Deep Learning With Convolutional Neural Networks For Cassava Leaf Diseases Via Line Bot: A Case Study Of Buriram Provincial Protection Service Group, Buriram Provincial Agriculture Office

Jiravadee Yoyram
Department of Information Technology, Faculty of Sciences, Buriram Rajabhat University
Prem Enkvetchakul
Department of Information Technology, Faculty of Sciences, Buriram Rajabhat University
Kittikoon Boonkate
Department of Applied Statistics, Faculty of Sciences, Buriram Rajabhat University

*** Coresponding Author:** Prem Enkvetchakul
Email: prem.ev@bru.ac.th

Abstract-This research aims to study and compare the effectiveness of deep convolutional neural networks (DCNN) suitable for detecting cassava leaf diseases. The objective is to develop a system for detecting cassava leaf diseases using a convolutional neural network through Line Bot, evaluate its performance with the assistance of experts, and assess the satisfaction of farmers who grow cassava regarding the usability of the system. The research tests the performance of four CNN architectures: MobileNetV2, NAS Net Mobile, EfficientNetV2B0, and EfficientNetV2B1, by adjusting the learning rates to 0.01 and 0.001 and comparing the results with and without data augmentation techniques using the iCassava 2019 dataset. The evaluation of the system was conducted with a sample group consisting of three expert evaluators and 30 farmers who grow cassava under the supervision of the Plant Protection Service Group, Buriram Provincial Agriculture Office. The assessment of the system's usability was obtained through purposive sampling. The research findings revealed statisticallysignificant differences in the accuracy of cassava leaf disease classification among the four tested architectures at a significance level of 0.01. The highest accuracy of 88.43% was achieved using the MobileNetV2 model combined with data augmentation. This system was further developed to detect cassava leaf diseases using the camera on a smartphone to capture images of abnormalities oncassava leaves. It also provided information on disease treatment to prevent the spread of diseases to nearby areas through Line Bot. Overall, the evaluation of the system's effectiveness by experts found it to be at a good level, and the overallsatisfaction with its usability was found to be at a very good level.

Keywords: Deep Learning, Convolutional Neural Networks, Cassava LeafDisease Detection, Line Bot

Introduction

Image classification, the task of categorizing images into different classes, has been continuously developed and is of great importance, as evidenced by its wide application in various fields. Currently, the use of convolutional neural networks (CNNs) for image classification has gained significant popularity. This is mainly due to the ease of deep learning and the increasing availability of large-scale image datasets. Additionally, the emergence of cloud computing services has made it more accessible and cost-effective to access computation units. Furthermore, CNNs can reduce the complexity of image classification tasks by utilizing traditional machine learning-based approaches.

Cassava (Manihot esculenta Crantz) is an economically important crop in Thailand due to its significant cultivation area, ranking as the world's third- largest producer after Nigeria and Brazil. Furthermore, Thailand has long been the world's leading exporter of cassava products. This is due to cassava being a beloved crop among Thai farmers, as it is an easy-to-grow crop with minimal production issues, and it adapts well to various soil conditions, even in areas withpoor soil quality (Changlek et al., 2019). The Biosensing and Bioprospecting Technology Research Group, National Center for Genetic Engineering and Biotechnology (BIOTEC) (Sripiban, 2022), states that cassava leaf diseases are important diseases that significantly impact cassava, which is the country's economic crop. Moreover, according to information from the Buriram Provincial Agriculture Office, the Plant Protection Service Group responsible for planning crop management operations in the province and monitoring the outbreak of plant pests has recognized the significance of cassava leaf diseases, which greatly impact farmers. Additionally, the current volatile environmental conditions make cassava susceptible to diseases. Farmers need to acquire knowledge about diseases and their treatment methods to prevent and mitigate their occurrence. Typically, farmers acquire such knowledge through consulting experts or searching for information on websites. It is found that there are currently numerous websites available that provide such information. However, it has been observed that the available websites usually provide only information, and the gathered information is often difficult to study due to its extensive nature. Therefore, obtaining the desired information can be time-consuming (Klaisuban et al., 2017). The limited accessibility of agricultural information makes it difficult for farmers to stay informed about various factors that contribute to the occurrence and spread of diseases. Moreover, disease diagnosis often requires the expertise of specialists, resulting in additional costs and time spent waiting for their assistance.

