98.2% paid employees, working owners, and unpaid workers [6]. In addition, the Labo Department of Agriculture (DOA) stated that the total number of rice farmers with no formal education is 421, elementary 558, high school 572, and college graduate 708 as of 2023. Adding that most farmers still use traditional sensory perception to diagnose and monitor the health and needs of their crops, and most farmers are uncertain about diagnosing diseases without the assistance of rice crop disease professionals. It was also mentioned that the traditional method of diagnosing rice crop diseases used by farmers may change depending on stress, experience, health, and age. Furthermore, farmers took leaf samples for examination and send it to the (DOA), while it takes 2-4 days before sending back the results and discuss the necessary process for preventing the spread of rice diseases. Moreover, with limited internet access in Labo, Camarines Norte specially in rice fields, most of the rice farmers are unable to communicate easily and not familiar with mobile applications.

On the other hand, having an accurate, rapid, and early diagnosis for plant diseases is necessary. Therefore, adapting machine learning and deep learning as a subset of artificial intelligence has shown promise in the same area using a mobile digital camera. In addition, deep learning architectures based on convolutional neural networks that performs convolution and creates a feature map with labels [7],[8] are popular for computer vision tasks like image classification that takes an input image and extracts meaningful features for effective image recognition and classification. This involves a multi-featured cameras instead of human vision that has been well utilized for agricultural operations [9] and demonstrates rapid and real-time tools for image analysis captured with high-resolution. In addition, machine learning with OpenCV was created to provide a common infrastructure for computer vision applications and to speed up the adoption of machine perception. It has been extensively studied by researchers to provide innovative solutions for modeling complex relationships and predicting agricultural data [10],[11],[12],[13],[14],[15],[16]. Moreover, some studies present a novel deep learning method for efficiency and accuracy in terms of multilingual opinion mining using ADAM optimizer [17], other studies compared the performance of Adam to SGDM optimizer for plant leaf disease detection [18], text summarization for news articles with RMSProp optimizer [19], and automated bacteria genera classification using Nadam optimizer [20].

Therefore, the objective of this study was:

1) to compared and evaluated different optimizers using several optimization techniques such as Stochastic Gradient Descent with Momentum (SGDM), Root Mean Squared Propagation (RMSProp), Nesterov-accelerated Adaptive Moment Estimation (Nadam), and Adaptive Moment Estimation (Adam) with different dataset partitioned by 80/20%, 60/40%, 50/50%, 40/60%, and 20/80% using cv2 module from OpenCV library for detecting and classifying common diseases found in rice leaf and;

2) to developed a deep learning mobile application considering having a maximum accuracy using cv2 and Nadam optimizer to diagnose 22 crop diseases including a healthy leaf, consisting a total of 23 datasets with 2,300 images. This solution does not require internet access and is free and simple to use.

II. Methods and Materials

A. Dataset Description

The study examines a total of 2,300 images, including 2,200 images of rice leaf diseases and 100 images of healthy leaves. The data was obtained and combined through UC Irvine Machine Learning Repository contributed by [21] (Shah Jitesh et al., 2019) and from Elsevier's Mendeley Data repository under Generalist Repository Ecosystem Initiative (GREI) contributed by [22] (Sethy, P. K et al., 2020) as references for rice crop disease classification, image captured by the researcher and from the department of agriculture. Combining dataset help the researcher to fills each class with same diseases. Each class label represents a crop-disease prediction based on images of crop leaves. Fig. 1 presents a representative sample from the rice crop-disease dataset, consisting of twenty-three (23) classes such as; Bacterial Leaf Streak, Leaf Blast, Eye Spot, Crown Sheath Rot, Bakanae, Sheath Blight, Flag Leaf Sheath, Kernel Smut, Yellow Mottle1, Sheath Spot, Bacterial Leaf Blight, Leaf Smut, Ragged Stunt Virus, Narrow Brown Leaf Spot, Tungro Virus, Leaf Scald, Sheath Rot, Grassy Stunt Virus, Kernel Smut, False Smut, Brown Spot, Aggregate Sheath, and a Healthy Leaf . In addition, before performing a model optimization and prediction, images are downscaled by 256 x 256 pixels.

