Original Research Article

Efficacy of Deep Learning Algorithm in Classifying Chilli Plant Growth Stages

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Abstract: Automatic plant growth monitoring has received considerable attention in recent years. The demand in this field has created various opportunities, especially for automatic classification using deep learning methods. In this paper, the efficiency of deep learning algorithms in classifying the growth stage of chili plants is studied. Chili is one of the high cash value crops, and automatic identification of chili plant growth stages is essential for crop productivity. Nevertheless, the study on automatic chili plant growth stage classification using deep learning approaches is not widely explored, and this is due to the unavailability of public datasets on the chili plant growth stages. Various deep learning methods, namely Inception V3, ResNet50, and VGG16, were used in the study, and the results have shown that these methods performed well in terms of accuracy and stability when tested on a dataset that consists of 2,320 images of *Capsicum annum* 'Bird's Eye' plants of various growth stages and imaging conditions. Nevertheless, the results have also shown that the deep learning methods have difficulty classifying images with a complex background where more than one chili plant was captured in an image.

1. Introduction

Chili or scientifically known as *Capsicum annum* is one of high cash crops values in Malaysia (Yusuf *et al*., 2016), and it has been recognized as among the top tenth of self-sufficiency ratio (SSR) with the highest import dependency ratio (IDR) of 73.6%

(Department of Statistics Malaysia, 2020). *Capsicum annum* 'Bird's Eye' and *Capsicum annum* 'Red' are among Malaysia's widely domesticated planted chili (Norfadzilah, 2018). Chili plants grow upright with green stem branches, and the leaves have a variety of colors, from light green to dark green (Suhaimi *et al.*, 2016).   According to Haifa Group (2021), the growth stage of chili plants can be classified into four stages; the first stage is the stage of vegetative growth that is from planting or seeding to the first flowering. The second stage is the period from flowering to fruit set, and the third stage is from fruit ripening to the first harvest. The last stage is the period from the first harvest to the last harvest. The duration of each stage may vary according to the growing method, characteristics of chili variety, and climatic conditions (Haifa Group, 2021). The growth stage of chili plants is typically measured manually, as discussed by Sharma & Kumar (2017). The manual way of identifying growth stages is inconsistent because the human factor and the process are time-consuming (Kim *et al.*, 2013). Nevertheless, the manual process still needs to be performed due to the requirement of different amounts of fertilizer and water for each growth stage, which is necessary for optimizing crop yields (Wayne, 2021).

In recent years, the automatic classification of the growth stage of plants using computer vision technology has received significant attention. This is because automatic plant growth classification or prediction is essential for analyzing growth patterns to aid the acceleration of plant cycles, the prediction of phenotypic traits, and the efficient execution of experiments (Yasrab *et al.*, 2021). The classical computer vision approaches are based on conventional image segmentation or structural analysis. The aim is to find the region of interest or structure analysis based on lines, curves, pixel intensities, and differentials (Spalding & Miller, 2013). The examples of the classical approaches are optimal thresholding and probability distribution methods (Otsu, 1979; Bouman & Shapiro, 1994) and machine learning approaches (Othman *et al.*, 2010; Yu *et al.*, 2011). The plant growth prediction using machine learning approaches has received significant attention in macroscopic phenotypes studies (Li *et al.*, 2020; Keller *et al.*, 2018; Mochida *et al.*, 2018; Van Dijk *et al.*, 2021). Even so, the problem of achieving high accuracy is still the main issue. This is mainly due to complex backgrounds, various illumination effects, and image sizes (Anugraheni *et al.*, 2019).

Furthermore, the best approach to extract distinguishable plant features that can produce high classification accuracy remains unestablished (Hao *et al.*, 2020). The same situation for the study of chili plant growth classification using machine learning. For

example, Suroso *et al.* (2016) showed that artificial neural networks and image processing methods could predict the required amount of water and fertilizer based on the plant image parameters. However, the result was only based on three stages of growth, and the used images were captured under a controlled environment (Soethe *et al.*, 2016).

Advance in data acquisition technology has created enormous opportunities to develop highly accurate and efficient classifiers such as deep learning classifiers. Deep learning refers to artificial neural network architectures with a significantly large number of layers of processing that can be easily adapted to changing environments (Learning & Rai, 2021). There are four categories of deep learning methods, namely Convolutional Neural Networks (CNNs), Restricted Boltzmann Machines (RBMs), Autoencoder, and Sparse Coding (Guo *et al.*, 2016). Among all the methods, Convolutional Neural Networks (CNNs) have been popularly used. A CNN consists of three main neural layers: convolutional layers, pooling layers, and fully connected layers. As discussed by Guo et al. (2016), there are many variations of the CNN methods, where the difference is basically in terms of the total number of convolutional layers. The CNN classifiers have demonstrated exceptional accuracy and precision in many agriculture applications (Khanramaki *et al.*, 2021; Alhnaity *et al.*, 2020; Ayan *et al.*, 2020; Chouhan *et al.*, 2019; Ferentinos, 2018; Habiba *et al.*, 2019), including in the field of plant phenotyping (Fuentes *et al.*, 2019; Wang *et al.*, 2019; Subetha *et al.*, 2021).

