Research Article

International Journal of Advanced Technology and Engineering Exploration, Vol 10(102)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2022.10100509

Classification of capsicum leaf disease from a complex cluster of leaves using an improved multiple layers ShuffleNet CNN model

Chyntia Jaby Entuni*, Tengku Mohd Afendi Zulcaffle and Kismet Hong Ping
Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Malaysia

Received: 06-December-2022; Revised: 20-May-2023; Accepted: 24-May-2023
©2023 Chyntia Jaby Entuni et al. This is an open access article distributed under the Creative Commons Attribution (CC BY) License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract
Capsicum, also known as chili pepper or bell pepper, is cultivated worldwide and holds significant economic importance as a condiment, vegetable, and medicinal plant. One of the major challenges in capsicum cultivation is the accurate identification of leaf diseases. Leaf diseases can have a detrimental effect on the quality of capsicum production, leading to substantial losses for farmers. Several machine learning (ML) algorithms and convolutional neural network (CNN) models have been developed to classify capsicum leaf diseases under controlled conditions, where leaves are uniform and backgrounds are uncomplicated. These models have achieved an average accuracy of classification. However, classifying diseases becomes relatively challenging when a diseased leaf grows alongside a cluster of other leaves. Having a reliable model that can accurately classify capsicum leaf diseases within a cluster of leaves would greatly benefit farmers. Therefore, the aim of this study was to propose a model capable of classifying capsicum leaf diseases both from a uniform background and within a complex cluster of leaves. Firstly, a dataset comprising images of diseased capsicum leaves, including discolored leaves, grey spots, and leaf curling, was acquired. Subsequently, an improved multiple-layer ShuffleNet CNN model was employed to classify the different types of capsicum leaf diseases. The proposed model demonstrated superior performance compared to existing models, achieving a classification accuracy of 99.30%. Furthermore, it was concluded that augmenting the layers of ShuffleNet, utilizing a 0.01 initial learning rate, employing 50 maximum epochs, using a minibatch size of 64, conducting 10 iterations, and incorporating 205 validation iterations all contributed to the improved ShuffleNet model's success.

Keywords
Capsicum, Leaf disease, Machine learning, Convolutional neural network, ShuffleNet.

1.Introduction
Capsicum has been intensely merged into the culture of Asians, Southeast Asians, Indians, Malaysians and Indonesians, and has even become an inextricable ingredient in the local diet in numerous gastronomies, as well as being used for medicinal purposes. It is found that in China, exigency for high-quality capsicum outnumbers supply, and the price has risen to 1.42 USD per 0.5 kg in March 2022, up from 0.79-0.95 USD in February 2022 [1]. While in India, capsicum consumption is skyrocketing due to increased demand from urban consumers; exports are also in high demand, but supply is limited due to low crop productivity [2]. Common leaf diseases in capsicum are leaf spot, rapid discolouration, mosaic, and leaf curl [4–6].

Leaf spot symptoms on capsicum are primarily circular lesions with a white centre resemble frog eyes. This depleted output is typically caused by capsicum contagion with diseases triggered by moulds, microbes, germs, and mycoplasmas, which radically diminish possible harvests [3]. The centre of the leaf spots frequently falls out, resulting in small holes. Discoloration is characterised by an unusual yellowing of the leaf, beginning at the tips and progressing to lower leaf. Normally, the oldest capsicum leaf will turn yellow first, followed by the rest of the leaves turning light green. Leaf curling, on the other hand, refers to the improper development of the leaf, causing it to curl or become distorted. This condition may be accompanied by the presence of brown spots on the leaf. In *Figure 1*, *Figure 2*, and *Figure 3*, the images depict examples of leaf spot, discolored leaves, and leaf curling in capsicum plants.

*Author for correspondence


Figure 1 Leaf spot


Figure 2 Discolour leaf


Figure 3 Leaf curling

Several methods for classifying capsicum leaf disease have been developed in order to reduce farmers' losses. However, based on the accuracy percentage of the developed model, the existing models of classifying capsicum leaf diseases perform moderately well. In addition, the existing models can only classify capsicum leaf disease through leaves that have been picked from the tree and placed on a uniform colour of background. Through these existing models, the process of segmentation and classification of capsicum leaf disease is easier.

Among the methods that are often used to classify plant leaf diseases is convolution neural network (CNN). Many variants of CNN architectures have been developed over the years to solve real-world problems. For example:

- AlexNet
- VGG-16
- VGG-19
- Inception
- GoogleNet
- ResNet
- SqueezeNet
- Enet
- ShuffleNet
- DenseNet

DenseNet and ShuffleNet, both developed in 2017, are the most recent CNN architectures. The performance of CNN models has gradually improved over time in the majority of cases [7].

Because of the rapid advancement of digital imaging equipment, exquisite photographs of plant leaves can now be seized, supplying a valuable resource for automated disease detection. Image processing techniques combined with deep learning algorithms have the prospect to reliably discern and categorise diseases based on visual symptoms exhibited on leaves. Nevertheless, there are some hurdles such as Lighting conditions, surroundings clutter, occlusions, and variations in leaf size and orientation all make it challenging to attain consistent and reliable results. Aside from that, precise demarcation of distinct leaves from the background is a vital phase in disease detection. Variations in leaf shapes, interspersed leaves, complex background textures, and occlusions caused by diseases or other elements present hurdles. As a result, the overall goal of this research is to develop a disease detection model capable of generalising well to new images of disease types. It is critical for real-world deployment to ensure scalability and adaptability across different environments and lighting conditions.

The literature review in the section 2 confirms that the previous model's performance in classifying chili leaf diseases is considered average. Furthermore, the researchers did not prioritize the development of models capable of distinguishing capsicum leaf diseases within a complex leaf cluster; their focus was primarily on classification from a uniform background. Consequently, there is a need for an efficient model that can achieve high classification accuracy in such scenarios. Section 3 presents the methodology employed in this study. The findings and results are then discussed in section 4. Section 5 focuses on investigating the impact of the results, and the study concludes in section 6.

2.Literature review

Many models established on machine learning (ML) as well as CNN have been developed around the world to classify different types of diseases on plant leaf [8].

Support vector machine (SVM) is used to identify eggplant (Solanum melongena) leaf images [9]. Cercospora leaf spot and two-spotted spider infestation are the types of leaf disease they are attempting to classify. Their research is based on images obtained from a mobile phone camera (Xiaomi Redmi Note 3) with a resolution of 16 megapixels. Because eggplant leaves grow vertically upwards, the camera is set perpendicular to the ground. The segmentation is then completed by removing the ground surface and any unnecessary odd leaflets. The Gray-level co-occurrence matrix (GLCM) with a 20-pixel offset along an image's rows is used for texture analysis. For classification, the split ratio is 80:20. The dataset is randomly divided into 10 subsets for 10-fold cross-validation. The classification accuracy is 78.32%.

Tomato leaf diseases is classified using a deep learning transfer learning AlexNet [10]. The image dataset is taken from a publicly available dataset on the PlantVillage website. Color standardisation and resizing are performed on the images before they are fed into the AlexNet model. To fit the transfer learning model, the images are first resized to 64 × 64 pixels. They are then pixel-by-pixel standardised with the Tensorflow function. The split is a ratio of 75:25 for classification. Three fully connected layers and a Softmax layer are used in the transfer learning implementation. The epoch count is 32, and the K-fold cross validation implemented is 10 folds. This model's validation accuracy was 89.8%.

Woody fruit plant leaf diseases are classified using deep learning of an improved ResNe101 [11]. To condense model training parameters, a universal average pooling layer is employed; layer normalization, dropout, and layer 2 (L_2) regularization are utilized to avert model overfitting; and the SENet attention mechanism is used to convalesce the model's aptitude to excerpt features. The dataset used in this article was obtained from the artificial intelligence (AI) Challenger 2018.

The Resnet101 network flinches with a complication layer, then quaternion sets of modules made up of lingering blocks, with apiece collection of modules using 3, 4, 23, 3 residual blocks and the identical sum of production conduits coating as [12]. Individually component in the primary remaining lump doubles the number of channel layers of the previous module while halving its stature and girth. The production sorting coating is then linked.

The algorithm of Stochastic incline ancestry with thrust also known as SGDM is also employed. The achieved accuracy is 85.90%. GoogleNet deep learning is utilized to classify potato leaf diseases [13]. A Plant Village Dataset is used. There are three channels and fifty epochs implemented. Max pooling and Conv layers are used to build the model. The secreted coats employ the non-lined initiation utility Relu, while the production coat exploits the SoftMax initiation utility. The layer employed is a 22-layer deep convolutional neural network. The classification accuracy achieved is 62.0%.