Based on the aforementioned importance, the researchers conducted a study and compared the effectiveness of deep convolutional neural networks (DCNN) that are suitable for developing a disease detection system for cassava leaves via Line Bot. This bot is capable of providing general news information, situations that may lead to diseases, and predictive data for farmers. This enables them to receive news and information, diagnose plant diseases, and independently learn preventive measures.

Purpose of Research

1. To study and compare the effectiveness of deep convolutional neural networks (DCNN) that are suitable for cassava leaf disease detection
2. To develop a disease detection system for cassava leaves using aconvolutional neural network (CNN) via Line Bot
3. To evaluate the system's performance through expert assessment and assess farmers' satisfaction with the system's usability

Literature Review

The convolutional neural network (CNN) is one of the architectures of feed-forward neural networks that is classified as deep learning. It aims to simulate human vision by analyzing image features such as color, patterns, and others in localized regions. These features are then combined to predict the content or classification of an image. The operation of a CNN involves four main processes (Cheewaprakobkit, 2019) as follows:

1) Convolution performs the identification of important features that arerelevant to the image.
2) Rectified Linear Unit (ReLU) transforms the matrix into a new matrixor feature map.
3) Pooling reduces the dimensionality of the feature map while preservingimportant image details.
4) Fully Connected Layer connects each layer completely based on the processes of the previous three steps.

There is a research work presented by LeCun (1998) that incorporates convolutional computations into the network, hence called Convolutional Neural Network (CNN). A CNN consists of convolutional layers, pooling layers, and fully connected layers, where the fully connected layers refer to the hidden layersand the output layers in the neural network. The CNN can extract distinctive features of images and perform classification tasks, making it a prominent aspect of CNN learning. This differs from the general machine-learning approaches that typically focus on data classification or grouping only (Sanooksan, 2019).

Khitthuk (2016) conducted a study on a system for diagnosing plant diseases from color images using co-occurrence matrices and artificial intelligence methods. It was found that when classifying grape leaf disease achieved an accuracy of over 90% in correctly diagnosing grape leaf diseases. Moreover, the proposed system can be further developed to be used in diagnosing various other types of plant diseases.

Pattanasarn & Sriwiboon (2020) conducted a study on image processingfor classifying the quality of Chok Anan mangoes by simulating human visual perception using deep learning with convolutional neural network algorithms. The maximum accuracy achieved was 99.79%.

Temniranrat et al. (2021) conducted a study on an automated rice disease detection system using unhusked rice images through a chatbot. They employed deep-learning neural network techniques to detect diseases in rice based on images. The performance of the model was evaluated using the average true positive point metric, and the average value obtained was 78.86%.

Adedamola et al. (2022) conducted a study on the intelligent mobile plant disease diagnostic system using NAS Net-Mobile deep learning. They found that plant diseases continue to pose a threat to global food security due to their detrimental effects on crop yield and income. However, the intelligent plant disease diagnosis system proved to be highly beneficial and significant. The objective of this study was to develop a mobile-based intelligent plant disease diagnosis system using NAS Net-Mobile, a convolutional neural network architecture (CNN), with plant leaf images for disease diagnosis. A mobileapplication was developed for both Android and iOS operating systems to capture plant leaf images, and the system operated on a web service that utilized the NAS Net-Mobile model for disease diagnosis. The plant leaf images captured by the mobile application were transmitted through the web service, and disease detection was achieved using the NAS Net-Mobile model with an accuracy of 99.31%.

Research Methodology

This research followed the System Development Life Cycle (SDLC), whichincluded the following steps:

1. System Problem Definition: Related data on the performance testing of CNN, including four

architectures: Mobile Net V2, NASNet Mobile,EfficientNetV2B0, and Efficient Net V2B1, was studied. Requirements dataregarding the Plant Protection Service Group, Buriram Provincial Agriculture Office, was gathered through interviews. In addition, data on image classification model creation using TensorFlow.js with pre-trained small-sized models using the iCassava2019 dataset was studied. A Line chatbot and application were developedusing the Python language.