Plant phenotyping is defined as assessing complex plant traits growth, resistance, architecture, physiology, and ecology by Li *et al.* (2015). Several works on plant phenotypes prediction based on spatial and temporal features of plant growth have been reported (Namin *et al.*, 2018; Sakurai *et al.*, 2019). Namin *et al.* (2018) reported that a combination of a multi-model Convolutional Neural Network with Long Short-Term Memory (LSTM) approaches offers exceptional accuracy for plant phenotypes and genotypes prediction, which is helpful in the automation of plant production and care. Sakurai *et al.* (2019) studied the performance of LSTMs with an encoder-decoder model for predicting the growth of plant leaves, where they found that this approach has limited capabilities for several data sets. Nevertheless, the study on the prediction of chili growth stages using deep learning has yet to be explored. The studies related to chili plants classify nutrient deficiency and quality (Bahtiar *et al.*, 2020; Sudianto *et al.*, 2020). Moreover, automatic classification of chili plants' growth stage using the images captured with a complex background and under various imaging conditions such as different scales, various illuminations, and angles has not yet been studied. Inspired by this fact, the efficiency of high-performance CNN algorithms, which are EfficientNet,

VGG16, ResNet50, and InceptionV3, in classifying the stages of chili plant growth from the images with various imaging conditions is studied

This paper is organized as follows. Section 2 describes the dataset used in the experiment that consists of chili growth images under an uncontrolled environment, followed by the explanations on VGG, ResNet50, InceptionV3, and EfficientNet architectures in Section 3. Section 4 presents the result and discussion of this study and conclusions in Section 5.

2. Materials and Methods

2.1 Chilli Plant Growth Dataset

This study's chili plant growth dataset consists of 2,320 images of *Capsicum annum* 'Bird's Eye' plants. The images were captured at all growth stages, ranging from seedling to harvesting stages, as described in Table 1. The images were collected every week under an uncontrolled environment and various image acquisition parameters, as in Table 2, to reflect the real-life scenarios. These images were captured in an open space in Kuantan, Malaysia, using the Samsung Galaxy S10 Plus. The phone consists of triple cameras with a 12-megapixel 12 mm wide-angle rear lens, a 12-megapixel telephoto lens, and a 16-megapixel ultrawide lens. The dimension of the produced images is 3024 x 4032 pixels. The parameters considered during image acquisition to create challenges for the classifiers are summarized in Table 2. These parameters are based on the situations when capturing the images in real-life scenarios.

Table 1. Chili growth stages (Majlis Ilmu, Kerajaan Negara Brunei Darussalam, 2018)

Growth Stage	Days
Seedling and transplanting	0–30
Vegetative	31–62
Flowering	57–92
Fruiting	88–120

Table 2. Summary of the image acquisition parameters.

Parameters	Description
Various distances	The distances of the camera facing the leaf range from 30 cm to 50 cm.
Various views	Three types of views were considered, namely top, side, and front views.
Various illuminations	The images were captured in the morning (8 AM to 9 AM) and afternoon (12 PM to 1 PM).

Figure 1. Some examples of the chili plant images used in the experiment.

Chili plant images under extreme exposure, namely underexposed and overexposed, with a complex background, were also considered. The underexposed and overexposed effects are due to the various illumination effects in the morning and afternoon, which are influenced by various weather conditions during the 22 weeks of the data collection. Image acquisition settings were not changed during image acquisition. These images were captured from the chili plants in a rain shelter at the Faculty of Engineering, Universiti Putra Malaysia, as shown in Figure 2. The total number of images is 480.

Figure 2. Some examples of images under extreme exposure.

2.2 Experimental Setup

In the experiments, the performance of the selected deep learning algorithms in classifying the chili plant growth stages was compared. All the algorithms were trained and

tested using the images from the developed dataset with a distribution of 80% and 20%, respectively. Hence, the total number of images used for training and testing for the images collected in Kuantan are 1,952 images and 488 images, respectively. The classification of the growth stage of chili plants is based on the weekly growth stages, which is based on the weekly data collection. As the data were collected for 22 weeks, 22 classes were used in the experiments, ranging from seeding to harvest.

