Comparative Evaluation of CNN Architectures for Corn Leaf Diseases Classification

M. Abdallah*, M. F. Abu-Elyazeed
Dept. of Electronics and Communication, Cairo University, Giza, Egypt

***Abstract*—Corn has particular importance in the global food industry. Many diseases attack the corn crops, which affects the crop yield. Early classification and detection of these diseases are pivotal to preventing damage and achieving high crop productivity. Although deep learning, especially convolutional neural networks, has accomplished remarkable results in image recognition, selecting the optimal architecture and using limited datasets remains a challenge. To address this gap, a transfer learning approach based on ImageNet weights was applied to classify three common corn diseases (i.e., gray spot, common rust, and blight), as well as the healthy plants. Six CNN architectures—DenseNet201, EfficientNetB0, VGG16, ResNet50, InceptionV3, and InceptionResNetV2—inclusive performance was evaluated for classification on a corn dataset. Based on evaluation metrics, EfficientNetB0 achieves the highest training accuracy of 97.67% with a fast computational time of 71 seconds. It performs more efficiently than the other architectures. These findings support the use of deep learning models, particularly EfficientNet, in the evolution of artificial intelligence image classification system applications.**

Keywords*—Artificial intelligence; Convolutional Neural Network; deep learning; image processing; corn diseases classification

I. Introduction

The population is predictable to extend to 8.5 billion by 2030 [1]. Therefore, there is an imperative request to increase the production of agricultural crops to cover the needs of the increasing population. Consequently, crop productivity is very important worldwide [2]. Plant diseases are one of the prime factors of crop loss, with huge amounts of wasted food each year globally [3]. Plant diseases have many species, which can be bacterial, viral, or fungal. The diseases attack leaves, fruits, or branches and causes damage in the crop. To avoid crop loss, early crop disease identification is critical to be considered in the future [4].

Corn, or maize, is a worldwide produced crop. Corn agriculture plays a substantial role on account of its possibility export and it provides a lot of people with food [5]. Various businesses use corn, including the food industries, oils, drinks, and animal feed. The corn is exhibition of many diseases that may attack many parts of it, such as leaves, trunk, and fruit [6]. This has a serious leverage on the yield of crop harvest and can cause a huge financial loss. Diseases that attack corn leaves are the most severe of these diseases. Therefore, this work uses three widespread leaf diseases: gray spot, common rust, and blight [7].

Plant disease detection and classification have become a decisive issue in recent years. Artificial intelligence presents significant help to smart agriculture by introducing various techniques in classifying and detecting crop leaf disease [8]. Deep learning approach is the best emerging technology in image processing. Within the deep learning environment, Convolutional Neural Network [9] is the most perfect used technique for image classification, object detection, and segmentation. However, applying DL models to agricultural issues faces some challenges [10], including the lack of considerable datasets, the complex processing cost, and the large processing time.

This study aims to develop a corn disease classification based on deep learning techniques to overcome dataset limitations and achieve high performance. DenseNet201, EfficientNetB0, VGG16, ResNet50, InceptionV3, and InceptionResNetV2 were discussed along with the detailed experimentation conducted. The work combines advanced deep learning models with a transfer learning approach to tackle the challenges of deep learning models in computational time and the amount of data. This helps create a smart and efficient system that enables timely interventions and minimizes crop loss. Moreover, the study explores future suggestions by proposing improvements through model deployment.

II. Related Works

Common deep learning techniques have been widely used in developing smart agriculture. This section discusses various research papers based on corn and plant disease classification using deep neural network models, specifically CNN. Arabinda et al. [11] used a dataset comprised of four classes and a total of 4988 images of the maize crop. They have used the Densenet201 model with fine-tuned the Support Vector Machine and Bayesian optimization techniques. Their model accomplished a classification accuracy of 94.6%. Wisnu et al. [12] used a free dataset coming from the Kaggle website. This dataset has four classes with a total of 4188 images. They used the CNN methods with two various architectures, the ResNet50 and EfficientNetB0 models. The accuracy result acquired for the model ResNet-50 is 93% and for the second model EfficientNet-B0, the accuracy is 94%. Neha et al. [13] used a dataset consisting of four classes and a total of 4,188 images of the corn crop. They have developed pre-trained (EfficientNetB0, ResNet50, InceptionV3, and VGG). It was found that EfficientNetB0 outperformed all of the other models with accuracy 92.33%.