2. System Analysis: Data from the System Problem Definition step was analyzed. In terms of requirement gathering, content analysis was conducted to summarize the needs of the Plant Protection Service Group, Buriram Provincial Agriculture Office. The workflow was designed in two parts: (1) Staff Section: Staff members were responsible for sending general news, public relations announcements, and activity updates, as well as situational data on potential diseases in case of fluctuating weather conditions and predictive data for affectedplots, to the bot server for data processing and sending back responses to all users. (2) User Section: Users could send data in two formats, images, and text, to the bot server. If it was an image, the bot server imported it into a model to diagnose cassava leaf diseases and sent the prediction results to the text processing component. The text processing component then responded to the user, indicatingthe likelihood of the image containing a disease, along with an example image of the disease and treatment methods, represented as a percentage. If it was text, the text was sent to wit.ai for intent processing. The intent was then sent to the text processing component, which generated a response and sent it back to the user using the Line Messaging API, as shown in Figure 1.

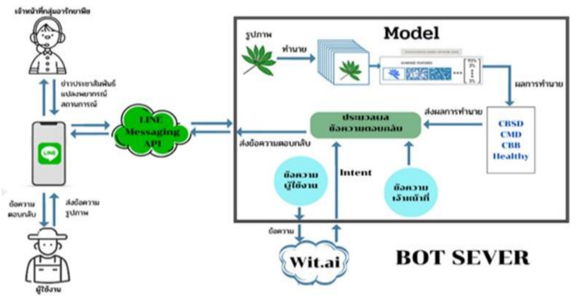

Figure 1. Overall Components of the Cassava Leaf Disease Detection System via Line Bot: A Case StudySystem Design: Based on problem analysis and relevant data study, theapplication was designed as follows:

Figure 2. Examples of Application User Interface Design and Program

3. System Development: In this stage, the disease detection system for cassava leaves was developed via Line Bot using the Python language. The system allowed users to access it through the ngrok URL, and the Line Messaging API was utilized as the intermediary for communication between the users and the server.
4. System Testing: In this stage, the researcher conducted tests on the developed application to evaluate its performance and ensure that it meets the specified objectives.
5. Program Implementation: After the developed program's errors were successfully resolved, the final step was to install the program. The Line Chatbot'sQR code was then distributed, allowing farmers to use the application through Line.
6. Maintenance: In order to ensure the system remains operational at all times, regular inspections and maintenance were conducted for both the softwareand hardware components.

Population and Sample

1. The population consisted of three experts and a group of registered cassava farmers in Buriram Province in the year 2023.
2. The sample included three experts who evaluated the system's performance, and a group of 30 registered cassava farmers under the supervision of the Plant Protection Service Group, Buriram Provincial Agriculture Office, assessed the system's satisfaction level through purposive sampling.

Research Tools

The tools used in the software development included the Python programming language, which was used for programming and creating convolutional neural network models for image recognition using deep learning techniques in plant disease prediction. The Flask web framework was utilized forPython to integrate with the web server. Text analysis for intent classification was performed using wit.ai. The server was simulated using ngrok, and the Line Messaging API served as the intermediary for communication between users andthe server.

Data Collection

In this research, the iCassava 2019 dataset was used, which consists of 5,656 images of five types of cassava leaves. The dataset includes 4 types of diseased cassava leaves and 1 type of healthy cassava leaves, collected from Uganda. The photographs were taken by farmers and sent to the National Crops Resources Research Institute (NaCRRI) for experts to classify the types of cassava leaves. Example images of cassava leaves are shown in Figure 3.

(1) (2) (3) (4)

Figure 3: Examples of images from the iCassava 2019 dataset representing all four categories used in the experiment: (1) Narrow Brown Spot Disease, (2) LeafBlight Disease, (3) Mosaic Disease, and (4) Healthy Leaves

Results

1. The results of the study and performance comparison of deep convolutional neural network (Deep CNN) models suitable for cassava leaf disease detection: In this experiment, the performance of four CNN models was tested, namely Mobile NetV2, NAS NetMobile, Efficient NetV2B0, and EfficientNetV2B1. The models were trained using fine-tuning with the parametersset as follows: epoch = 100, batch size = 32, and optimizer = stochastic gradient descent (SGD) algorithm with learning rates of 0.01 and 0.001. Additionally, the experiment was conducted with and without data augmentation techniques. The results of the experiment are presented in Table 1.

