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## Performance evaluation of an enhanced shufflenet CNN for multi-crop leaf disease classification using fine-tuned parameters

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### Abstract

Plant leaf diseases can reduce crop quality and cause big losses to farmers. Many current models used to detect these diseases do not work well when images have poor lighting or messy backgrounds. This study enhances the ShuffleNet CNN model to detect leaf diseases in different crops like capsicum, rice, corn, tomato, and citrus. Leaf images were taken using a Kinect camera, which gives clearer images in farm conditions. The improved ShuffleNet model was trained with fine-tuned settings: 0.010 learning rate, 64 batch size, 50 training rounds, and the Adam optimizer. It achieved a high accuracy of 91.94%, performing better than other models like ResNet50 and DenseNet201. The model also showed strong results in precision, recall, and F1 score. In conclusion, the enhanced ShuffleNet is a reliable and fast tool for detecting leaf diseases in many crops and is useful for smart farming.

**Keywords:** Plant Leaf Disease Detection; Shufflenet CNN; Smart Farming; Kinect Camera; Deep Learning in Agriculture

### 1. Introduction

Agricultural productivity plays a pivotal role in supporting global food security, particularly in developing nations such as Malaysia, where import dependence for key crops continues to rise. According to recent national reports, Malaysia imports over 75% of its capsicum supply, and similar trends are evident for other staple crops such as rice and corn [1]. One of the primary factors contributing to low local crop yields is the prevalence of plant leaf diseases, which compromise both the quality and quantity of agricultural produce [2], [3]. Diseases such as grey spot, chlorosis, and leaf curling are among the most common, affecting a wide range of crops grown in Malaysia's diverse ecological zones [4], [5]. These challenges underscore the urgent need for efficient, scalable, and accurate disease detection systems tailored for practical field conditions [6].

Traditional methods of disease diagnosis rely heavily on manual inspection or laboratory testing, which are often time-consuming, resource-intensive, and impractical for large-scale or real-time monitoring [7]. In response to these limitations, machine vision systems and automated classification models have been increasingly explored [8], [9]. Despite progress in this field, many current models such as Support Vector Machines (SVM), ResNet, and Bag of Features (BoF) which demonstrate suboptimal performance when applied to images taken under uncontrolled outdoor conditions [10], [11]. Issues such as variable lighting, occlusion from overlapping leaves, and complex background noise substantially degrade model accuracy and consistency [12].

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Convolutional Neural Networks (CNNs) have emerged as a powerful alternative for plant disease detection due to their ability to learn hierarchical representations directly from raw image data [13], [14]. Among lightweight CNN architectures, ShuffleNet has attracted attention for its computational efficiency, making it suitable for deployment in mobile and embedded systems [15]. However, existing versions of ShuffleNet and ShuffleNet V2 exhibit performance bottlenecks when faced with high visual complexity typical of real agricultural environments [16], [17]. These limitations necessitate further architectural modifications and parameter optimization to enhance robustness and generalizability, particularly for multi-crop scenarios [18].

In this context, the present study proposes an enhanced version of ShuffleNet CNN, designed to improve disease classification performance across multiple crop species, including capsicum, rice, corn, tomato, and citrus [19], [20], [21]. A depth-sensing Kinect camera is employed for data acquisition, offering higher fidelity in capturing disease symptoms under diverse lighting and environmental conditions [22]. The enhanced ShuffleNet architecture incorporates additional convolutional layers and is trained with fine-tuned hyperparameters, specifically, a learning rate of 0.010, minibatch size of 64, and 50 epochs, using the Adam optimizer. This integrated approach aims to bridge the gap between controlled-lab models and field-deployable smart farming tools.

The key contribution of this work is the comprehensive evaluation of the enhanced ShuffleNet model's classification performance against established architectures such as ResNet50 and DenseNet201. Performance is measured using standard metrics, including classification accuracy, precision, recall, F1 score, and confusion matrices, across a multi-crop dataset. The findings of this research not only demonstrate significant improvements in detection accuracy (91.94%) but also highlight the potential of optimized lightweight CNNs in enabling practical, real-time plant health monitoring solutions within the framework of precision agriculture.