*Corresponding author.

Imran et al. [14] used the public Plant-Village dataset. It contains different types of corn. They used ten classes with a total of 20,202 data after the augmentation. They applied transfer learning for accurate classify to disease in corn. They used four models: (ResNet50, VGG16, Inception V3, and InceptionResNetV2). Seema et al. [15] developed three diverse algorithms: ResNet18, VGG16, and AlexNet. Architectures were carefully selected due to their previous achievement in similar tasks. The models were designed using a pre-trained method. The dataset was used from Kaggle website consisting of 4,188 images of corn leaves with disease besides healthy leaves. On the other work, Quy Thanh Lu et al. [16] discussed CNN models, including EfficientNetB5, MobileNet, VGG16, ResNet50, and InceptionV3, for plant disease classification. The methodology includes using transfer learning. EfficientNetB5 model achieved 92% and VGG16 achieved 91% in training accuracy. Vaishali et al. [17] presented a CNN-based method for plant disease classification. VGG16, VGG19, and ResNet are trained on the Plant-Village dataset with a maximum accuracy 85.28%.

Emmanuel et al. [18] introduced a study on the classification and detection of plant diseases using several models by using datasets of healthy and infected plant leaves. They employed several CNN models, such as VGG16, InceptionV3, and InceptionResNetV2, with a maximum accuracy 92.9%. Theodora et al. [19] developed different pre-trained models for tomato leaf disease identification. ResNet50, VGG16, InceptionV3, and proposed models achieved performances of 92.18%, 93.14%, 94.91%, and 96.02%, respectively. Xu et al. [20] proposed an amended ResNet50 model. The authors have used the maize dataset. The improved ResNet50 model achieved 96.02% accuracy. Compared to DenseNet, VGG16, and AlexNet, the validation accuracy was greater. Table I shows the comparison of the previous works.

TABLE I. COMPARISON OF RELATED WORKS

Authors (year)	Task	Model	Acc. (%)
Arabinda et al. (2023) [11]	Corn diseases classification	DenseNet201	94.6
Wisnu et al. (2023) [12]	Corn diseases classification	ResNet50 EfficientNetB0	94
Neha et al. (2023) [13]	Corn diseases classification	ResNet50, VGG16, Inception V3, InceptionResNetV2	92.33
Seema et al. (2024) [15]	Corn diseases classification	ResNet18, VGG16, AlexNet	95.5
Quy Thanh Lu et al. (2023) [16]	Plant diseases classification and detection	EfficientNetB5, MobileNet, ResNet50, InceptionV3, VGG16	92
Vaishali et al. (2023) [17]	Plant diseases classification	VGG16, VGG19, ResNet	85.28
Emmanuel et al. (2023) [18]	Plant diseases classification and detection	VGG16, InceptionV3, InceptionResNetV2	92.85
Theodora et al. (2023) [19]	Tomato diseases classification	VGGNet	96.02
Xu et al. (2023) [20]	Corn diseases classification	DenseNet, VGG16, AlexNet	96

III. MATERIALS AND METHODS

This study employed to enhancement of a six different CNN architectures (VGG16, DenseNet201, EfficientNetB0, ResNet50, InceptionV3, and InceptionResNetV2) to automatically classify corn diseases. The methodology is divided into several stages. A block diagram describing the research stages is shown in Fig. 1, which declares the work process flow of corn classification using CNN models.

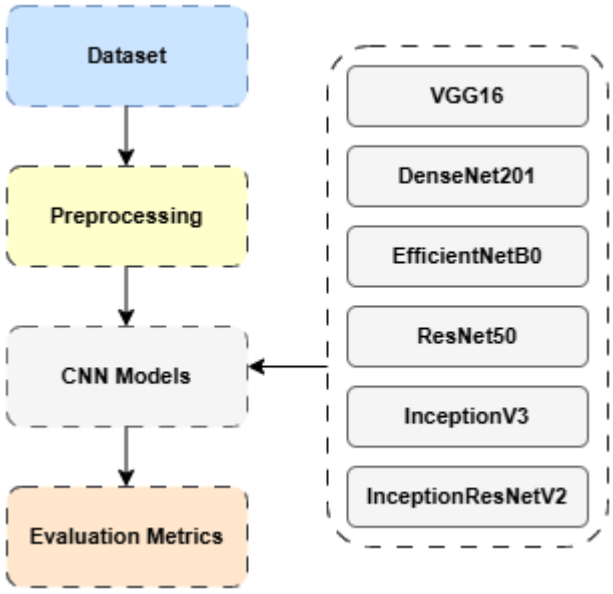

Fig. 1. Flowchart of our research.

