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SMART AGRICULTURAL MONITORING SOLUTION FOR CHILLI LEAF DISEASES USING A LOW-COST KINECT CAMERA AND AN IMPROVED CNN ALGORITHM

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Graphical abstract

Abstract

Chilli is extensively grown all over the globe and is particularly important as a food. One of the most difficult issues confronting chilli cultivation is the requirement for accurate identification of leaf diseases. Leaf diseases have a negative impact on chilli production quality, resulting in significant losses for farmers. Numerous Machine Learning (ML) and Convolutional Neural Network (CNN) models have been developed for classifying chilli leaf diseases under uniform background and uncomplicated leaf conditions, with an average classification accuracy achieved. However, a diseased leaf usually grows alongside a cluster of other leaves, making it difficult to classify the disease. It will be easier for farmers if there is a reliable model that can classify a chilli leaf disease in a cluster of leaves. The aim of this study was to propose a model for classifying chilli leaf disease from both a uniform background and a complex cluster of leaves. Images of diseased chilli leaves are acquired using a low-cost Kinect camera, which include discoloration, grey spots, and leaf curling. The different types of chilli leaf disease are then classified using an improved ShuffleNet CNN model. With a classification accuracy of 99.82%, the proposed model outperformed the other existing models.

Keywords: Chilli, leaf disease, Machine Learning, Convolutional Neural Network, ShuffleNet

Abstrak

Cili ditanam secara meluas di seluruh dunia dan amat penting sebagai makanan. Salah satu isu paling sukar yang dihadapi dalam penanaman cili adalah keperluan untuk mengenal pasti penyakit daun dengan tepat. Penyakit daun memberi kesan negatif terhadap kualiti pengeluaran cili sehingga mengakibatkan kerugian yang ketara kepada petani. Terdapat banyak model Machine Learning (ML) dan Convolutional Neural Network (CNN) telah dibangunkan untuk mengklasifikasikan penyakit daun cili dari latar belakang gambar yang seragam dan dalam keadaan daun yang tidak rumit, dengan ketepatan pengelasan sederhana dicapai. Walau bagaimanapun, daun yang berpenyakit biasanya tumbuh bersama gugusan daun lain, menjadikannya sukar untuk mengklasifikasikan penyakit. Adalah lebih mudah bagi petani jika terdapat model yang boleh dipercayai yang boleh mengklasifikasikan penyakit daun cili dalam kelompok daun lain. Matlamat kajian ini adalah untuk mencadangkan model bagi mengklasifikasikan penyakit daun cili dari gambar yang berlatarbelakang seragam dan gambar dari kelompok daun yang kompleks. Imej daun cili berpenyakit diperoleh menggunakan kamera Kinect kos rendah, yang merangkumi penyakit daun kuning, bintik kelabu dan daun bergulung. Jenis penyakit daun cili tersebut kemudiannya dikelaskan menggunakan model ShuffleNet CNN yang ditambahbaik. Dengan ketepatan klasifikasi 99.82%, model yang dicadangkan mengatasi model sedia ada yang lain.

Kata kunci: Cili, penyakit daun, Machine Learning, Convolutional Neural Network, ShuffleNet

1.0 INTRODUCTION

Chilli has been deeply ingrained in the culture of Asians, Southeast Asians, Indians, Malaysians, and Indonesians and has even become an inseparable component of the local diet in a variety of cuisines, in addition to being used for medicinal purposes [1]. According to Wei (2022) [2], the demand for high-quality chilli in China 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.

While in India, Chand *et al*. (2021) [3] stated that chilli consumption is increasing due to increased demand from urban consumers; exports are also in high demand, but supply is limited due to low crop productivity. According to Jadon *et al*. (2016) [4], this depleted output is typically caused by chilli contagion with diseases caused by moulds, microbes, germs, and mycoplasmas, which drastically reduce possible harvests. Common leaf diseases in chilli are leaf spot according to Jain *et al*. (2019) [5], rapid discolouration according to Hami *et al*. (2021) [6], mosaic and leaf curl as stated by Khan *et al*. (2020) [7].