Table 1 *Experimental Results for Cassava Leaf Disease Classification Using CNN with 4Architectures, Adjusting Learning Rates to 0.01 and 0.001, with and without Data Augmentation Techniques on the iCassava 2019 Dataset*

CNN Architectures	Learning rate	Original Images		Data augmentation techniques		F	P-value
		5-cv	Test	5-cv	Test		
MobileNetV2	0.01	88.14 ± 1.32	85.98%	81.49 ± 2.50	82.19%	10.258	0.000
	0.001	87.85 ± 1.95	84.44%	87.84 ± 1.32	87.10%		
NASNetMobile	0.01	86.24 ± 0.54	86.69%	84.66 ± 1.68	85.47%		
	0.001	82.64 ± 1.28	83.42%	86.99 ± 1.02	86.28%		
EfficientNetV2B0	0.01	86.66 ± 1.20	86.39%	82.36 ± 0.89	84.14%		
	0.001	83.95 ± 0.92	84.54%	85.74 ± 2.46	88.02%		
EfficientNetV2B1	0.01	87.89 ± 0.80	87.41%	85.36 ± 1.43	84.95%		
	0.001	85.87 ± 0.64	86.67%	87.30 ± 1.96	**88.43%**		

From Table 1, the experimental results for cassava leaf disease classification using CNN with 4 architectures, adjusting the learning rates to 0.01 and 0.001, with and without data augmentation techniques on the iCassava 2019 dataset, showed that the comparison of accuracies for classifying cassava leaf disease among the 4 models yielded a statistical F-value of 10.258 and a p-value of 0.000, indicating a statistically significant difference at the 0.01 level. The results obtained from the experiments using MobileNetV2, NAS Net Mobile, EfficientNetV2B0, and EfficientNetV2B1 with the iCassava 2019 dataset are shown in Table 1. It can be observed that when tested on the test set, models withan adjusted learning rate of 0.001 combined with data augmentation achieved the highest accuracy of 88.43%, compared to models without augmentation, which increased the accuracy by approximately 4%. In addition, in every model that hadthe learning rate adjusted from 0.01 to 0.001, it was found that the model accuracy improved. Specifically, MobileNetV2 showed a significant increase in accuracy, with an improvement of 5% compared to its previous performance.

2. The results of the development of a cassava leaf disease detection system using a convolutional neural network via Line Bot: The collected requirements from an unstructured interview with Mr. Phaisan Kaewbutdee, the head of the Plant Protection Service Group, include the following: the need to enhance the dissemination of agricultural news to farmers; the requirement for an easily accessible application suitable for farmers' usage; an application capable of providing agricultural advice for cassava cultivation; and an application capable of detecting cassava leaf diseases from images. Therefore, a system was developed by classifying cassava leaf diseases using MobileNetV2 with learning rate adjustments of 0.01 and 0.001. Additionally, experiments were conducted with and without the use of data augmentation techniques on the iCassava 2019 dataset. Users could access the system by adding the chatbot as a friend on Line Messenger using the provided QR code. The system featured a menu and a disease detection interface, and the classification results are presented in Table 2.

Table 2 *Experimental Results for Cassava Leaf Disease Classification Using MobileNetV2 with Learning Rate Adjustments of 0.01 and 0.001, with andwithout the Data Augmentation Technique, on the iCassava 2019 Dataset*

CNN Architectures	**Learning rate**	**Original Images**		**Data augmentation techniques**	
		5-cv	**Test**	**5-cv**	**Test**
MobileNetV2	0.01	88.12 ± 1.29	85.98 %	81.48 ±2.49	82.19%
	0.001	87.14 ± 1.55	84.44 %	87.83 ±1.32	**87.10%**

Table 2 is an experimental comparison that demonstrates the effectiveness of various data augmentation techniques and learning rates. It was found that using the data augmentation technique with a learning rate adjustment of 0.001 achieved the highest accuracy rate of 87.10%. Therefore, the researchers applied this model to the subsequent system development, and the system's performance results are shown in Figure 4.