A. Dataset

The CNN models were trained on corn leaves images to classify the image as healthy or diseased, and classify the kind of disease on image. The open and free corn dataset was used from the Kaggle website [21] for this study. It consists of four corn classes, as shown in Fig. 2. A total of 4,188 images are contained in the dataset. It has 1,306 common rust images, 1,146 blight images, 574 gray spot images, and 1,162 healthy images.

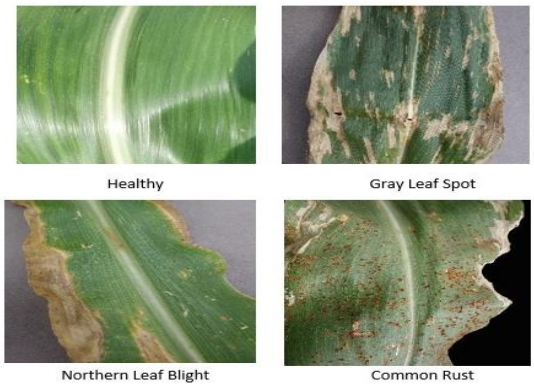

Fig. 2. Image samples from the corn dataset.

The corn dataset images are colored images of different sizes. The images are resized to 224×224 for DenseNet201, EfficientNetB0, VGG16, and ResNet50 architectures.

Otherwise, for the InceptionV3 and InceptionResNetV2 architectures, the images are resized to 299×299 pixels. The dataset was divided into training and validation data with a ratio of 80% and 20%, respectively.

B. CNN Architectures

Convolutional Neural Network was famed as a remarkable deep learning architecture for image recognition [22]. In this work, six pre-trained CNN models—VGG16, DenseNet201, EfficientNetB0, ResNet50, InceptionV3, and InceptionResNetV2—were applied. The models had been pre-trained using the ImageNet dataset and were available from the Keras library [23].

1) VGG16: VGG is a CNN model brought by Simonyan and Zisserman in 2015 [24]. It has 3×3 convolutional layers and max pooling to reduce the size of the kernels. Moreover, three dense layers, two have 4096 nodes, the third contains "one channel" for each class, and a softmax classifier [25]. VGG16 comprises 13 convolutional layers and 3 dense layers. VGG16 can transfer learned features to many tasks, making it a favorite choice for transfer learning.

2) DenseNet architecture: DenseNet was an innovative architecture introduced by Huang et al. in 2016 [26]. The DenseNet was inspired, subordinate the same direction of ResNet and the Highway network. To enhance the performance and to have most information stream between layers, all layers are connected in a feed-forward way. For each layer, the feature maps of all previous layers are utilized as inputs to all the next layers. It relieves the vanishing gradient and has decreased the number of parameters [27]. For this study, the DenseNets model with 201 layers has chosen.

3) EfficientNet: EfficientNet strives to attain great performance with few computational compared to other models. it was innovated by Mingxing Tan and Quoc V. Le in 2019 [28]. The key idea of EfficientNet is a scaling mechanism that scales the dimensions of width, depth, and resolution by using a compound coefficient [29]. This technique guarantees that the model adjusts easily to differing computational constraints while keeping its performance across various scales. There are a series of EfficientNet models, ranging from B0 to B7. For this task, B0 was chosen. Because of the smaller input size and fewer parameters, it is easier to test and has lower computing capabilities.

4) ResNet: ResNet has many versions. In this work, a ResNet50 was chosen which consisted of 50 layers of a neural network. It presented the concept of shortcut connections to solve the vanishing gradient problem, which happened when the network increased in the depth [30]. Because of this connections, gradients could pass in deeper layers without being reduced. These improve the performance and the accuracy.