The experiments were executed using Python in a Jupyter notebook environment, running on Intel ® Core™ i5-5200U processor with a Turbo Core Technology Up to 2.7GHz and 8GB DDR3L RAM. Adam optimizer was also used to reduce loss due to inappropriate selection of learning rate and weights in the algorithm. According to Kingma *et al.* (2014), this optimizer is computationally efficient and well suited for significant problems in terms of data or parameters. The images used for training and testing were resized to 128×128 pixels, and these images were selected randomly by python software. The selection of the input image size is based on the recommendation by Habiba *et al.* (2020) and Sujatha *et al.* (2021). The small image size should be used for optimizing classifier performance. Other than that, the batch size, which is the number of samples to be processed, is set to 32, and the total number of epochs that is the total number of iterations, is set to 10.

2.3 Deep Learning Algorithm Architectures

According to Chouhan et al. (2019), deep learning is a subset of machine learning. The architecture consists of many processing layers and optimizers that are suitable for efficiently classifying complex problems (Sujatha *et al.*, 2021; Ferentinos, 2018). Alhnaity *et al.* (2020) claimed that the complex models employed in deep learning could improve classification accuracy and reduce regression problems. In this study, the efficiency of four widely used deep learning algorithms, namely VGG16, ResNet50, Inception V3, and EffcientNet algorithms, in classifying the growth stage of chili plants is compared. The architectures of the selected deep learning algorithms are explained in the following subsections.

2.3.1 VGG16

Simonyan and Zisserman developed visual Geometry Group 16 or VGG16 (2015). This algorithm achieved 71.3% in the top five accuracy category and 90.1% in the top one accuracy when tested using the ImageNet dataset. The algorithm has shown good performance when classifying leaves or plants (Habiba *et al.*, 2019; Rangarajan &

Purushothaman, 2020). The algorithm consists of 16 layers that combine 13 convolutional layers, five top pooling layers between the convolutional layers, and three fully connected layers (FC). In the convolutional layers, various feature maps are generated through the convolution of images using various kernels. The pooling layer is used to reduce the dimensions of feature maps and network parameters. A rectified linear activation function (ReLU) in the architecture is applied to the first two FC layers. This is because the function allows faster learning and decreases the likelihood of vanishing gradient problems. At the final FC layer, a softmax function is used to normalize the classification vector. The VGG model processes the input image and outputs as a vector of thousands of values. The vector represents the probability of classification for the corresponding class. Figure 3 shows the architecture of VGG16.
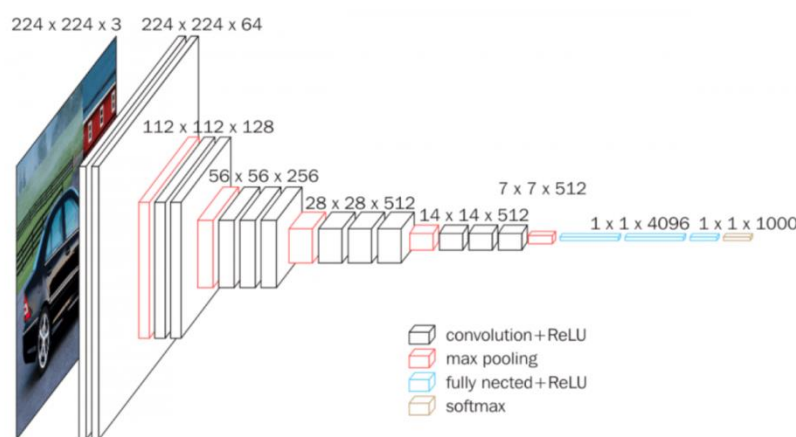

Figure 3. VGG16 Architecture (Zhang *et al.*, 2016)

2.3.2 ResNet50

ResNet or Residual Network was introduced in 2015 by He *et al.* (2016), and the algorithm has shown exceptional performance when classifying the ImageNet dataset. The algorithm consists of a combination of 50 layers deep of convolutional block and identity block, in which each block has three convolutional layers. ResNet utilizes the skip connection concept that allows the algorithm to learn an identity function that would enable the higher layer to perform well as the lower layer. Figure 4 shows the architecture of ResNet50.
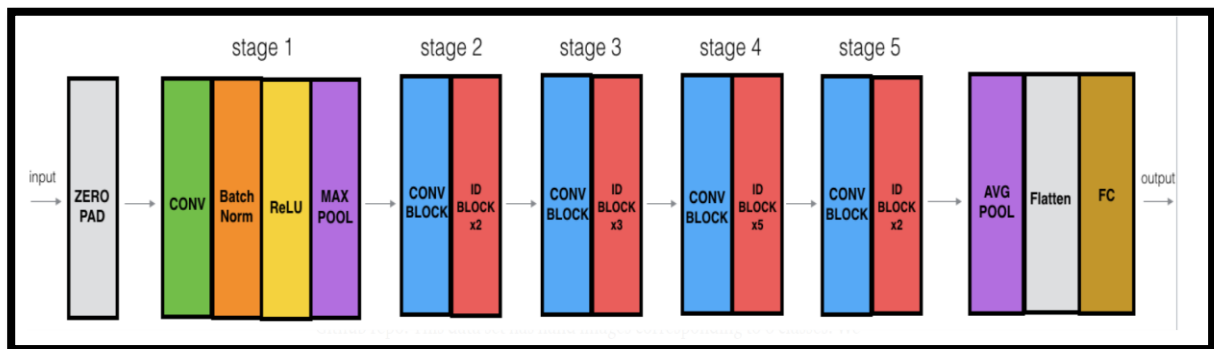
Figure 4. ResNet50 Architecture (Peng *et al*., 2019)

