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Grape Leaf Disease Detection Using Deep Learning: A Hybrid Approach with Efficientnet and Mobilenet

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ABSTRACT:
Viticulture faces challenges from grape leaf diseases that threaten crop yield and quality. This paper aims to introduce a hybrid EfficientNet - MobileNet model and determine how the hybrid model can improve the accuracy and efficiency in identifying leaf diseases from plant images. The datasets used are the grape leaf datasets from the PlantVillage' dataset, Leaf Health Classification and Disease Detection, and from reliable agricultural websites and research publications which comprise black rot, esca, and leaf blight classes. A total of four thousand one hundred fifty - four (4154) images were used. Fifty images were also used for disease classification. The hybrid model was evaluated using accuracy, recall, precision, and f1 – score. A confusion matrix was also generated. The results revealed a 98.4838% accuracy rating. Forty-six out of fifty images were correctly classified using the hybrid model. The performance of the hybrid model as well as its prediction percentage implies that the hybrid model is reliable for grape leaf disease detection. This further implied that the hybrid model has the potential to enhance image classification techniques in detecting grape leaf diseases. Their use may result in more precise and effective grapevine health monitoring, which could change viticulture's approaches to disease control. This could promote sustainable farming methods and maximize crop productivity by enabling earlier identification, better yield management, and less dependence on chemical treatments. Increasing the dataset, fine-tuning with more feature extraction, and modifying augmentation techniques may be used to enhance the model's performance.
KEYWORDS:*deep learning, efficientNet – mobileNet, grape leaf diseases, hybrid approach, image classification*

1) INTRODUCTION:

The urgent need to produce food sustainably is significantly impacting agriculture [1]. Challenges such as urbanization, environmental factors, and climate change have made food security a problem [2]. Promoting sustainable agriculture globally is necessary to provide food security, increase incomes, enhance nutrition, and preserve the balance of natural ecosystems [3]. Also, technology plays a critical role in agriculture by boosting output through better crop management, resource optimization, and data-driven decision-making, which leads to more efficient and sustainable farming methods [4] [5] [6] [7] [8] [9].

One of the major concerns of farmers is the existence of diseases [10]. These diseases significantly affect the quality and quantity of agricultural produce [11][12]. Diseases destroy harvests, impacting farmers' livelihoods [13]. They have existed for millions of years, with historical evidence found in fossils and documented instances causing famines and financial misery [14].

Infectious plant leaf diseases appear as wilting, spots, mold, rot, or unusual growth, often leading to tissue damage. These illnesses are primarily caused by fungi, bacteria, viruses, and parasites, spreading through various means like air, water, animals, and people, and can sometimes last for years [15]. While some plant diseases may contribute to ecosystem balance by regulating plant populations, outbreaks are rare in diverse plant communities; however, crops grown in large, uniform groups create ideal conditions for rapid disease spread [16].

Grapes are susceptible to diseases that significantly threaten crop yield and quality. Traditional disease detection methods rely on manual inspection, which can be time-consuming and prone to errors. Farmers and gardeners often consult gardening books and websites to identify diseases by matching symptoms to images, or they may seek guidance from local garden centers with plant samples or photos [17]. Early detection of diseases is crucial for protecting plantations, enabling timely intervention through fungicide application or the use of resistant crop varieties while helping to contain and prevent further spread [18]. If plant diseases are not diagnosed and treated quickly, they can spread rapidly, potentially wiping out an entire field in just 24 hours. Misdiagnosing diseases based solely on appearance can lead to unnecessary fungicide use, causing more harm than good [19]. Incorrect identification of a plant disease can result in unnecessary treatments, pesticides, and other interventions, all of which cost time and money [20].

Deep learning (DL) has become popular in scientific computing and is utilized by industries to address complex problems [21]. DL brings human-like intelligence to Artificial Intelligence (AI) to handle complex data across technology, healthcare, and manufacturing [22]. DL models are capable of learning classification and identification patterns in multimodal data, as well as interpreting images and transcribing audio [23]. DL also plays a transformative role in agriculture by providing advanced capabilities for analyzing complex agricultural data, particularly image data, to improve efficiency and sustainability [24].

DL's pre-trained models can effectively identify patterns and objects by learning from massive datasets. Their adaptable nature allows developers to tailor them to specific applications, reducing the need for extensive processing power and training data [25]. EfficientNet is a Convolutional Neural Network architecture that optimizes performance by scaling its structure in a balanced way, making it both accurate and efficient [27]. MobileNet is a lightweight model developed by Google for efficient and rapid image classification, making it ideal for mobile and edge devices [28]. It is especially well-suited for devices with constrained processing resources for tasks like object detection, semantic segmentation, and image classification [29].
The objective of this paper is to introduce a hybrid EfficientNet - MobileNet model and determine how this hybrid model can improve the accuracy and efficiency in identifying grape leaf diseases from plant images, with the aim of aiding in the early detection of grape leaf diseases.