DenseNet201 is exploited to classify rice leaf diseases [14]. The dataset, titled Rice Leaf, is obtained from the University of California Irvine (UCI) repository via the Kaggle site. The image is reduced to 224224 pixels in size. Separation of image data has been completed with 70% for training, 20% for validating, and 10% for testing. This study's augmentation makes use of Tensorflow's ImageDataGenerator image preprocessing feature. Each layer is linked, as are feature-maps to all subsequent layers, and the next layer receives input feature-maps from all previous layers. A number of layers are added to the next layer. The mentioned layers are average pooling layer, dropout layer, dense layer, and activation function. The confusion matrix is used to represent the prediction results with the actual dataset conditions. The classification accuracy achieved is 82.99%.

To categorise tomato leaf diseases, deep learning transfer learning is used [15]. A publicly accessible dataset on the PlantVillage website is where the image dataset was obtained. The images are resized and color-standardized before being incorporated into the AlexNet model. The images are first downsized to 6464 pixels in order to fit the transfer learning model. The Tensorflow function then standardises them pixel by pixel. 75:25 is how the split is divided for classification. 32 epochs were used, and 10 folds of K-fold cross validation were used. The validation accuracy of this model was 89.8%.

Potato leaf diseases are classified using GoogleNet deep learning [16]. 50 epochs and three channels have been implemented. To construct the model, Max pooling and Conv layers are used. The production coat makes use of the softmax initiation utility while the secreted coats use the non-lined initiation utility Relu. A 22-layer deep convolutional neural network is used as the layer. The achieved classification accuracy is 62.0%.

To identify pepper bell or capsicum leaf diseases, the local binary pattern (LBP) and GLCM is exploited [17]. Sony DSC-Rx100/13 20.2MP high-definition (HD) camera was used to capture the images of the sick leaf. The obtained detection accuracy is 82.66%. This is because LBP and GLCM have a prohibitively high potential for performing image spoofing [18].

In order to identify the diseases affecting capsicum leaves from actual images taken with a digital camera in various orientations [19] used feed-forward neural networks (FFNN). The images that were captured have different sizes, backgrounds, lighting levels, and positions. The proliferation learning algorithm discards the Restricted Boltzmann machine (RBM). It controls the appropriate gradient and adjusts the parameters for the best detection from the output layer using the labelled training datasets. The accuracy of the detection is 91.16%. Deep learning needs a lot of data to function well, so the detection accuracy achieved is imperfect [20].

While the existing CNN models, AlexNet and GoogleNet is utilized to classify plant leaf diseases of apple, cherry, blueberry, corn, grape, orange, peach, bell paper, potato, raspberry, soybean, squash, strawberry and tomato [21]. A total of 54,306 images are used. AlexNet and GoogleNet have been trained to identify 14 crop diseases. When classifying plant leaf diseases from images with uniform backgrounds, the models achieved an accuracy of 99.35%, but this dropped to 31.4% when images from a different set of environments are tested.

As a result, previous methods in the field of plant leaf disease detection made important advances but also had limitations.

A thorough examination of these disadvantages can shed light on the limitations of previous strategies. The foremost prevalent disadvantages of earlier approaches for detecting plant leaf disease is that many previous methods were susceptible to changes in lighting, image quality, and environmental surrounding conditions. These variations can introduce noise and inconsistencies in the captured leaf images, lowering the performance of disease detection algorithms. The methods' generalizability and real-world applicability are limited by their lack of robustness to such variations.

2.1Problem statement

However, in real life, diseased leaf grows in clusters with other leaves, making classification hard due to the difficulty of segmenting between the healthy leaf part, the unhealthy leaf part, and the complex background.

There is no existing model for classifying capsicum leaf disease from a complex leaf cluster. Farmers will find it easier if there is a model that can classify capsicum leaf disease from a complex background because they will only need to take pictures at the scene rather than picking the diseased leaf and placing it on a uniform background before analysing the type of disease. *Figure 4* and *Figure 5* show the comparison between capsicum leaf with uniform background and capsicum leaf with complex cluster of leaves. Aside from that, the existing models perform on average, with classification accuracy ranging from 31.40% to 89.80% for uniform background cases and difficulty classifying disease types from real-world conditions. Therefore, a better model must be proposed that outperforms the existing models in terms of classification accuracy.

Figure 4 Uniform background

Figure 5 Complex background

3.Methodology

The process of image-based disease detection in this study entails several steps. At first, images of plant leaves are captured using imaging devices. These images are then pre-processed to improve their quality in preparation for further analysis. Following that, feature extraction techniques are used to identify relevant features from the images that can be used to differentiate the images. Deep learning algorithms are used to train models using labelled datasets after the features are extracted. These models learn to classify leaves based on extracted features and accurately detect disease presence. *Figure 6* illustrates the research framework flow chart for this study, from image acquisition to image classification using a proposed method of an improved multiple layers ShuffleNet cnn model.

ShuffleNet is a new cnn model that uses pointwise group convolution as well as a novel channel shuffle operation to improve information flow across feature channels [22]. ShuffleNet supports more feature map channels, allowing for more information to be encoded and is especially important for very small network performance. In terms of configuration, the ShuffleNet architecture has 50 layers. The second pointwise group convolution's purpose is to recover the channel dimension to match the shortcut path. *Table 1* depicts the overall ShuffleNet architecture.

It is made up of three stages of ShuffleNet units stacked on top of each other. The connection sparsity of pointwise convolutions is controlled by the group number g in *Table 1*. Simultaneously, g is assigned different numbers so that the output channels layers can be computed and evaluated to ensure that the total computational costs are roughly the same (~140 machine learning operations (MFLOPs)). The network can be freely customised to the desired level of complexity. Simply apply a scale factor s to the number of channels layers to accomplish this. For example, if the networks are denoted in *Table 1* as "ShuffleNet 1×," then " ShuffleNet s×" means multiplying the number of filters in ShuffleNet 1× by s, resulting in an overall complexity of roughly s squared times ShuffleNet 1×. All components in the ShuffleNet unit can be computed efficiently because of the pointwise group convolution with channel shuffle layers.

3.1Image acquisition

The chilli leaf images were taken on a farm with a complex uniform background. They are from varieties named Kulai, Hot Beauty, and Tarat, three most popular and frequently requested chilies in Malaysia. The dataset images of diseased capsicum leaf comprising of leaf spot, discolour leaf and leaf curling in this study are acquired employing a mobile phone camera with specifications:

•Wide
✓ 13 Megapixels Phase-detection autofocus
✓ f/2.2 or 23 mm aperture of lens wide
•Depth
✓2 Megapixels
✓f/2.4 or 25 mm aperture of lens depth
•LED flash with Panorama features
•1080p@30fps frame rate

The images of diseased capsicum leaves were captured under two different conditions: uniform background and complex background. In the case of a uniform background, the dataset consists of 96 images for leaf spot, 80 images for discolored leaves, and 75 images for leaf curling. On the other hand, for the complex background, there are 100 images for discolored leaves, 96 images for leaf spot, and 88 images for leaf curling.

The images are then imported via image acquisition tools for analysis and manipulation using Matlab R2022a to a laptop with the following specifications:

- Computer System
✓ Laptop Computer
✓ Acer Aspire
- Microprocessor
✓ Intel® Core™ i3-CPU
- Microprocessor Clock Speed
✓ 1.90GHz
- Random Access Memory (RAM)
✓ 6.00GB
- Operating System
✓ Windows 8.1 Single Language with Bing

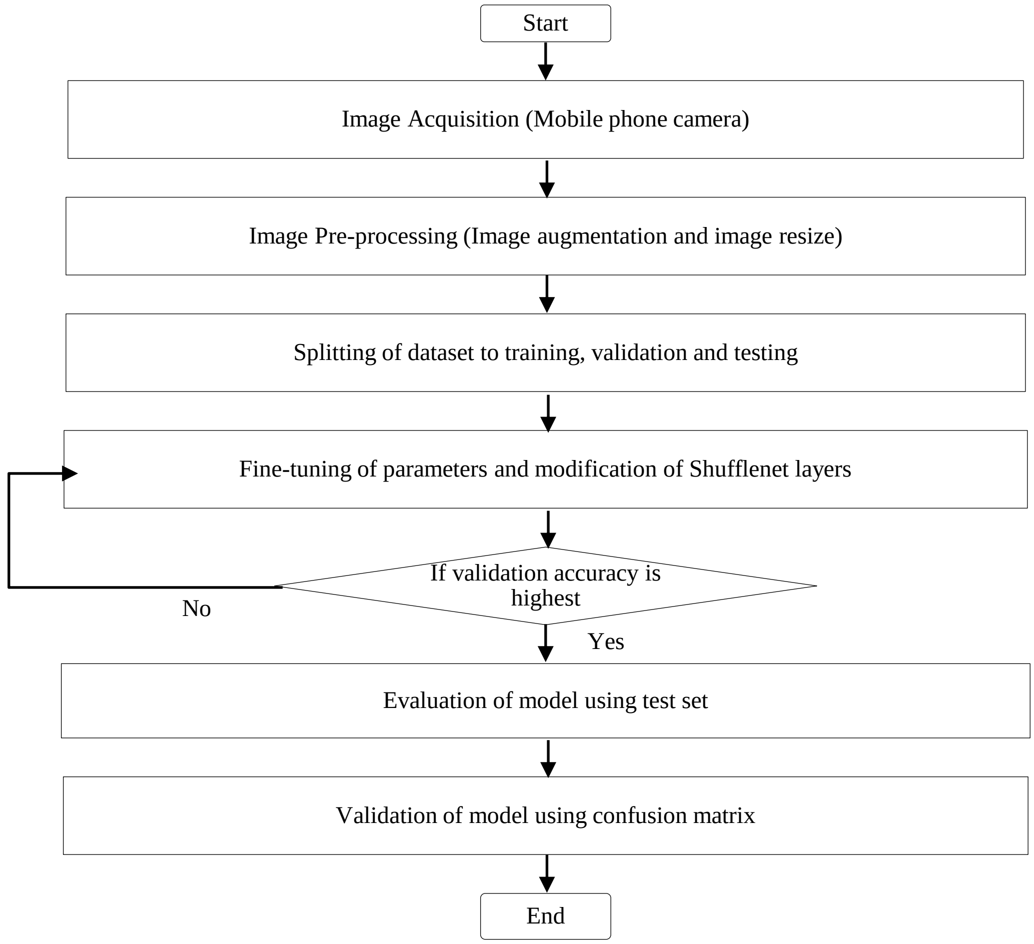


Figure 6 Flowchart of identification of capsicum leaf diseases using an improved ShuffleNet model