Chilli leaf spot symptoms are primarily circular lesions with a white centre that resemble frog eyes. The leaf spot's centre frequently falls out, resulting in small holes [8]. Discoloration is distinguished by an unusual yellowing of the leaf, which begins at the tips and progresses to the lower leaf. The oldest chilli leaf will typically turn yellow first, followed by the remaining leaves turning light green [9]. Leaf curling, on the other hand, occurs when the leaf fails to develop normally and begins to curl or fluff. This may be accompanied by brown spots on the leaf [10]. Chilli leaf spots, discoloration, and leaf curling captured through the Kinect camera are depicted in Figures 1, 2, and 3.

Figure 1 Chilli leaf spots

Figure 2 Chilli discolour leaf

Figure 3 Chilli leaf curling

In order to reduce farmer losses, several methods for classifying chilli leaf disease have been developed. However, based on the developed model's accuracy percentage, existing models for classifying chilli leaf diseases perform moderately well [11], as explained in the next paragraph. Furthermore, existing models can only classify chilli leaf disease using leaves picked from the tree and placed on a uniform background colour. The process of segmentation and classification of chilli leaf disease is simplified but ineffective using these existing models. In contrast to a complex background, which includes multiple elements like other leaves and the surrounding environment, a uniform background refers to a background that is consistent in colour or texture throughout an image of a chilli.

Among the models that are often used to classify plant leaf diseases is Convolutional 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 and DenseNet. The most recent CNN architectures are DenseNet and ShuffleNet, both developed in 2017. According to Khan *et al*. (2019) [12], in the majority of cases, the performance of CNN models has gradually improved over time.

Many models based on Machine Learning (ML) and Convolutional Neural Networks (CNN) have been developed around the world to classify various types of diseases on plant leaves, as Alzubaidi *et al*. (2021) [13] mention.

Rangarajan *et al*. 2021 [14] used a machine learning Support Vector Machine (SVM) to identify eggplant (*Solanum melongena*) leaf images. *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 gotten from a mobile phone camera (the 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 finalized by detaching the terrain exterior and some superfluous peculiar 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%.

Shahi *et al*. 2022 [15] classified tomato leaf diseases using a deep learning transfer learning AlexNet. 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 partaken 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%.

Wu *et al*. (2022) [16] classified woody fruit plant leaf diseases using deep learning of an improved ResNe101. To condense model training parameters, a universal average pooling layer is employed; layer stabilization, dropout, and L2 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 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 Chung *et al*. (2019) [17]. Individually component in the primary remaining lump duplicates the sum of channel layers of the former 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%.

Kothari *et al*. (2022) [18] used GoogleNet deep learning to classify potato leaf diseases. A PlantVillage 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%.

Sitompul *et al*. (2022) [19] used DenseNet201 to classify rice leaf diseases. The dataset, titled Rice Leaf, is obtained from the UCI Machine Learning 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%.

While Mohanty *et al*. (2016) [20] used existing CNN models, AlexNet and GoogleNet to classify plant leaf diseases of apple, cherry, blueberry, corn, grape, orange, peach, bell paper, potato, raspberry, soybean, squash, strawberry and tomato. 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.

In reality, however, diseased leaves grow in clusters with other leaves, making classification difficult due to the difficulty of distinguishing between the healthy leaf part, the unhealthy leaf part, and the complex background. There is currently no model for distinguishing chilli leaf disease from a complex leaf cluster. Farmers will benefit from a model that can classify chilli leaf disease from a complex background because they will only need to take photos 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 5 compare a chilli leaf with a uniform background to a chilli leaf with a complex cluster of leaves taken using Kinect camera.