5) InceptionV3: The "Inception" idea was first presented by Szegedy et al. (2015) in the GoogLeNet architecture. The sequential aspect of the GoogLeNet architecture has been referred to as Inception vN, with N going into the version number [31]. InceptionV3 used "spatial factorization" to reduce the computational cost and applied a "stem module" to enhance the flow of information. It also introduced "label smoothing" to regularize the network's output and improve its performance. It has a depth of 189.

6) InceptionResNetV2: It was introduced in 2016 and 2017, merging the ResNet with the Inception architecture [32]. The architecture combined residual connections and "inception modules" to enhance the performance and accuracy of the network. It has 55.9 million parameters, 215 MB, depth 449, and 164 layers.

C. Transfer Learning

Transfer learning is a computer vision approach that implicit building a fresh model on top of an old one [33]. The goal is to enable the fresh model to learn features from the existing one. That is allowing the incoming model to be faster and use less data. Through transfer learning, the dense layers of the network are stripped and replaced with another new layers. The term "transfer learning" describes what this strategy requires: transfer information from one model to another model that can utilize from its knowledge [34]. The transfer learning technique has been applied on the CNNs architectures to accelerate learning. The models were designed and loaded with pre-trained ImageNet weights. Transfer learning of the models was done by removing the original dense layers and substitute them with another.

D. Evaluation Metrics

The model's performance was tested for oracular fastness utilizing accuracy, precision, and recall in this study [35]. The metrics were thoughtful based on the data from the confusion matrix, which compared the actual data with model-predicted data results. The accuracy includes (true positives 'TP', true negatives 'TN') to the total number of prospects. The Precision is the proportion of correctly classified to the total number of positive states. The Recall is the proportion of positive instances to the sum of true positive and false negative instances [36]. F1-Score combines two key metrics: precision and recall. The formulas for accuracy, precision, recall, and F1-Score were introduced in Eq. (1) to Eq. (4), respectively.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+FP+TN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+TF}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

$$\text{F1 score} = 2\left(\frac{\text{Recall.Precision}}{\text{Recall+Precision}}\right) \quad (4)$$

IV. Results and Discussion

The experiments were done on (GPU) on Google Colab. All testing was done on Windows 10 64-bit, utilizing a Core i7 processor operating at 2.3 GHz, 16 GB of RAM, and the programming language, Python. TensorFlow library was used in software coding. Also, Keras was used for pre-trained models loaded.

A. Results

The proposed method used DenseNet201, EfficientNetB0, VGG16, ResNet50, InceptionV3, and InceptionResNetV2 models. The pre-trained weights from ImageNet, the dense layers were removed in charge of the classification and were replaced with new dense layers that are particular to the task. The classification layers were trained, while the other layers remained frozen. Adam optimizer was used with a learning rate of 0.001, and batch size 16.

For every experiment, accuracy and categorical cross-entropy loss are used for evaluation of the models. The performances are graphically drawn for each model with accuracy and loss. Generally, the loss score and accuracy based on the test dataset are computed and used to set the performance of the models. Each of the experiment runs for 50 epochs. Training process graphs of EfficientNetB0, DenseNet201, VGG16, ResNet50, InceptionV3, and InceptionResNetV2 models are shown in Fig. 3 to Fig. 8. The figures describe the training and validation accuracy phases. Also, they describe the training and validation loss phases. The accuracy graphs show a steady increase in accuracy. The loss graphs show a piecemeal decrease in value as the number of epochs increases. These graphs distinguish issues, such as overfitting and underfitting.

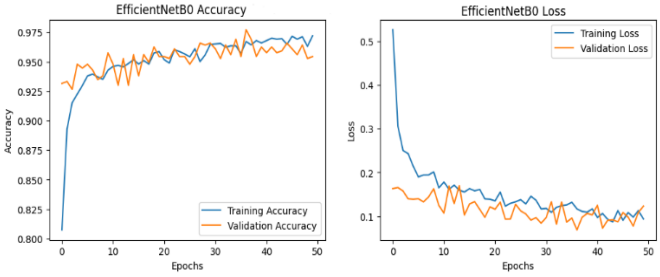

Fig. 3. Training graph of the EfficientNetB0 model.