Table 1 ShuffleNet architecture

Layer	**Output size**	**KSize**	**Stride**	**Repeat**	**Output channels (*g* groups)**				
					***g* = 1**	***g* = 2**	***g* = 3**	***g* = 4**	***g* = 8**
Image	224×224	-	-	-	3	3	3	3	3
Conv1	112×112	3×3	2	1	24	24	24	24	24
MaxPool	56×56	3×3	2						
Stage2[1]	28×28	-	2	1	144	200	240	272	384
	28×28		1	3	144	200	240	272	384
Stage3	14×14	-	2	1	288	400	480	544	768
	14×14		1	7	288	400	480	544	768
Stage4	7×7	-	2	1	576	800	960	1088	1536
	7×7		1	3	576	800	960	1088	1536
GlobalPool	1×1	7×7	-	-	-	-	-	-	-
FC	-	-	-	-	1,000	1,000	1,000	1,000	1,000
Intricacy[2]	-	-	-	-	143 M	140 M	137 M	133 M	137 M

3.2Image pre-processing

Before the diseased capsicum leaf images are utilized by model training and inference, and to enhance the images quality so that they can be more effectively analysed, the images are pre-processed using two techniques which are image augmentation and resize.

Figure 7 illustrates an original image being transformed into some augmented images using the random reflection technique in this study. Data augmentation of random left/right reflections and X/Y is used in this.

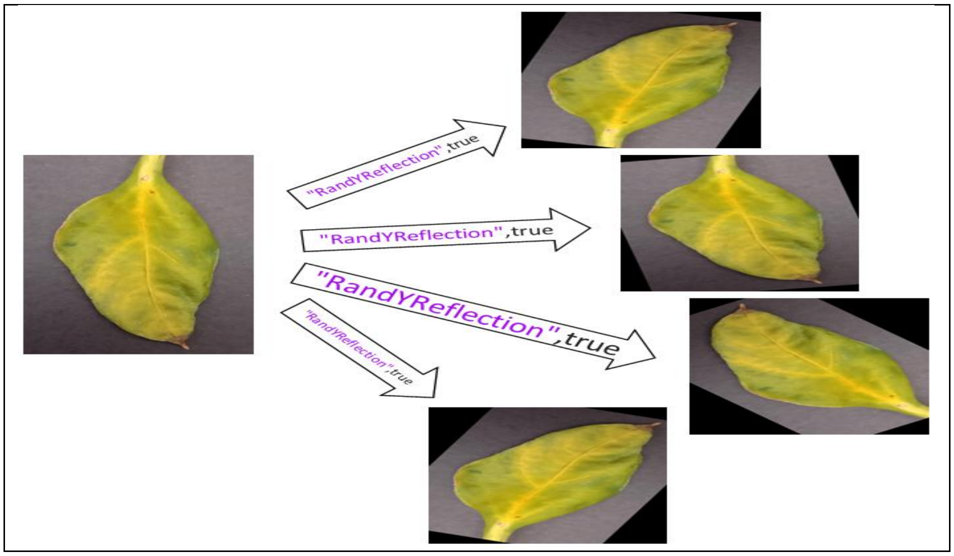


Figure 7 Random reflection technique

Image augmentation is performed only in cases of uniform background, while images with complex background are left unaltered to maintain their authenticity as in real-world conditions. Type of data augmentation applied is the random reflection technique using '"RandYReflection", true'. A logical scalar representing random reflection in the top-bottom direction. When the RandYReflection parameter is set to true (1), each input image flips with a 50% possibility in each dimension. No images are reflected when RandYReflection is false (0). One original image is roughly transformed into 23 to 30 augmented images. Following image augmentation, the images of leaf spot become 1,334, discolour leaf become 1,240, and leaf curling become 936 in total.

Data augmentation can improve the classifier accuracy as it enhances the training of CNN [23]. Then, the images augmented are resized to fit the network input layer. The augmented store then automatically resizes. The ShuffleNet model requires an input image of a specific dimension of 224×224 [24], and hence all images after being augmented are resized to 224×224×3.

3.3Splitting of dataset

In this study, the ShuffleNet network is trained using 70% of the data and validated on 15% of the data. The remaining 15% is allocated for testing purposes. The imageDatastore is divided into training, validation, and testing sets using the splitEachLabel function. Due to image augmentation, the total number of diseased capsicum leaf images has been increased to 3,510. The division of data into training, validation, and test sets is detailed in *Table 2.*

Table 2 The study's data set

Capsicum leaf disease	Original	Testing dataset	Training dataset	Validation dataset	Augmented
Grey spot	96	200	934	200	1,334
Discolour leaf	80	186	868	186	1,240
Leaf curling	75	141	654	141	936
Total	251	527	2,456	527	3,510

Data from data augmentation that has been using the random reflection technique are used in the data resampling process. For each category of chilli leaf diseases, the data were still unbalanced. The confusion matrix was used for the model's evaluation where other performance matrices were taken into account in order to prevent this from creating bias in the final determination of the performance of the improved ShuffleNet being proposed.

3.4Fine-tuning parameters and modification of shufflenet layers

Table 3 shows the hyperparameters that are fine-tuned for the training of the ShuffleNet model used in this study. Also in this study, after each epoch, the dataset is set to be shuffled. Then, prior to performing the training manoeuvre, a few layers of ShuffleNet are altered to detect capsicum leaf diseases. The copiously associated, softmax, and classification coats have been substituted with new-fangled diagnostic layers. The network branches are also added to the layer graph. Every branch is a linear array of layers. Then, all the branches of the network are connected to produce the network graph which connects a set of nodes that provide information about the diseased capsicum leaf for classification.

Table 3 Hyperparameter structure

Hyperparameter	**Value**
Initial learn rate	0.01
Maximum epoch	50
Minibatch size	64
Validation frequency	10 iterations
Optimization algorithm	SGDM optimizer
Execution environment	'auto'
Validation iterations	205

For quicker convergence, the parameters in the copiously associated coats were arbitrarily make ready and necessitate a sophisticated erudition rate than the pre-trained layers. The ShuffleNet models are then fine-tuned to conform to the hyperparameter settings listed in *Table 3*.

3.5Analysis of validation accuracy

In order to obtain the best validated model, multiple iterations of fine-tuning parameters and adjusting ShuffleNet layers are conducted to identify the optimal values that yield the best performance. The trial-and-error process continues until the program converges, i.e., when further adjustments no longer result in significant changes. Once the optimal fine-tuning parameters and ShuffleNet layers are determined, the validation model is employed to assess the accuracy of the proposed model in classifying capsicum leaf diseases using the test set.

3.6Evaluation of model using test set

The validated models are tested employing an augmented test set to grant an unbiased evaluation of the final tuned model's performance in order to assess the final model. The final percentage accuracy of the model following the training process is discovered and printed in the Matlab model for the reference.

3.7Validation of model using confusion matrix

Then, classification accuracy is validated using the confusion matrix to determine the classification type with two output classes as shown in the *Table 4*.

Table 4 Two output classes

Class	**Classified +ve**	**Classified -ve**
+ve	$TP\ (True\ +ve)$	$TN\ (True\ -ve)$
-ve	$FP\ (False\ +ve)$	$FN\ (False\ -ve)$

Confusion matrix is an imperative metric for appraising the classification model's accuracy and it generates three outputs, specifically recall, precision, and F1 score, using the following Equation 1, Equation 2, and Equation 3.

$$Recall = \frac{TP}{FN+TP} \times 100\% \quad (1)$$

$$Precission = \frac{TP}{FP+TP} \times 100\% \quad (2)$$

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100\% \quad (3)$$

4.Results

The proposed ShuffleNet model demonstrates proficiency in classifying capsicum leaf diseases using a training dataset comprising 205 iterations of validation. *Figure 8* depicts the training progress, including the minibatch accuracy and loss value of the proposed model. Initially, the validation dataset exhibits a modest accuracy in the range of 20% to 30% before training with the pre-trained topographies. Although this value may seem low, it indicates that some fundamental features necessary for analysis have already been learned, contributing significantly to the initial classification outcomes. Interestingly, after 205 iterations in the first epoch, the validation accuracy rises to approximately 90%. By the end of five epochs, the final validation accuracy achieved is 99.30%.