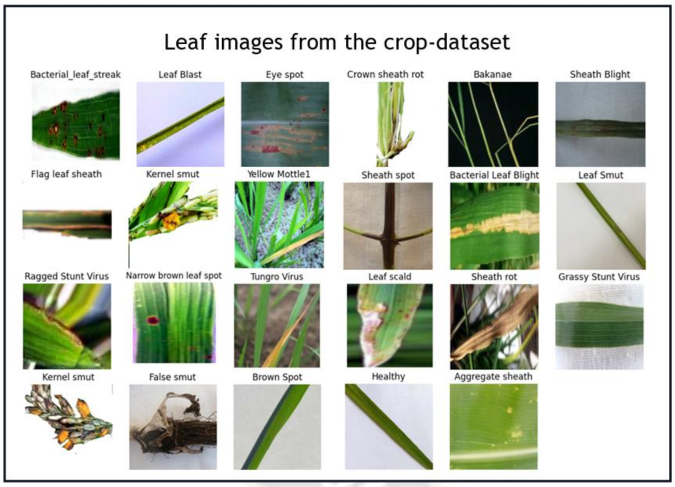

Figure 1. Example of leaf images from the dataset.

B. Dataset Partitioning

To find the best CNN architecture, trial and error techniques were used in this study, and an experiment was carried out by replacing some of the CNN model's convolution layers. There are different possible outputs from the model assessment score can be obtained by running fifty (50) epochs with different partitioning amounts of datasets. Additionally, the study conducted four experiments, each with a different dataset split for training, testing, and validation. The splits were as follows: 80-10-10%, 60-20-20%, 50-25-25%, 40-30-30%, and finally 20-40-40% as shown in Table 1 for SGD, Table 2 for Adam, Table 3 for RMSProp, and Table 4 for Nadam optimizer. Additionally, the researcher employs data testing for different optimizers to determine the model's suitability.

TABLE I. Experiments usigng tirial-and-error with SGD optimizers

SGD Optimizer's Accuracy		
Dataset Partitioning (%)	*Lowest (%)*	*Highest (%)*
80-20	53.62	99.67
60-40	25.90	83.35
50-50	29.20	81.72
40-60	30.23	73.74
20-80	11.12	30.29

TABLE II. Experiments usigng tirial-and-error with Adam optimizers

ADAM Optimizer's Accuracy		
Dataset Partitioning (%)	*Lowest (%)*	*Highest (%)*
80-20	63.06	100.00
60-40	47.02	100.00
50-50	82.09	100.00
40-60	55.94	100.00
20-80	31.78	96.86

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TABLE III. EXPERIMENTS USIGNG TIRIAL-AND-ERROR WITH RMSPROP OPTIMIZERS

RMSProp Optimizer's Accuracy		
Dataset Partitioning (%)	*Lowest (%)*	*Highest (%)*
80-20	60.33	100.00
60-40	59.72	100.00
50-50	51.20	100.00
40-60	34.75	99.68
20-80	32.25	99.54

TABLE IV. EXPERIMENTS USIGNG TIRIAL-AND-ERROR WITH NADAM OPTIMIZERS

NADAM Optimizer's Accuracy		
Dataset Partitioning (%)	*Lowest (%)*	*Highest (%)*
80-20	97.67	100.00
60-40	88.17	100.00
50-50	84.93	100.00
40-60	64.67	100.00
20-80	37.03	99.90

C. *Hardware and Software Specification*

The research used different libraries including OpenCV (cv2 version 4.8.0) for image processing, TensorFlow (version 2.15.0) for model simulation and validation, and Matplotlib (version 3.5.2) for visualizing results. It experimented with four optimization techniques (SGDM, RMSProp, Nadam, and Adam) on Google Colab's deep learning server using TensorFlow and Keras. The hardware setup included an Nvidia GeForce RTX 3050 Laptop GPU (version 512.78) and an AMD Ryzen 7 4800H CPU 8GB with 2.90 GHz. Mobile application testing was performed on a Realme GT Master Edition Android smartphone equipped with a Qualcomm Snapdragon 778G with Qualcomm Adreno 642L GPU.

D. *Model Validation and Testing*

The research converted the model into TensorFlow Lite (tflite) and was tested on the smartphone device with 2300 collected images. The study involved the collection of field images, taking into account variations in illumination and daylight conditions. These images were obtained from different sources, including Generalist Repository Ecosystem Initiative (GREI), UC Irvine Machine Learning Repository, images captured by the Department of Agriculture (DOA), and some were captured by the researcher. It is important to note that many agricultural fields often exhibit more than one disease on plant parts. In addition, a set of images was created to simulate such conditions by randomly combining collected images. To test the classification model, 100 images were created for each of the 22 disease classes, as well as one healthy leaf sample.

