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A Review of Plant Disease Detection Based on Deep Learning Models

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Abstract

The agricultural sector is crucial in addressing the global food supply crisis. Global agricultural sustainability is severely threatened by growing populations, changing climatic patterns, and widespread plant diseases. It is challenging as traditional farming methods are not enough to sustain the demand for agricultural production. Thus, the automation method of artificial intelligent technology, such as deep learning, was introduced to increase production and prevent loss in agriculture. This study researches deep learning approaches in real-time agricultural applications to avoid plant disease. The research focused on publications between 2018 and 2023, and the study discussed the effectiveness of using this method in improving the efficiency of plant disease detection. The results of this study will serve as a reference for academics and specialists in agriculture to comprehend better the applications of deep learning in decision-making and problem-solving.

1. Introduction

Agriculture is one of the world's largest sectors and is crucial to the food system's economic growth and sustainability. In Malaysia, this sector contributes relatively significantly to the country, especially in agricultural product commodities such as palm oil, rubber, and cocoa. Malaysia's global agricultural trade reached $59.4 billion in 2021, with exports of $36.1 billion and imports of $23.3 billion [1]. The demand for farm products is rising due to the growth of the population. However, various environmental factors, such as extreme weather, pollution, and plant disease, lead to production losses. The plant disease problem is not only affected in Malaysia but also in the global food system. Further, this situation impacts the food price and threatens human societies and biodiversity. Hence, early detection of plant disease plays an essential role in the decision-making process to provide effective prevention and control of the disease.

Commonly, various types of disease usually infect plants. It can be visualized on the leaves, stems, flower or fruits. These signs typically present a unique pattern that can be used to diagnose abnormalities. Early detection is needed as disease attack is a primary reason for plant loss [2]. The typical method to prevent pests and control disease is by using pesticides [3]. However, excessive use of pesticides may harm the quality of plant growth, affect the environment, and risk human health. Generally, agricultural experts can diagnose abnormalities based on their experience. However, this manual method is challenging as it requires many labourers with comprehensive knowledge of plant disease. It is time-consuming, prone to subjective assumption, and inefficient [4].

Artificial intelligence technologies, such as machine learning and deep learning, have been widely employed today. This method enables machines to interact with people to understand their needs and perform the tasks usually performed by people [2]. For decades, deep learning has been used in different fields such as medicine and healthcare [5]-[7], internet security [8]-[9], object detection, the entertainment industry [10]-[12] and other applications. The industry based on agriculture is also evolving from manual to computerized technology due to the high significance of disease control. In this paper, the study will concisely review the development of deep learning in real-time agriculture applications. In this context, the deep learning method is focused on plant disease detection and its applicability in controlling disease. This paper is intended to be helpful to experts in the agriculture industry and researchers interested in gaining knowledge in deep learning.

This paper aims to review current research on deep learning models and their application in plant disease detection. Section 2 presents the framework of deep learning. Section 3 mentions the review of current research done. Section 4 summarized the deep knowledge of plant disease detection.

2. Deep Learning Framework

Deep learning is a subset of machine learning that analyzes data using a logical structure that mimics the biological human brain [13]. Machine learning is an artificial intelligence application with algorithms that learn from data to perform a task. The trained data was applied to make informed decisions such as prediction and classification. Deep learning is an evolution of machine learning with similar functions but different capabilities. Deep learning can be simplified as in Fig.1[31].

