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Article

DEEP LEARNING-BASED DETECTION AND CLASSIFICATION OF CARABAO MANGO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract: Leaf damages are mainly caused due to pests and diseases. Diseased leaves reduce crop production and affect the agricultural economy. The Philippines is one tropical country that produces carabao mango. However, its climate causes the variation of plant diseases that affect the yield of the agriculturist and the growth of mango trees. Agriculture plays a vital role in the economy; thus, image processing and machine learning technique are effective mechanisms to detect and recognize problem in an early stage. This study anal-yses the performance of two neural networks, a multilayer perceptron (MLP) an older type of network and convolutional neural network (CNN), a modern type of network as basis for the detection and recognition of carabao mango leaf diseases namely: anthrac-nose, sooty mold, red rust, and healthy leaf. There were 2856 disease and healthy leaf images captured using a mobile smartphone from the real cultivation conditions area. The 80% or 2285 was utilized for training and 20% or 571 were used for the validation tests of both healthy and disease leaves. Experimental results revealed that MLP achieved a performance rate of 86.30% and CNN generated 93.30% accuracy in the detection and recognition of carabao mango leaf diseases. From the result presented, the CNN and MLP neural network performance accuracy provide sufficient clues for the classification of a healthy and non-healthy carabao mango leaf

Keywords Image processing, Multilayer Perceptron, Carabao Mango Leaf Diseases, Backpropagation.)

1. INTRODUCTION

In agricultural research, images serve as a valuable source of data and information for analysis and decision-making. Mango, a widely cultivated tropical fruit, exhibits con-siderable variation in color, taste, aroma, yield, and utilization across different varieties. Historical records indicate that mango was first domesticated in India around 2000 BC and was later introduced to the Philippines during the 15th century. Over time, mango cultivation has expanded throughout tropical regions, including Asia, Central America, the Caribbean, and Africa, where it has become an important agricultural commodity and a significant source of livelihood for many communities.

The Philippines is a tropical country that possesses the ideal climate for mango growing. Today, mango is the third most important fruit crop in the Philippines, next to banana and pineapple. Its importance does not only come from the export side, but also from a local industry that made a perfect pack of ripe dried mangoes. There are three well-known varieties of mango in the Philippines, and these are Carabao mango, Pico, and Indian mango. However, the Carabao mango is the dominant variety that is widely grown throughout the country and is the sole exported variety. The Philippine carabao mango (1), or Manila mango, was named after the carabao, a native Filipino breed of domesticated water buffalo, a national animal of the Philippines (2). This mango variety was listed as the sweetest fruit in the world in the 1995 edition of the Guinness Book of World Records (3). With its golden color that signifies richness and a heart shape that symbolizes a very important part of human anatomy, the Manila mango is the traditional fruit of the country. The flesh or the meat of the carabao mango has an almost velvety texture and is really sweet.

The Philippine Statistics Authority reported that the country has produced 711.7 thousand metric tons of Carabao mangoes. Luzon region distributed production of 45.0 percent, the Visayas region distributed 17.30 percent and Mindanao (4) region shared

37.63 percent. The highest carabao mango producing province in 2018 is the Ilocos Re-gion with 23.55 percent, followed by the Zamboanga Peninsula, contributing to 11%. Central Visayas recorded production of 73.519 thousand metric tons, representing 10.33 percent of the national output. During the third quarter of 2019, the carabao mango variety contributed 81.2 percent of the total mango production (5). On record the Philippines is ranked 7th place among the top mango producing countries in the world, where India was ranked number 1, with production reaching 18 million tonnes, which is approximately 50% in the global mango industry. The second-largest mango producer is China, with

4.77 million tonnes (6; 7). The volume of production and yield of mangoes has signifi-cantly deteriorated. Furthermore, the export quality of fresh mangoes remains very low. This alarming situation, coupled with the increasing cost of production, prompted many mango growers to abandon their mango orchards or plant them to other crops or uses. The factors contributing to this trend are pests and diseases (8). Mangoes sold in super-markets and stalls show the status of how these fruits are taken care of in their source of production. The supply, color, texture, aroma, and even the taste define how these prod-ucts are protected in the plantation. The use of commercial pest control measures upon the decision made using the classical approach for detection and identification of plant diseases, which is naked eye observation by experts. However, consultation with experts is time-consuming and costly due to distance, location, and their availability.

