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Cucumber Disease Classification with Ensemble Learning Method for Complex Datasets

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ABSTRACT

Many researchers are taking into account the algorithm's ability to detect diseases in plants since it can save expenses and deliver more accurate results. However, there are various obstacles in detecting diseases, particularly in cucumber plants, such as disease similarities and the ability of models to adapt to the information they have. To address this issue, we propose an ensemble learning strategy based on the averaging method to improve the model's ability to generalize to different cucumber plant environments. According to the results, the ensemble learning approach outperforms the feature fusion method with a test accuracy of 94.20% and a loss of 0.01105. Feature fusion and ensemble learning techniques, in general, have the potential to increase the model's capacity to classify difficult data.

Keywords: *cucumber disease, ensemble, feature fusion, classification, efficientnet, resnet*

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1. INTRODUCTION

The cucumber plant garners considerable interest from individuals across the globe [1]. In the year 2018, the global output of cucumbers amounted to approximately 75.2 million metric tons, thereby exerting a significant positive influence on the economy. Similar to other plants, cucumbers exhibit a range of diseases, including anthracnose, bacterial wilt, downy mildew, sticky stem blight, belly rot, and pythium fruit rot. Plant diseases are a significant contributing cause to the decline in both the amount and quality of agricultural production [2]. The agricultural sector is currently experiencing a significant economic downturn as a result of disease-induced deterioration in the production process. This decline has been projected to cause an annual loss of approximately 220 billion US dollars [3]. The majority of disease detection systems in plants continue to rely on manual approaches, necessitating the involvement of skilled professionals to perform the necessary inspections. This phenomenon is widely acknowledged as being expensive and necessitating a greater investment of time.

Typically, the identification of diseases in cucumbers relies on visual observation by individuals. However, many diseases exhibit inconspicuous symptoms, rendering their detection challenging in the absence of specialized expertise [4]. Cucumber infections exhibit discernible physical attributes, rendering them detectable through the utilization of a camera equipped with an algorithm designed to classify the specific type of disease affecting cucumbers. The classification task is commonly addressed using two prevalent methodologies, namely classical machine learning and deep learning. Deep learning necessitates datasets comprising of images or videos, which serve the purpose of furnishing algorithms with discernible patterns [5]. Numerous research have been conducted employing deep learning methodologies to identify diseases, including banana leaf disease detection [6], Tomato disease detection [7], and potato leaf disease detection [8].

[9] introduced a sparse representation method for the purpose of detecting illnesses in cucumber plants. This approach operates by identifying characteristics that possess the ability to effectively represent an object, hence exhibiting a non-zero value. The dataset included in this study comprises a total of 420 photos, encompassing seven distinct forms of leaf diseases observed on cucumber plants. The findings of this study indicate that sparse representation outperforms Support Vector Machines (SVM), K-means, and texture features, with an accuracy rate of 91.25%. Sparse representation is widely regarded as having greater processing performance due to its ability to transform complicated characteristics into simpler ones, resulting in a reduced number of non-zero values. Nevertheless, the sparse representation method may be limited in its ability to capture intricate details due to the simplifying process it undergoes.

Subsequently, a study has been conducted employing conventional machine learning techniques [10]. This involved the integration of features extracted from Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and color characteristics, which were subsequently utilized as input for different types of Support Vector Machines (SVM) and K-Nearest Neighbor (KNN) algorithms. The dataset employed in this study comprises 1262 photos, encompassing six distinct classes of diseases affecting cucumber plants. However, it is important to note that the distribution of data across these classes is not balanced. The findings indicate that the integration of HOG, LBP, and color characteristics enhances the classification efficacy for cucumber disease, yielding a classification accuracy of 94.6% when employing the K-Nearest Neighbors (KNN) algorithm. Nevertheless, this work demonstrates that the K-nearest neighbors (KNN) algorithm has a high degree of sensitivity, resulting in a significantly reduced classification success rate for specific classes when confronted with imbalanced data.