2.3.3 Inception V3

Inception V3 is a convolutional neural network (CNN) architecture from the Inception model that consists of 48 layers (Sujatha *et al*., 2021). The algorithm has some advanced features, such as factorized convolutions, and it can lower the number of computational complexities because of the efficient grid size reduction (Ayan *et al*., 2020). Inception architecture uses an image model block to approximate an optimal local sparse structure in a CNN that allows for more effective computation. The applied dimensionality reduction has made the algorithm more efficient. The Inception V3 has also proven to significantly reduce the number of parameters and computational complexity with efficient grid size reduction. Figure 5 shows the architecture of Inception V3.
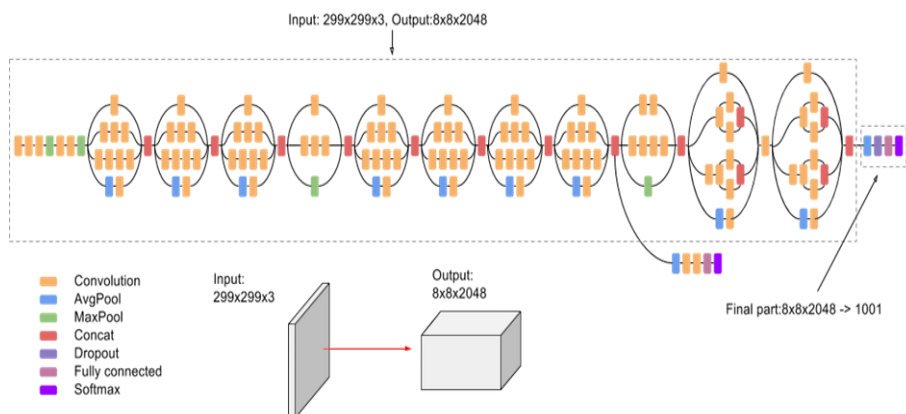

Figure 5. Inception V3 Architecture (Szegedy *et al*., 2015)

2.3.4 EfficientNet

EffcientNet was developed based on model scaling, in which the algorithm uses compound scaling to rescale depth, width, and image resolution. The algorithm has seven versions, and all the versions utilize Inverted Residual Blocks or MBConv Block, where a

single convolutional filter is applied to each input channel for better efficiency (Tan & Le, 2019; Sandler *et al*., 2018). In this experiment, only the first three versions of EfficientNet algorithms were considered: EfficientNet B0, EfficientNet B1, and EfficientNet B2. Figure 6 shows the basic version, which is EfficientNet B0. Each version is upgraded in terms of increasing the number of Module 3 and different repetition patterns. According to Tan & Le (2019), EfficientNet algorithms have also shown good performance when classifying images from ImageNet. Inspired by this finding, the performance of the EfficientNet algorithm in classifying chili plant growth stages under uncontrolled conditions is investigated. This is to see how well the baseline and the advanced architectures classify complex images.
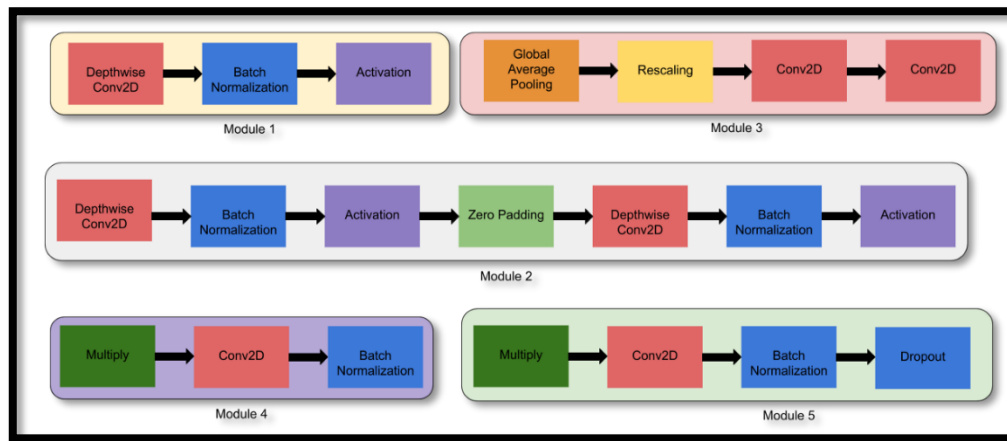

Figure 6. Efficient Net B0 architecture.