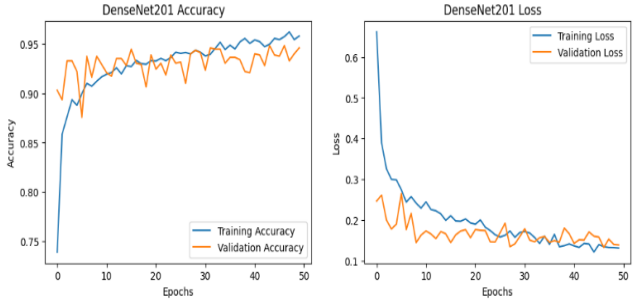

Fig. 4. Training graph of the DenseNet201 model.

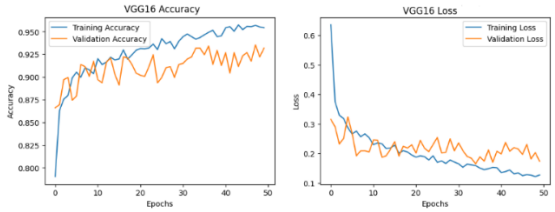

Fig. 5. Training graph of the VGG16 model.

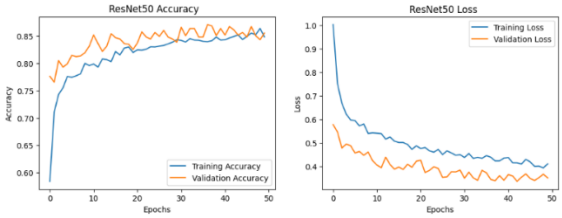

Fig. 6. Training graph of the ResNet50 model.

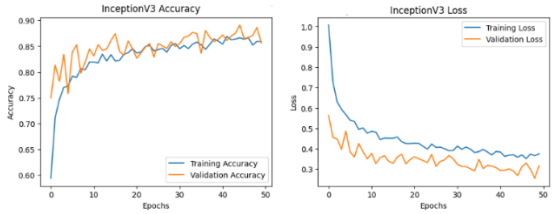

Fig. 7. Training graph of the InceptionV3 model.

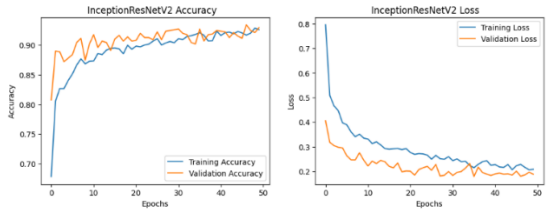

Fig. 8. Training graph of the InceptionResNetV2 model.

The experiments on the six models were executed by using a transfer learning approach, where some layers of the pre-trained model were kept frozen, while the classification layers were trained using the corn dataset. This technique allows the model to have the general knowledge gained from large datasets such as ImageNet dataset to the certain features of the used dataset in this work. Also, dropout was applied to the model in ratio 0.4 and 0.3. The dropout used to reduce the chance of overfitting while keeping the ability to capture important details from the training data. The results show no sign of the overfitting. Table II shows the results of the models, including the training accuracy, validation accuracy, loss, precision, recall, f- score, and training time per epoch of each model.

TABLE II. COMPARISION OF MODEL TESTING RESULT

Model	Training Acc. (%)	Training Loss (%)	Validation Acc. (%)	Validation Loss (%)	Precision (%)	Recall (%)	F-Score (%)	Time/Epoch
EfficientNetB0	97.67	0.06	94.85	0.15	94	94	94	71 s
DenseNet201	97.32	0.07	94.86	0.13	93	93	93	91 s
VGG16	95.22	0.12	94.54	0.16	92	92	92	76 s
ResNet50	87.44	0.33	86.48	0.34	84	84	84	80 s
InceptionV3	88.93	0.27	86.84	0.31	86	86	86	67 s
InceptionResNetV2	93.82	0.15	92.22	0.19	91	91	91	137 s

Based on the experiments result, the three superior models for corn classification are EfficientNetB0, DenseNet201, and VGG16. EfficientNetB0 shows the top performance with the highest accuracy of 97.67%, as well as equally high recall, precision, and F1-score (94%), making it the most efficient model. DenseNet201 is also an efficient model with competitive accuracy of up to 97%. Meanwhile, VGG16 achieved high accuracy (up to 95%) with a good inference time (76 seconds). On the other hand, ResNet50 shows the lowest accuracy.