Apart from employing conventional machine learning methods, there exists scholarly investigation that employs a deep learning technique, namely leveraging the EfficientNet algorithm, for the purpose of disease detection in cucumber plants [11]. The EfficientNet algorithm [12], is a convolutional neural network (CNN) that possesses the ability to change the coefficient values in order to scale the width, height, and resolution. EfficientNet encompasses a range of variants, denoted as EfficientNet B0 to B7, which exhibit a linear progression in terms of parameter count. The

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equation employed in EfficientNet for the purpose of optimizing the model's accuracy is as follows: The user's text is a simple word, "equation." [11] conducted research aimed at detecting cucumber illness. They employed EfficientNet in combination with the ranger optimizer and achieved higher accuracy results compared to other models such as AlexNet, Visual Geometry Group (VGG) family, Inception family, ResNet family, SqueezeNet, and DenseNet. The test accuracy values obtained were reported to be 96.39%. The utilization of Ranger optimization has demonstrated enhanced accuracy in comparison to alternative optimization strategies in the context of EfficientNetB4. However, the generalizability of the model in accurately classifying various cucumber diseases has not been established solely based on accuracy metrics.

[13] proposed a fusion feature technique for the detection of cucumber disease. The suggested methodology employs the VGG and InceptionV3 algorithms to integrate the extracted and classified features following the feature selection procedure. The classification procedure is conducted utilizing the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) methods. The dataset employed in this study comprises a total of 339 photos, encompassing five distinct categories of cucumber illnesses. In order to address the issue of imbalanced data, a technique known as augmentation is employed to ensure that each class contains an equal number of 500 photos. The experimental outcomes derived from feature fusion, employing VGG and Inception as feature extractors, yield an accuracy of 95.2% when combined with the K-Nearest Neighbors (KNN) method.

Another approach to cucumber disease detection has been conducted by [14], utilizing feature fusion on DeepLabV3+ and U-Net for segmenting the input picture. The training process consists of two stages. The first stage involves utilizing 1000 images to train the DeepLabV3+ model, while the second stage involves using 450 images to train the U-Net model. The disease detection process consists of two stages. Once the input image has been successfully extracted from the DeepLabV3 model, it will then serve as the input for the U-Net model. The research findings indicate that the average precision obtained is 93.27%. In general, the utilization of the segmentation method is characterized by greater complexity compared to the classification method; however, the corresponding improvement in accuracy is not particularly substantial.

This research uses a novel framework with the weight averaging ensemble learning method on EfficientNet and ResNet50 to increase model performance. Previous studies have employed feature fusion and feature selection techniques to enhance the performance of models. However, it is important to acknowledge that both strategies have certain limitations. The process of feature selection can lead to overfitting in a model as a result of an unrepresentative distribution of data [15]. Additionally, it has the capacity to exclude significant information that could enhance the model's ability to identify patterns [16]. In the context of data fusion, it is important to consider the potential occurrence of data noise when combining features from two models that exhibit significant discrepancies. In order to address the limitations inherent in feature fusion method, ensemble learning is employed in this research as a means to enhance the precision of the model utilized for the detection of cucumber disease.

Ensemble learning can reduce noise by combining prediction calculation results from 2 or more models because it does not combine features directly in the same model [17]. EfficientNet was chosen as the base model since it has been shown to identify illness in cassava [18], peach [19], palm oil ripeness [20] and corn plants [21]. The utilization of ensemble learning, namely the averaging method, can contribute to the enhancement of model generalization and the prevention of overfitting, even in scenarios where the dataset employed is constrained [22].

2. METHODS

The data utilized in this investigation are accessible to the public [4]. There exist eight distinct categories of cucumber plant ailments, which include Anthracnose, Bacterial Wilt, Belly Rot, Downy Mildew, Pythium Fruit Rot, Gummy Stem Blight, Fresh leaves, and Fresh cucumber. The graphical representation of the frequency distribution of the number of photos for each class is depicted in Figure 1. Each condition present in cucumber has distinct features that can be discerned by employing the

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Convolutional Neural Network (CNN) technique for feature extraction.

Figure 2 illustrates the sequential progression of the research process, commencing with data pre-processing and culminating in the final stage. In the section dedicated to data pre-processing, the dimensions of the picture data are specified as 2296 x 1724. Subsequently, these dimensions are partitioned according to a ratio of 7:1:2 for the purposes of training, validation, and testing. Subsequently, the data is resized to a 224 x 224 format to enhance the efficiency of the training process. This resizing is performed with the use of the Pytorch Dataset module, which facilitates the conversion of the data into a feature-based representation. The detailed distribution of datasets in each class for train, validation and testing is shown in table 1. The models EfficientNet-B0 and ResNet50 were started, and the hyperparameter learning rate was set to 0.001 using the Adam optimizer. A batch size of 16 was employed. The output of the fully connected layer for each model was aggregated by summing them and then dividing by the total number of models employed. This averaging technique was used to provide prediction results.

