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Research Article

Analysis of Deep Learning Algorithms for Grape Leaf Disease Detection

Ellen Flores Mangaoang[1*], Thelma D. Palaoag[2], Jeffrey S. Ingosan[3]

[1] College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines. efm6960@students.uc-bcf.edu.ph

[2] College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines. tdpalaoag@uc-bcf.edu.ph

[3] College of Information Technology and Computer Science, University of the Cordilleras, Baguio City, Philippines. jsingosan@uc-bcf.edu.ph

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ABSTRACT

Plant leaf diseases are crucial in agriculture as they can affect food security. Grapes are one of the important fruits we consume for health considerations. This paper aims to investigate the various deep learning algorithms focused on plant disease detection. A systematic literature review was conducted to determine the top three deep learning algorithms to be utilized in this paper. It intends to compare the performance of the top three deep learning algorithms with appropriate performance metrics. The top three deep learning algorithms identified were Convolutional Neural Network, EfficientNet, and MobileNetV2. The grape leaf images from the PlantVillage dataset which comprise Black Rot, ESCA, and Leaf Blight were used in this paper. There are three thousand two hundred twenty-five (3225) images which were divided into 80% training, 10% testing, and 10% validation. Normalization, augmentation, and hyperparameters were implemented in the training. The results revealed that the EfficientNet model got 100% accuracy, while MobileNetV2 and CNN got 98% and 78% respectively. In terms of prediction, the EfficientNet and MobileNetV2 models also successfully predicted all three images while the Convolutional Neural Network model only predicted two images correctly. This finding suggests that the deep learning models EfficientNet and MobileNetV2 hold significant promise for enhancing image classification techniques in the detection of grape leaf diseases. Their application could lead to more accurate and efficient monitoring of grapevine health, potentially revolutionizing disease management practices in viticulture. This could result in earlier detection, improved yield management, and reduced reliance on chemical treatments, fostering sustainable agricultural practices and optimizing crop productivity.

Keywords: CNN, Deep Learning, efficientNet, Grape Leaf Diseases, mobileNetV2

INTRODUCTION

Plant illnesses pose a major challenge to farming output, causing considerable financial damage [1]. Traditional methods for plant disease detection, however, are often limited by their subjective nature, labor-intensive and time-consuming processes, and susceptibility to errors [2]. The weather also has a significant impact on disease development, further complicating management [3].

Agricultural research aims to improve product quantity and quality while also reducing costs [4]. This study focuses specifically on grape leaf diseases, which pose a major threat to vineyards worldwide. Grapes are a globally significant crop, but they are susceptible to various diseases [5]. Grapevine diseases can harm local economies that rely on grape production. Fungi, such as grey mold, powdery mildew, and downy mildew, are common threats to grapevines [6][7]. The global impact of these diseases is evident in Italy in 2023 with a 12% drop in wine production due to downy mildew [8]. Also, Australian wine grape farmers have experienced significant losses due to downy mildew infestations [9]. Weather conditions, such as prolonged periods of rain and humidity, contribute to the proliferation of these diseases [10]. Kenyan grape growers also faced challenges with pests and diseases, such as powdery mildew and downy mildew [11].

The field of disease identification has advanced significantly with the advent of Deep Learning (DL). Improvements in computing power, storage capacity, and the accessibility of big datasets are responsible for these developments

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[12]. Many picture recognition problems have been resolved and research results in areas such as automatic plant disease identification, natural language processing, and medical diagnosis have been enhanced by the employment of DL models in several applications [13]. It has gained prominence due to its ability to analyze complex image data and identify intricate patterns [14]. DL algorithms play a crucial role in the development of frameworks and applications aimed at bolstering agricultural output [15]. Since diseased crops lead to declines in both harvest quality and productivity, which in turn diminish crop value, the strategic implementation of DL algorithms is vital for the precise identification and classification of plant diseases [16]. However, limitations in technology adoption, distribution, and application must be addressed [17].

The objective of this paper is to investigate the various deep learning algorithms focused on plant disease detection. It also intends to compare the performance and accuracy of the deep learning algorithms with appropriate performance metrics.