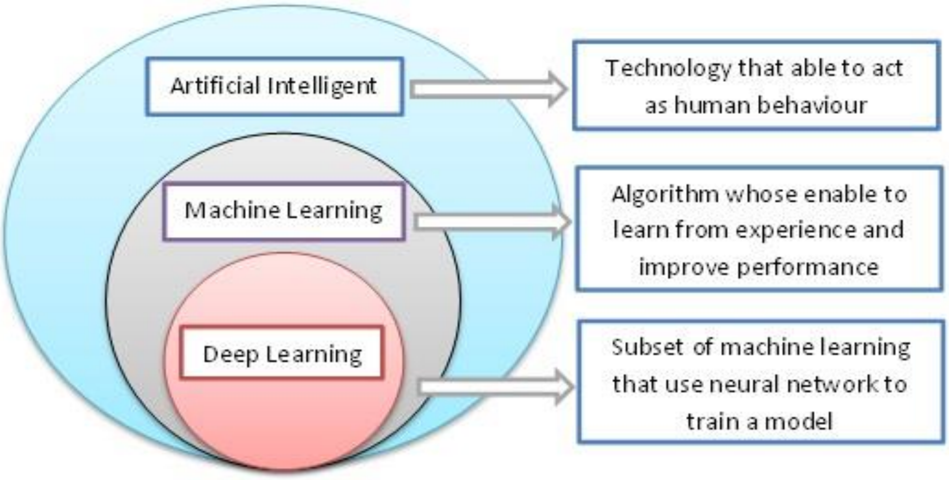

Fig. 1 *Deep learning architecture*

The deep learning model is based on the programmable neural network concept that enables machines to resemble the function of neurons in the human brain to make accurate decisions. It uses a layered structure of algorithms to complete an analysis. Each network has many layers that transfer the input data to output by progressively learning higher-level features [14]. The automatic extraction of features from raw data or feature learning is one of the benefits of deep learning [15]. An illustration of an artificial neural network neuron is shown in Fig. 2 [16].

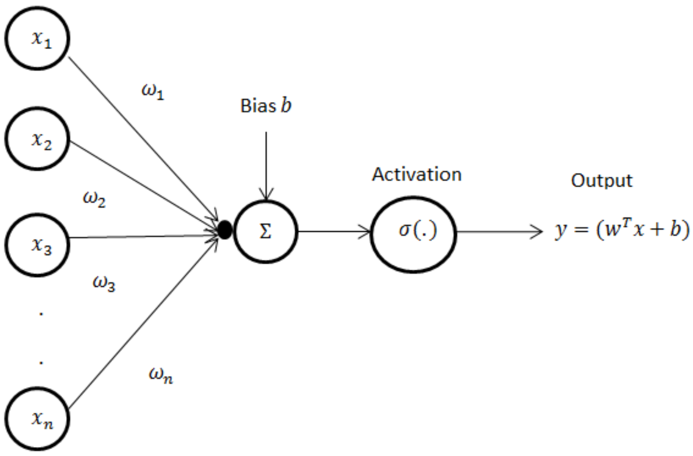

Fig. 2 *Neuron illustration*

Penerbit UTHM

The line represents the weight ω and additive bias b while the node represents non-linear activation $\sigma(.)$. A neural network's most fundamental building block is shown in Eq. (1) [16].

$$h_\theta(x) = \sigma(\omega^T x + b), \theta = \{\omega, b\} \tag{1}$$

It is a mapping $h_\theta: R^N \leftrightarrow R$ comprised of a parametric affine mapping (dictated by θ) followed by some non-linear element-wise function $\sigma: R^N \leftrightarrow R$ referred to as activation. Stacking the multiple neurons in parallel yields a layer. A layer with M neurons can be written as $h_\theta: R^N \leftrightarrow R^M$ and its mapping is given by

$$h_\theta(x) = \sigma(Wx + b), \theta = \{W, b\} \tag{2}$$

where the activation of $\sigma(.)$ apply element-wise. Activation functions are often fixed; for example, their mapping is not parametric.

Multiple layers are used to obtain more flexible parameterized mappings if the layer mapping in (2) may be limited in capturing complex mappings. This kind of composition is referred to as multi-layered perceptron. Specifically, a deep neural network f_θ consists of K layers $\{h_1, \ldots, \ldots, h_k\}$ maps the input x to the output $\hat{s} = f_\theta = h_k{}^\circ \ldots\ldots{}^\circ h_1(x)$ where $^\circ$ denotes the function of composition.

