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Corn Leaf Disease Recognition System Using Convolutional Neural Network With The Implementation of Xception Model

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HIGHLIGHTS

- Early diagnosis of symptoms can both prevent loss and increase corn production.
- The recognition system is a method for identifying disease on corn leaves without the need for human interference.
- Convolutional Neural Network (CNN) identifies patterns in visual data, such as images, and is a type of deep learning algorithm that is frequently used for image recognition.
- The Xception model, which is an abbreviation for "Extreme Inception," is a deep convolutional neural network architecture included in the Keras deep learning library.

ABSTRACT

Monitoring a plant's health and looking for signs of infection are two highly important aspects of sustainable agriculture. Monitoring plant diseases by manually is an extremely time-consuming and tedious task. It takes a significant amount of time, a substantial amount of labor, as well as knowledge in plant diseases to achieve. Image processing is thus used in the process of detecting plant diseases. This project mainly focuses on corn leaves disease recognition using convolutional neural network. The Xception model, which is a part of a convolutional neural network capable of classifying images into broad object categories, would be the model of choice for this image classification. Using Convolutional Neural Network (CNN), this study aims to build and test an image classification system for identifying corn leaf diseases recognition. This research dataset is trained by analyzing a big dataset that contains pictures of various diseases that might affect corn leaves as well as pictures of corn leaves that are healthy in order to precisely identify them. The data were then analysed using a methodology known as the Agile model, which included phases for planning, requirement analysis, design, development, testing, and documentation. The findings from the study provide evidence on the precision with which the Xception model performs when applied to the datasets that have been gathered. Strongly, the results of the study will emphasize the need for developing a thorough image classification system in detecting plant diseases without human intervention.

Keywords: *corn leaf, disease recognition, Convolutional Neural Network (CNN), Xception model*

INTRODUCTION

Corn is one of the conventional crops in Malaysia. The two types of corn that are most frequently grown in Malaysia are grain corn and sweet corn (Syauqi Nazmi et al., 2021). Perak, Johor, and Sarawak are the states in Malaysia that are the highest corn producers. Despite the fact that both grain corn and sweet corn are grown most commonly, sweet corn has already been replacing grain corn in production due to its better price and higher consumer demand (Syauqi Nazmi et al., 2021). Despite being one of Malaysia's most important crops, corn is prone to get diseases. Corn is vulnerable to a number of diseases, including gray leaf spot, common rust, leaf blight and many other diseases. Corn leaf diseases may have numerous diseases present at once or share symptoms (Corn Leaf Diseases, 2018). In Malaysia, almost all farmers still use manual identification instead of a more sophisticated system. Thus, it will lead to human errors, such as misdiagnosing one disease as another which will eventually lead to more severe issues like giving the wrong fertilize to overcome the disease. As a result of these errors, the tree will result in damage. Plus, manually detecting plant disease is a tedious job. Hence, computational approaches must be developed to ensure that the disease recognition and classification procedure is precise.

The majority of research focuses on machine learning, which, while producing positive results, tends to work with smaller datasets. In the near future, the number of diseases may increase, resulting in machine learning accuracy remaining unchanged or declining. Also, machine learning, as comparison to deep learning, requires a more complex development process and human intervention (Abdu et al., 2020). Besides, although some experts have been able to precisely identify the types of diseases and pests, this approach has several weak points. For instance, corn farmers often do not see the need to hire an expert for their crops just to help them in making diagnoses about the diseases that their corn crops may contract. Furthermore, employing professionals may be costly, resulting in an increase in cost and energy, potentially demotivating corn farmers. Plus, the number of corn experts may be insufficient in comparison to the number of corn farmers to manage all of the crops (Wan et al., 2020). Two research objectives are created based on the problem statements which are to develop an image classification system that includes deep learning technology which is convolutional neural network with Xception model to detect corn leaf diseases based on the symptoms of specific diseases and to run performance testing of the corn leaf diseases recognition system in terms of accuracy identifying disease types based on the symptoms. Additionally, this disease recognition system will save corn farmers time by eliminating the need to manually identify which diseases the plant may contract. In fact, issues like mistakenly identifying the type of diseases could be avoided. Also, this approach will benefit other agriculture researchers in the implementation of various plants such as mangoes, dragon fruits, guava, and others.

Previous work on recognition and classification system was for cashew plant diseases and using Transfer Learning with a CNN (ResNet-50) pre-trained deep learning network was published by (Oluwafemi, 2021). The dataset consists of 1050 sample photos from three different elements of the cashew plant, including the leaf, nut and stem as well as for training, validation and testing, the database was categorized into three sets in the proportions of 50%, 30% and 20% respectively. Specificity, sensitivity, accuracy, and error rate were used to measure the systems' overall performance. ResNet has shown to be effective in a variety of applications, but one negative point is that deeper networks typically take weeks to train, rendering them almost unusable for practical applications.