METHODOLOGY

To have an understanding of DL algorithms, a systematic literature review was conducted thoroughly through internet research as well as a review of research publications and articles focused on plant diseases. A thorough analysis and comparison were conducted in terms of their performance. The literature review is conducted to understand the different deep learning algorithms used in plant disease detection and how they performed. After a thorough search for articles and published research papers, the list is refined to only plant diseases. The publication date is also taken into consideration. After this, a summary of the literature's findings was prepared. There are nine articles included in this paper.

After the literature review was carried out, the top three deep learning algorithms were identified and trained with the dataset. A comparison of the top three deep learning models was then performed. The first stage is the collection of the dataset to be used for training. This is carried out through the search of datasets that focus on grape leaf diseases from public datasets and research publications. The dataset utilized was derived from PlantVillage [18], particularly Black rot, Esca, and Leaf blight images. After the dataset is collected, data pre-processing which involves dataset cleaning was the next step. The dataset comprised a total of 3225 images, with each class containing 1075 images, and was partitioned into training (80%), validation (10%), and testing (10%). Also, one image from each class was segregated from the dataset to be used for prediction. The first image is from the Black rot class, the second image is from the ESCA class and the third image is from the Leaf blight class. The images were resized to 180 x 180, 224 x 224. and 224 x 224 for CNN, EfficientNet, and MobileNetV2 respectively. Normalization and augmentation techniques were also implemented. After this, training of the algorithms was carried out using the dataset. The top three deep learning algorithms used in the training are CNN, EfficientNet, and MobileNetV2. The hyperparameters implemented were batch size=8, epochs = 25, learning rate=0.0001, optimizers, and activation functions. To prevent overfitting, regularization was also implemented. The models were evaluated using appropriate performance metrics.

RESULTS AND DISCUSSION

The literature review was conducted to investigate the different DL algorithms utilized in the detection of plant leaf diseases. It provided a deeper understanding of the different DL algorithms on the application of disease detection for plant diseases. It also provided different approaches and perspectives that can be utilized in this paper.

A popular algorithm for classifying images is the Convolutional Neural Network (CNN) [19]. For detection and classification tasks including weed identification, crop pest classification, and plant disease diagnosis, CNN approaches are growing in use in the agricultural industry [20]. [21] proposed a CNN-based Satsuma fruit disease detection algorithm which is a mobile and web application to assist satsuma growers in disease detection and reporting. [22] utilized a CNN model to classify bamboo shoots and garnered an accuracy rating of 97.94%. It was further emphasized that the CNN model has superior prediction performance which is valuable in the determination of diseases for the agricultural industry. The purpose of [23] was to identify apple leaf illnesses in their early stages and to stop them from spreading. The Local Binary Pattern (LBP) method was used to extract features from the segmented region of interest after the pictures had been pre-processed to improve their quality. The CNN prediction models achieved a 98.5% accuracy rating.

EfficientNet, created by Google researchers, automatically determines the optimal architecture for a given processing. It uses compound scaling, which scales depth, width, and resolution uniformly to balance model accuracy with computing efficiency [24]. Also, the architecture's robust and lightweight design, squeeze-and-excitation optimization, and Mobile Inverted Bottleneck layers all combine to deliver consistently good results on a range of computer vision activities [25]. The EfficientNetB0 architecture achieved the highest classification accuracy of 99.56% with reduced training time compared to InceptionV3, InceptionResNetV2, and MobileNetV2 [26].

Google's open-source MobileNet class of CNN is a great place to start when building quick and compact classifiers [27]. MobileNetV2 is an improved MobileNet that utilizes thin bottleneck layers for input and output, and inverted constrained computational resources are possible due to MobileNetV2's lightweight designs [28]. Its accuracy is competitive compared to larger and more costly models. Due to its compact size, the model is suitable for real-time applications [29]. Aside from the disease classification, severity was also identified using the best model identified. MobileNet garnered an accuracy of 97.33% with severity detection accuracies of 87.08 and 88.75 for tomato early blight and tomato bacterial spot [30].