It is evident that the discrepancies in both minibatch accuracy and loss value of the proposed ShuffleNet model are minimal, indicating that the data inputs are closely clustered around the mean or desired value. This demonstrates the confidence in the learned features of the proposed ShuffleNet model, which are crucial for accurate diagnosis of capsicum leaf diseases. To further evaluate the classification performance, the confusion matrix, as presented in *Figure 9*, is utilized. This allows for an assessment of the model's performance, particularly considering the imbalanced nature of the dataset. Sensitivity and specificity are important metrics that provide insights into the model's performance and its ability to correctly classify positive and negative instances. It can be calculated employing true $+ve$ (TP), true $-ve$ (TN), false $+ve$ (FP), and false $-ve$ (FN). For instance, the proposed model of ShuffleNet has TP, TN, FP and FN of 200, 368, 0 and 0, respectively as illustrated in *Figure 9*. The value for true $+ve$ (TP), true $-ve$ (TN), false $+ve$ (FP), and false $-ve$ $(FN$ calculated as in Equation 4, Equation 5, Equation 6, and Equation 7.

$$True\ +ve, (TP) = cell\ 1 = 21.4 \quad (4)$$

$$True\ -ve, (TN) = (cell\ 5\ +\ cell\ 6\ +\ cell\ 8\ +\ cell\ 9)\ = (21.4 + 0 + 0 + 25.0 = 46.4 \quad (5)$$

$$False\ +ve, (FP) = (cell\ 4\ +\ cell\ 7)\ = 0 + 0 = 0 \quad (6)$$

$$False\ -ve\ , (FN) = (cell\ 2\ +\ cell3)\ = 3.6 + 0 = 3.6 \quad (7)$$

Based on the above values, the assessed sensitivity as well as specificity of the proposed ShuffleNet are both 100%, calculated using the following Equation 8 and Equation 9.

$$Sensitivity = \frac{TP}{TP+FN} \times 100\% = \frac{21.4}{21.4+3.6} \times 100\% = 85.6\% \quad (8)$$

$$Specificity = \frac{TN}{TN+FP} \times 100\% = \frac{46.4}{46.4+0} \times 100\% = 100\% \quad (9)$$

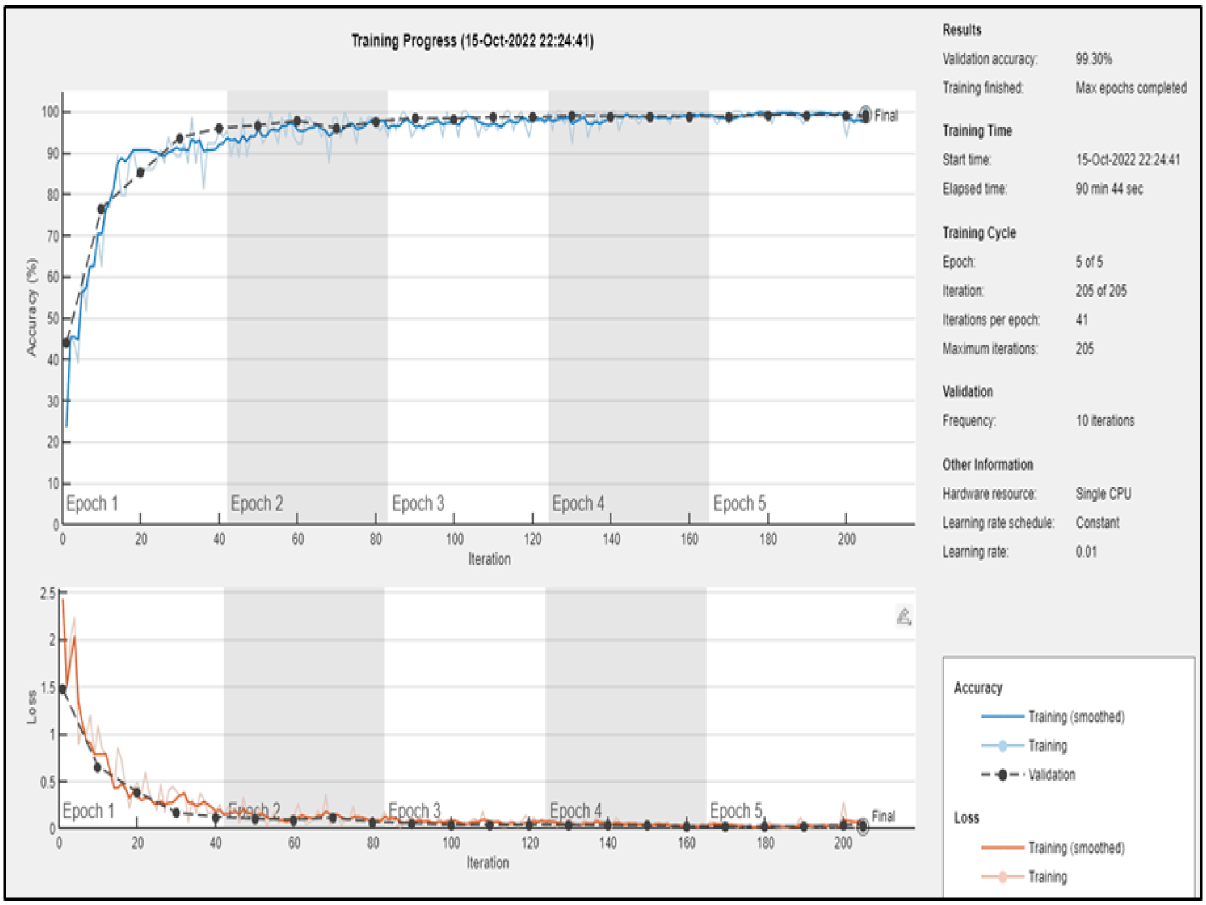


Figure 8 Training progress of the proposed ShuffleNet model

		Predicted Values		
Actual Values		cell 1	cell 2	cell 3
		cell 4	cell 5	cell 6
		cell 7	cell 8	cell 9

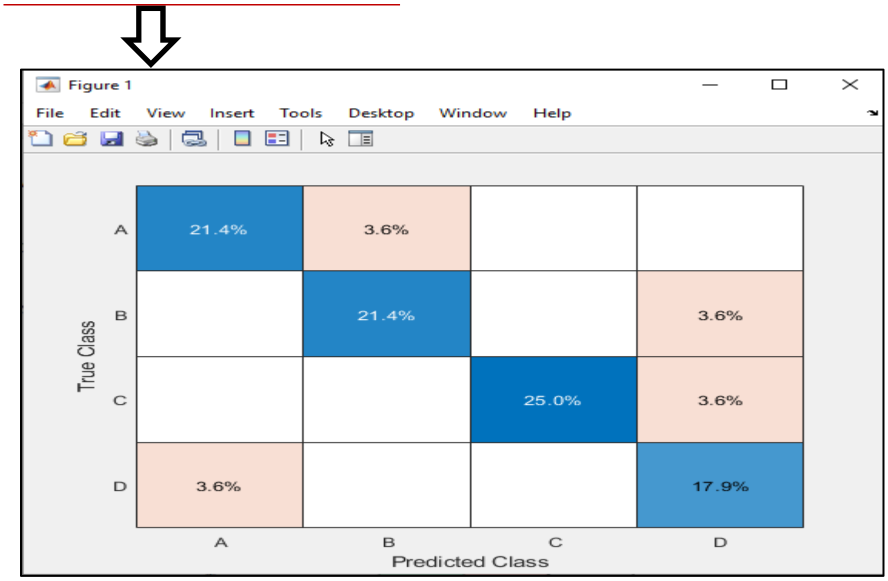


Figure 9 Confusion matrix of proposed ShuffleNet model

An 85.6% sensitivity in the test indicates that almost all individuals with the disease are correctly identified as diseased, resulting in very few false negatives. This is particularly important as the sensitivity calculation considers all capsicum leaves with the disease, demonstrating that the proposed ShuffleNet model is not significantly influenced by the prevalence of the disease.

On the other hand, a test with 100% specificity means that all healthy parts of the capsicum leaf are correctly identified as healthy, resulting in no false positives. A perfectly specific test implies that no healthy parts of the capsicum leaf are mistakenly identified as diseased. Furthermore, as depicted in *Table 5*, the evaluation is supported by utilizing performance metrics assessed from the confusion matrix. This is where precision, sensitivity, negative predictive value, specificity, miss rate, false discovery rate, fall out, F1 score, and false commission rate are presented in tabular form. Meanwhile, the accuracy of the proposed ShuffleNet, identified through the model itself, is displayed in *Figure 10.*

From *Table 5*, it is evident that the proposed model achieves a precision of 100%, indicating that it produces no false positives. This means that there are no instances where negative events (uninfected parts) are incorrectly classified as positive (false positives/predicted as infected parts), and there are no actual negative events misclassified as positive.