III. RESULTS AND DISCUSSION

This application was developed after conducting data testing and analysis. Dataset partitioning using various optimizers was tested and analyzed to determine which was most relevant and had the highest classification accuracy. Nadam achieved a very high accuracy result in all dataset partitioning from the initial partitioning 80-20% (80% for training set, 10% for testing set, and 10% for validation set) with an accuracy result of 97.67-100.00% , the second partition from 60-40% (60% for training set, 20% for testing set, and 20% for validation set) with an accuracy result of 88.17-100.00%, the third partition from 50-50% (50% for training set, 25% for testing set, and 25% for validation set) with an accuracy result of 84.93-100.00%, the fourth partition from 40-60% (40% for training set, 30% for testing set, and 30% for validation set) with an accuracy result of 64.67-100.00%, and in fourth partition from 20-80% (20% for training set, 40% for testing set, and 40% for validation set) with an accuracy result of 37.03-99.90%. Other optimizers, such as Adam, achieved a high accuracy of 82.09-100.00% in dataset partitioning within 50-50%, while RMSProp achieved a low accuracy of 60.33-100% in 80-20% partitioning, and SGD achieved the lowest accuracy of 53.62-99.67% in dataset partitioning 80-20%. Therefore, Nadam performs better than other optimizers in terms of accuracy, as illustrated in Fig. 2. While Nadam, RMSProp, and SGD had the same dataset partitioning with different results, the figure shows the compared training and validation accuracy, as well as training and validation loss, during the training process to predicted results. Also, Nadam and Adam optimizers had the same dataset partitioning with different results, shown in Figure 3.

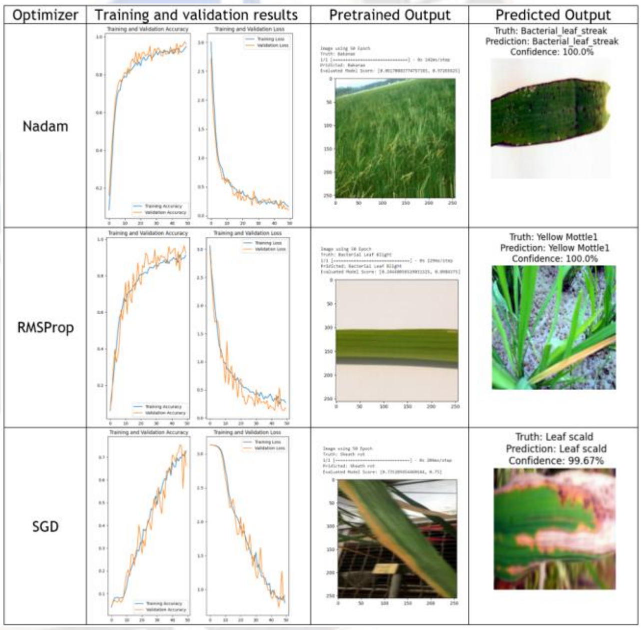

Figure 2. Training and validation in 80-20% dataset partitioning.

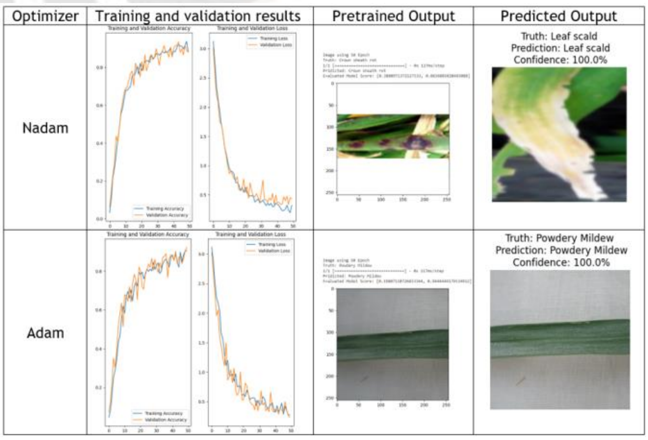

Figure 3. Training and validation in 50-50% dataset partitioning.