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 [12–20]. 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

Because of its low-cost depth mapping sensor, the Kinect camera, a new controller-free gaming device used in the Xbox 360 console, has been widely used in a variety of applications [21]. The Kinect camera has a 640 × 480 32-bit RGB colour camera and a 320*240 16-bit depth camera both running at 30 frames per second. The field of view (FOV) of cameras are 57° horizontally and 43° vertically. It features a motorised angle driver that can tile both cameras 27° vertically. The Kinect camera can extract image information using an active time-of-flight technique (TOF). The majority of cameras capture light in the red, green, and blue wavelength ranges (RGB). The primary distinction is that a 3D TOF camera illuminates the entire prospect, provides image depth information, has a larger field of view, and a higher sensor resolution [22].

2.0 METHODOLOGY

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.

As stated by Hellin *et al.* (2020) [23], 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. ShuffleNet supports more feature map channels, allowing for more information to be encoded and is especially important for very small network performance [24]. In terms of configuration, the ShuffleNet architecture has 50 layers and the subsequent pointwise group convolution's purpose is to recuperate the channel breadth to match the crosscut path [25]. 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 output group channels that simultaneously 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 MFLOPs). The network can be freely customised to the desired level of complexity. Merely exploit 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 machineries in the ShuffleNet unit can be calculated efficiently because of the pointwise group convolution with channel shuffle layers.

The dataset images of diseased chilli leaf comprising of leaf spots, discolour leaf and leaf curling are acquired employing a Kinect camera with both the 640*480 32-bit RGB colour camera and the 320*240 16-bit depth camera operate at 30 frames per second.

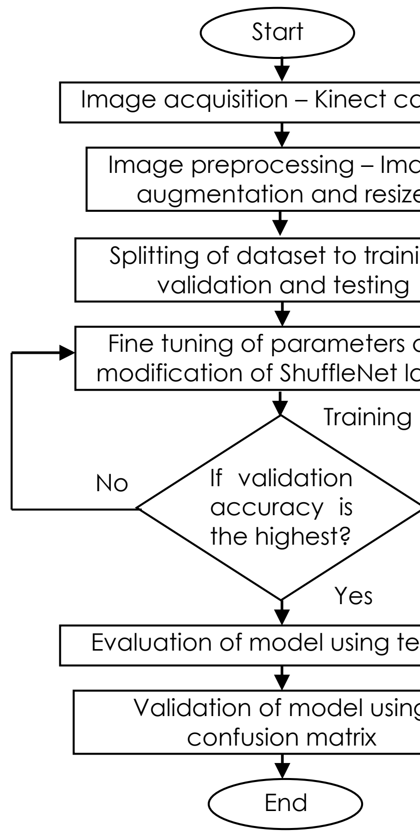


Figure 6 Flowchart of identification of *Capsicum*leaf diseases using an improved ShuffleNet model

The diseased chilli leaf images are captured under two conditions which are uniform background and complex background. For uniform background, there are 96 images for leaf spot, 80 images for discolour leaf, and 75 images for leaf curling. While for complex background, there are 100 images for discolour leaf, 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 specifications of Intel® Core™ i3-CPU microprocessor, 1.90GHz clock speed and 6.00GB RAM. Figure 7 shows the set-up of the experimentation.

Figure 7 Experimentation set-up

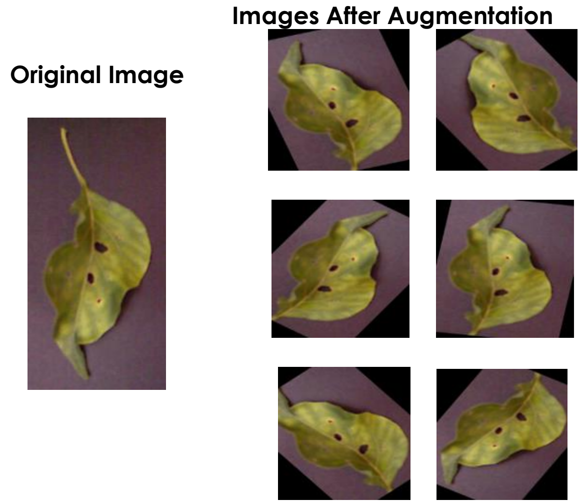


Figure 8 Random reflection technique

Before the diseased chilli leaf images are utilized by model training and inference, and to enhance the images quality so that they can be more effectively analyzed, the images are pre-processed using two techniques which are image augmentation and resize. Figure 8 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.