The high negative predictive value (92.8%) indicates that a high proportion of cases receiving negative test results correctly classify uninfected leaf parts. It represents the ratio of subjects that are truly negative to all leaves that obtained a negative test result (including leaves containing one of the uninfected parts). The achievement of a high negative predictive value also signifies the effectiveness of this proposed model as a screening program. This is because the program incorporates the concept that the more sensitive a test is, the less likely it is for an individual leaf with a negative test (uninfected part) to have the disease, thereby resulting in a higher negative predictive value.

The low miss rate (14.4%) indicates that the percentage of requested data not present in the cache is small. This implies that the program operates efficiently since the proportion of data that needs to be retrieved from the main memory each time the program is executed is minimal.

The 0% fall-out observed indicates that no discrepancies occurred in the program when predicting the uninfected part of the capsicum leaf. This means that none of the negative values (uninfected parts) were incorrectly predicted as positive (infected parts) by the model.

The low false omission rate (7.2%) signifies that the proportion of capsicum leaves with a negative predicted value (uninfected part) for which the true label is positive (infected part) is low. This demonstrates the effectiveness of the proposed model in minimizing false negatives among all negative instances.

The F1 score of 92.24% indicates that the proposed model, used for classifying imbalanced classes of capsicum leaf diseases, achieves a good balance between precision and recall. This means that the model exhibits low false positives and false negatives, correctly identifying real threats without being significantly affected by false alarms where the test results indicate the presence of a condition (such as a disease) when it is not actually present.

The improved ShuffleNet model builds upon the efficiency and compactness of the original ShuffleNet architecture, utilizing grouped pointwise convolutions and channel shuffling to reduce computational complexity. The model has been modified and enhanced to improve its disease detection capabilities specifically for capsicum plants. The performance of the improved ShuffleNet model, including accuracy, precision, recall, and F1 score, is evaluated to assess its effectiveness in detecting capsicum leaf diseases. Standard evaluation metrics are also identified to specify the specific metrics or thresholds used to evaluate the model's performance for different disease classes. Furthermore, this study demonstrates the efficacy of the improved ShuffleNet model by comparing it to baseline models or existing state-of-the-art models. This allows for an evaluation of the model's advancements in terms of accuracy, computational efficiency, and generalization capabilities. The limitations of the improved ShuffleNet model in terms of fine-tuning parameters are also honestly addressed, including potential challenges in detection, computational resource requirements, or scalability constraints. Moreover, indirect suggestions for future improvements or research directions, such as incorporating transfer learning techniques or exploring multi-scale approaches, are provided.

Table 5 Assessment of the proposed ShuffleNet model

Model	**Sensitivity**	**Specificity**	**Precision**	**Negative predictive value**	**Miss rate**	**Fall out**	**False omission rate**	**F1 score**
Proposed ShuffleNet model	$\frac{TP}{TP+FN}\times 100\%$	$\frac{TN}{TN+FP}\times 100\%$	$\frac{TP}{FP+TP}\times 100\%$	$\frac{TN}{FN+TN}\times 100\%$	$\frac{FN}{FN+TP}\times 100\%$	$\frac{FP}{FP+TN}\times 100\%$	$\frac{FN}{FN+TN}\times 100\%$	$2\times\frac{Precision\times Recall}{Precision+Recall}\times 100\%$
	$= 85.6\%$	$= 100\%$	$= 100\%$	$= 92.8\%$	$= 14.4\%$	$= 0\%$	$= 7.2\%$	$= 92.24\%$

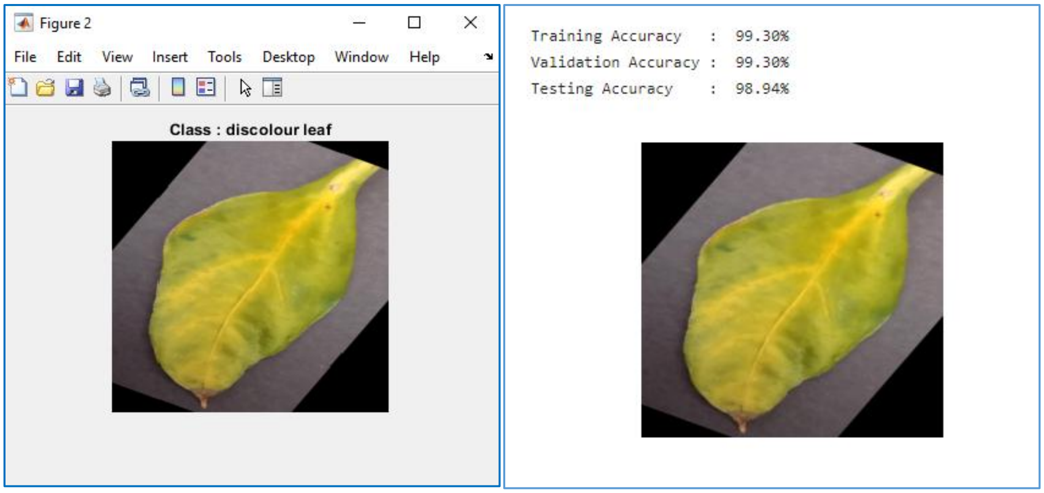


Figure 10 Performance of the proposed classification model of ShuffleNet

5.Discussion

The proposed ShuffleNet model achieves a classification accuracy of 99.30%. Due to the imbalanced nature of the data classes, the model's classification accuracy needs to be validated using a confusion matrix [25]. This occurs when one or more classes have a greater number of samples compared to the other classes. For instance, in this study, the class of leaf spot has 1,334 samples, discolored leaf has 1,240 samples, and leaf curling has 936 samples. Following the validation of the proposed ShuffleNet model, all the assessments tabulated in *Table 5* indicate that the proposed model in this study is highly efficient.

The performance of the proposed ShuffleNet model is compared to other prominent ML algorithms such as bag of features (BoF) and CNN models like DenseNet201 and ResNet50. The primary purpose of this study is to propose a superior model that surpasses existing models in terms of classification accuracy. *Figure 11* illustrates the comparison of their performances. From *Figure 11*, it is evident that the accuracy of the proposed ShuffleNet model outperforms the performance of the existing models. When compared to BoF (80.0%), ResNet50 (89.27%), and DenseNet201 (97.02%), the proposed ShuffleNet model achieves the highest classification accuracy.

The BoF model has been widely used in various computer vision tasks, including image classification [26]. It is a popular model for content-based image classification [27]. Previous studies [28–31] have utilized BoF to identify lesion leaves from plants and classify plant leaf diseases. According to [32], ResNet-50 is a 50-layer deep convolutional neural network that can load a pretrained model trained on over many images from the ImageNet dataset and classify images into 1,000 categories. Researchers [33–36] have employed ResNet50 to classify plant leaf diseases. DenseNet201 is a pretrained network with 201 layers that can classify images into 1,000 categories [37]. It has been used by the researchers [38–41] to classify leaf diseases. These three models have demonstrated active usage in image processing, particularly in classifying different types of plant leaf diseases. Therefore, they are suitable for comparison with the proposed model in this study. *Figure 12*, *Figure 13*, and *Figure 14* display the confusion matrix of the existing models.

Since the dataset used is still imbalanced, the existing models are also validated using the confusion matrix to analyze their performance compared to the proposed ShuffleNet model. The confusion matrix illustrates the relationship between the classifier's outputs and the true labels [42], and for accurate evaluation, an imbalanced dataset requires a confusion matrix [43].

Furthermore, *Figure 15* demonstrates the comparison of the performance of the proposed ShuffleNet model and other existing models based on their confusion matrix using precision. Precision is the ratio of true positives to the sum of true positives and false positives, and it measures how many false positives are included in the predictions. A precision of 100% indicates zero false positives (FPs), while an increase in FPs decreases the precision. A good classifier should ideally have a high or close to 100% precision [44]. A model with high precision is considered the best classifier, and many researchers [45] optimize the hyperparameters of their classifiers to develop efficient deep neural network models.