The deep neural network structure is model agnostic in which the unique characteristic of scenarios is encapsulated in the weight learned from data [16]. Commonly, it is treated as black boxes and incorporated at the same level as domain knowledge in the selection of network architecture. The typical architecture of deep learning networks is Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

3. Evolution of Deep Learning

Deep learning was introduced in 1943 when Walter Pitts and Warren Mc Culloch created a mathematical formulation based on a combination of algorithms and mathematics to mimic the thinking process in the human brain [17]. The evolution of deep learning is divided into three stages of development [18]. The first generation originated in 1943 and the 1970s and was composed of superficial neural layers for perceptron. The computation has limitations in dealing with linear classification problems. The concept of backpropagation, essential for training neural networks, emerged in the early 1960s.

The second generation of neural networks evolved from 1986 until 1998 and used backpropagation to update the neurons' weights according to error rates [19]. This approach was effectively solving the nonlinear classification and learning problems. During this time, the neural network improved by giving better results as more training data was added.

The third generation of neural network deep learning started in 2006 when Hinton's gradient disappeared in deep web training and was put forward in the problem solution [18]. Since then, the study based on deep learning neural networks has been revolving up until now. The implementation of this method was increased according to the necessity of enhancing the accuracy and efficiency of the process. Summarization of the deep learning timeline from 1943 until the present is shown in Fig 3. A detailed overview of the evolution and history of deep learning was provided in [18]-[20].

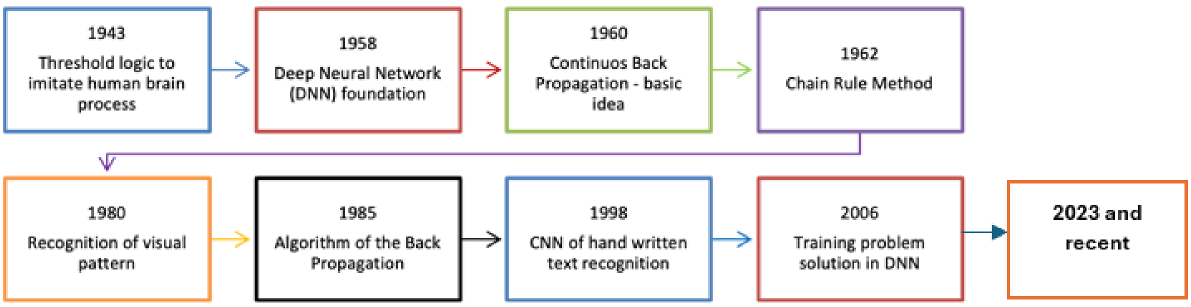

Fig. 3 *Deep learning timeline summarization*

4. Deep Learning Application in Plant Disease

The deep learning approach has been increasingly used in agriculture in recent years. A deep learning-based model can potentially optimize plant growth and improve crop yield compared to manual methods. Deep learning can automate the disease identification and prediction task, which usually requires extensive data. Furthermore, this method can reduce the need for human interpretation and increase the accuracy of the task. The following approaches employed deep learning and the CNNs model for plant disease to help farmers and agricultural experts take appropriate action to prevent crop losses.

In 2019, Saleem et al., published a paper review of deep learning implementation to detect and classify the symptom of plant disease [19]. In this paper, the evolution of deep learning architecture has been explained, along with the different techniques used to evaluate the model to achieve better results. An actual agricultural environment should be considered in the practical experimentation to assess the performance of the deep learning model in plant disease detection.