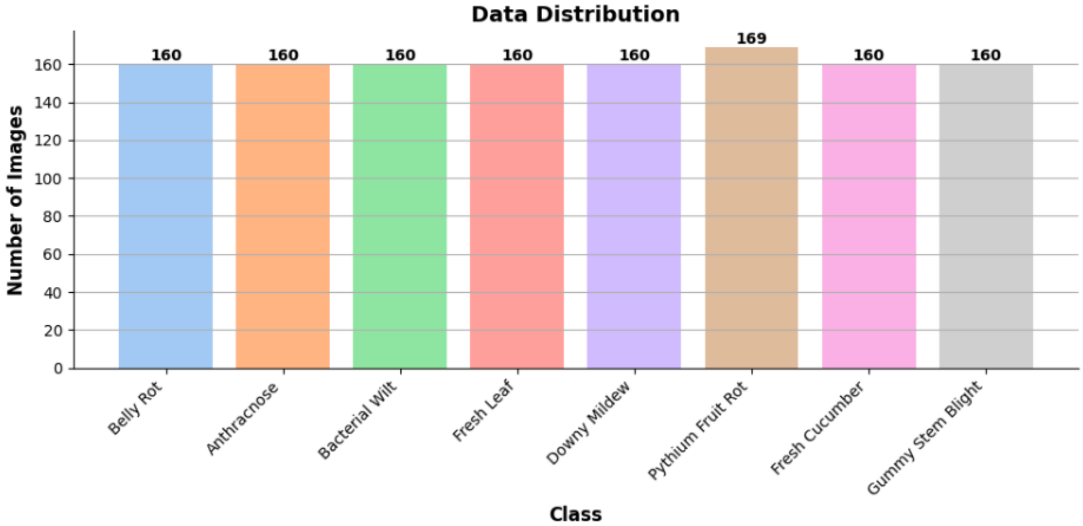

Figure 1.Dataset class distribution

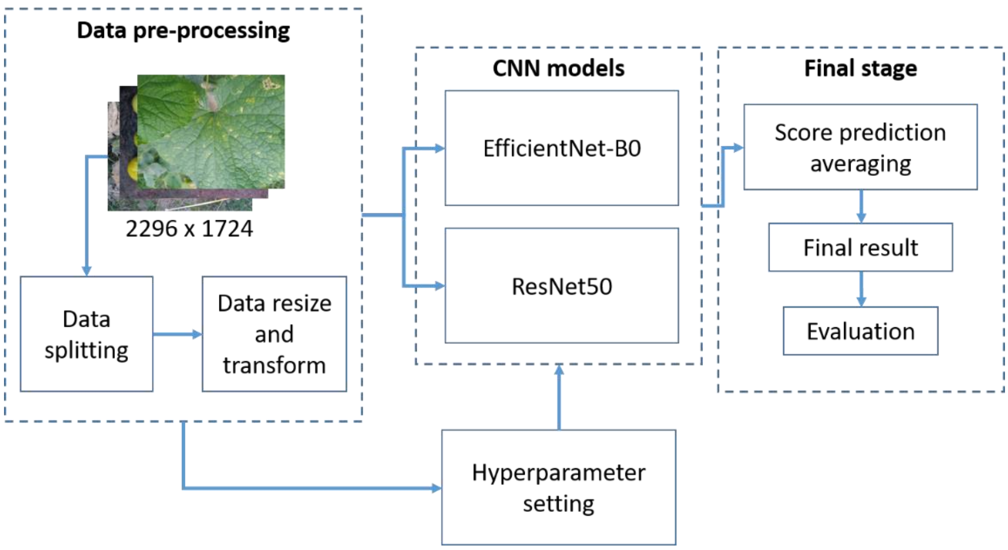

Figure 2.Proposed method diagram

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Table 1. Detail distribution of dataset