2) METHODOLOGY:

The first phase undertaken is the collection of the dataset. The dataset utilized was derived from the PlantVillage [30] dataset particularly grape leaf's black rot, esca, and leaf blight classes, and Leaf Health Classification and Disease Detection [31]. Other images were obtained from reliable agricultural websites and research publications. A total of four thousand one hundred fifty - four (4154) images were used in this paper which comprised: 1681, 1408, and 1065 images for black rot, esca and leaf blight classes respectively. After the dataset was collected, data pre-processing which involves dataset cleaning was undertaken. Duplicate samples were removed, and the images were resized to 224 x 224.

To increase diversity for consistent processing, augmentation techniques such as rescaling, rotation, flipping, and shifting were employed to the images. A hybrid EfficientNetBo - MobileNetV2 model was utilized in the training. This hybrid model was selected due to EfficientNetBo's accuracy due to compound scaling and MobileNetV2 being a lightweight model which is ideal for feature extraction. The hyperparameters implemented were batch size=8, epochs = 25, learning rate=0.0001, optimizers, and activation functions. Table 1 presents the distribution of the grape leaf dataset across ten folds for training and validation, specifying the number of images allocated for the classes within each fold. The 10-fold cross-validation was used to ensure a robust model evaluation, where 90% of the dataset was used for training and 10% for validation in each fold. Class distributions were preserved across folds to lessen bias due to class imbalance. Class imbalance happens when some categories have more examples than others, causing the model to favor the larger group and struggle to recognize the other classes [32]. The models were evaluated using appropriate performance metrics: accuracy, precision, recall, f1-score, and confusion matrix. Fifty (50) images were utilized for disease prediction which comprised twenty black rot, seventeen esca, and thirteen leaf blight images.

Table 1. 10 - Fold Training and Validation Sample Distribution

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Fold Number		Training Sample	Validation Samples	Black rot	ESCA	Leaf blight
1		3738	416	169	140	107
2		3738	416	168	141	107
3		3738	416	168	141	107
4		3738	416	168	141	107
5		3739	415	168	141	106
6		3739	415	168	141	106
7		3739	415	168	141	106
8		3739	415	168	141	106
9		3739	415	168	141	106
10		3739	415	168	140	107
Total		37386	4154	1681	1408	1065

3) RESULTS AND DISCUSSION:

To evaluate the performance of the hybrid EfficientNet – MobileNet model, a 10-fold cross-validation was undertaken, and a classification report was generated. Table 2 presents the overall performance metrics of the hybrid EfficientNet – MobileNet model across the 10-fold cross-validation process in terms of accuracy, precision, recall, and f1-score. These high scores imply that the model is highly reliable for grape leaf disease detection and possesses the potential to significantly enhance image classification techniques in this domain.

Table 2. 10 - Fold Classification Report

Fold Number	Accuracy	Precision	Recall	F1-Score
1	97.5962	98.00	98.00	98.00
2	97.8365	98.00	98.00	98.00
3	98.7981	99.00	99.00	99.00
4	97.8365	98.00	98.00	98.00
5	99.2771	99.00	99.00	99.00
6	99.0361	99.00	99.00	99.00
7	98.3133	98.00	98.00	98.00
8	98.3133	98.00	98.00	98.00
9	99.0361	99.00	99.00	99.00
10	98.7952	99.00	99.00	99.00

Table 3 provides a more granular view of the hybrid model's performance by displaying the average precision, recall, and f1-score for each disease class. The hybrid model achieved an accuracy rating of 98.4838%, indicating minimal errors in classification. It also garnered 98% average rating for precision, recall and f1-score. A significant implication is the exceptional performance for the leaf blight class, which achieved a perfect 100% in precision, recall, and f1-score, signifying a nearly flawless classification for these samples. In contrast, while still high at 98% for all metrics, the black rot and esca classes showed a slight reduction. This implies that for black rot and esca images, there were instances of false positives or misclassifications, which can be attributed to the similarity in visual features of the diseased leaf symptoms between these two classes. This further implies that the hybrid model performed well in classifying the leaf blight images.

Table 3. Average Classification Report

Class	Precision	Recall	F1-Score
Black rot	98.00	98.00	98.00
ESCA	98.00	98.00	98.00
Leaf blight	1.00	1.00	1.00
Weighted Average	98.00	98.00	98.00
Accuracy			98.4838

For figure 1 which is the Training and Validation Graph of the hybrid model, it presents the learning progress of the EfficientNet – MobileNet model during its training phase. It clearly shows that the training and validation accuracy were consistently increasing, while, simultaneously, the training and validation loss graph steadily decreased. This is a strong indicator that the model is learning effectively from the data and is generalizing well to unseen examples, rather than merely memorizing the training data. This is an indication that the hybrid model is robust and not overfitting, suggesting its predictions will be reliable when applied to new, real-world grape leaf images for disease detection.