In 2020, Chohan et al., proposed a deep learning-based model with the ability to detect several diseases of plants by using leaves image [22]. This paper used augmentation to increase the sample size before implementing CNNs with multiple convolutions and pooling layers. Convolution was used to detect the edges of a pattern in an image, while pooling reduces the image size. CNNs can extract features from images and provide many plant leaf images to be trained and predict the disease. The experiment used two datasets of 15 and 38 classes containing different plants. The model achieved 95% accuracy in the images, whether the plants were healthy or unhealthy. The result shows that the deep learning model can achieve an automated system for plant disease detection.

Mohameth et al. [23] implemented deep feature extraction and deep learning techniques to detect plant disease based on an open-source dataset from a plant village. Three different types of CNN architecture were applied in this study: Resnet 50, Google Net, and VGG-16. Support Vector Networks (SVM) and K- Nearest Neighborhood (KNN) were two different classifiers used to extract features for the research. For feature extraction, the result shows that ResNet 50 performed the higher accuracy using the SVM classifier.

Ganatra and Patel [4] applied a deep CNNs model VGG 16, Inception V4, ResNet 50 and ResNet 101 for plant leaf disease identification and classification. This study used a dataset with 87000 images of healthy plants and plants infected with the disease. This dataset is divided into 38 classes. The ratio of the training set and validation test is 80:20, respectively. The result shows that the accuracy of ResNet 50 and ResNet 101 is higher than that of other models.

Trivedi et al. [24] implemented deep CNNs in their study to identify and analyze an early stage of tomato leaf disease. The experiment in this study used 3000 images of healthy and infected leaves caused by fungal and bacterial pathogens such as blight, blast and brown tomato leaves. This study mainly focused on investigating solutions to detect tomato leaf disease. The result showed that the model's accuracy was 98.4%.

Chowdhury et al. [21] proposed a deep-learning model of CNN to classify tomato disease. The model used in this study is called EfficientNet for segmentation images: EfficientNet-B0, EfficientNet-B4 and EfficientNet-B7. Global Average Pooling (GAP) was added to the convolution layer final network to minimize overfitting and enhance accuracy. The model's performance was evaluated by comparing it with U-Net architecture. As a result, EfficientNet-B4 achieved a higher accuracy of 99.89% for ten class classifications using segmented images.

Ahmed and Reddy [25] present a mobile-based system based on the CNN model to automate plant leaf disease diagnosis. The CNN model was used as an underlying deep-learning engine to classify disease categories. 38 categories of diseases were included from the dataset containing 46206 leaf images, both healthy and infected plants. This mobile application allowed farmers to capture photos of the infected leaves by developing an Android user interface. This application gave farmers a better opportunity to keep their crops healthy. The performance of this model achieved 94% accuracy.

Rashid et al. [26] developed a multi-level deep-learning model for potato leaf disease recognition. For the first level, potato leaves were extracted from the image segmentation technique of YOLOv5. In the second level, the CNN model was implemented to detect the early blight and light blight of potato leaf disease. This experiment used two datasets: a dataset from Plant Village and a potato image collected from the Central Punjab region of Pakistan, which consisted of 4062 images. This model also gave a higher accuracy of 99.75%.

Pandian et al. [27] proposed a 14-layer deep CNN (14DCNN) for plant leaf image detection. This research used open datasets to create a new dataset consisting of 147500 images of 58 different categories of disease classes for model training. Different data augmentation techniques, BIM, DCGAN and NST, were used to create an even number of images in each class and reduce overfitting. The main reason for using different data augmentation techniques is to enhance model performance. The model was trained to detect 42 leaf diseases in 16 plants through leaf images. The result showed that the proposed 14DCNN model achieved 99.96% classification accuracy.

Sharma et al. [28] applied a CNN model for the rice and potato plant leaf disease classification. The rice leaf was classified into five categories: bacterial blight, blast, brown spot and tungro disease, based on a dataset of 5932 images. The potato leaf image was identified by three classes of healthy leaves, early blight and late blight disease, based on a dataset of 1500 images. The results of this study demonstrate that the model performs with better accuracy than other machine learning image classifiers like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, and Random Forest. The classification accuracy for rice leaf is 99.58%, and for potato leaf, 97.66%.