3. Results and Discussions

The performance of the selected deep learning algorithms was evaluated based on the accuracy and loss, as in equation (1) and equation (2). The accuracy is the number of correctly identified samples during the cross-entropy loss between actual and predicted data.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Loss} = \sum_{j=1}^{K} n_j \log(P_j) \tag{2}$$

TP, TN, FP, and FN are genuinely positive, true negative, false positive, and false negative, respectively. The training and validation accuracy and loss produced by the VGG16, ResNet50, InceptionV3, and EfficientNet algorithms are illustrated in Figure 7 until Figure 10.
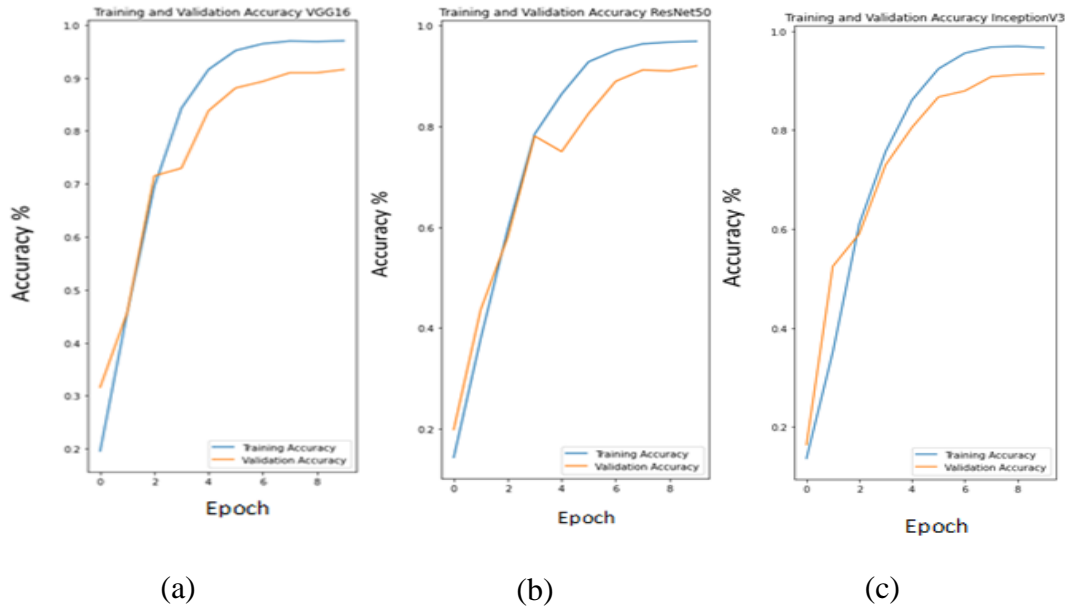
(a)   (b)   (c)

Figure 7. Training and validation accuracies produced by (a) VGG16, (b) ResNet50, and (c) Inception V3.