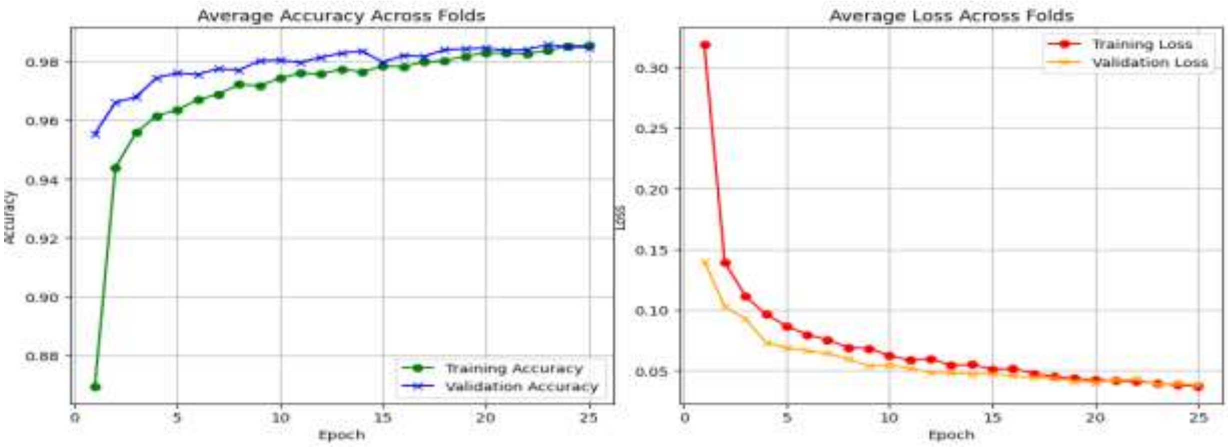

Figure 1 Training and Validation Graph of the Hybrid Model

Figure 2 presents the confusion matrix which provides a detailed breakdown of the model's performance in classifying specific grape leaf diseases by showing actual versus predicted classifications. It can be seen from the table that 33 black rot images were misclassified as esca, whereas 29 esca images were also misclassified as black rot. Furthermore, only 1 leaf blight image was misclassified as black rot. This implies that the hybrid model was more accurate in terms of classifying the leaf blight images as evidenced the by 100% precision, recall, and f1-score it garnered. The confusion between the black rot and esca classes is also supported by the precision, recall, and f1-score ratings garnered by the hybrid model.

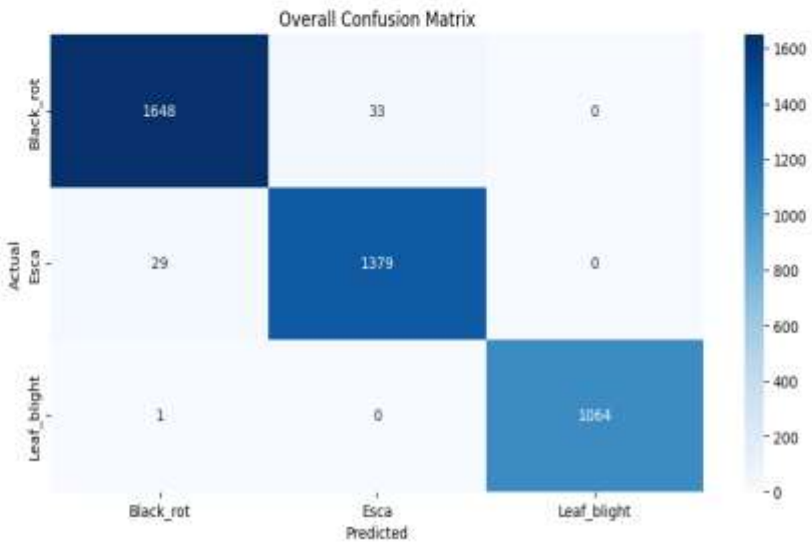

Figure 2 Confusion Matrix of the Hybrid Model

Table 4 presents the classification result of the hybrid model where fifty images were selected to test the model's performance in predicting the images' disease classification. The utilization of the images for performance testing was intended to gauge the initial model's effectiveness on unseen images, specifically selected to simulate a real-world application scenario and gauge the model's initial effectiveness on new data. It can be seen from the table that 46 out of 50 images were correctly classified achieving a 92% prediction accuracy on this test set. The model predicted 16 out of 20 black rot images correctly. The model misclassified the images as esca. Whereas, for the esca and leaf blight images, the model classified and predicted all correctly. The misclassification may be due to the similarity in visual features of the grape leaf diseases and varying environmental conditions. There is also a possibility of different lighting exposures, quality, and background. Also, this can be attributed to the number of images in the dataset and the augmentation techniques applied. Despite these specific challenges, this demonstrates the hybrid model's considerable potential for practical image classification in grape leaf disease detection.