Identification of damages or deficiencies caused by diseases is usually carried out by frequent monitoring of the plant leaves, flowers, fruits, or trunks. For backyard mango farmers, early detection of this deficiency is possible and allows them to control the dis-eases by using a minimal number of pesticides or plant chemical control. For small- and large-scale farmers, frequent monitoring and early detection of diseases is not possible,

and it could result in a severe outbreak of the diseases that cannot be controlled by organic means. In this situation, farmers are forced to use poisonous chemicals to eradicate the plant pathogen in order to retain the crop.

Digital image processing and machine learning have exhibited an impressive growth in the past decade in terms of theory and applications. It constitutes a leading technol-ogy in a number of essential areas such as medical imaging, intelligent sensing systems, remote sensing, telecommunications, robotics, facial recognition, and printing. Convo-lutional neural network (CNN), and Multilayer Perceptron (MLP) are neural networks used primarily to classify images. A neural network is a brain-based machine learning method to simulate the functions of a system of connected neurons. Neural networks are often constructed out of three types of layers: input layer, hidden layer(s), and out-put layer. Each layer is built on an arbitrary number of nodes that are connected to each other from different layers. Recent advances in computer vision and deep learning have demonstrated significant potential in automated image analysis across various domains, including medical imaging, textile analysis, agricultural inspection, and grain quality as-sessment (9; 10; 11; 12; 13).

Detection and recognition of diseases is an important aspect for plant breeders and plant pathologists. Plant diseases have a profound effect on harvested yield and, subsequently, the economy. There were various efforts to breed different crop plant geno-types with improved disease tolerance to curb the impact of diseases. Currently, com-mon plant leaf diseases are based on visual assessment, where the farmer would have to visually inspect individual plant diseases. Plant diseases remain a major challenge in agriculture, causing significant yield losses and economic impacts worldwide. Recent advances in computer vision and deep learning have enabled accurate and automated dis-ease detection systems that support precision agriculture and early intervention strategies (14; 15; 16). CNNs have become the dominant approach for plant disease recognition due to their ability to automatically learn discriminative features from leaf images and achieve superior classification performance compared with traditional machine learning methods (16; 17; 18)

On the other hand, Duke University Center on Globalization, on behalf of the USAID/Philippines, through the Science, Technology, Research and Innovation Develop-ment (STRIDE) with the Department of Trade and Industry, 2017, reported that mango yield in the Philippines is below that of other countries. They mentioned that the Philip-pines has an opportunity to expand the export trades of fresh mango, not only in regional markets but also to developing country markets. However, these markets require products with low levels of chemicals and free of diseases (19).

This study presents a comparative model of a convolutional neural network and a multilayer perceptron; both are machine learning algorithms as a basis for the detection and recognition of mango damages, specifically the carabao mango leaf diseases captured from a real cultivation area.

Currently, there is no publicly available large dataset for carabao mango leaf dis-eases. The Department of Agriculture Region VII and the Guimaras Mango National Crop Research and Production Support Center presented that the agency has a very lim-ited number of data collected.

This study is limited to the detection and classification of Carabao mango leaf diseases, namely anthracnose, sooty mold, and red rust. Disease images were collected

under natural cultivation conditions and validated using established agricultural standards and guidelines. The performance of CNN and MLP was compared using three models for each approach.

Common Carabao Mango Leaf Diseases

The Agricultural Training Institute (ATI) under the Department of Agriculture creates an integrated pest management guideline for mango production. According to ATI mangoes are prone to insect infestation and disease infection at any stage of their development. ATI added that without proper pest management, the quality of fruits may not be produced. The agency also mentioned that the current control measurement for pests attacking the mango still relies on the use of pesticides. In addition, excessive use of pesticides can cause pest resistance and destruction of natural enemies(20). Anthracnose, red rust, and sooty mold are the identified diseases of a carabao mango leaf as shown in Figure 1. The damage caused by these diseases affects the quality and quantity of crops. Proper identification is necessary to avoid the spread of this syndrome.

Anthracnose

The infection can occur at any growth stage and is visible on leaves, stems, petioles, and pods. Anthracnose diseases on mango leaves cause a serious loss of crops. Large brown lesions can affect flush leaves or older leaves. Small spots may coalesce into larger lesions. Dark lesions may occur on young leaves or fruit or on near-mature green fruit. The disease is more common in the areas where there is rain, fog, and high humidity in the early season. Symptoms are worse in stressed trees (20).