	Train	Validation	Test
Anthracnose	110	19	37
Bacterial wilt	109	11	34
Belly Rot	125	24	32
Downy Mildew	111	15	32
Fresh Cucumber	114	11	33
Fresh Leaf	114	15	27
Gummy Stem Blight	106	19	29
Pythium Fruit Rot	113	14	35

This research employed EfficientNet-B0, which is characterized by a compound coefficient consisting of alpha 1.2, beta 1.1, and gamma 1.15. These coefficient values were discovered by a limited grid search, taking into account the specified constraints [23].

$$\alpha \cdot \beta^2 \cdot \gamma^2 = 2 \quad (1)$$

Meanwhile, the ResNet50 used in this research has the ability to skip connection where the initial input (x) value will be conjugated with the input value that has passed the convolutional operation function (F(x)) and the activation function so that the completeness of the information is maintained for the classification process. The following is the equation used to skip connection on ResNet50 [24]:

$$Output = F(x) + x \quad (2)$$

Table 2.Model evaluation using test set

Model	Precision	Recall	F1-Score	Accuracy	Loss
ResNet50	1.0	0.66	0.77	89.57%	0.01882
EfficientNet-B0	1.0	1.0	1.0	**94.98%**	0.02050
Feature Fusion (ResNet50 + EfficientNet-B0)	1.0	1.0	1.0	93.05%	0.15032
Ensemble (ResNet50 + EfficientNet-B0)	1.0	1.0	1.0	94.20%	**0.01105**