Another previous study was proposed by (Matin, 2021) that conducted research on recognition of Covid-19 from CT image using CNN architecture which is LeNet-5. For the design of the system, they used 80% of the lung CT frames for training and 20% of the frames for testing. During the data pre-processing stage, the CT image was turned into greyscale, and the pixel values were rescaled from 0 to 1. This is called normalization. As a result, after 157 iterations, the LeNet-5 COVID-19 disease recognition model reached an accuracy of 86.06 percent, a loss of 0.369 percent, a f1 score of 87 percent, a precision of 85 percent, and a recall of 89 percent.

METHODOLOGY

The Convolutional Neural Network (CNN) with the implementation of Xception model was adapted in this project. The first phase methodology of this project will start by explaining the flowchart of the proposed project, followed by the elaboration of the dataset's requirements. At the last phase, the overall process diagram will be explained.

Flowchart of the Proposed Project

Figure 1 is a flowchart displaying how corn leaf disease recognition would operate. The Xception model will be trained and applied to generate the final corn leaf disease based on the dataset's symptoms. The process of entering an image from a dataset containing corn leaf disease symptoms will be the first step in this system. The system will then load the set of images and pre-process them. After the Xception model has trained and analysed the images, the results will be evaluated by recognizing the type of leaf disease.

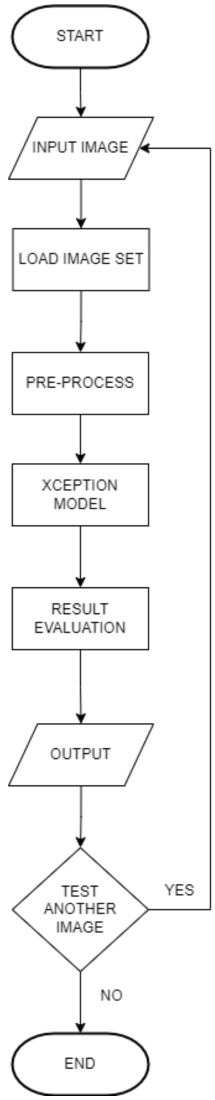


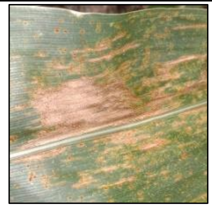
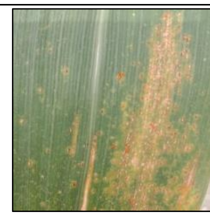
Figure 1: Flowchart for corn leaf disease recognition system

Data Requirements

The types of data that were used in this study can be considered as falling into the categorical type. This is because these data sets need to be sorted in accordance with the criteria that distinguish one disease from another. In fact, in order to train the deep learning model, the data sets itself have to be in the form of pictures. In particular, the data sets with pictures of diseases were collected from corn crops that were located in Chemor, which is situated in the state of Perak.

Table 1: Corn leaf that have been collected from a crop in Chemor

No	Corn leaf	Picture

1	Leaf blight	
2	Leaf common rust	
3	Leaf grey spot	
4	Leaf eaten by snail	
5	Healthy leaf	

Moreover, each image has been rotated at three separate angles of 90, 180, and 270 degrees. This stage is important for improving the model's capacity to generalize and introduces variability to the data so that the model will function more effectively and precisely. For instance, the table below shows how a common rust disease image may be rotated to generate other images.

Table 2: *Datasets augmented into certain degree*

Image	**Rotation Degrees**

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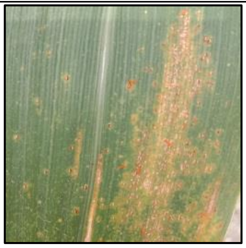
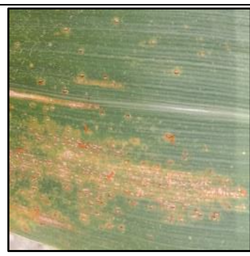
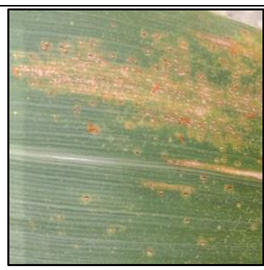
	Original
	90°
	180°
	270°

Diagram of Overall Process

Figure 2 depicts the entire process flow of how the disease recognition system operates. The very first step in the process requires the users to snap photos of the contaminated leaves. Users were required to access the system when they had completed taking photos and begin the process of uploading the photos. The Xception model will then proceed to load the photos and do the necessary pre-processing. As a final point of interest, the result will then be produced by the system and displayed depending on the photos that were taken.