Sooty Mold

Sooty mold can be found on mango trees and any other plants that have previously been fed upon by insects. Gray-white powdery growth on leaves, flowers and or fruit, curled, distorted shoots, fruit aborted and dropping from the tree (21). The mold actually grows on honeydew, a sticky, sugary secretion that is produced by some insects to attract fellow bugs (23). Using the honeydew as a food source, the mold covers the surface of the affected leaf part, coloring it in various shades of black. Sooty molds affect the ability of the plant to perform photosynthesis and to exchange gases with the atmosphere. Severely infected leaves may die and fall off, thereby affecting the plant's growth and survival.

Red Rust

Red rust disease, caused by an alga, has been observed in mango-growing areas. The algal attack causes a reduction in photosynthetic activity and defoliation of leaves, thereby lowering the vitality of the host plant. The disease is recognized by the rusty spots mainly on leaves and sometimes on petioles and bark of young twigs (22). The spots are initially circular, slightly elevated, and later coalesce to form irregular spots. Spores mature, fall off, and leave a cream to white velvety texture on the surface of the leaf (24).

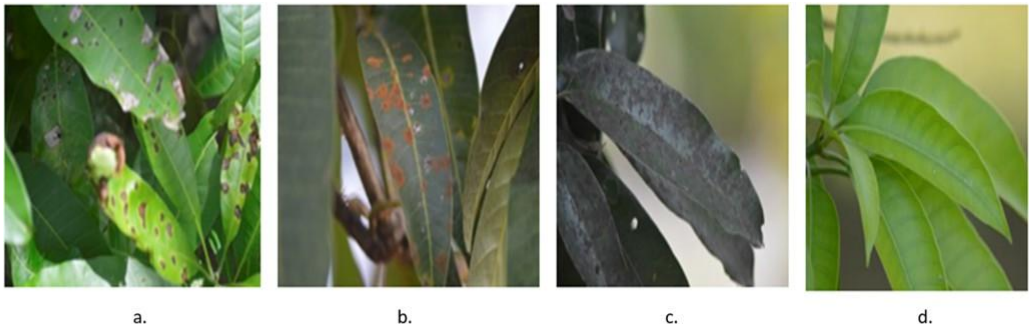

Figure 1. Disease (a. Anthracnose b. Sooty Mold c. Red Rust) and Healthy Carabao Mango Leaf (d).

Healthy Leaf

Carabao mango healthy leaves are dark green in color; there are no signs of disease. Mango leaf extract promotes wound healing, known as a treatment for diabetes, chronic lung diseases, asthma, and colds.

Methodology

In this study, the convolutional neural network and multilayer perceptron were used to de-tect and recognize the infected and healthy carabao mango leaves, details of the method-ology are shown in Figure 2.

Crop Diseases

Three different carabao mango leaf diseases have been used, namely: anthracnose, sooty mold, and red rust. Anthracnose diseases are caused by fungal diseases that cause irreg-ular brown spots in young leaves, while mature leaves get distorted with "shotholes" in various shapes and sizes. Sooty molds affect the ability of a plant to perform photosyn-thesis and to exchange gases with the atmosphere. Severely infected leaves may die and fall off, thereby affecting the plants' growth and survival. Red rust is recognized by the rusty spots mainly on leaves and sometimes on petioles and bark of young twigs.

Image Acquisition

With the help of mango growers and farmers, the researchers identified the carabao mango variety. Carabao mango leaves have aromas like the fruit. The Mature leaves of carabao mango are the largest among the mango varieties. The old leaves' color is light green with a tinge of brown. They are also the only ones with an abrupt acuminate leaf tip. The easier way to determine the carabao mango variety is by its fruit. The fruit is oblong with a blunt apex. The peel is smooth and bright yellow when ripe and has a delicate aroma. But the easiest way to determine or to identify the carabao mango tree is by asking the owner or the tenant about the variety of the mango tree.

In Table 1, a set of 2856 images of disease and healthy carabao mango leaves was collected from Western Visayas, the Guimaras Island 10 ° 35 ' 21" N 122 ° 34'43" E, the