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 convolutional neural networks as mentioned by Zhang *et al*. (2012) [26]. 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 according to Munadi *et al*. (2022) [27], and hence all images after augmentation are resized to 224×224×3. In this study, the network of ShuffleNet is trained on 70% of the data and validated on 15% of the data. The remaining 15% is allocated to testing. The imageDatastore is alienated into training, validation, and testing sets using the splitEachLabel function. The entire amount of diseased chilli leaf images has been amplified to 3,510 as a result of image augmentation.

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 chilli 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 chilli leaf for classification. 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 1.

Table 1 Hyperparameter structure

Hyperparameter	Value
Initial learn rate	0.01
Maximum epoch	5
Minibatch size	64
Validation frequency	10 iterations
Optimizer	Stochastic gradient descent with momentum (SGDM)
Execution environment	'auto'
Validation iterations	205

To obtain the best validated model, several trials and errors of fine-tuning parameters and ShuffleNet layers are performed in order to bargain the ideal values that provide the finest possible performance. When the programme converges (stops changing), the trial-and-error process is set to end. After determining the optimal fine-tuning parameters and ShuffleNet layers, the validation model is used to test the proposed model's accuracy in classifying chilli leaf diseases 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.

3.0 RESULTS AND DISCUSSION

The proposed ShuffleNet model for classifying chilli leaf diseases is proficient exploiting a training dataset with 205 iterations of validation. Figure 9 shows the training evolution along amid the minibatch accuracy as well as loss value of the proposed model.

The validation dataset's preliminary accuracy prior to training with the pre-trained topographies is in the 20% to 30% range. Although the value is small, it indicates that certain of the rudimentary topographies obligatory for analysis have already been cultured, which subsidized significantly to the preliminary classification outcome. However, fascinatingly later 205 iterations in the first epoch, the validation accuracy reached about 90%. The finishing validation accuracy gotten at the end of five epochs is 99.82%. The full performance of the proposed improved ShuffleNet model is tabularized in Table 2 and the confusion matrix is depicts in Figure 10.