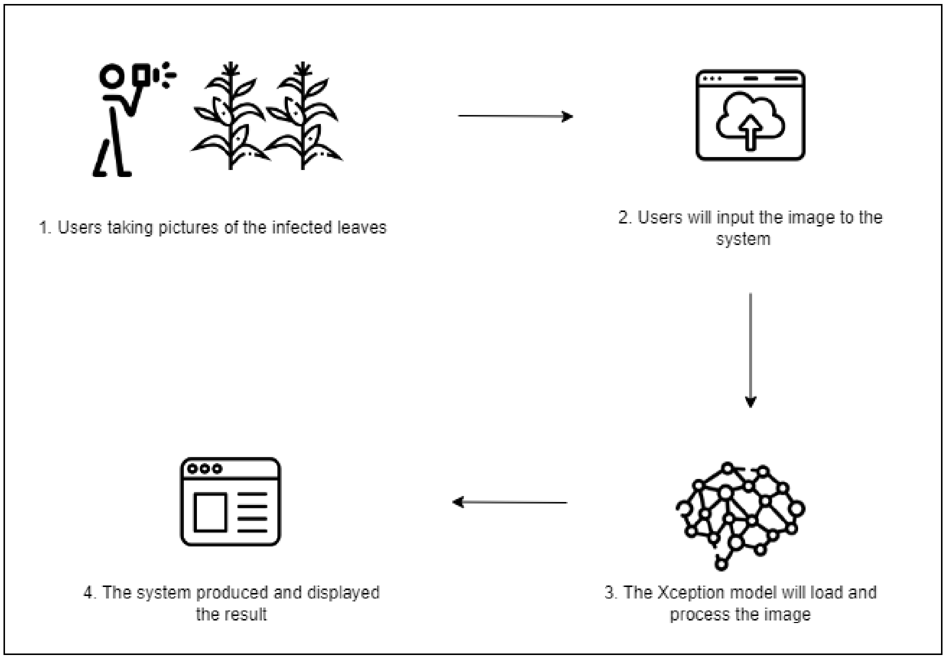


Figure 2: Overall Process Diagram

FINDINGS AND DISCUSSIONS

Testing of the functionality of each element was carried out to verify that all of them corresponded to the requirement description for the project. The Xception model was evaluated to determine the accuracy of the type of corn leaves diseases. There were five classes of diseases were used to train the model which are leaf blight, leaf gray spot, leaf common rust, leaf eaten by snail and healthy leaf. There were around 963 pictures in all that included all of the disease pictures.

The training and validation accuracy model as well as loss model were plotted at different epochs in other to identify over-fitting. After 10 experiments, this project can conclude that when batch size = 60, epoch = 15, image size = 256*256, the model achieved the highest classification accuracy of the corn leaf diseases image data set. Additionally, the loss function curve in Figure 3 and the accuracy curve in Figure 3 of the training set and the validation set fit together the best.