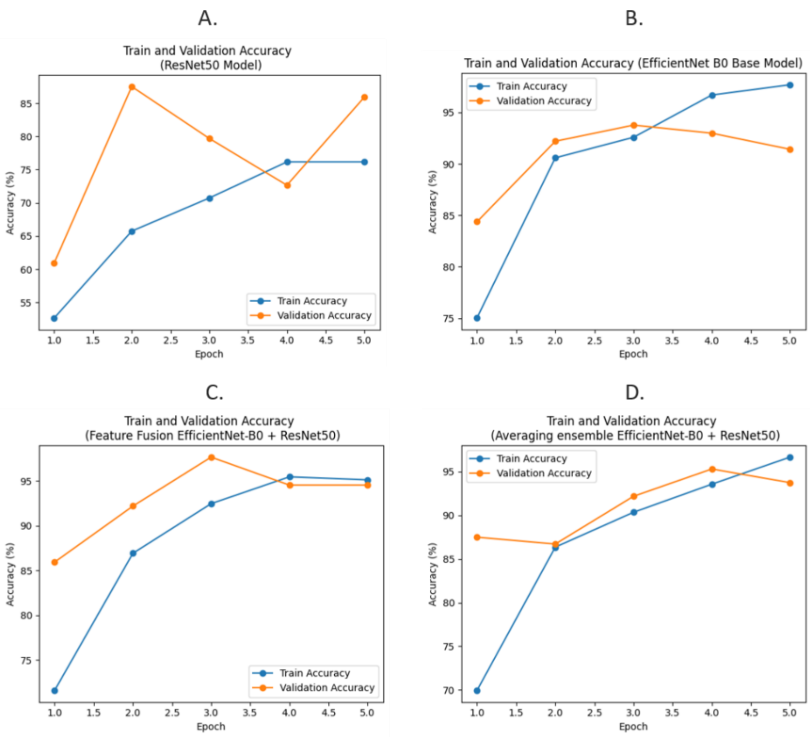

Figure 3. Train and validation accuracy from each experiments

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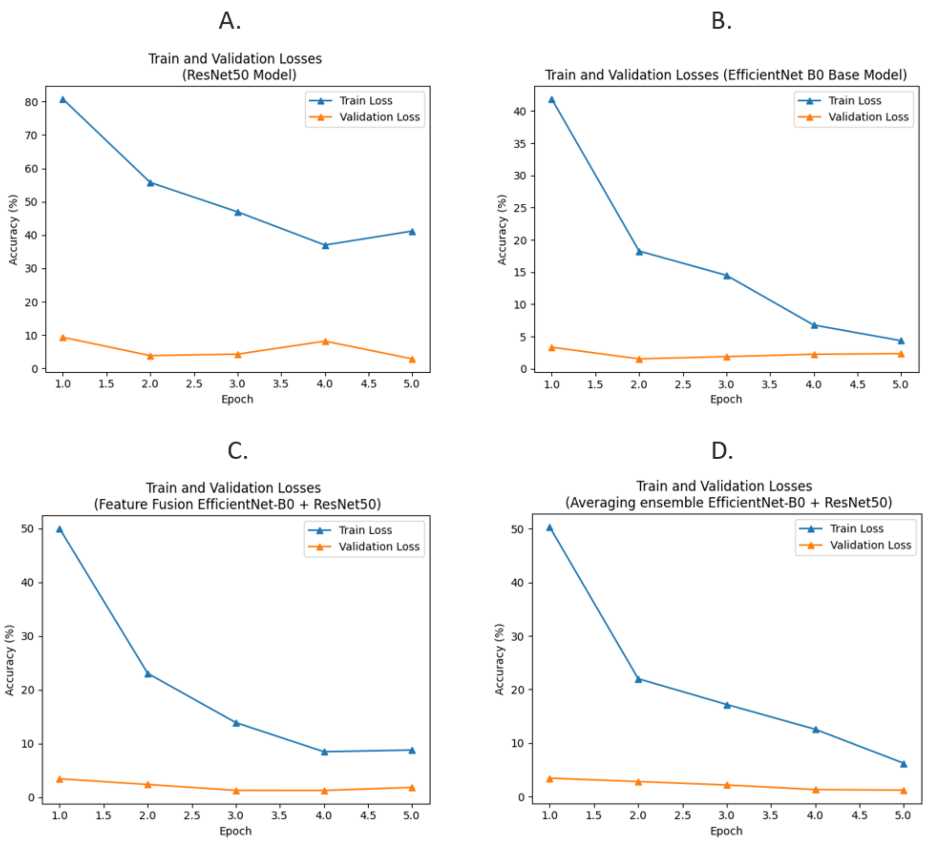

Figure 4. Train and validation loss from each experiments

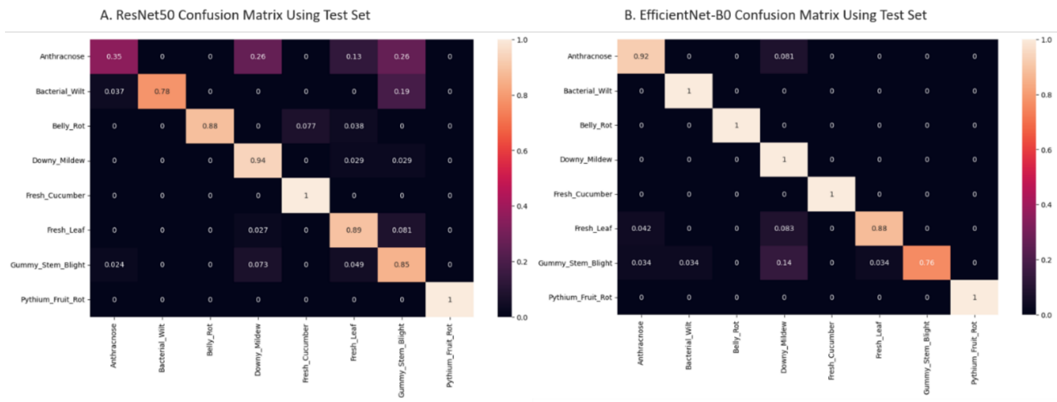

Figure 5.Confusion matrix result using test set : (A) ResNet50 and (B) EfficientNet-B0