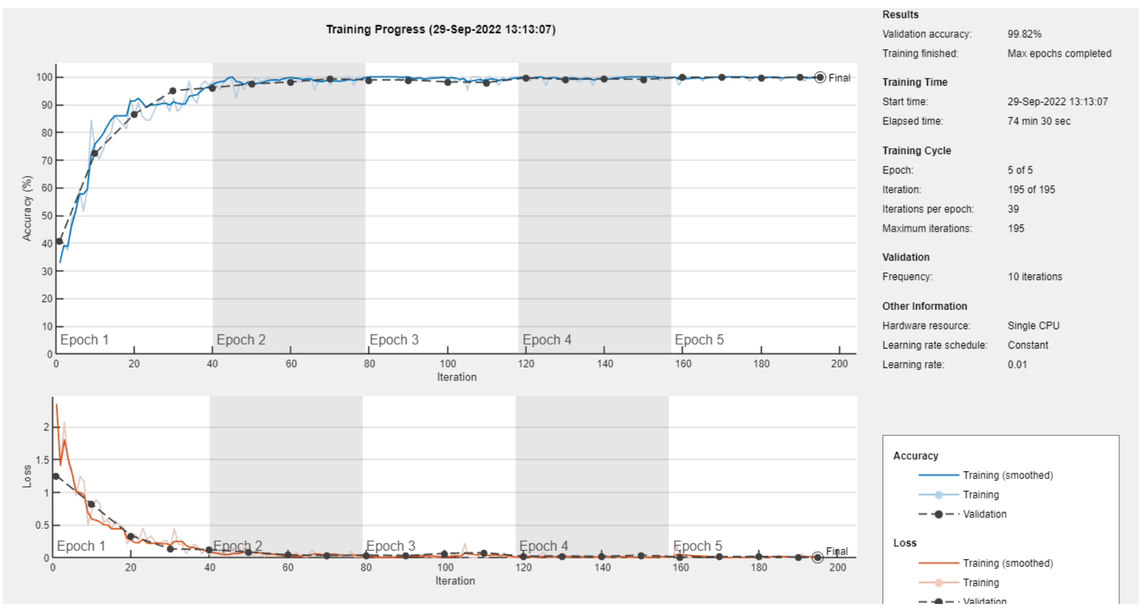


Figure 9 Training progress of the proposed ShuffleNet model

Table 2 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	TP/(TP+FN)×100%	TN/(TN+FP)×100%	TP/(FP+TP)×100%	TN/(FN+TN)×100%	FN/(FN+TP)×100%	FP/(FP+TN)×100%	FN/(FN+TN)×100%	2×(Precision×Recall)/(Precision+Recall)×100%
	85.6	100	100	92.8	14.4	0	7.2	92.24

Figure 10 Confusion matrix of proposed ShuffleNet model

An 85.6% sensitive test means that nearly all diseased entities are appropriately acknowledged as diseased, that is there are only insufficient false negatives. Most prominently, because the calculation comprises all chilli leaves with the disease, it is shown that the proposed ShuffleNet model is less intermittent by disease's occurrence.

While a test that is 100% specific means all healthy parts of the chilli leaf are appropriately recognized as healthy, that is there are no false positives. A flawlessly specific test means that no healthy parts of the chilli are recognized as diseased.

In addition, as shown in Table 2, the valuation is supported ready exploiting recital metrics appraised after 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 tabularized. While the accuracy of the proposed ShuffleNet identified through the model itself is displays in Figure 10.

From Table 2, with a precision of 100%, it demonstrates that the proposed model produces no false positives. It demonstrates that there are zero negative events (uninfected parts) that are incorrectly classified as positive (false positives/predicted as infected parts) and zero actual negative events (notwithstanding of classification).

The high negative predictive value (92.8%) indicates that the proportion of cases giving negative test results classifying uninfected leaf parts is high. It is the ratio of subjects that are actually found to be negative to all leaves that had a negative test result (including leaves containing one of the uninfected parts).

The high negative predictive value achieved also indicates that this proposed model is an effective screening program. This is due to the fact that the program already applies the concept that the extra sensitive a test, the less probable an individual leaf with a negative test (uninfected part) will have the disease, and thus the higher the negative predictive value.

The low miss rate (14.4%) denotes that the percentage of data requested that does not reside in the cache is small. This means that the programme is efficient because the percentage of data that must be retrieved from the main memory every time the program is run, is small.

The 0% fall out produced reveals that there is no disagreement occurred in the programme when the uninfected part of the chilli leaf is predicted. It means that none of the observed negative (uninfected part) values are predicted incorrectly (positive/predicted as infected part) by the model.

The low false omission rate (7.2%) shows that the ratio of the number of individuals chilli leaf with a negative predicted (uninfected part) value for which the true label is positive (positive/predicted as infected part) by the model is low. It explains that the pervasiveness of the proposed model is prominent as the false negatives among all negative transactions are greatly penetrated.

The 92.24% F1 score indicates that this proposed model that is used for classifying class of chilli leaf diseases which are imbalanced, has a good arithmetic mean of precision and recall. This signifies that the proposed model has minor false positives and small false negatives, so it is appropriately classifying real threats and is not troubled by false alarms where a test result inaccurately designates the incidence of a condition, such as a disease when it is not existing.

Calculated from Figure 8, the proposed model of ShuffleNet has True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) of 200, 368, 0 and 0, respectively. So, the assessed sensitivity as well as specificity of the proposed ShuffleNet are both 100% as calculated in the Equation (1) and (2).