Figure 4. QR Code for Adding Friends, Line Messenger Greeting Page,Menu, and Cassava Leaf Disease Detection Interface

3. The performance evaluation results of the cassava leaf disease detection system via Line Bot: Three experts assessed the performance of the system by evaluating its effectiveness using an evaluation form. The data were then analyzed using basic statistical measures, compared against predefined criteria, and summarized. The results are presented in Table 3.

Table 3 *The Performance Assessment Results of the Cassava Leaf Disease DetectionSystem via Line Bot*

Item	**Mean**	**SD**	**Interpretation**
1. System processing operation	4.00	0.00	Good
2. System display interface operation	4.67	0.58	Very good
3. Responsive within a suitable timeframe	3.67	0.58	Good
4. Security in system usage	4.33	0.58	Good
5. Suitability of the tools used	4.33	0.58	Good
6. Convenience in system usage	4.67	0.58	Very good
7. Real-world applicability	4.00	1.00	Good
8. Speed of operation	4.00	1.00	Good
9. Accuracy of the obtained results	4.33	0.58	Good
10. Appropriateness of design	4.67	0.58	Very good
Overall	**4.30**	**0.47**	**Good**

From Table 3, the performance evaluation results from experts indicated anoverall average score of 4.30, which was considered good. The highest average score was in the system display interface operation, convenience in system usage, and appropriateness of design, with a score of 4.67. The lowest average score was responsive within a suitable timeframe, with a score of 3.67.

4. The satisfaction evaluation results of the cassava leaf disease detection system's usage via Line bot: A total of 30 users participated in the evaluation using a satisfaction assessment form. The data were then analyzed using basic statistical measures, compared to the criteria, and summarized. The results are presented in Table 4.

Table 4 *The Satisfaction Evaluation Results of the Cassava Leaf Disease DetectionSystem via Line Bot*

Item	Mean	SD	Interpretation
1. System design	4.66	0.63	Very good
2. Speed of usage	4.46	0.76	Good
3. Accuracy of the operation	4.56	0.50	Very good
4. Security in systemusage	4.54	0.71	Very good
5. Benefits of usage	4.74	0.44	Very good
Overall	**4.59**	**0.62**	**Very good**

From Table 4, it was found that the overall average satisfaction rating of the system users is 4.59, which is considered very good. The highest average satisfaction rating is in the aspect of benefits of usage, with an average score of 4.74. The next highest rating is in the aspect of system design, with an average score of 4.66. The lowest rating is in the aspect of speed of usage, with an averagescore of 4.46.

Discussion

This study is about deep learning with convolutional neural networks for cassava leaf disease detection via Line Bot: A case study of the Plant Protection Service Group, Buriram Provincial Agriculture Office. The research results align with the objectives, which are as follows: 1) The comparison of accuracy in classifying cassava leaf diseases among the four different architectures yielded statistically significant differences at a significance level of 0.01. The highest accuracy result was achieved by using MobileNetV2 with data augmentation, reaching 88.43%. 2) The developed system can operate by using the smartphone camera to capture images of abnormal cassava leaves and predict the most closelyrelated cassava leaf disease. The system achieved an accuracy rate of 87.10% in predicting the disease. Additionally, it presented a treatment method when the disease occurs to prevent the spread to nearby areas, aligning with Khitthuk's (2016) research on a system for diagnosing plant diseases from color images using co-occurrence matrices and artificial intelligence methods. 3) The overall user satisfaction with the Line Bot application is very good, which is consistent with the research conducted by Jomsri et al. (2021) on the development of an intelligent agriculture system for diagnosing leaf diseases of marigold using IoT technology. They found that using photographic data for the detection and assessment of plant disease outbreaks has yielded excellent results in preventing significant reductions in crop yields. Additionally, the application of support vector machine techniques has been utilized to aid in the evaluation of marigold leaf diseases. The results obtained from the sample group of diseased marigold leaves demonstrated an accuracy of 86% and received the highest level of user satisfaction with an excellent rating of 4.46.