The "Rice Crop Diseases Classification" application's usability in the presence of multiple disease occurrences was tested on a Realme GT Master Edition Android with over 2,300 images (23 data classes, each with 100 images) and a CNN architecture. This Android application can also be utilized to conduct real-time field studies in intensely influenced regions and farther districts of creating countries. Given that the application does not require an internet connection to operate, field studies may be more helpful for town agronomists and young agriculturists.

Fig. 4 illustrates the block diagram for the "Rice Crop Diseases Classification (RCDC)" flow. The image will first be captured or uploaded using the application, after which it will be preprocessed using image acquisition from 22 different types of diseases and a healthy one. Second, the model will be resized and rescaled. Third, model will be randomly flipped, rotated, and contrasted with image augmentation. Fourth, it will train and validate the model by 80-20% over 50 epochs. Finally, the model's performance is evaluated and compared using the Nadam optimizer, followed by the final image classification and confidence result. In Fig. 5, Shows the user interface of the smartphone Android application, as well as a disease detection demonstration.

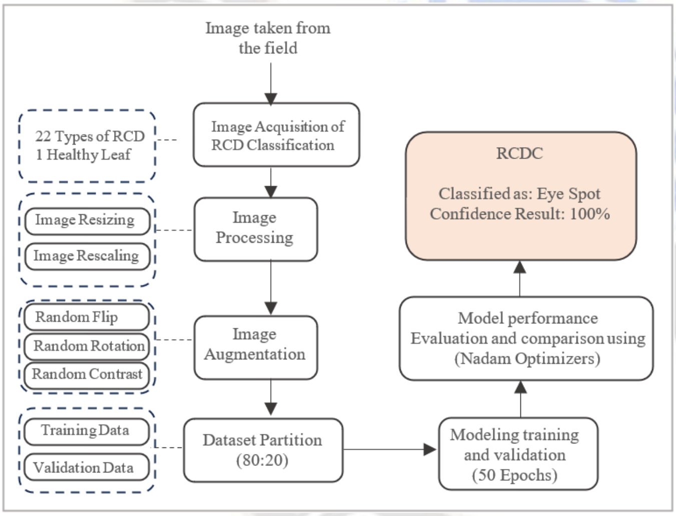

Figure 4. Block diagram showing the working of the "Rice Crop Diseases Classification" android application.

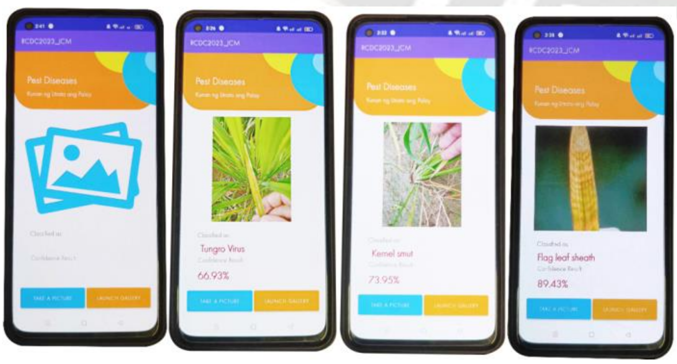

Figure 5. The smartphone Android application's user interface, which includes a demonstration of detected diseases.

The method described above can be used to develop models for other valuable crops, with practical model parameter adjustments. Currently, the application focuses on rice crop diseases affecting the leaf, stem, and root areas; however, spot segmentation can be improved to detect disease spots on other affected plant parts. The neural networks used were not trained to detect micronutrient and deficiency symptoms due to a lack of sufficient images, which can be investigated in the future. Finally, additional research is required to evaluate the application on smartphones with various hardware configurations.

IV. Conclusion

This study assessed the performance of Convolutional Neural Network with Nadam optimization for classifying rice crop diseases from smartphone images. The Nadam outperformed Adam, SGD, and RMSProp. Finally, the Android application "Rice Crop Disease Classification" successfully identified multiple disease occurrences in a single capture, demonstrating the potential of the tested optimizer for future rapid and on-field rice disease detection. This study aimed to detect complex situations, including multiple crop disease occurrences in the field. Notably, the best optimizer for application development was chosen because of its quick prediction time, ability to handle a large image dataset, and small size, which makes it compatible with the majority of farmers' smartphones.

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