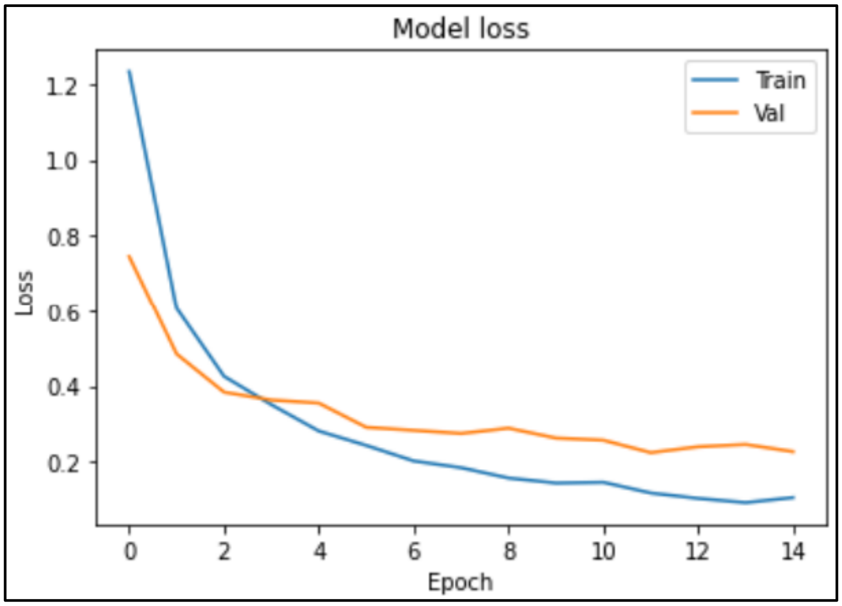


Figure 3: Graph of Training Loss against Validation Loss

Figure 4 shows that the early stages of the model accuracy graph demonstrate a significant increase in accuracy on the training set, but the validation accuracy improves slowly and then rapidly decreases. In an accuracy graph, this is referred to as overfitting. This shows that the model learns the training data too well but does not adapt effectively to new, previously unknown data. However, after the fourth epoch, the training accuracy line and validation line were in the moderate range, indicating that this model is capable of achieving its best accuracy. When the model is neither overfitting or underfitting, the range of the difference between validation and training accuracy and loss are considered acceptable. If the range is too narrow, the model is likely to be underfitting; if the range is too wide, the model is likely to be overfitting. Therefore, this Xception model have a small range, suggesting that its performance on the validation set is comparable to that on the training set.

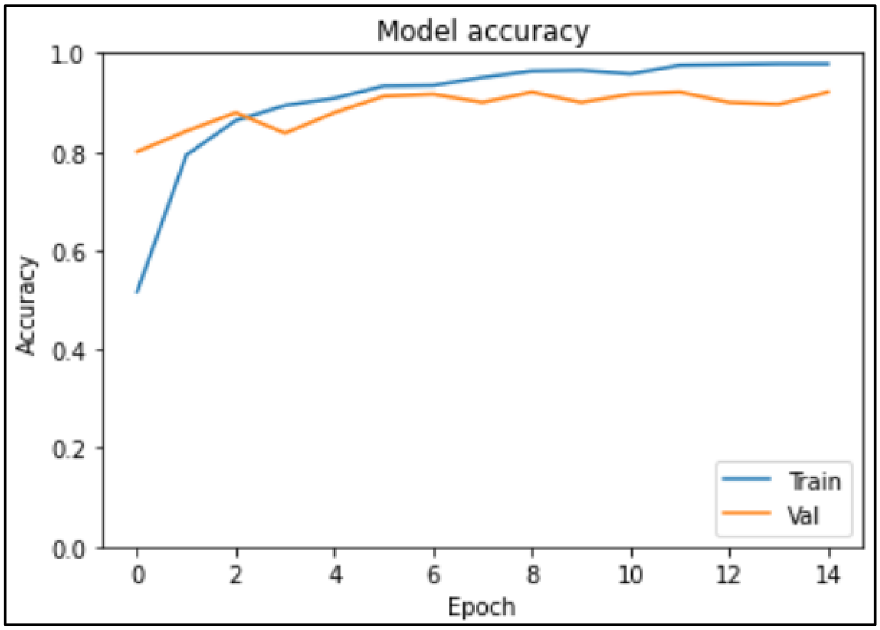


Figure 4: Graph of Training Accuracy against Validation Accuracy

Furthermore, Figure 5 illustrates the confusion matrix that has been generated in order to better observe the performance of the Xception model in each class which are blight, common_rust, gray_spot, healthy and snail. The values in each row depict the expected classes of the outcomes, and the values in each column indicate the model's predictions, as shown in Figure 33. For this system that makes predictions among 5 classes, the confusion matrix would have 5x5 = 25 entries. To begin, the system correctly identified 91 percent of the samples as having blight disease, while the system incorrectly identified 9.1 percent of the samples as having common rust disease. Next, the system accurately diagnosed 78 percent of the samples as having common rust disease, while the system falsely diagnosed by the system as having blight disease for 16 percent and gray spot for 5.9 percent. The system correctly identified 94 percent of the samples as having gray spot disease. However, the system also incorrectly identified 4.7 percent of the samples as having blight disease and 1.6 percent as having common rust disease. Moreover, the system accurately diagnosed 98 percent of the samples as having healthy leaves, while the system falsely diagnosed by the system as having gray spot disease for 2 45 percent. Lastly, the system was correctly diagnosed the samples as having leaves eaten by snail for 100 percent accuracy. Therefore, the recognition results demonstrate that the model proposed in this research may decrease the needs for collecting corn leaf images and has a high degree of accuracy for classifying corn leaf diseases.