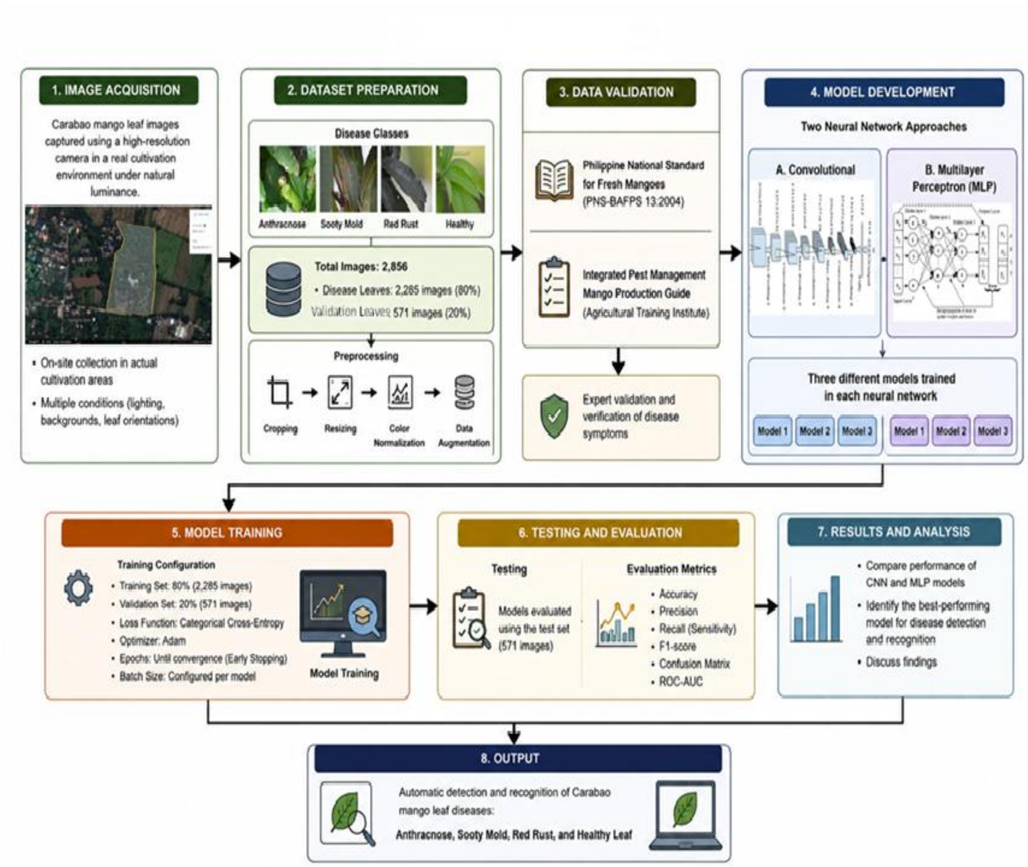

Figure 2. Methodological Framework for Automated Detection and Classification of Carabao Mango Leaf Diseases Using Deep Learning and Machine Learning Techniques.

Province of Aklan, and Central Visayas, Cebu, Philippines. All leaf samples were cap-tured carefully using a mobile smartphone with a 16 megapixel camera at the maximum resolution from the real cultivation environment. All the data gathered has been manually validated by an expert in plant pathology to make sure that the symptoms are related to the carabao mango leaf diseases. The data have been captured between the times of 7:00 am and 9:00 am, and 3:00 pm to 5:00 pm, to contribute a soft blend of brightness to the image and background.

Table 1. Disease-infected and healthy carabao mango leaf

No.	Disease	Count	Weight
1	Anthracnose	800	800
2	Sooty Mold	800	800
3	Red Rust	456	456
4	Healthy Leaf	800	800

Image Preparation and Data Validation

One of the pre-processing steps for the image data is manually cleaning out some blurred files (if any). After cleaning out, a small program implemented in Python is used to rename all files with consecutive numbers. This is done for simplicity and to obtain the class names of the instances automatically. After renaming the data, all images were then resized to 256 x 256 pixels before being fed to the network. Data must be converted to some numerical format. In order to handle this conversion, image filters are applied to datasets. Filtering is transforming pixel intensity values to obtain some numeric data, and this data reveals the image characteristics. The red, green, and blue values of the images were unchanged. These were then applied to a batch filter for extracting the color layout features using 33 MPEG-7 color layout filters. This filter adds data about the spatial distribution of colors in an image. This filter divides an image into 64 blocks and computes the average color for each block, and then features are calculated from the averages.