B. Discussion

This section discusses the best performance achieved from the research results, namely the EfficientNetB0, DenseNet201, and VGG16 models. The first result from EfficientNetB0 produced a test accuracy of 94% and a loss of 15%. Fig. 9 shows the results of the testing data, while Fig. 10 shows the confusion matrix of the EfficientNetB0 model.

	precision	recall	f1-score	support
0	0.92	0.87	0.89	208.99999999999923
1	0.98	0.99	0.99	208.9999999999991
2	0.90	0.91	0.90	209.00000000000028
3	0.97	1.00	0.99	209.00000000000088
accuracy			0.94	835.9999999999995
macro avg	0.94	0.94	0.94	835.9999999999995
weighted avg	0.94	0.94	0.94	835.9999999999995

Fig. 9. Classification report of EfficientNetB0 model.

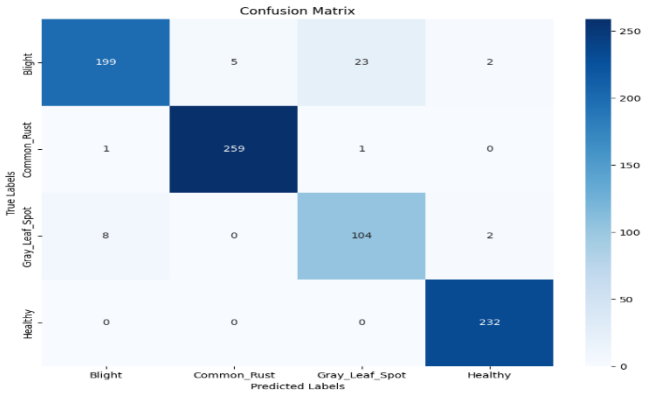

Fig. 10. Confusion matrix of EfficientNetB0 model.

Based on Fig. 9, the EfficientNetB0 model show a very high performance in classifying four corn classes. The precision value, recall, and F1-score of the healthy class are 97%, 100%, and 99%, respectively. The gray leaf class shows 90%, 91%, and 90%. The common rust class shows 98%, 99%, and 99%. Whereas, the blight class shows 92%, 87%, and 89%. The comprehensive test accuracy of the model reaches 94.85%.

	precision	recall	f1-score	support
0	0.86	0.88	0.87	208.99999999999923
1	0.97	1.00	0.98	208.9999999999991
2	0.90	0.84	0.87	209.00000000000028
3	1.00	1.00	1.00	209.00000000000088
accuracy			0.93	835.9999999999995
macro avg	0.93	0.93	0.93	835.9999999999995
weighted avg	0.93	0.93	0.93	835.9999999999995

Fig. 11. Classification report of DenseNet201 model.

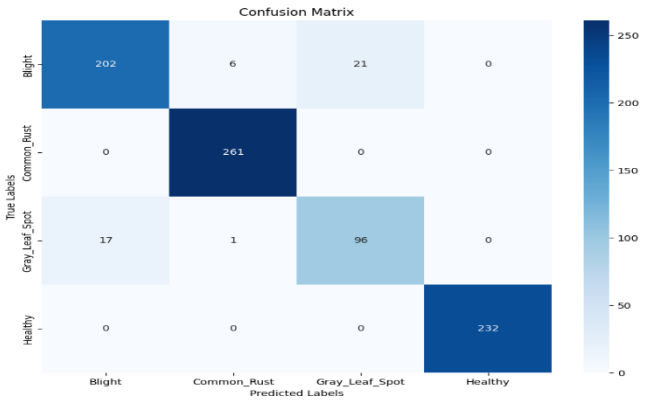

Fig. 12. Confusion matrix of DenseNet201model.

Second, the DenseNet201 model showed as well high classification performance with total test accuracy of 94.86%. In the healthy class, the model produced equally value of precision, recall, and F1-score reaching 100%. It suggested how well the model's strength can classify healthy cases. Also, the common rust class shows efficient performance of 97%, 100%, and 98%. The gray leaf class shows 90%, 84%, and 87%. The blight class shows slightly low performance of 86%, 88%, and 87%. Fig. 11 shows the classification report for the DenseNet201 model, while Fig. 12 shows its confusion matrix.

	precision	recall	f1-score	support
0	0.88	0.83	0.85	208.99999999999923
1	0.97	1.00	0.98	208.9999999999991
2	0.87	0.87	0.87	209.00000000000028
3	0.98	1.00	0.99	209.00000000000088
accuracy			0.92	835.9999999999995
macro avg	0.92	0.92	0.92	835.9999999999995
weighted avg	0.92	0.92	0.92	835.9999999999995

Fig. 13. Classification report of the VGG16 model.