VGG-16, a CNN model trained and utilized for image classification is made up of max-pooling layers after a stack of convolutional layers with progressively deeper layers which enables the model to acquire intricate hierarchical representations of visual attributes, resulting in precise and dependable predictions [31]. [32] demonstrates the potential for fruit disease detection when optimized with suitable datasets, pre-trained weights, and training protocols. However, its effectiveness is contingent upon project-specific requirements and objectives, necessitating careful consideration of factors such as data quality, resource availability, and deployment limitations.

The Residual Neural Network (ResNet) addressed the fading gradients, a major challenge in neural network development. It enables several feature layers to be learned by the network [33]. With an accuracy rating of 95.42%, the enhanced ResNet-50 model showed resilience to shifting lighting, angles, and illness severity [34].

The GoogleNet architecture is designed to enhance accuracy and maintain computational efficiency through the development of a deeper model capable of extracting hierarchical features and identifying intricate patterns [35]. GoogleNet introduced inception modules that enabled parallel data processing at various scales [36]. [37] examined the impact of hyperparameters, namely the number of training epochs, on deep learning model accuracy. The findings showed how important hyperparameter optimization is to reach the best possible model performance during training and validation, emphasizing the necessity of choosing hyperparameter combinations carefully for accuracy and effectiveness. To improve model accuracy even more, future studies could investigate transfer learning and other methods.

A Recurrent Neural Network (RNN) comprises multiple interconnected components that mimic the sequential data transformations inherent in human processing [38]. It performed well in applications that need sequential real-time data processing, including processing sensor data to identify anomalies in brief intervals, where predictions must be produced instantly based on the most recent inputs and inputs received one at a time [39]. The accuracy of picture recognition is greatly increased by using incomplete or ambiguous foundation images, which is made possible by the RNNs' high degree of internal failure adaptation. The findings demonstrate the potential of employing RNNs to evaluate and identify plant diseases in olive oil, which can greatly improve the ranch's ability to recognize disease [40].

Long Short-Term Memory (LSTM) is a variant of Recurrent Neural Networks (RNNs) characterized by memory cells that incorporate input, output, and forget gates. LSTM networks effectively address the challenges posed by vanishing or exploding gradients, which can occur during the training of conventional RNNs with sequential data. This makes LSTM particularly well-suited for sequential data applications, including time series forecasting, speech recognition, and natural language processing (NLP) [41]. To automatically identify and classify plant leaf diseases, [42] presents an algorithm for image segmentation. It also goes over a review of several classification methods that can be applied to the study of plant leaf anatomy. A significant challenge arises in generating a fixed-length feature vector capable of representing all sequences due to the variability in the lengths of the infected sections. A straightforward solution to this problem is provided by RNN. In this work, LSTM was used to segregate a feature vector. Recursively repeating

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and focusing on two constrained vectors, the LSTM network's link produces a finite-length vector representation. The LSTM model was able to get an accuracy rating of 95.79%.

Table 1 presents the different DL algorithms as well as the dataset utilized with their accuracies.

Table 1. Information of the Nine Articles

Algorithms	Title	Dataset	Accuracy
CNN	Unlocking Machine Learning Algorithms for Bambooshoots.AI: Revolutionizing Agricultural Applications with Computer Science	Bamboo shoots	CNN - 97.94 SVM – 57.14
CNN	Disease Detection in Apple Leaves Using Image Processing Techniques	240 images of apple leaves	CNN – 98.5 SVM – 82.25 KNN – 70.3
EfficientNet	Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach	Plant Village dataset	EfficientNetB0 - 99.56 InceptionResNetV2 -99.11 InceptionV3 - 98.42 MobileNetV2 - 97.02
MobileNet	Classification of Plant Leaf Disease Using Deep Learning	24,156 images of bell pepper, tomato, potato, rice, apple, and sorghum	MobileNet - 97.33 AlexNet - 91.19 CNN - 84.24
VGG16	Identification of Fruit Severity and Disease Detection Using Deep Learning Frameworks	Public domain - healthy and diseased fruit crops	VGG-16 – 96.10 MobileNetV2 – 94.45 MobileNet – 92.70 Xception -92.40 Inception-ResnetV2 – 91.30 InceptionV3 – 83.55 ResNet59 – 82.30
ResNet	Evaluation of Enhanced ResNet-50 Based Deep Learning Classifier for Tomato Leaf Disease Detection and Classification	18345 tomato leaf images	ResNet – 95.42
GoogleNet	Classification of Diseases in Oil Palm Leaves Using the GoogleNet Model	1230 oil palm leaf images	GoogleNet – 93.22
RNN	Image Analysis and Detection of Olive Leaf Diseases Using Recurrent Neural Networks	80 olive leaf images	RNN – 89.8
LSTM	Long Short-Term Memory Recurrent Neural Network for Plant Disease Identification	7130 images	LSTM – 95.79 Random Forest – 94.95 KNN -93.19