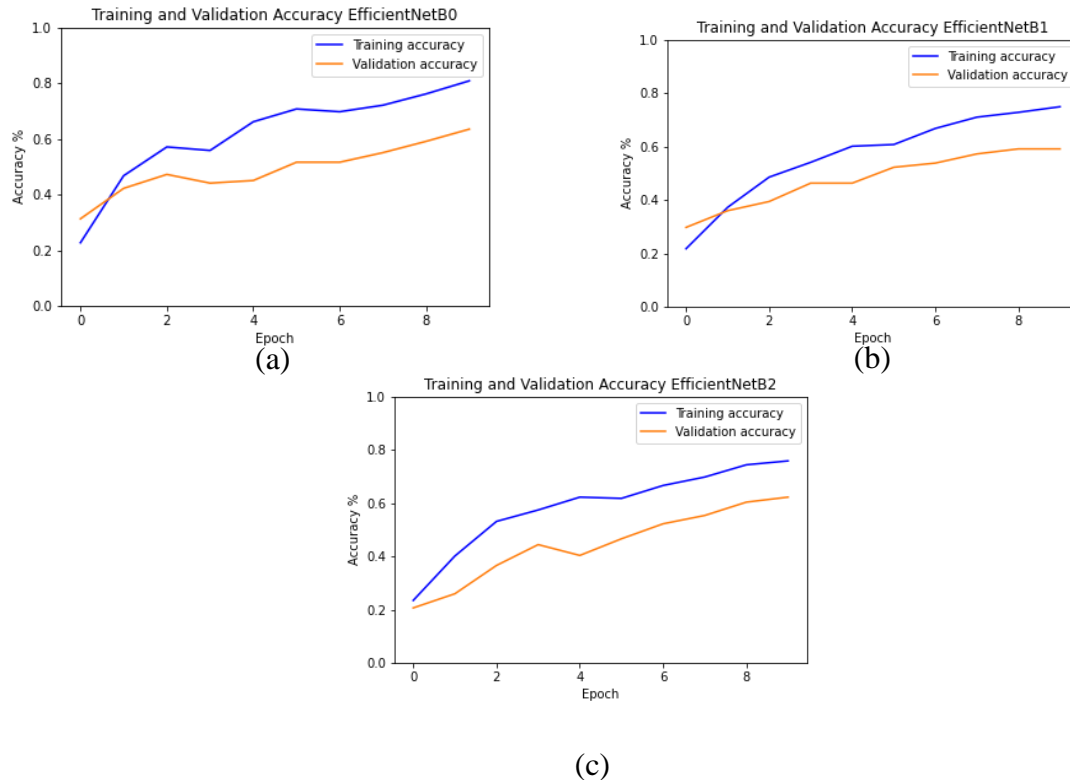(a)   (b)

(c)

Figure 8. Training and validation accuracies produced by (a) EfficientNetB0, (b) EfficientNetB1 and (c) EfficientNetB3.
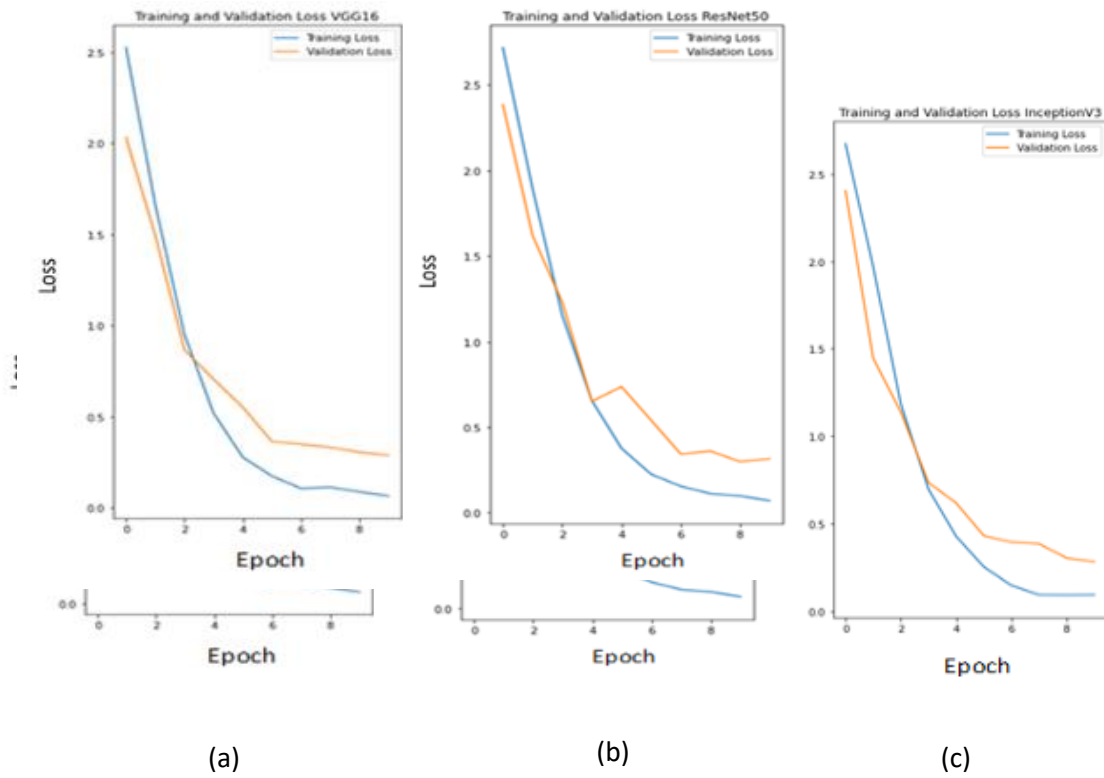
Figure 9. Training and validation loss produced by (a) VGG16, (b) ResNet50, and (c) Inception V3.
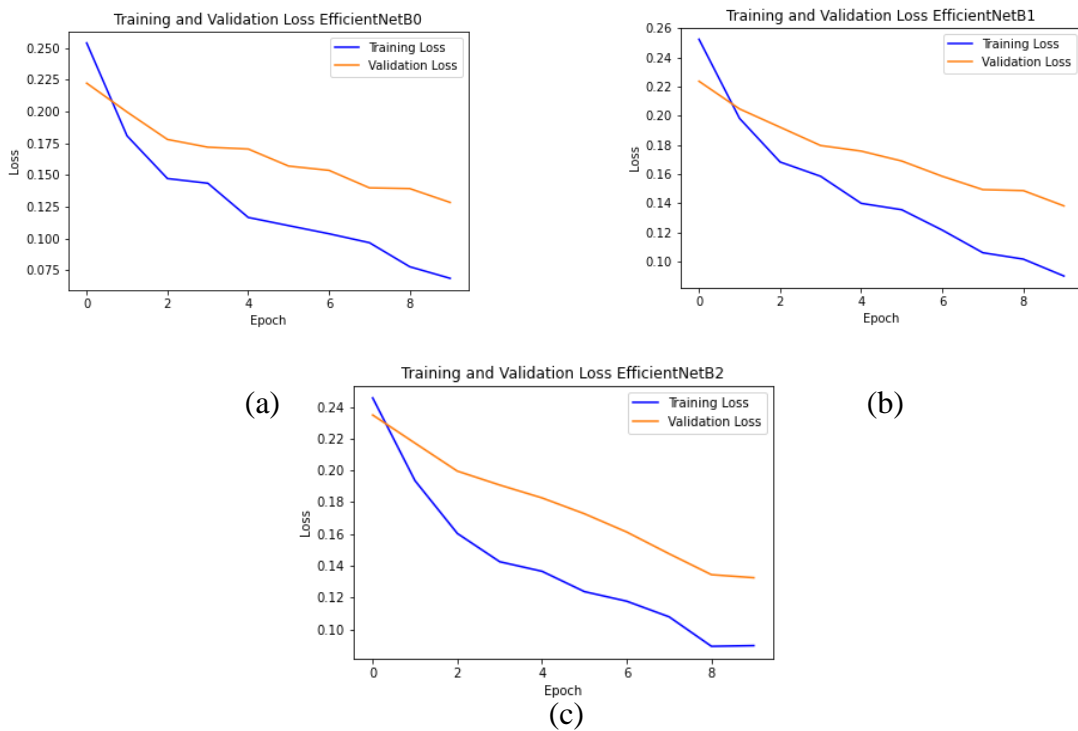