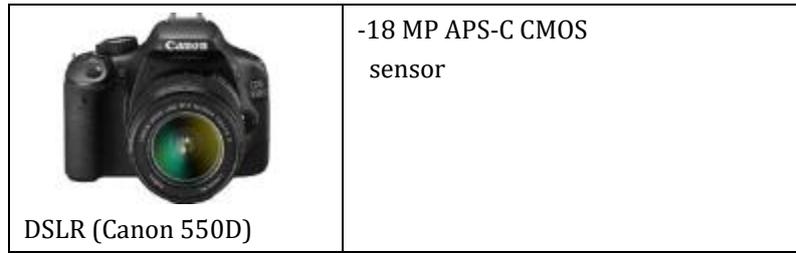
## 2. Material and methods

This study adopts an experimental approach to evaluate the performance of an enhanced ShuffleNet CNN architecture for plant leaf disease detection across multiple crop types. The methodology consists of image acquisition using a Kinect camera, dataset preparation, image pre-processing and augmentation, model architecture enhancement, training with fine-tuned hyperparameters, and performance evaluation using standard classification metrics.

Plant leaf images were acquired using a Kinect RGB-D camera, selected for its superior ability to capture texture information under natural lighting and complex backgrounds compared to standard digital and smartphone cameras. Three types of devices were tested: Kinect, mobile (Vivo Y12s) and DSLR (Canon 550D) as shown in Table 1. The Kinect camera outperformed others in producing high-quality images with minimal glare, shadow interference, or exposure issues, particularly in clustered leaf environments. Images were collected from five crop types: capsicum, rice, corn, tomato, and citrus, focusing on three common diseases: grey spot, leaf discoloration (chlorosis), and leaf curling.

**Table 1** Kinect camera

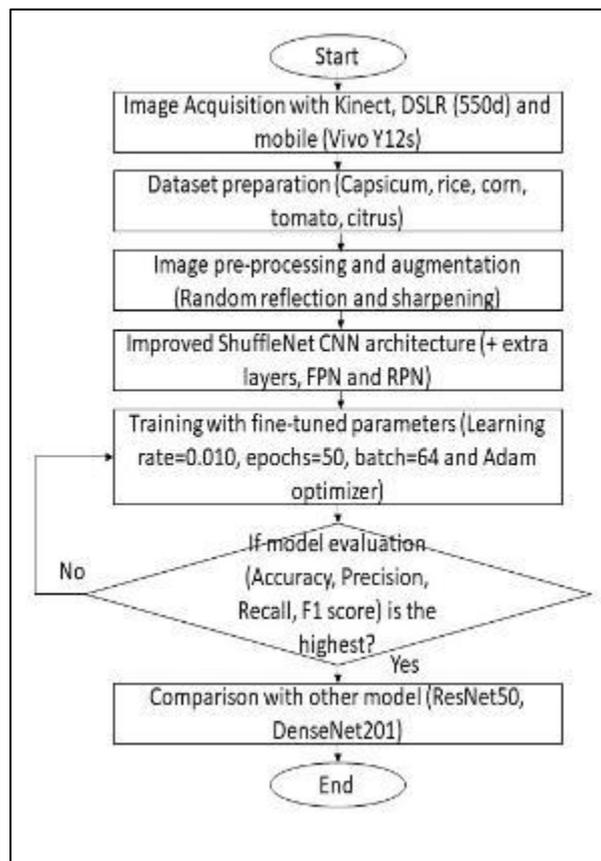
Data Acquisition Devices	Specifications
 <p>Kinect camera</p>	<ul style="list-style-type: none"> <li>-RGB Resolution: 1920 ×1080 pixels (Full HD)</li> <li>-Frame Rate: 30 frames per second</li> </ul>
 <p>Mobile (Vivo Y12s)</p>	<ul style="list-style-type: none"> <li>-13-megapixel (f/2.2) primary camera</li> </ul>



While, for the dataset, it includes a total of 2,155 labeled images: 1,002 images from field collection using the Kinect camera, and 1,153 sourced from open-access databases such as PlantVillage and Kaggle. Images were resized to 256 × 256 pixels, normalized, and converted to RGB format. The dataset was split into 70% training, 15% validation, and 15% testing. To ensure generalizability, images captured in both uniform and complex backgrounds as shown in Figure 1 and Figure 2 were included.