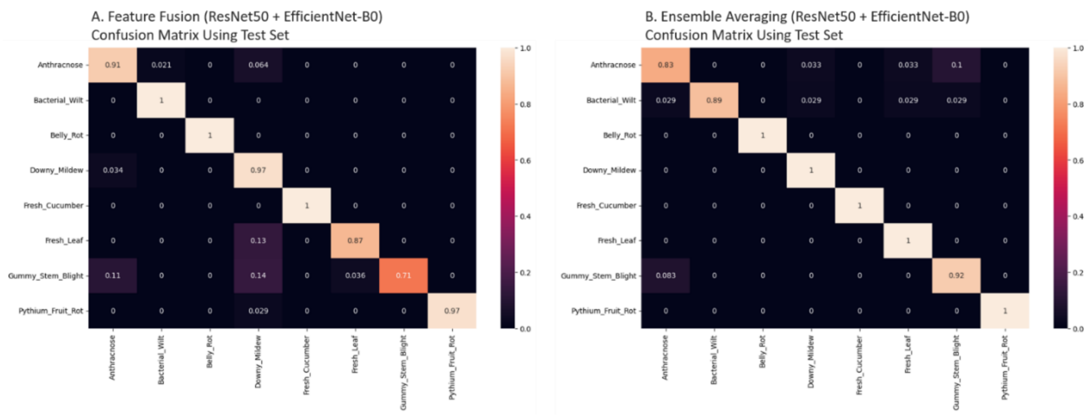

Figure 6.Confusion matrix result using test set : (A) Feature fusion ResNet50 and EfficientNet-B0, and (B) Ensemble learning ResNet50 and EfficientNet-B0

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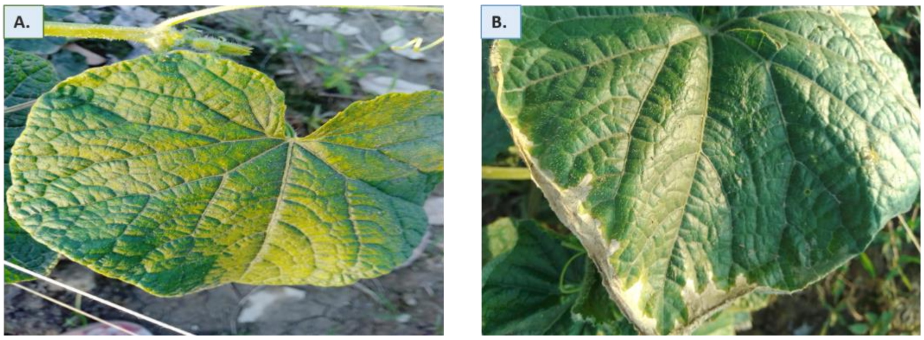

Figure 7.Character similarities between (A) fresh leaf and (B) stem gummy blight classes data

The prediction scores generated by each model will be aggregated and subsequently divided by the total number of models employed. Subsequently, during the ultimate phase, an assessment of the model will be conducted employing the test data that has been prepared. We also compare the ensemble results obtained with feature concatenation, which is a feature fusion technique. Both models utilize the Adaptive Moment Estimation (Adam) optimizer, which has been empirically demonstrated to enhance the precision and efficiency of neural networks by the utilization of the subsequent equation.

$$m_t = \beta_1 m_t - 1 + (1 - \beta_1)\left[\frac{\delta L}{\delta \omega_t}\right] \quad (3)$$

$$vt = \beta_2 v_t - 1 + (1 - \beta_2)\left[\frac{\delta L}{\delta \omega_t}\right] \quad (4)$$

The bias, denoted as m_t, is subject to updating based on its prior value. The parameters β_1 and β_2 represent exponential decay rates, while the variable ut is utilized to execute exponential updates to the weighted infinity norm.

3. RESULTS AND DISCUSSION

This section will display all data gathered from experiments conducted using the approach outlined. The complete training and evaluation procedure is conducted on Google Colaboratory, utilizing a computational environment equipped with a 12 GB RAM capacity and an Nvidia Tesla T4 GPU.

3.1. Experiment Result

Multiple model training scenarios are conducted in order to enhance the efficacy of the suggested methodology. The initial performance of the model was evaluated through separate training sessions using ResNet50 and EfficientNet-B0 as base models. Subsequently, we proceed with feature fusion by concatenating the features extracted from both models. Ultimately, we evaluate the efficacy of the proposed ensemble learning technique. The results of the testing conducted on a predetermined test set consisting of 259 photos from 8 distinct classes of cucumber circumstances are presented in Table 2. The ResNet50 model achieved an accuracy score of 89.57%, which was the lowest among the models evaluated. However, the feature fusion model combining ResNet50 and EfficientNet-B0 exhibited the greatest loss value of 0.15032. The model with the highest accuracy value is EfficientNet-B0, achieving a performance of 94.98%. On the other hand, the models ResNet50 and EfficientNet-B0 exhibit the lowest loss, both yielding a value of 0.01105 when constructed. The accuracy and loss values are recorded during the training process, which involves a substantial dataset of 902 training instances and 128 validation instances. These values are depicted in Figure 3 and Figure 4, respectively. In order to assess the model's ability to accurately categorize each class, we constructed a confusion matrix for analysis, as depicted in Figure 5 and Figure 6.