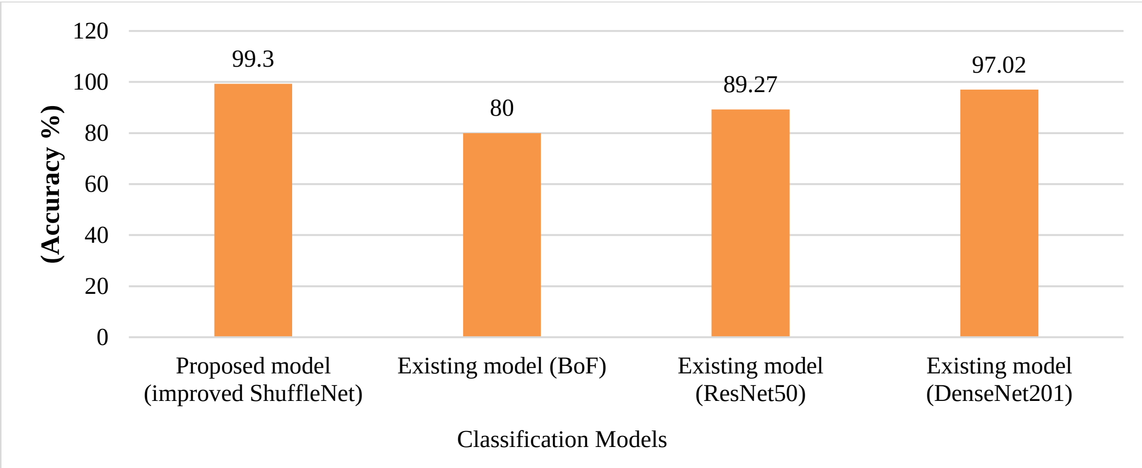


Figure 11 Classification accuracy of the models

Figure 12 Confusion matrix of BOF

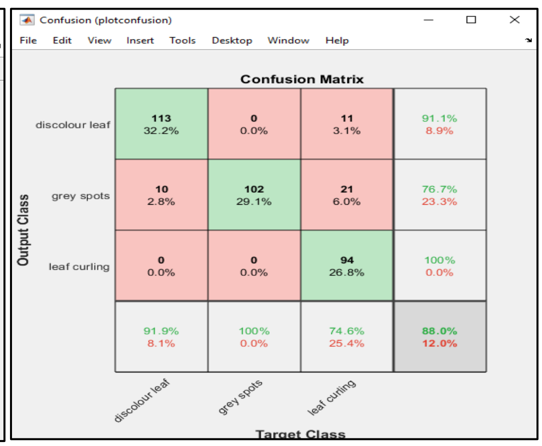


Figure 13 Confusion matrix of ResNet50

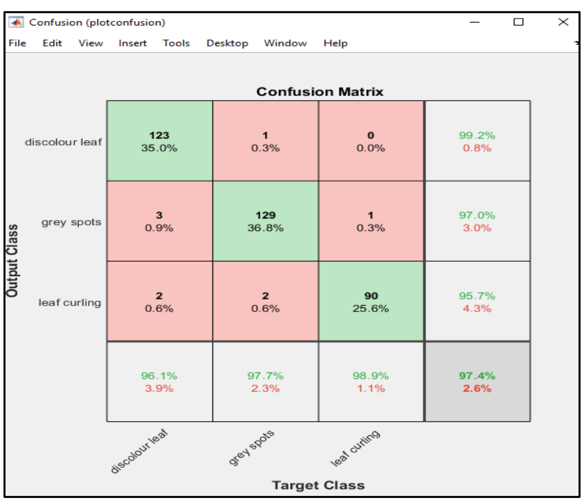


Figure 14 Confusion matrix of DenseNet201

As depicted in *Figure 15*, the proposed ShuffleNet model achieves the highest precision of 100% compared to the existing models, BoF (33.33%), ResNet50 (92%), and DenseNet201 (95.89%). This means that in this study, when the model predicts that a leaf has a grey spot, discolored leaf, or leaf curling disease, it is almost always correct in classifying the leaf as having the corresponding disease. These results confirm the reliability of the proposed model in accurately classifying new data of diseased capsicum leaves. Accuracy refers to the closeness of a measurement to its true value, while precision refers to the accuracy of repeated measurements for new data under the same conditions [46].

Therefore, the proposed model is considered reliable in achieving the other objective of this study, which is to classify new data of diseased capsicum leaves from a complex cluster of leaves representing real-world conditions. Several images of diseased capsicum leaves, including 40 grey spots, 50 discolored leaves, and 44 leaf curling leaves, were acquired using a mobile camera for experimentation and classified using the proposed ShuffleNet model with the addition of the "Img=imcrop(imread(filename))" function to the code. The code was modified by adding layers and functions to the ShuffleNet model. In summary, the improved ShuffleNet model in this study was adjusted on two levels by increasing the layers and incorporating additional functions. *Table 6* presents some of the results of classifying capsicum leaf diseases from a complex cluster of leaves using the improved ShuffleNet model.

Table 6 demonstrates that the proposed method successfully classifies capsicum leaf diseases from a complex cluster of leaves. Specifically, the proposed model accurately classified all 142 diseased capsicum leaf images used in the experimentation with the complex background case.

Table 7, compares the accuracy and time taken using ShuffleNet and the improved ShuffleNet with 200 datasets for each type of disease.

The improved ShuffleNet model achieved an accuracy of 99.62%, compared to 90.86% with the original ShuffleNet model. However, training the improved model took longer, 95 seconds compared to 86 seconds for the original model. Adjusting the ShuffleNet layers and fine-tuning can enhance the performance of a pre-trained model, but this may require more processing time.

The performance comparison for different feature combinations, specifically the epoch feature is shown in *Table 8*. It shows the classification accuracy achieved for the improved ShuffleNet model with different epoch values.

The accuracy of the improved ShuffleNet model increases as the number of epochs rises. During training, the model adjusts its parameters based on the discrepancy between the predicted output and the actual output for each example in the training data. By repeating this process over multiple epochs, the model refines its parameters and improves its ability to generalize to new, unseen data. However, there may be a point of diminishing returns beyond which additional training does not significantly improve performance or may lead to overfitting, as observed in epoch 60.

Finally, *Figure 16* compares the training time and various performance metrics for the improved ShuffleNet model and the original ShuffleNet model. It is evident that the improved ShuffleNet model exhibits higher sensitivity, specificity, precision, negative predictive value, and F1 score compared to the original ShuffleNet model.

A complete list of abbreviations is shown in *Appendix I.*

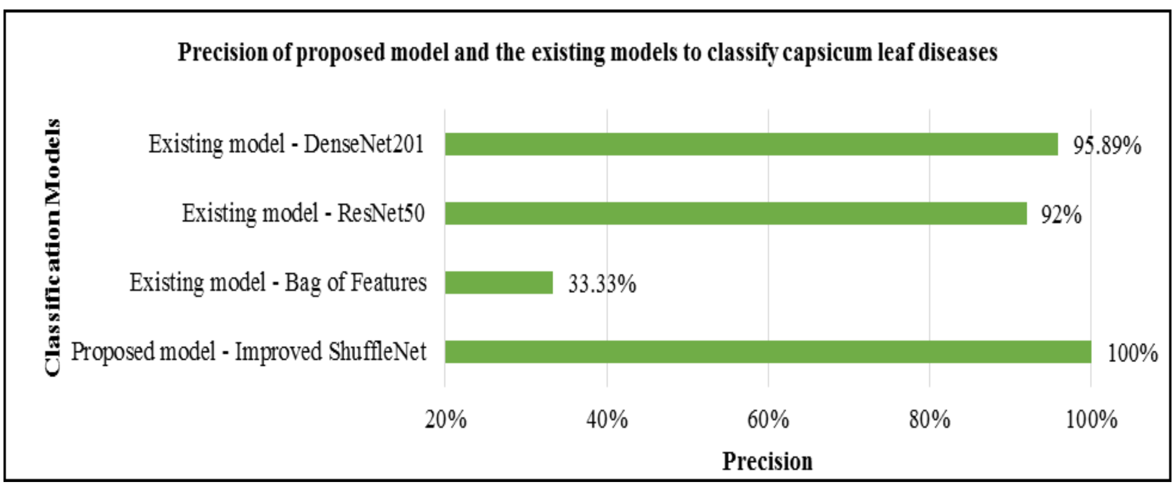


Figure 15 Precision of the models

Table 6 Classification of capsicum leaf disease from a complex cluster of leaves using an improved ShuffleNet model