After the literature review, the top three algorithms were then identified and trained with the dataset which has three classes namely: Black Rot, ESCA, and Leaf Blight. Figure 1 presents the summary of the accuracies of the deep learning models. It can be seen from the table that the top three models are: EfficientNet, CNN, and MobileNet with accuracies of 99.56%, 98.5%, and 97.33% respectively. In this paper, the baseline CNN, EfficientNetB0, and MobileNetV2 were implemented in the training of the models. To analyze the performance of the deep learning models, accuracy, precision, recall, and f1-score were computed and interpreted. Models for classifying images have been greatly enhanced by DL, which frequently surpasses human accuracy. However, assessing these models' dependability and efficacy in practical situations is essential [43].

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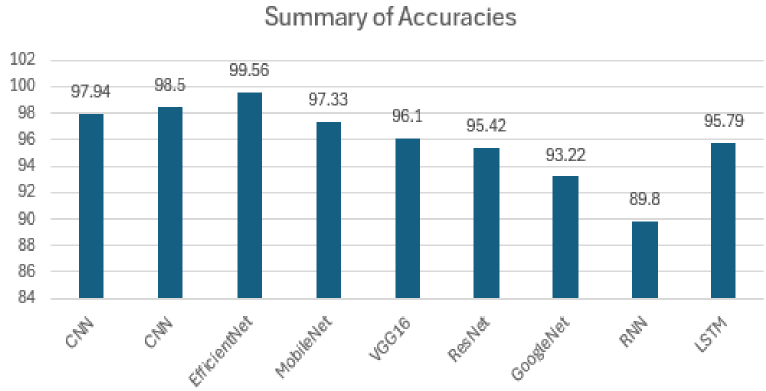

Figure 1 Summary of Accuracies of the Deep Learning Models

The classification report, shown in Table 2, details the performance metrics of the three deep learning models. The CNN model correctly classified 78% of the grape leaf disease images and was 84% correct when predicting a certain class of grape leaf disease. The model suggests a nuanced ability to detect grape leaf diseases, indicating the model is generally accurate when it identifies a disease and captures a high proportion of actual cases, though there's room to improve in balancing precision and recall. The perfect scores of the EfficientNet model, with 100% accuracy, precision, recall, and F1-score, indicate that it flawlessly classified all instances of grape leaf diseases in the dataset, demonstrating exceptional performance in both identifying and correctly predicting each disease class. Whereas, the EfficientNet model, achieving 98% accuracy, 98% precision, 98% recall, and an F1-score of 98% demonstrates a high level of competence in accurately classifying grape leaf diseases, signifying its ability to reliably identify and predict disease classes within the dataset.

Table 2. Classification Report of the Deep Learning Models

Deep Learning Models	Accuracy	Precision	Recall	F1-Score
CNN	**0.78**	**0.8**	**0.96**	**0.87**
EfficientNet	**1.00**	**1.00**	**1.00**	**1.00**
MobileNetV2	**0.98**	**0.98**	**0.98**	**0.98**

The training and validation curves in figure 2 indicate that the model's training accuracy increases while the validation accuracy fluctuates. The validation loss also fluctuates while the training loss decreases. This is an indication that the model is unstable. The confusion matrix implies that the model was able to correctly predict all instances of the leaf blight class and 106 instances from the esca class. However, for the black rot class, it was only able to predict 38 instances correctly while 61 instances were incorrectly predicted as black rot. Also, 9 instances were incorrectly predicted as belonging to the other classes. The incorrect predictions on the black rot class are indicative of the low metric values. Traces of overfitting can also be seen in the results. Though the model has low performance in predicting the black rot class, it shows promising predictions in the Esca and leaf blight classes.