Model Development

Convolutional Neural network

Recent studies have demonstrated that advanced CNN architectures, including attention-based and hybrid models, significantly improve disease classification accuracy under varying environmental conditions (25; 26). In this study, the input image was resized to 256x256 pixels before being fed to the CNN network. The red, green, and blue values of the images were unchanged. The images were then passed through the hidden layers. The convolutional neural network produced four classifications; the reason why the out-put layer had a dimension of 1x4. There were four convolutional operations in the model, and after every convolution, it was made up of 32, 64, 128, and 256, respectively, and the output was fed to a max-pooling layer later. The filter sizes for all the convolutional and max-pooling layers were 5x5, while the stride was 1. There were two fully connected

layers in the last part of the model. The first fully connected layer had 1x512 dimensions, while the final fully connected layer, which was also the output layer, had a size of 1x4. After the first fully connected layer, a dropout of 80% was implemented. Adam optimizer and ReLU layer were used to increase the network performance and the training process. The CNN model utilized the Adam optimizer due to its computational efficiency,

low memory requirements, and ability to adapt learning rates for individual parameters. Adam also requires minimal hyperparameter tuning and performs well on large and noisy datasets (27).

The Rectified Linear Unit (ReLU) was used as the activation function. ReLU outputs zero for negative inputs and the input value itself for positive inputs, helping mitigate the vanishing gradient problem and accelerating model training.

Pooling layers were applied after convolutional layers to reduce the spatial dimen-sions of feature maps and improve computational efficiency. Max-pooling was used to retain the most significant features by selecting the maximum activation value within each region. This process reduces feature map size while enhancing robustness to translation and rotation variations in the input data (28).

Multilayer Perceptron

The extracted color layout features from the image pre-processing were used as input data for the training of the MLP neural network to classify the carabao mango leaf diseases. A split of an 80-20 ratio is applied, or 80% of the images were used as training data and 20% used for the test dataset.

A multilayer perceptron is known as a feed-forward artificial neural network hav-ing an input layer with one or more hidden layers of sigmoid neurons. A neuron, also called a node or Perceptron, is a computational unit that has one or more weighted input connections, a transfer function that combines the inputs in some way, and an output con-nection. Network architecture is determined by the number of hidden layers and by the number of neurons in each hidden layer(29). The network is trained using the backprop-agation learning rule. They are generally used for pattern recognition, classification of input patterns, prediction based on the input information, and approximation.

Evaluation metrics

Once the neural network had been trained with 2285 or 80% of the 2856 instances, they were provided with new validation data, in the form of 571 or 20% images that had never been seen before by the network. Performance comparison in terms of accuracy for train-ing and validation test, training and testing elapsed time, confusion matrix, 5-fold cross-validation, and evaluation metrics were achieved from MLP and CNN.

2. RESULTS AND ANALYSIS

A total of 2856 carabao mango leaf images were captured from the real cultivation envi-ronment, including 800 images of anthracnose, 800 of sooty mold, 456 red rust diseases, and 800 healthy leaves.

To verify the performance of the model, a set of 1000 epochs was initialized for every model training test using the actual dataset captured from the real cultivation envi-