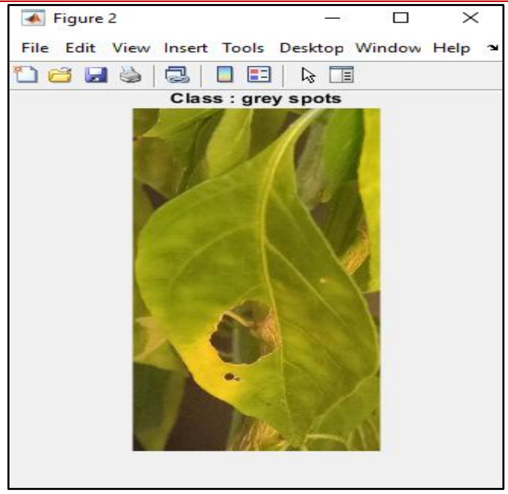
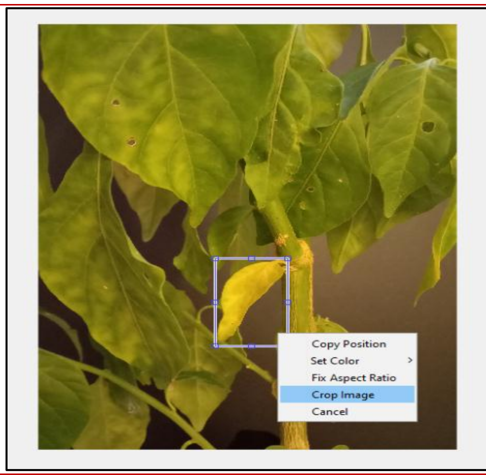
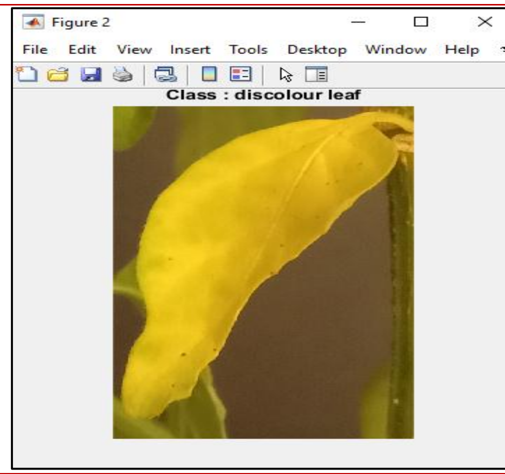
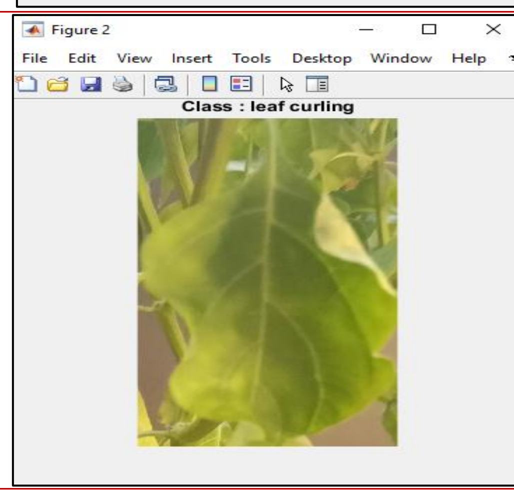
Disease	Classification	Result
Grey spot		
Discolour leaf		
Leaf curling		

Table 7 Comparison performance of an improved ShuffleNet and an original ShuffleNet model

Model	Classification accuracy (%)	Time taken (s)
ShuffleNet	90.86	86
Improved ShuffleNet	99.62	95

Table 8 Performance of an improved ShuffleNet model upon different epoch value

Epoch	Classification accuracy (%)
10	87.31
20	91.83
30	94.56
40	95.21
50	99.62
60	95.43

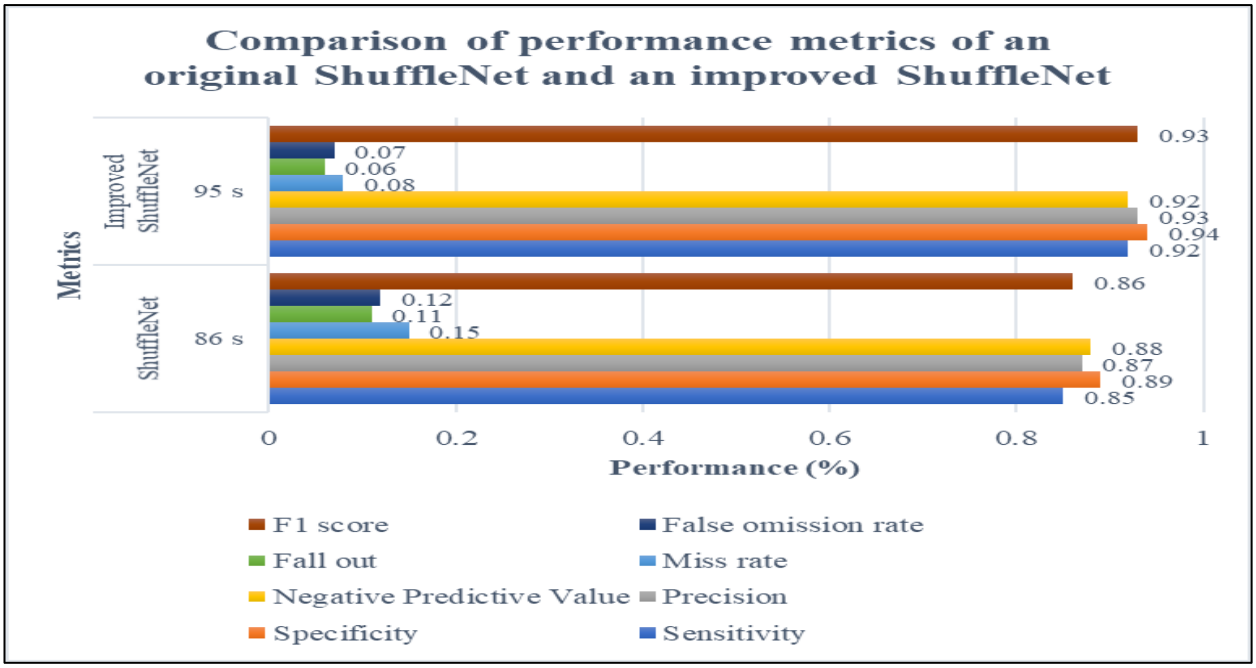


Figure 16 Detailed comparison performance of an improved ShuffleNet and an original ShuffleNet model

6.Conclusion and future work

With a classification accuracy of 99.30%, the proposed ShuffleNet model outperformed other existing models in classifying capsicum leaf diseases. Additionally, the proposed model is capable of accurately classifying diseased images of capsicum from diverse environments, reflecting real-world conditions where the diseased leaf is obtained alongside a cluster of other leaves, making disease classification challenging.

In future studies, it is recommended to expand the existing dataset by including additional plant varieties and plant diseases of various types. This expansion will help improve the trained models. In this study, the proposed ShuffleNet model achieved a precision of 100%, a recall of 85.6%, and an F1 score of 92.24%. However, it is worth exploring other CNN models that employ different learning rates and optimizers to further enhance the model's performance and accuracy, particularly aiming for higher recall and F1 score values.

It is important to note that while this study experimented with real-world cases, it did not consider external factors such as inclement weather conditions like rain or low light environments. Hence, when developing new models, it is crucial to consider these factors, including weather conditions and light intensity of the environment. The performance of the classifier can be affected by variations in weather and light conditions, as images captured under different circumstances may differ significantly.

Another practical finding from this study is that ShuffleNet, like most deep learning models, requires a substantial amount of data to train efficiently. Insufficient data can lead to challenges in effectively training the model, potentially resulting in overfitting or inadequate generalization. Additionally, it is worth noting that ShuffleNet is not as widely accessible online compared to other deep learning models, as it is still a relatively new architecture. This limited availability may pose challenges when attempting to apply ShuffleNet to certain tasks or datasets.

Acknowledgment

The authors express their gratitude to Prof. (Dr.) Amit Baran Sharangi from the Department of Plantation, Spices, Medicinal & Aromatic Crops, BCKV-Agricultural University, Mohanpur 741252, India for his valuable evaluation of the capsicum leaf diseases.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Chyntia Jaby Entuni: Conceptualization, investigation, data curation, writing, reviewing and editing. **Tengku Mohd Afendi Zulcaffle:** Conceptualization, supervision and review. **Kismet Hong Ping:** Study conception and supervision.

References

[1] Wei X. Hainan chili peppers enjoy optimistic market prospects as price continues to rise. Fresh Plaza. 2022; 3(2):16–9.

[2] Chand R, Joshi P, Khadka S. Indian agriculture towards 2030: pathways for enhancing farmers' income, nutritional security and sustainable food and farm systems. Springer Nature; 2022:1-332 .

[3] Jadon KS, Shah R, Gour HN, Sharma P. Management of blight of bell pepper (Capsicum annuum var. grossum) caused by Drechslera bicolor. Brazilian Journal of Microbiology. 2016; 47:1020-9.

[4] Jain A, Sarsaiya S, Wu Q, Lu Y, Shi J. A review of plant leaf fungal diseases and its environment speciation. Bioengineered. 2019; 10(1):409-24.

[5] Hami A, Rasool RS, Khan NA, Mansoor S, Mir MA, Ahmed N, et al. Morpho-molecular identification and first report of Fusarium equiseti in causing chilli wilt from Kashmir (Northern Himalayas). Scientific Reports. 2021; 11(1):1-14.

[6] Khan SM, Raj SK, Bano T, Garg VK. Incidence and management of mosaic and leaf curl diseases in cultivars of chilli (Capsicum annuum). Journal of Food Agriculture and Environment. 2006; 4(1):171-4.

[7] Khan A, Sohail A, Zahoora U, Qureshi AS. A survey of the recent architectures of deep convolutional neural networks. Artificial Intelligence Review. 2020; 53:5455-516.