Table 4. Classification Result of the Hybrid Model.

#	Classification	Predicted Class	Black rot	ESCA	Leaf blight
1	Black rot	Black rot	97.3999	2.5987	0.0014
2	Black rot	Black rot	99.5568	0.4109	0.0324
3	Black rot	Esca	20.9195	79.0672	0.0133
4	Black rot	Black rot	95.9081	4.0885	0.0034
5	Black rot	Black rot	99.9185	0.0799	0.0016
6	Black rot	Black rot	99.9967	0.0031	0.0002
7	Black rot	Black rot	53.7316	46.2379	0.0305
8	Black rot	Black rot	99.0681	0.9318	0
9	Black rot	Black rot	99.986	0.0134	0.0006
10	Black rot	Black rot	73.8952	26.1042	0.0006
11	Black rot	Esca	8.299	91.7005	0.0005
12	Black rot	Black rot	99.9561	0.0415	0.0024
13	Black rot	Black rot	99.9948	0.0051	0
14	Black rot	Black rot	86.741	13.2585	0.0005
15	Black rot	Esca	0.4735	59.2031	40.3233
16	Black rot	Black rot	99.8524	0.1471	0.0005
17	Black rot	Black rot	99.9236	0.0646	0.0118
18	Black rot	Black rot	99.9622	0.0374	0.0004
19	Black rot	Esca	21.5006	78.4993	0.0001
20	Black rot	Black rot	99.9907	0.0091	0.0001
21	Esca	Esca	0	100	0
22	Esca	Esca	0.0023	99.9977	0
23	Esca	Esca	6.9805	93.0106	0.0089
24	Esca	Esca	0.0449	99.9551	0
25	Esca	Esca	0.4776	99.5223	0.0001
26	Esca	Esca	0.1702	99.825	0.0048
27	Esca	Esca	0.0002	99.9998	0
28	Esca	Esca	0.0321	99.9679	0
29	Esca	Esca	0.0001	99.9999	0
30	Esca	Esca	0.0465	99.951	0.0026
31	Esca	Esca	0.3084	99.6907	0.0009
32	Esca	Esca	0.049	99.9483	0.0026
33	Esca	Esca	2.3095	97.5974	0.0932
34	Esca	Esca	1.0886	98.9109	0.0004
35	Esca	Esca	0.195	99.8049	0.0001
36	Esca	Esca	15.9504	84.0475	0.0022
37	Esca	Esca	0.6237	99.376	0.0003
38	Leaf blight	Leaf blight	0.1436	0.0001	99.8563
39	Leaf blight	Leaf blight	0.0115	0.0028	99.9857
40	Leaf blight	Leaf blight	0	0	100
41	Leaf blight	Leaf blight	0.0002	0.0002	99.9997
42	Leaf blight	Leaf blight	0	0	100
43	Leaf blight	Leaf blight	0.0073	0.0059	99.9868
44	Leaf blight	Leaf blight	0.0027	0.0035	99.9938
45	Leaf blight	Leaf blight	0	0	100

46	Leaf blight	Leaf blight	0.0002	0	99.9998
47	Leaf blight	Leaf blight	6.9188	0.0032	93.0779
48	Leaf blight	Leaf blight	0.0055	0.0007	99.9937
49	Leaf blight	Leaf blight	0.0044	0	99.9956
50	Leaf blight	Leaf blight	0.0002	0.0005	99.9993

In summary, the hybrid model did very well in classifying the diseases as evidenced by its prediction and metrics for the leaf blight images. Though there were lapses in the classification of black rot and esca samples, the hybrid model was still able to classify most of the images correctly. The misclassification can be attributed to an overlap of possible confusion in visual features. This further implies that the hybrid model shows great potential for image classification in grape leaf disease detection.

4) CONCLUSION:

The objective of this paper was to introduce a hybrid EfficientNet - MobileNet model and determine how the hybrid model can improve accuracy and efficiency in identifying grape leaf diseases from plant images which aims to aid in the early detection of grape leaf diseases. The performance of the hybrid model as well as its prediction percentage implies that the hybrid model is reliable for grape leaf disease detection. The hybrid model has a probability of improving image classification methods for grape leaf disease diagnosis. Its use may result in more precise and effective grapevine health monitoring, which could change viticulture's approaches to disease control. This could promote sustainable farming methods and maximize crop productivity by enabling earlier identification, better yield management, and less dependence on chemical treatments. Increasing the dataset, fine-tuning with additional feature extraction, and adjusting augmentation techniques may be employed to enhance the hybrid model's performance.

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