3.2. Discussion

The dataset employed in this research presents a distinctive challenge due to the presence of classes that exhibit a high degree of resemblance, as depicted in Figure 7. The accuracy of the model in distinguishing between fresh leaf and sticky stem blight classes might be hindered by several factors, including lighting conditions and shooting angles, which affect the similarity of the image data. The challenge in accurately identifying this particular class is evident in the confusion matrix depicted in Figure 5, parts A and B. These figures illustrate that the sticky stem blight and fresh leaf classes exhibit the lowest values in terms of predictive accuracy. The experimental findings demonstrate that the ensemble learning technique, specifically through the averaging of prediction scores, effectively enhances the model's capacity to distinguish between fresh leaf and sticky stem blight classes. In the interim, the outcomes of the training procedure depicted in Figure 3, parts C, and D, demonstrate that the feature fusion and the utilization of ensemble learning techniques can enhance the accuracy of the model. Furthermore, these approaches serve to mitigate the issue of overfitting, which arises from the model's inability to attain validation values that closely align with accuracy. Figure 4, part D demonstrates the model's effective detection capabilities, as evidenced by the comparatively minor loss results. This observation is further reinforced by the outcomes of the confusion matrix computations depicted in Figure 6, parts A and B. Based on the results obtained, we believe that feature fusion and ensemble learning are promising methods in the future because there are still challenges in the agricultural sector such as obstructed objects, dynamic lighting levels, similarities between classes and small object detection.

CONCLUSION

This research employs an ensemble learning technique known as averaging, wherein the predictions generated by many models are aggregated and averaged to ascertain the prediction score for each class. The efficacy of this strategy has been demonstrated to surpass that of feature fusion due to the distinct traits exhibited by each model, which effectively compensate for the limitations of other models. Empirical evidence demonstrates that the ResNet50 model exhibits superior performance in the identification of fresh leaf and sticky stem blight categories when compared to the EfficientNet-B0 model. In contrast, the performance of EfficientNet-B0 in detecting the remaining 6 classes surpasses that of ResNet50. The combination of two distinct model properties in an ensemble enhances the model's capacity for generalization. In the context of machine learning, the technique of feature fusion involves the integration of different features during the training phase. This approach, however, has the risk of introducing data noise into the resulting features. In a generic context, both feature fusion and ensemble learning exhibit considerable promise for enhancing model performance, contingent upon the characteristics of the dataset employed.

REFERENCES

[1] B. Z. Yuan, Z. L. Bie, and J. Sun, “Bibliometric analysis of cucumber (Cucumis sativus L.) research publications from horticulture category based on the web of science,” *HortScience*, vol. 56, no. 11, pp. 1304–1314, 2021, doi: 10.21273/HORTSCI16083-21.

[2] Anjna, M. Sood, and P. K. Singh, “Hybrid System for Detection and Classification of Plant Disease Using Qualitative Texture Features Analysis,” *Procedia Comput. Sci.*, vol. 167, no. 2019, pp. 1056–1065, 2020, doi: 10.1016/j.procs.2020.03.404.

[3] “Pathogens, precipitation and produce prices,” *Nat. Clim. Chang.*, vol. 11, no. 8, p. 635, 2021, doi: 10.1038/s41558-021-01124-4.

[4] N. Sultana, S. B. Shorif, M. Akter, and M. S. Uddin, “A dataset for successful recognition of cucumber diseases,” *Data Br.*, vol. 49, p. 109320, 2023, doi: 10.1016/j.dib.2023.109320.

[5] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[6] N. Saranya, L. Pavithra, N. Kanthimathi, B. Ragavi, and P. Sandhiyadevi, “Detection of Banana Leaf and Fruit Diseases Using Neural Networks,” in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2020, pp. 493–499, doi: 10.1109/ICIRCA48905.2020.9183006.

[7] H. Hong, J. Lin, and F. Huang, “Tomato Disease Detection and Classification by Deep Learning,” in *2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2020, pp. 25–29, doi: 10.1109/ICBAIE49996.2020.00012.

[8] D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, and S. Bhardwaj,

"Potato Leaf Diseases Detection Using Deep Learning," in *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2020, pp. 461–466, doi: 10.1109/ICICCS48265.2020.9121067.