Figure 10. Training and validation loss produced by (a) EfficientNet B0, (b) EfficientNet B1, and (c) EfficientNet B2.

It is shown in Figure 7 that VGG16, ResNet50, and Inception V3 algorithms have produced approximately similar percentages of accuracy, which range from 91% to 92%, where ResNet50 is shown to outperform the rest of the algorithms by achieving the highest accuracy. Nevertheless, in terms of stability, VGG16 is shown to outperform the rest. Meanwhile, in Figure 8, EfficientNet algorithms have shown lower accuracy than VGG16, ResNet50, and Inception V3, where the accuracy produced by EfficientNetB0, EfficientNetB1, and EfficientNetB2 are only 63%, 59%, and 62%, respectively. The validation losses produced by the VGG16, ResNet50, and InceptionV3 algorithms, as shown in Figure 9, are much lower than the validation losses produced by EfficientNetB0, EfficientNetB1, and EfficientNetB2 algorithms, as shown in Figure 10. This shows that the dataset used in the experiment is very complex and challenging for efficient classifiers.

Moreover, EfficientNet algorithms need to be trained by an extensive dataset such as the ImageNet dataset to efficiently classify the data, as Tan (2019) discussed. The effect of image size on the performance of the deep learning algorithms is also studied. For this purpose, only VGG16, ResNet50, and Inception V3 were considered as these three algorithms can produce high accuracy when classifying images from the chili plant growth dataset. The results are shown in Table 3, and it is observed that a larger image size slightly influenced the performance of VGG16 and Inception V3. Nevertheless, the accuracy of ResNet50 is greatly affected by the size of the image, where it is shown in Table 3 that large-sized images decrease the accuracy of classification.

Table 3. Comparison of accuracy and loss for different image sizes.