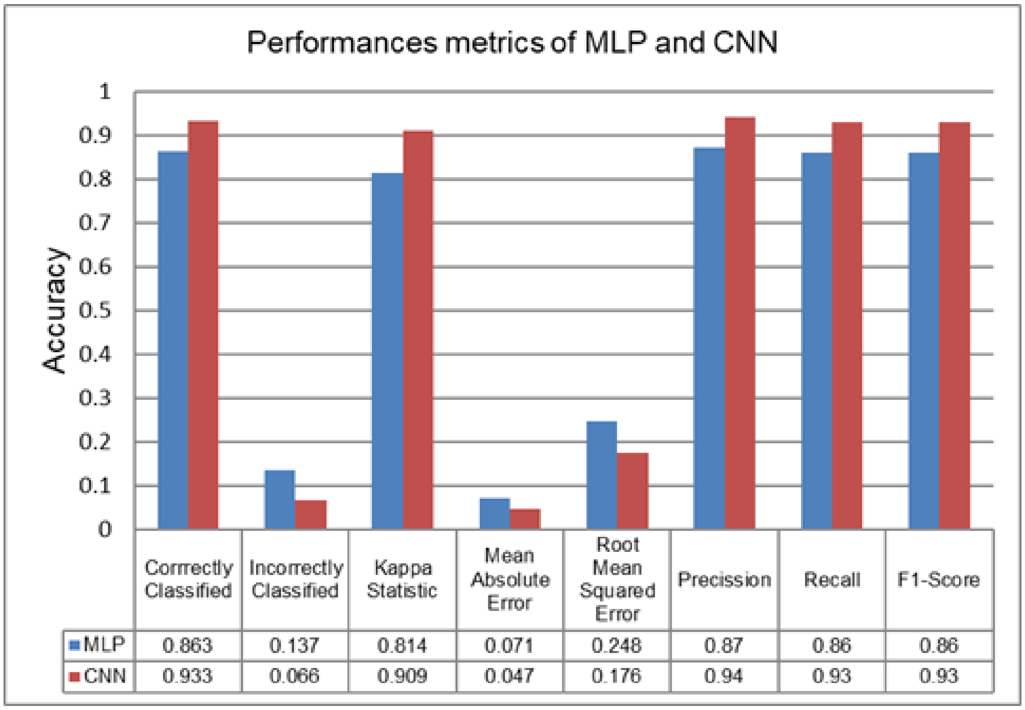

Figure 3. Performance metrics of MLP and CNN model.

ronment that poses with size, orientation, illumination, and backgrounds. Three training and validation tests were generated for CNN and MLP to ensure the persistence of the best model to be used to identify the carabao mango leaf diseases.

Out of 2856 instances, 2285 or 80% were used for training, and 571 or 20% were used as validation test datasets for both MLP and CNN.

Figure 3 presents the performance comparison between the Multilayer Percep-tron and Convolutional Neural Network models. The CNN consistently outperformed the MLP across all evaluation metrics. CNN achieved a higher classification accuracy of 93.3% compared to 86.3% for MLP, while also obtaining a higher Kappa statistic (0.909) than MLP (0.814), indicating stronger classification agreement.

In terms of error measures, CNN recorded lower mean absolute error (0.047) and root mean squared error (0.176) than MLP, which obtained 0.071 and 0.248, respectively. Furthermore, CNN demonstrated superior precision (0.94), recall (0.93), and F1-score (0.93) compared with MLP values of 0.87, 0.86, and 0.86. The lower misclassification rate of CNN (6.6%) relative to MLP (13.7%) further confirms its effectiveness in distin-guishing healthy and diseased Carabao mango leaves.

These results indicate that CNN provides more accurate and reliable performance for automated Carabao mango leaf disease detection and recognition than the MLP model.

To further assess model robustness, a 5-fold cross-validation was performed. The results as shown in Table 2, that the CNN model consistently achieved higher classifica-tion accuracy across all folds, with an average accuracy of 90.80%, compared to 86.16% for the MLP model. Moreover, CNN required less computational time, with an average elapsed time of 113.63 seconds, while MLP required 280.64 seconds.

The findings demonstrate that CNN not only provides superior classification per-formance but also exhibits greater computational efficiency than MLP. These results con-

firm the suitability of CNN for automated detection and recognition of Carabao mango leaf diseases under varying field conditions. The superior performance of CNN ob-served in this study is consistent with recent findings that deep learning models provide robust feature extraction and classification capabilities for plant disease detection tasks (30; 31; 32)

Table 2. Five-Fold Cross-Validation Performance Comparison of MLP and CNN Models

Fold used for training	Fold used for testing	Elapsed time(s)		Test data accuracy%	
		MLP	CNN	MLP	CNN
1,2,3 and 4	5	282.49	108.33	84.41	90.48
1,2,3 and 5	4	280.75	115.21	90.01	88.65
1,2,4 and 5	3	279.72	102.56	82.13	91.79
1,3,4 and 5	2	280.50	123.16	86.86	90.84
2,3,4 and 5	1	279.74	118.92	87.41	92.27
Average		280.64 sec	113.63%	86.16%	90.80%

3. CONCLUSIONS

This study is structured to investigate, particularly focusing on the performance of MLP and CNN, as a basis for the detection and recognition of carabao mango leaf damages. There were 2856 carabao mango disease and healthy leaf images captured from the real cultivation environment with different illuminations, lighting conditions, and complex backgrounds, which is possible using a multilayer perceptron and a convolutional neural network. Out of 2856 instances, 2285 or 80% were used for training and 571 or 20% were used for the validation dataset.

A statistical experiment was conducted to test the performance of two neural net-works as the basis for carabao mango leaf disease detection and recognition using cross-validation in a randomized training and test set. Both MLP and CNN generated an ac-ceptable performance rate of 86.3% and 93.3% in the classification. The results further support the growing adoption of deep learning and CNN-based approaches as effective tools for intelligent agricultural monitoring and disease diagnosis systems (16; 25; 31). From the result presented, it is concluded that both the CNN and MLP algorithms' per-formance accuracy provides sufficient clues for the detection and recognition of healthy and non-healthy carabao mango leaves..

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