[9] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," *Comput. Electron. Agric.*, vol. 134, pp. 135–141, 2017, doi: 10.1016/j.compag.2017.01.014.

[10] J. Kainat, S. Sajid Ullah, F. S. Alharithi, R. Alroobaea, S. Hussain, and S. Nazir, "Blended Features Classification of Leaf-Based Cucumber Disease Using Image Processing Techniques," *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/9736179.

[11] P. Zhang, L. Yang, and D. Li, "EfficientNet-B4-Ranger: A novel method for greenhouse cucumber disease recognition under natural complex environment," *Comput. Electron. Agric.*, vol. 176, no. January, p. 105652, 2020, doi: 10.1016/j.compag.2020.105652.

[12] M. Tan, R. Pang, and Q. V. Le, "EfficientDet: Scalable and efficient object detection," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 10778–10787, 2020, doi: 10.1109/CVPR42600.2020.01079.

[13] N. Hussain *et al.*, "Multiclass cucumber leaf diseases recognition using best feature selection," *Comput. Mater. Contin.*, vol. 70, no. 2, pp. 3281–3294, 2022, doi: 10.32604/cmc.2022.019036.

[14] C. Wang, P. Du, H. Wu, J. Li, C. Zhao, and H. Zhu, "A cucumber leaf disease severity classification method based on the fusion of DeepLabV3+ and U-Net," *Comput. Electron. Agric.*, vol. 189, no. August, p. 106373, 2021, doi: 10.1016/j.compag.2021.106373.

[15] M. Mera-Gaona, D. M. López, R. Vargas-Canas, and U. Neumann, "Framework for the ensemble of feature selection methods," *Appl. Sci.*, vol. 11, no. 17, pp. 1–16, 2021, doi: 10.3390/app11178122.

[16] N. Pudjihartono, T. Fadason, A. W. Kempa-Liehr, and J. M. O'Sullivan, "A Review of Feature Selection Methods for Machine Learning-Based Disease Risk Prediction," *Front. Bioinforma.*, vol. 2, no. June, pp. 1–17, 2022, doi: 10.3389/fbinf.2022.927312.

[17] M. A. Ganaie, M. Hu, A. K. Malik, M. Tanveer, and P. N. Suganthan, "Ensemble deep learning: A review," *Eng. Appl. Artif. Intell.*, vol. 115, 2022, doi: 10.1016/j.engappai.2022.105151.

[18] F. Gao, J. Sa, Z. Wang, and Z. Zhao, "Cassava Disease Detection Method Based on EfficientNet," in *2021 7th International Conference on Systems and Informatics (ICSAI)*, 2021, pp. 1–6, doi: 10.1109/ICSAI53574.2021.9664101.

[19] H. Farman, J. Ahmad, B. Jan, Y. Shahzad, M. Abdullah, and A. Ullah, "Efficientnet-based robust recognition of peach plant diseases in field images," *Comput. Mater. Contin.*, vol. 71, no. 1, pp. 2073–2089, 2022, doi: 10.32604/cmc.2022.018961.

[20] M. Rifqi and Suharjito, "Deteksi Kematangan Tandan Buah Segar (Tbs) Kelapa Sawit Berdasarkan Komposisi Warna Menggunakan Deep Learning," *J. Tek. Inform. Atmaluhur*, vol. 6, no. 1, p. 40, 2021, doi: 10.15408/jti.v14i2.23295.

[21] F. Rajeena P. P., A. S. U., M. A. Moustafa, and M. A. S. Ali, "Detecting Plant Disease in Corn Leaf Using EfficientNet Architecture—An Analytical Approach," *Electronics*, vol. 12, no. 8, 2023, doi: 10.3390/electronics12081938.

[22] E. M. G. Younis, S. M. Zaki, E. Kanjo, and E. H. Houssein, "Evaluating Ensemble Learning Methods for Multi-Modal Emotion Recognition Using Sensor Data Fusion," *Sensors*, vol. 22, no. 15, 2022, doi: 10.3390/s22155611.

[23] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," *36th Int. Conf. Mach. Learn. ICML 2019*, vol. 2019-June, pp. 10691–10700, 2019.

[24] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 2016-Decem, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.