Algorithm	128×128 pixels		256×256 pixels	
	Accuracy	Loss	Accuracy	Loss
VGG16	91.60%	0.2877	91.19%	0.2505
ResNet50	92.01%	0.3162	87.91%	0.4192
InceptionV3	91.39%	0.2828	90.57%	0.3367

Although VGG16, ResNet50, and InceptionV3 algorithms have shown good performance when classifying the growth stage of chili plants from images under a runaway condition, the performance of these algorithms when classifying images with different complexity is investigated as well. The training and validation accuracy produced by each algorithm is illustrated in Figure 11. The results showed that VGG16, ResNet50, and InceptionV3 produced inadequate training and validation accuracies of less than 80% and 30%, respectively. Moreover, the algorithms showed inconsistent stability as the number of

epoch increased. Hence, we can conclude that images under extreme exposure with a complex background consisting of multiple chili plants are too challenging for the classifiers.

Furthermore, the total number of images used to train and validate the algorithms is too small. This is due to the difficulty and challenges faced by the researchers to collect the data during the movement control order (MCO) period in Malaysia. Even so, the complex chili plant images will create more opportunities for the researchers to produce a highly accurate algorithm.
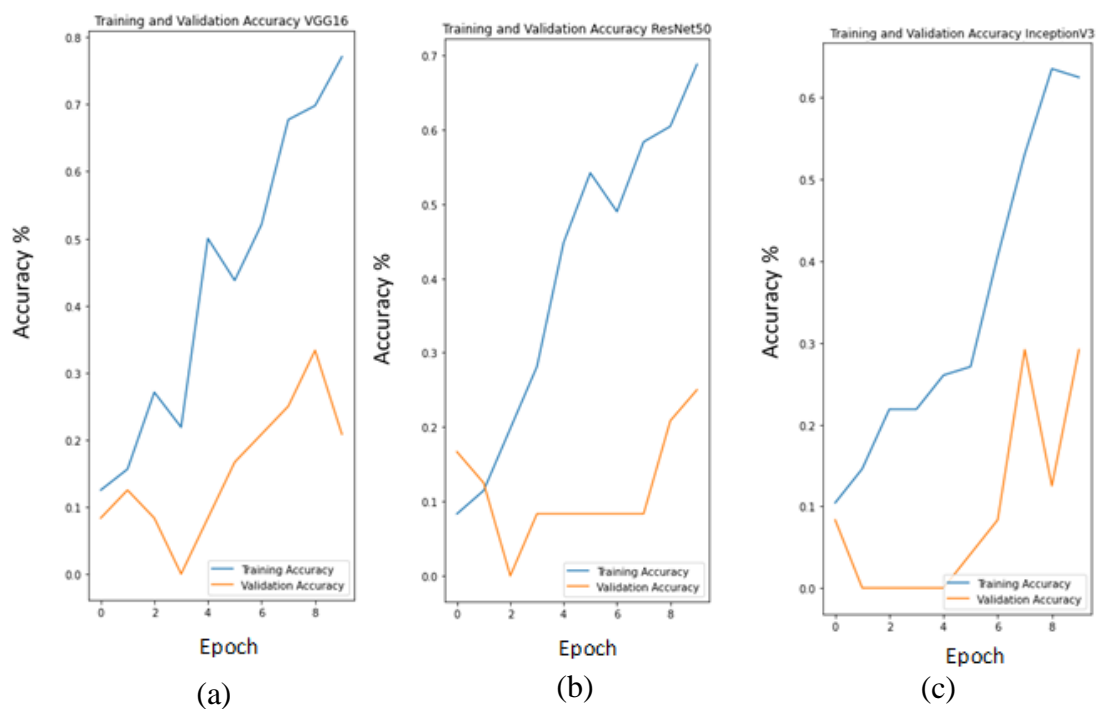

(a)   (b)   (c)

Figure 11. Training and validation accuracies produced by (a) VGG16, (b) ResNet50, and (c) Inception V3.

4. Conclusions

The efficacy of deep learning algorithms, namely VGG16, ResNet50, Inception V3, EfficientNet B0, EfficientNet B1and EfficientNet B2 algorithms in classifying the growth stage of chili plants from a dataset that consists of 2,320 plant images in a runaway condition is demonstrated. The experiment results showed that VGG16, ResNet50, and Inception V3 are far more accurate and stable than the EfficientNet algorithms. It is also found that the accuracy of the deep learning algorithms is greatly affected by the complexity of the images. Under extreme exposure, the algorithms have difficulty classifying the images correctly. The size of the dataset also plays a vital role in producing a highly accurate classifier.

In conclusion, the VGG16, ResNet50, and Inception V3 algorithms have shown great potential for classifying the growth stage of chili plants. The performance of the algorithms can be further improved by exposing them to images with high complexity, such as images rotated at various angles, images scaled to various sizes and exposed to various lighting effects. This will create more opportunities for developing an advanced classifier.

Conflicts of Interest: The authors declare no conflict of interest.

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