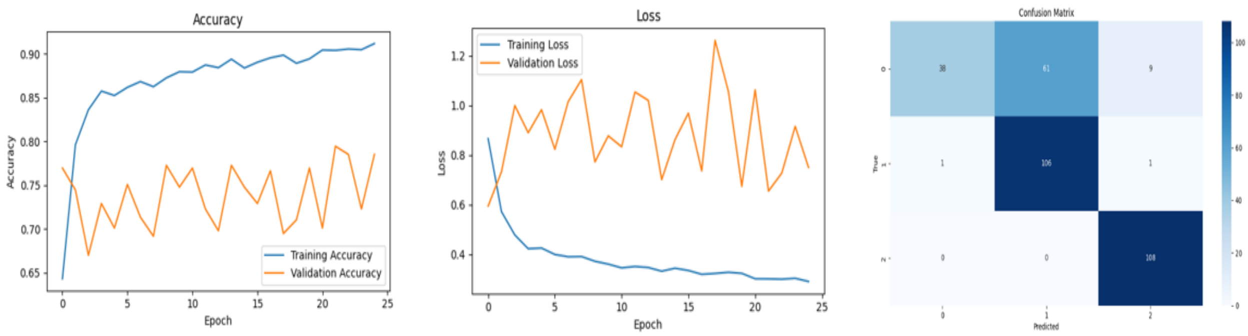

Figure 2 Performance of the CNN Model

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Also, it can be seen from figure 3 that EfficientNet steadily increases in its training and validation accuracy over the epochs while the training and validation loss decreases. As for the confusion matrix, the diagonal elements which represent correct predictions are all 108 while there were no mispredictions that indicate that the model correctly classified all instances. Though the model has achieved a flawless performance, it might not be the same case in real-world scenarios, especially for complex and larger datasets.

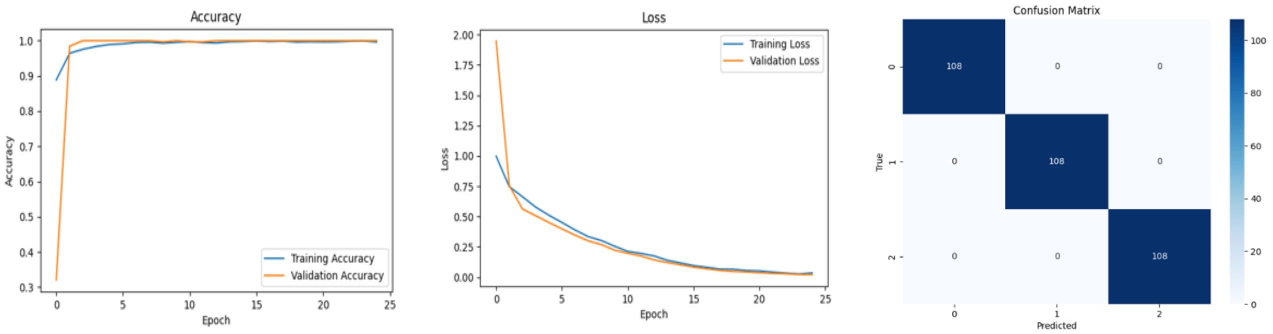


Figure 3 Performance of the EfficientNet Model

As per figure 4, though the validation and training accuracy were increasing, there were instances of fluctuations which means that the model might be a bit unstable. For the confusion matrix, the model was able to perform well, however, there were minimal misclassifications in the black rot and esca classes as evidenced by 106 instances and 105 instances of correctly predicted images. The model performed best in the leaf blight class by correctly predicting all instances. Overall, the model performed well with high metric values.