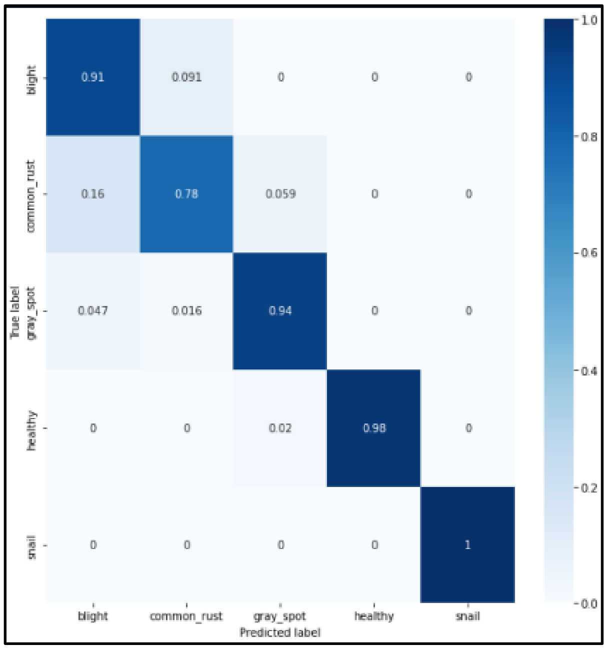


Figure 5: Confusion Matrix for five classes of corn leaf diseases

The result of Perceived Usefulness (PU) of User Acceptance Testing is plotted into a bar chart as shown in Figure 6. Question 1 for this section which is "This corn leaf diseases recognition system allows me to use new pictures of diseases corn leaves" displays that the mean score achieved is 4.53 which indicates that the respondents are agreed that this system allows them to use new pictures of diseases corn leaves. In contrast, the mean score for Question 2 which is "The corn leaf disease recognition system accurately predicts the diseases based on the symptoms" is a little bit lower than Question 1 which is 4.4. In conclusion, it was expected that respondents would find this convolutional neural network disease recognition method for corn leaves beneficial.

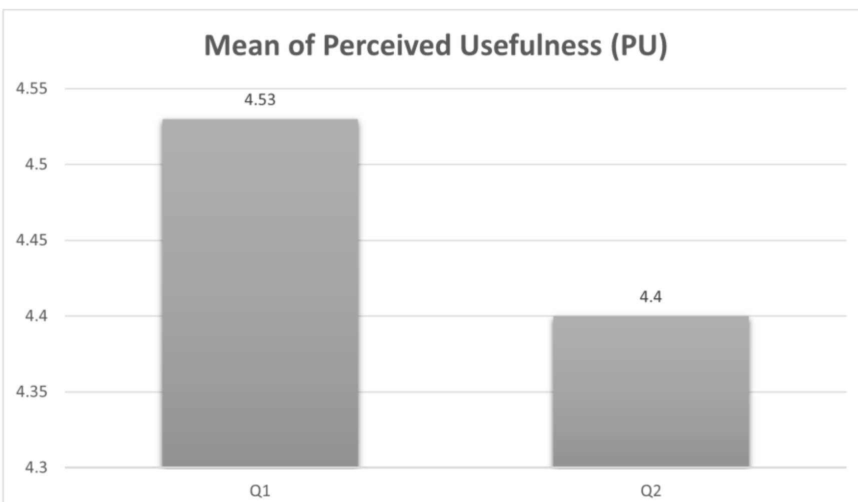


Figure 6: Bar graph of mean score for Perceived Usefulness (PU) result

CONCLUSION AND RECOMMENDATIONS

This research was carried out with the purpose of developing a corn leaf disease recognition system with the implementation of Xception model. The project was a success, and it met all of its objectives. The first objective of this project was to develop an image classification system that includes deep learning technology which is convolutional neural network with the implementation of Xception model to detect corn leaf diseases based on the symptoms of specific diseases. This successfully designed system might be a useful starting point for applying technology to the identification of diseases in the agricultural sector. The second objective of this project was to run performance testing of the corn leaf diseases recognition system in terms of accuracy identifying disease types based on the symptoms. It has been proven that the Xception model has an accuracy of 92.11 percent in diagnosing corn leaf diseases from sample of local corn crops. The researcher also performed user acceptance testing with 30 respondents in order to evaluate the system's usefulness, attitude, and intent to use which describe that this system was deemed acceptable by the users. Further, this system reveals some suggestions for future research and development to enhance the quality and usefulness of the established system which includes incorporating more data sources such as integrating humidity and temperature into weather data may assist in determining environmental factors that may contribute to the emergence of plant diseases. Plus, improving data collection by integrating automated data gathering techniques, such as the use of drones or Internet of Things (IoT) devices, may allow the rapid acquisition of massive volumes of data is one of the suggestions for future research.

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CONFLICT OF INTEREST DISCLOSURE

The authors declared that they have no conflicts of interest to disclose.

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