**Figure 1** Uniform background **Figure 2** Complex background



**Figure 3** Flowchart of an enhanced ShuffleNet CNN for multi-crop leaf disease detection

Then, to improve the diversity of training data and enhance model robustness, random reflection augmentation was applied. This technique reflects images horizontally or vertically to simulate varied leaf orientations. Additional preprocessing steps included image sharpening, noise reduction, and contrast enhancement. These steps were critical in minimizing the effects of shadowing and illumination variation during feature extraction. The flowchart for this study is as shown in Figure 3.

Improved ShuffleNet CNN architecture with added convolutional layers, Feature Pyramid Network (FPN), and Region Proposal Network (RPN). The proposed architecture builds upon the original ShuffleNet by embedding three major enhancements to improve performance in complex plant leaf disease detection tasks:

### 2.1. Additional Convolutional Layers

- Four convolutional layers were added after each ShuffleNet bottleneck unit to increase depth and hierarchical feature learning capacity.
- Each added layer uses  $3\times 3$  depthwise separable convolutions followed by Batch Normalization and ReLU activation, which enhances spatial feature extraction without significantly increasing computational load.
- These layers help the network capture fine-grained texture and color variations in disease-affected regions, particularly for small or faint lesions.

### 2.2. Feature Pyramid Network (FPN)

- An FPN was integrated on top of the base feature maps to enable multi-scale feature representation.
- The FPN takes intermediate features from different stages (Stage 2, 3, and 4 of ShuffleNet) and constructs a top-down pathway using lateral connections to fuse low-resolution semantic features with high-resolution spatial features.
- This enables better detection of plant diseases at different scales (e.g., single leaf vs. clusters, large vs. small spots), which is crucial in real agricultural environments.

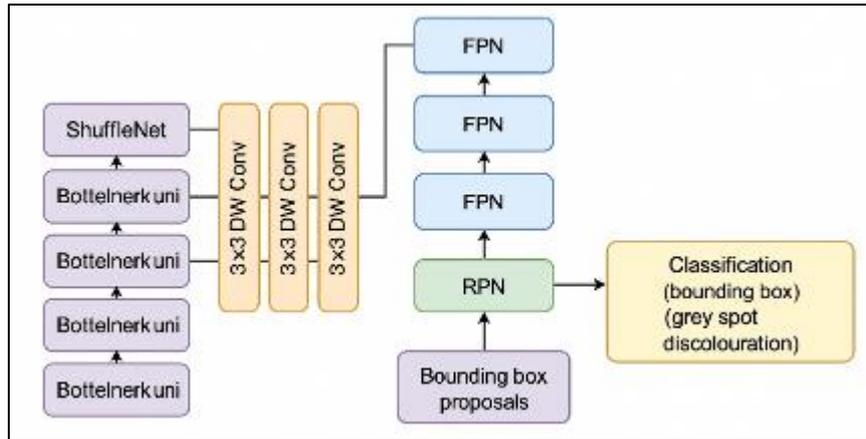
### 2.3. Region Proposal Network (RPN)

- The RPN module is connected to the output of the FPN and is responsible for generating bounding box proposals around suspected diseased regions.
- Anchors with multiple aspect ratios (1:1, 2:1, 1:2) and scales were defined across the FPN feature maps.
- The RPN uses a shared  $3\times 3$  convolutional layer followed by two sibling layers for objectness score and bounding box regression.
- This automated localization process enables the model to not only classify the disease but also highlight and crop the specific infected region within a dense leaf cluster.