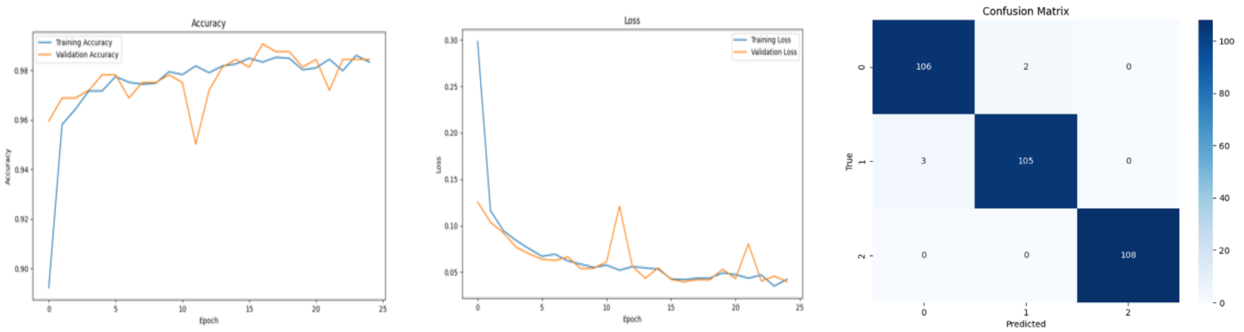
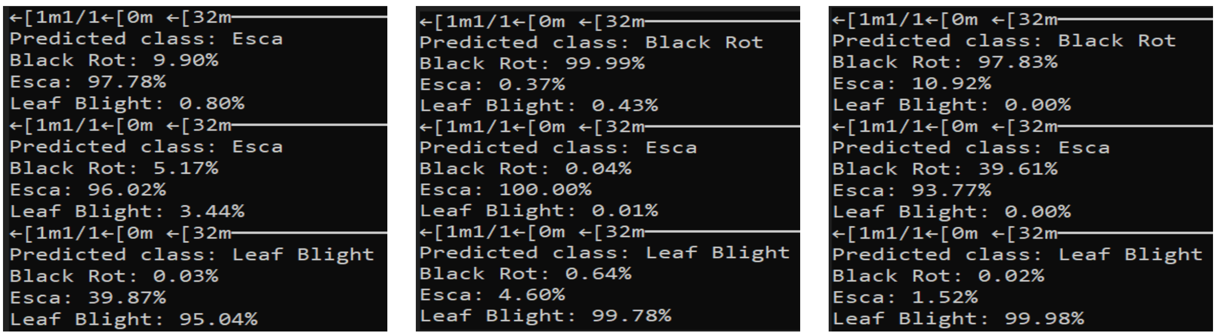


Figure 4 Performance of the MobileNetV2 Model

Figure 5 presents the performance of the models in predicting the classes of the images. It can be seen from the figure that EfficientNet and MobileNetV2 models were able to accurately identify the correct diseases for the three images. There is also a big disparity in terms of the prediction values which means that these models are certain that the image belonged to their predicted classes. However, the CNN model misclassified the first image as esca and was able to classify the last two images correctly. This misclassification can be attributed to CNN's metric values and confusion matrix results.



CNN EfficientNet MobileNetV2

Figure 5 Prediction Performance of the Deep Learning Models

With the results presented, EfficientNet and MobileNetV2 models were able to classify the images better as compared to the CNN model as evidenced by their performance results. However, signs of overfitting may be present. The results suggest that both EfficientNet and MobileNetV2 have potential for application in grape leaf disease detection. The integration of DL methodologies in plant leaf disease detection may provide valuable assistance to growers or farmers in early disease detection which is essential for effective crop and resource management.

CONCLUSION

This paper aims to investigate the various deep learning algorithms focused on plant disease detection and compare the performance and accuracy using appropriate performance metrics. The finding implies that the deep learning models EfficientNet and MobileNetV2 have the potential to detect grape leaf diseases. This finding suggests that the DL models EfficientNet and MobileNetV2 hold significant promise for enhancing image classification techniques in the detection of grape leaf diseases. Their application could lead to more accurate and efficient monitoring of grapevine health, potentially revolutionizing disease management practices in viticulture. This could result in earlier detection, improved yield management, and reduced reliance on chemical treatments, fostering sustainable agricultural practices and optimizing crop productivity.

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