Shahi et al. [29] reviewed the progress of implementing machine learning and deep learning techniques in crop disease detection using Unmanned Aerial Vehicles (UAV) remote sensing. UAVs and drones were used to collect data on crop images in agriculture fields. Using UAVs allows users to view fields at any time and capture a spatial resolution image as they can fly very close to crops. The collected image data were then analyzed and summarized the disease using machine learning and deep learning methods.

Table 1 *Summary of studies on deep learning techniques for plant disease detection*

Year	Authors	Model/Technique	Dataset Details	Accuracy	Key Findings
2019	Saleem et al. [19]	Deep Learning Review	N/A	N/A	Discussed evolution of deep learning for plant disease detection.
2020	Chohan et al. [22]	CNN with Augmentation	2 datasets: 15 and 38 classes	95%	Achieved automated detection of plant diseases.
2020	Mohameth et al. [23]	CNN (ResNet 50, Google Net, VGG-16)	Open-source dataset from Plant Village	Higher accuracy for ResNet 50 with SVM	Effective feature extraction for plant disease detection.
2020	Ganatra and Patel [4]	CNN (VGG 16, Inception V4, ResNet)	87,000 images, 38 classes	Higher accuracy for ResNet 50 and 101	Identified and classified plant leaf diseases.
2021	Trivedi et al. [24]	Deep CNN	3000 images of tomato leaves	98.4%	Focused on early detection of tomato leaf diseases.
2021	Chowdhury et al. [21]	EfficientNet (B0, B4, B7)	N/A	99.89%	EfficientNet-B4 outperformed U-Net in accuracy.
2021	Ahmed and Reddy [25]	Mobile-based CNN system	38 disease categories, 46,206 images	94%	Developed mobile app for farmer use in disease diagnosis.
2022	Rashid et al. [26]	Multi-level CNN	4062 images from Plant Village and Central Punjab	99.75%	Early detection of potato leaf diseases.
2022	Pandian et al. [27]	14-layer Deep CNN	New dataset: 147,500 images, 58 disease classes	99.96%	Enhanced model performance using data augmentation.
2022	Sharma et al. [28]	CNN	Rice: 5932 images; Potato: 1500 images	Rice: 99.58%, Potato: 97.66%	Outperformed traditional classifiers in disease detection.
2023	Shahi et al. [29]	Machine Learning and Deep Learning	UAV remote sensing for crop image collection	Reviewed advancements in using UAVs for crop disease detection.	Machine Learning and Deep Learning

The study showed promising results for disease detection in agriculture when using machine learning and deep learning methods for estimation. This table summarizes the key elements of each study, including the year, authors, model or technique used, dataset details, accuracy achieved, and key findings. Most of the works showed that deep learning provides the highest accuracy for plant disease estimation, followed by machine learning.

5. Conclusion

The paper presents a basic knowledge of deep learning and its history. Comprehensive reviews of recent research in plant disease detection were also presented. Regarding current work, CNN is commonly used in the agricultural field in different categories such as ResNet 50, VGG, EfficientNet, etc. CNN was widely used as it can receive data input, including images, videos, sounds, and speech using natural language [30]. Most of the research used a dataset from Plant Village for the experiment. The study showed that deep learning successfully achieves better performance for disease detection. The paper concludes that deep learning-based approaches, especially using CNNs, have demonstrated superior performance in plant disease detection compared to other methods. This shows the critical potential of deep learning in improving the accuracy and reliability of plant disease identification and diagnosis.

Deep learning and machine learning research for crop disease detection can significantly impact future agricultural practices and policies, including better disease management, precision agriculture, policy development, training and education, improved crop breeding, market opportunity, and sustainable goals. Incorporating cutting-edge technologies into agriculture can result in more intelligent and environmentally friendly farming methods, ultimately supporting environmental preservation and global food security.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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