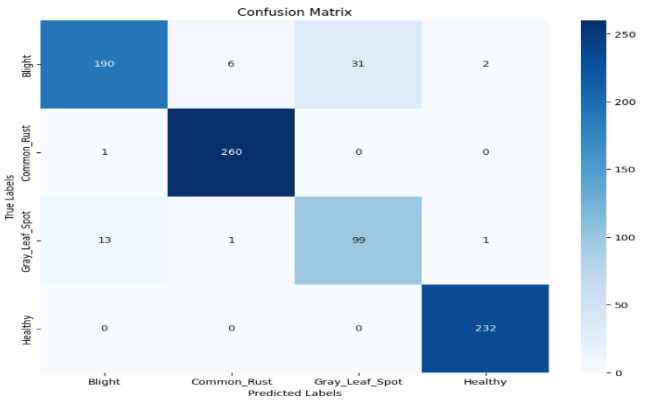

Fig. 14. Confusion matrix of VGG16 model.

And at last, VGG16, obtained a test accuracy of 94.54% and a loss of 16%. The test results of VGG16 model and its confusion matrix is shown in Fig. 13 and Fig. 14, respectively. The model introduced a good performance in identifying the corn categories. The blight class has a precision value of 88%, recall of 83%, and F1-score of 85%, signing that it is lower effective in identifying most blight cases. In contrast, in the rust class, the precision value is registered as higher, 97%, recall of 100%, and F1-score of 98%. In healthy class, the model achieved very good values of precision of 98%, recall of 100%, and F1-score of 99%. In the gray class, the model produced equally value of precision, recall, and F1-score reaching 87%. Despite some variance in identification between classes, the model still shows high performance for using in corn image classification.

TABLE III. COMPARISON OF MODEL EVALUATION RESULT WITH PREVIOUS STUDIES

Proposed Method	Acc (%) This Study	Acc (%) [11]	Acc (%) [12]	Acc (%) [13]	Acc (%) [18]	Acc (%) [20]
EfficientNetB0	97.67	-	94	-	-	-
DenseNet201	97.3	94.6	-	-	-	96
VGG16	95.5	-	-	92.33	92.58	-

While this study essentially focuses on classification accuracy, future research may discuss detection of corn images and use of agriculture robots to control the diseases. Table III provides a detailed comparison between the results of this study relative to these in previous works.

V. CONCLUSION

This study evaluated six deep learning architectures, namely, DenseNet201, EfficientNetB0, VGG16, ResNet50, InceptionV3, and InceptionResNetV2, for corn leaf diseases classification. Among the models, EfficientNetB0 achieved the highest accuracy of 97.67%, showing superior efficiency and balanced precision-recall-f-score performance with fast inference time. DenseNet201 and VGG16 also showed competitive accuracy (97.32% and 95.22%). This study exposes the use of a transfer learning approach that was applied to overcome dataset limitations and to achieve high accuracy with fast computational time. These findings confirm that the transfer learning approach can provide a stable and efficient framework for plant disease classification.

Overall, the experiments result manifest that CNN-based architectures, especially EfficientNetB0, can be used in advanced AI image classification applications. In the future, it may help smart agriculture robots by using digital image processing and detection. It is imperative to apply smart techniques to safeguard plants and assist farmers in disease species and control. Such great efforts will go a long way to help farmers to tackle corn diseases, maintain their sustenance, and support the economy.

REFERENCES

[1] V. Dhaka, S. Meena, G. Rani, D. Sinwar, Kavita , M. Ijaz, and M. Wo´zniak, "A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases," Sensors 21, no. 14: 4749, 2021, doi: 10.3390/s21144749.

[2] E. Too , L. Yujian , S. Njuki, L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, pp. 272-279, 2019, doi: 10.1016/j.compag.2018.03.032.

[3] G. Storey, Q. Meng, and B. Li, "Leaf Disease Segmentation and Detection in Apple Orchards for Precise Smart Spraying in Sustainable Agriculture," Sustainability 14, 2022, doi: 10.3390/su14031458.