[8] Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of big Data. 2021; 8:1-74.

[9] Rangarajan AK, Purushothaman R, Prabhakar M, Szczepański C. Crop identification and disease classification using traditional machine learning and deep learning approaches. Journal of Engineering Research. 2021; 4(4):518–31.

[10] Chung I, Gupta A, Ogunfunmi T. Remote crop disease detection using deep learning with IoT. In IEEE global humanitarian technology conference 2022 (pp. 353-60). IEEE.

[11] Wu Z, Jiang F, Cao R. Research on recognition method of leaf diseases of woody fruit plants based on transfer learning. Scientific Reports. 2022; 12(1).

[12] Shahi TB, Sitaula C, Neupane A, Guo W. Fruit classification using attention-based MobileNetV2 for industrial applications. Plos one. 2022; 17(2):1-21.

[13] Shukla PK, Sathiya S. Early detection of potato leaf diseases using convolutional neural network with web application. In world conference on applied intelligence and computing 2022 (pp. 277-82). IEEE.

[14] Sitompul P, Okprana H, Prasetio A. Identification of rice plant diseases through leaf image using DenseNet 201. JOMLAI: Journal of Machine Learning and Artificial Intelligence. 2022; 1(2):143-50.

[15] Qin Y, Tang Q, Xin J, Yang C, Zhang Z, Yang X. A Rapid identification technique of moving loads based on MobileNetV2 and transfer learning. Buildings. 2023; 13(2):1-21.

[16] Tiwari D, Ashish M, Gangwar N, Sharma A, Patel S, Bhardwaj S. Potato leaf diseases detection using deep learning. In 4th international conference on intelligent computing and control systems 2020 (pp. 461-6). IEEE.

[17] Kaur S, Pandey S, Goel S. Semi-automatic leaf disease detection and classification system for soybean culture. IET Image Processing. 2018; 12(6):1038-48.

[18] Sthevanie F, Ramadhani KN. Spoofing detection on facial images recognition using LBP and GLCM combination. In journal of physics: conference series 2018 (pp. 1-10). IOP Publishing.

[19] Jana S, Begum AR, Selvaganesan S. Design and analysis of pepper leaf disease detection using deep belief network. European Journal of Molecular & Clinical Medicine. 2020; 7(9):1724-31.

[20] Najafabadi MM, Villanustre F, Khoshgoftaar TM, Seliya N, Wald R, Muharemagic E. Deep learning applications and challenges in big data analytics. Journal of Big Data. 2015; 2(1):1-21.

[21] Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Frontiers in Plant Science. 2016; 7:1-10.

[22] Zhang X, Zhou X, Lin M, Sun J. Shufflenet: an extremely efficient convolutional neural network for mobile devices. In proceedings of the conference on computer vision and pattern recognition 2018 (pp. 6848-56).

[23] Zhang R, Zhou B, Lu C, Ma M. The performance research of the data augmentation method for image

classification. Mathematical Problems in Engineering. 2022; 2022:1-10.
[24] Munadi K, Saddami K, Oktiana M, Roslidar R, Muchtar K, Melinda M, et al. A deep learning method for early detection of diabetic foot using decision fusion and thermal images. Applied Sciences. 2022; 12(15):1-22.
[25] Johnson JM, Khoshgoftaar TM. Survey on deep learning with class imbalance. Journal of Big Data. 2019; 6(1):1-54.
[26] Panda SK, Panda CS. A review on image classification using bag of features approach. International Journal of Computer Sciences and Engineering. 2019; 7(6):538-42.
[27] Gavali P, Banu JS. Deep convolutional neural network for image classification on CUDA platform. In deep learning and parallel computing environment for bioengineering systems 2019 Jan 1 (pp. 99-122). Academic Press.
[28] Pal R, Mittal H, Pandey A, Saraswat M. An efficient bag-of-features for diseased plant identification. Computer Vision and Machine Learning in Agriculture. 2021:159-72.
[29] Singh DA, Leavline EJ, Abirami AK, Dhivya M. Plant disease detection system using bag of visual words. International Journal of Information Technology and Computer Science. 2018; 8(9):57-63.
[30] Setiawan W, Syarief M, Prastiti N. Maize leaf disease image classification using bag of features. Jurnal Infotel. 2019; 11(2):48-54.
[31] Aravind KR, Raja P, Mukesh KV, Aniirudh R, Ashiwin R, Szczepanski C. Disease classification in maize crop using bag of features and multiclass support vector machine. In 2nd international conference on inventive systems and control 2018 (pp. 1191-6). IEEE.
[32] Garg A. Image classification using Resnet50 deep learning model. Analytic Vidhya. 2022; 2(3):31–7.
[33] Pandian JA, Kumar VD, Geman O, Hnatiuc M, Arif M, Kanchanadevi K. Plant disease detection using deep convolutional neural network. Applied Sciences. 2022; 12(14):1-17.
[34] Mukti IZ, Biswas D. Transfer learning based plant diseases detection using ResNet50. In 4th international conference on electrical information and communication technology 2019 (pp. 1-6). IEEE.
[35] Wei SJ, Al Riza DF, Nugroho H. Comparative study on the performance of deep learning implementation in the edge computing: case study on the plant leaf disease identification. Journal of Agriculture and Food Research. 2022; 10:1-7.
[36] Ramkumar MO, Catharin SS, Ramachandran V, Sakthikumar A. Cercospora identification in spinach leaves through resnet-50 based image processing. In journal of physics: conference series 2021 (pp.1-8). IOP Publishing.
[37] Pham TD. A comprehensive study on classification of COVID-19 on computed tomography with pretrained convolutional neural networks. Scientific Reports. 2020; 10(1):1-8.
[38] Bakr M, Abdel-Gaber S, Nasr M, Hazman M. DenseNet based model for plant diseases diagnosis. European Journal of Electrical Engineering and Computer Science. 2022; 6(5):1-9.
[39] Puangsuwan T, Surinta O. Enhancement of plant leaf disease classification based on snapshot ensemble convolutional neural network. ICIC Express Letters. 2021; 15(6):669-80.
[40] Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E. Identification of plant-leaf diseases using CNN and transfer-learning approach. Electronics. 2021; 10(12):1-19.
[41] ÇETİNER H. Classification of apple leaf diseases using the proposed convolution neural network approach. Mühendislik Bilimleri ve Tasarım Dergisi. 2021; 9(4):1130-40.
[42] Krstinić D, Braović M, Šerić L, Božić-Štulić D. Multi-label classifier performance evaluation with confusion matrix. Computer Science & Information Technology. 2020:1-14.
[43] Saito T, Rehmsmeier M. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. PloS one. 2015; 10(3):1-21.
[44] Chen RC, Dewi C, Huang SW, Caraka RE. Selecting critical features for data classification based on machine learning methods. Journal of Big Data. 2020; 7(1):1-26.
[45] Wu J, Chen XY, Zhang H, Xiong LD, Lei H, Deng SH. Hyperparameter optimization for machine learning models based on Bayesian optimization. Journal of Electronic Science and Technology. 2019; 17(1):26-40.
[46] Squara P, Scheeren TW, Aya HD, Bakker J, Cecconi M, Einav S, et al. Metrology part 1: definition of quality criteria. Journal of Clinical Monitoring and Computing. 2021; 35(1):17-25.

Chyntia Jaby Entuni completed her Bachelor's and Master's degrees in Electrical and Electronics Engineering from Universiti Malaysia Sarawak. Currently, she is pursuing her PhD at the same university, with a research focus on Image Processing and Deep Learning.
Email: 22010072@siswa.unimas.my

Tengku Mohd Afendi Zulcaffle received his PhD in Computer Vision from Queen's University Belfast and his Bachelor's Degree in Electronics (Computer) Engineering and Master's degree in Intelligent Systems from Universiti Putra Malaysia. He is currently working as a senior lecturer in the Department of Electrical and Electronics Engineering, Universiti Malaysia Sarawak.
Email:ztmafendi@unimas.my

Kismet Hong Ping received his PhD in Systems Science from Nagasaki University, Master of Science in Digital Communication System from University of Loughborough and Bachelor of Engineering in Electronic Telecomunication Engineering from Universiti Malaysia Sarawak. He is currently working as an Associate Professor in the Department of Electrical and Electronics Engineering, Universiti Malaysia Sarawak.
Email: hpkismet@unimas.my

Appendix I

S. No.	Abbreviation	Description
1	AI	Artificial Intelligence
2	BoF	Bag of Features
3	CNN	Convolutional Neural Network
4	CPU	Central Processing Unit
5	FFNN	Feed-Forward Neural Network
6	GLCM	Gray-level Co-Occurrence Matrix
7	LBP	Local Binary Pattern
8	L2	Layer 2
9	MFLOP	Machine Learning Operation
10	ML	Machine Learning
11	RAM	Random Access Memory
12	RBM	Restricted Boltzmann Machine
13	SGDM	Stochastic Incline Ancestry
14	SVM	Support Vector Machine
15	UCI	University of California Irvine
16	VGG	Visual Geometry Group