In addition, Figure 11 shows the result for uniform background and Table 3 displays some of the results of classification of chilli leaf disease from a complex cluster of leaves using an improved ShuffleNet model. Effectively, the proposed model correctly classified all 142 diseased chilli leaf images used in the experimentation of the complex background case.

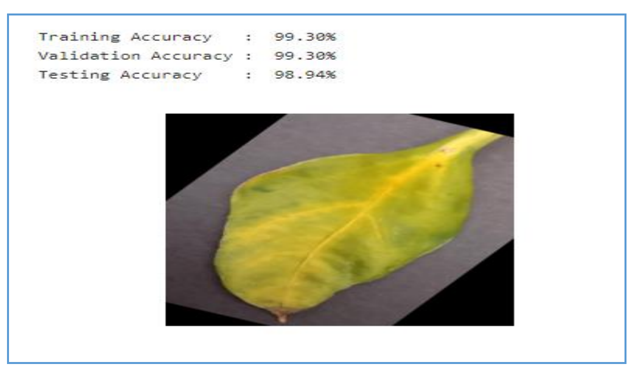
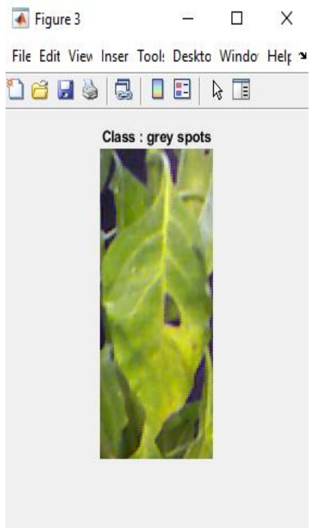
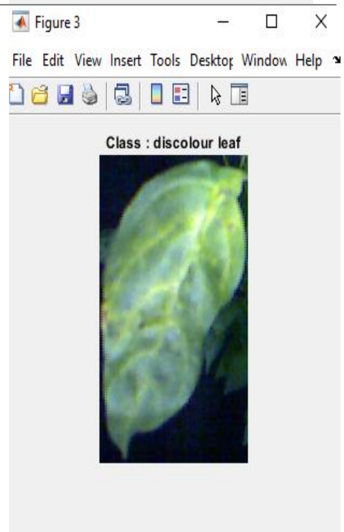
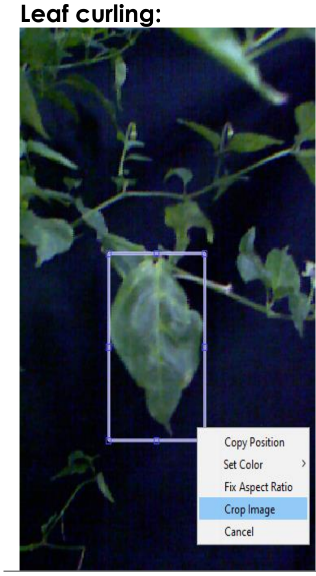
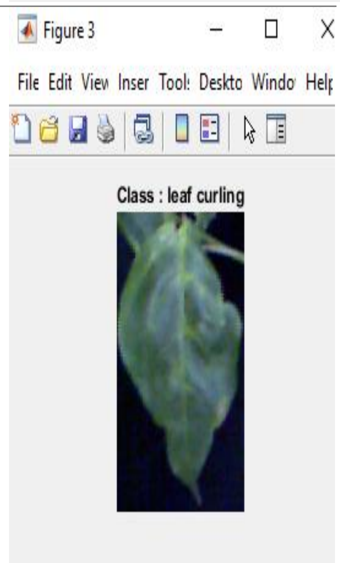


Figure 11 Classification of chilli leaf disease from a uniform background using an improved ShuffleNet model

Table 3 Classification of chilli leaf disease from a complex cluster of leaves using an improved ShuffleNet model

Disease		Classification result
Grey spots: 		
Discolour leaf: 		
Leaf curling: 		

To strengthen this study, the proposed model's performance in term of accuracy of classification is compared to that of the existing models, and the results are shown in Figure 12. While comparison in term of precision is shown in Figure 13.