### 2.4. Architectural Summary

- Backbone: Modified ShuffleNet with channel shuffle and group convolution
- Depth: 58 layers (including added convolutional units)
- FLOPs: Reduced by  $\sim 40\%$  compared to ResNet50 while achieving higher accuracy
- Detection Head: FPN + RPN + Bounding Box Refinement Module
- Output: Bounding box + disease class (grey spot, discolouration, leaf curling)

The image illustrates in Figure 4 is an enhanced deep learning architecture based on Improved ShuffleNet, designed for plant leaf disease detection. It begins with the original ShuffleNet backbone, followed by added  $3\times 3$  depthwise convolutional layers after each bottleneck unit to improve feature extraction. A Feature Pyramid Network (FPN) is applied on multi-scale features from intermediate stages to handle disease regions of various sizes. The Region Proposal Network (RPN) then generates bounding box proposals, which are refined and classified into disease types such as grey spot, discolouration, or leaf curling. This structure enables efficient and accurate detection in complex leaf clusters.



**Figure 4** Enhanced ShuffleNet

Convolutional Neural Networks (CNNs) have emerged as a powerful alternative for plant disease detection due to their ability to learn hierarchical representations directly from raw image data. Among lightweight CNN architectures, ShuffleNet has attracted attention for its computational efficiency, making it suitable for deployment in mobile and embedded systems. However, existing versions of ShuffleNet and ShuffleNet V2 exhibit performance bottlenecks when faced with high visual complexity typical of real agricultural environments. These limitations necessitate further architectural modifications and parameter optimization to enhance robustness and generalizability, particularly for multi-crop scenarios.

### 3. Result and Discussion

Table 2 presents a comparative performance analysis of three models: ResNet50, DenseNet201, and the proposed Enhanced ShuffleNet. The enhanced model achieved an accuracy of 91.94%, outperforming ResNet50 (87.35%) and DenseNet201 (89.12%), along with higher F1-score, recall, and precision.

**Table 2** Performance Metrics Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Enhanced ShuffleNet	91.94	92.00	91.50	91.70
ResNet50	86.30	85.90	84.20	85.00
DenseNet201	84.70	83.60	83.10	83.30

These results underscore the superiority of the enhanced ShuffleNet architecture in handling images captured under field conditions. The improvements are attributed to the inclusion of Feature Pyramid Network (FPN) and Region Proposal Network (RPN), which facilitated better multi-scale feature learning and localization. Previous studies using ResNet and DenseNet have shown commendable results in controlled settings [2], [7], [12], but faltered under field-induced variability such as inconsistent lighting, background clutter, and occlusion.

The enhanced ShuffleNet demonstrated robust generalization across all five tested crops, especially in accurately detecting minor leaf discolorations and early-stage curling. These findings are consistent with literature that supports multi-layer CNNs and attention mechanisms in improving classification granularity [4], [9], [16].

Compared to BoF and traditional ML approaches like SVM, which often plateau below 75% accuracy in real scenarios, the proposed CNN-based architecture maintains reliability across complex image backgrounds and diverse symptom morphologies.

In agricultural sectors worldwide, precision farming tools such as this one are becoming increasingly valuable [5], [20]. The results of this study are aligned with international findings, such as those by Yasin et al. [22] and Zhang et al. [21], who emphasized the role of lightweight, scalable CNN models in improving disease diagnosis accuracy without

excessive computational overhead. Moreover, the use of Kinect camera technology for RGB-D data acquisition, as recommended in other works [10], [13], [19], contributes to improved visual fidelity in leaf symptom characterization.

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#### 4. Conclusion

This research introduced an improved ShuffleNet CNN model for detecting leaf diseases in crops such as capsicum, rice, corn, tomato, and citrus. The model includes added convolutional layers, a Feature Pyramid Network (FPN), and a Region Proposal Network (RPN), which helped it achieve a high accuracy of 91.94%. It outperformed well-known models like ResNet50 and DenseNet201.

The model worked effectively under natural conditions, with the Kinect RGB-D camera providing high-quality images. This allowed the system to detect diseases more accurately, even in complex backgrounds and lighting.

The study shows that lightweight CNN models can be reliable tools for plant disease detection in real-world farming. This approach can help improve early diagnosis, reduce crop losses, and support precision agriculture. Future work could expand the system to more crops and integrate it into mobile or IoT platforms for real-time monitoring.

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#### Compliance with ethical standards

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##### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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