Recommendations

The research findings indicate that deep convolutional neural networks, specifically using the MobileNetV2 architecture, combined with data augmentation, are suitable for detecting cassava leaf diseases. This approach has shown the highest accuracy rate and utilizes transfer learning techniques, which help reduce learning time. Deep learning typically requires a large dataset of images to enhance learning efficiency. In future research, additional techniques may be introduced, such as ensemble learning, which could further improve the learning process and increase overall effectiveness.

Acknowledgments

The authors gratefully acknowledge the financial support of Buriram Rajabhat University for the publication of this article.

References

1. Adedoja, A. O., Owolawi, P. A., Mapayi, T., & Tu, C. (2022). Intelligent Mobile Plant Disease Diagnostic System Using NASNet-Mobile Deep Learning. IAENG International Journal of Computer Science, 49(1), 216-231.
2. Changlek, P., et al. (2019). Cassava: Alternative Food and Energy Source for the World. Retrieved from http://www3.rdi.ku.ac.th/exhibition/52/04plant/prapart/plant_00.html?fbclid=IwAR2J-
3. POQmAGDe22yBfH9DzZcdS6z9vgQf6lgbpX67ZoLxRqpM_17I7YQTE4 Cheewaprakobkit, P. (2019). Improving the Performance of an Image Classification with Convolutional Neural Network Model by Using Image Augmentations Technique. TNI Journal of Engineering and Technology Engineering and Technology, 7(1). Retrieved from https://ph01.tci- thaijo.org/

index.php/TNIJournal/article/download/182318/137882/ 600590
4. Department of Agriculture Extension. Buriram Provincial Agriculture Office. Retrieved from http://www.buriram.doae.go.th/page/1.html
5. Jomsri, P., Prangchumpon, D., & Ieamthanakun, B. (2021). Development of an Intelligent Agriculture System for Diagnosing Leaf Diseases of Marigold Using IoT Technology. Journal of Information Science and Technology, 2(2), 15-24.
6. Khitthuk, C. (2016). Plant Disease Diagnosis System from Color Images usingCo-occurrence Matrix and Artificial Intelligence Techniques. Master of Engineering Thesis, Department of Electrical Engineering, Suranaree University of Technology.
7. Klaisuban, K., Manjit, K., & Sriurai, W. (2017). Development of a Classification System and Analysis of Cassava Varieties and Diseases Using Rule-Based Techniques. Retrieved from https://li01.tci- thaijo.org/index.php/sci_ubu/article/view/214323/149192
8. Pattanasarn, N., & Sriwiboon, N. (2020). Image Processing for Classifying the Quality of Chok Anan Mangoes by Simulating Human Vision with Deep Learning. Retrieved from https://ph02.tci- thaijo.org/index.php/JIST/article/view/234447/163970?fbclid= IwAR337VT9v1CI7NjDI2BJL4GBsuoVuE_SWKAvnS6LyLX44T02NvO 7GhRAmMo
9. Promrangka, P., Waenthong, S., & Chuphan, R. (2023). Mobile Application for Bird Species Classification Using Deep Learning. Retrieved from https://ph02.tci-thaijo.org/index.php/JIST/article/view/245836/167558
10. Sanooksan, C. (2019). Application of Deep Learning Techniques for TreeRecognition in the Natural Environment. Master of Science Thesis, Department of Information Technology, Mahasarakham University. Retrieved from http://202.28.34.124/dspace/handle/123456789/550
11. Sripiban, C. (2022). Strip Test Kit for Detecting Cassava Mosaic Disease. Retrieved from https://www.nstda.or.th/home/news_post/slcmv/?fbclid=IwAR3ZF0qqzv9N I8xN4m1ZFgEYWiZ5mYulh_I_LcYyBZ9I_0MVe0WhZgWuG30
12. Temniranrat, P., Kiratiratanapruk, K., Kitvimonrat, A., Sinthupinyo, W., & Patarapuwadol, S. (2021). A system for automatic rice disease detection from rice paddy images serviced via a Chatbot. Computers and Electronicsin Agriculture, 185, 106156.