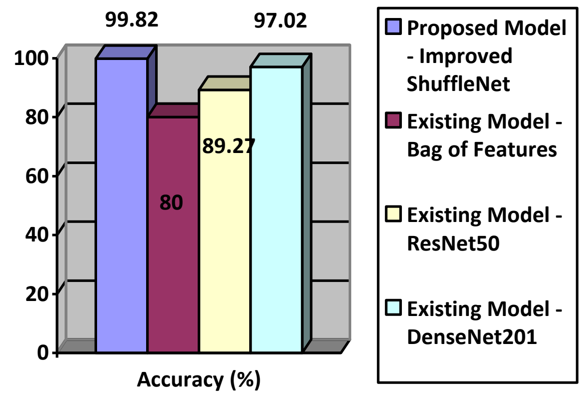


Figure 12 Comparison accuracy of classification of the proposed model and the existing models

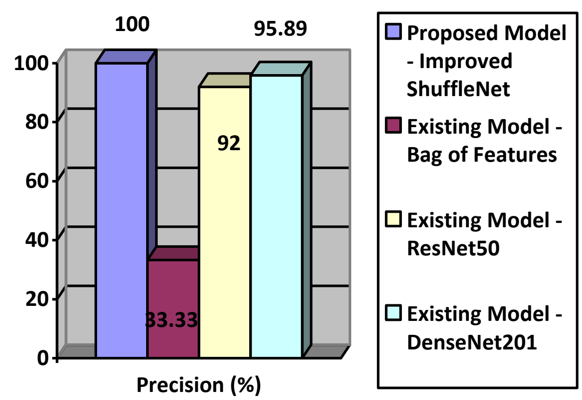


Figure 13 Comparison precision of classification of the proposed model and the existing models

As shown by Figure 13, the proposed ShuffleNet model has the uppermost precision of 100% once equated to the existing models of Bag of Features (33.33%), ResNet50 (92%), and DenseNet201 (95.89%). As a result, in this study, the infected part of the leaf that we correctly classify as having diseases according to their type out of all the leaf that actually has it is 100%, which means that when it predicts that a leaf has a grey spot, discolour leaf, and leaf curling disease, it will almost always correct. With these great relevant data points from the proposed model, it is confirmed that the model is not simply treating the new set of chilli leaf, which does not have a disease but predicted to have it. Squara *et al*. (2021) [28] states that accuracy is the degree to which a measurement is close to its true value, whereas precision is the degree to which repeated measurements for new data under the same conditions are accurate. So, the proposed model is assumed to be reliable for resolving the other objective of this study, which is to classify the new data of diseased chilli leaf from the complex cluster of leaf that represents the real-world condition.

4.0 CONCLUSION

With a classification accuracy of 99.82%, the proposed ShuffleNet model outperformed other existing models in classifying chilli leaf diseases. Other than that, the proposed model is also able to classify the diseased images of chilli from a dissimilar set of environments, which is the real-world condition where the diseased leaf is obtained along with other cluster of leaves where classification of diseases is arduous.

In the future, additional plant varieties and plant diseases of various types may be added to the existing dataset to improve the trained models. In this study, the proposed ShuffleNet model has a precision of 100%, a recall of 85.6%, and an F1 score of 92.24%. Hence, other CNN models may use diverse learning rates and optimizers to test the model's performance and accuracy in order to attain a higher recall and F1 score value.

Aside from that, while the real-world case is experimented in this study, it does not take into account any other factor, such as when the images are taken in inclement weather, such as rain, or in a dark environment. Therefore, when developing their model, the new model should consider other factors such as weather condition and light intensity of the environment because images taken in good weather, bad weather, high light intensity, and low light intensity are not the same and will affect the performance of the classifier.

In addition, time taken is also crucial to be considered to act as a benchmark to hasten the development of new models and to allocate the computational resources more effectively.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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