[4] Yuan, Yongqi, Jinhua Sun, and Qian Zhang, "An Enhanced Deep Learning Model for Effective Crop Pest and Disease Detection," Journal of Imaging 10, no. 11, 2024, doi: 10.3390/jimaging10110279.

[5] Rajeena P. P., Fathimathul, Aswathy S. U., Mohamed A. Moustafa, and Mona A. S. Ali, "Detecting Plant Disease in Corn Leaf Using EfficientNet Architecture—An Analytical Approach," Electronics 12, no. 8, 2023, doi: 10.3390/electronics12081938.

[6] M. Fraiwan, E. Faouri, N. Khasawneh, "Classification of Corn Diseases from Leaf Images Using Deep Transfer Learning," Plants 11, 2022, doi:10.3390/plants11202668.

[7] A. Waheed, M. Goyal, D. Gupta, A. Khanna, A. E. Hassanien, and H. M. Pandey, "An Optimized Dense Convolutional Neural Network Model for Disease Recognition and Classification in Corn Leaf," Comput. Electron. Agric., 175, 105456, 2020, doi: 10.1016/j.compag.2020.105456.

[8] I. Ahmed, and P. Yadav, "A Systematic Analysis of Machine Learning and Deep Learning Based Approaches for Identifying and Diagnosing Plant Diseases," Sustainable Operations and Computers, Elsevier, vol. 4, pp. 96-104, 2023, doi: 10.1016/j.susoc.2023.03.001.

[9] Yuan, Yongqi, Jinhua Sun, and Qian Zhang, "An Enhanced Deep Learning Model for Effective Crop Pest and Disease Detection," Journal of Imaging 10, no. 11, 2024, doi: 10.3390/jimaging10110279.

[10] Shereen Essam Elbohy, Mona M. Nasr and Farid Ali Mousa, "Automatic Detection of Natural Disasters Using Faster R-CNN with ResNet50 Backbone," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 16, no. 6, 2025. doi: 10.14569/IJACSA.2025.0160633.

[11] Arabinda Dash, Prabira Kumar Sethy, and Santi Kumari Behera, "Maize Disease Identification Based on Optimized Support Vector Machine using Deep Feature of DenseNet201," Journal of Agriculture and Food Research, vol. 14, 100824, ISSN 2666-1543, 2023, doi: 10.1016/j.jafr.2023.100824.

[12] Wisnu Pamungkas, Wardhana, Machammad, Zamah Sari, Azhar, Yufiz, "Leaf Image Identification: CNN with EfficientNet-B0 and ResNet-50 Used to Classified Corn Disease," Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), vol. 7, 326-333, 2023, doi: 10.29207/resti.v7i2.4736.

[13] Neha Sandotra1, Palak Mahajan1, Pawanesh Abrol, and Parveen Kumar Lehana, "Analyzing Performance of Deep Learning Models under the Presence of Distortions in Identifying Plant Leaf Disease," International Journal of Informatics and Communication Technology (IJ-ICT), vol. 12, pp. 115-126, 2023, doi: 10.11591/ijict.v12i2.pp115-126.

[14] Imran Khan, Shahab Saquib Sohail, Dag Øivind Madsen, and Brajesh Kumar Khare, "Deep Transfer Learning for Fine-Grained Maize Leaf Disease Classification," Journal of Agriculture and Food Research, vol. 16, 101148, ISSN 2666-1543, 2024, doi: 10.1016/j.jafr.2024.101148.

[15] Seema Vishwakarma, and Sachin Bhoite, "Classification of Corn Leaf Disease using Resnet18, Alexnet and VGG16," Grenze International Journal of Engineering and Technology (ACT2024), no. 2, pp.1333-1339, 2024.

[16] Q. Lu, "An Approach for Classification of Diseases on Leaves," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 14, no. 10, 2023, doi: 10.14569/IJACSA.2023.01406128.

[17] V. Suryawanshi, S. Adivarekar, K. Bajaj, and R. Badami, "Comparative Study of Regularization Techniques for VGG16, VGG19, and ResNet-50 for Plant Disease Detection," ICCCT 2023, Proceedings of International Conference on Communication and Computational Technologies, Springers, 2023, pp. 771-781, doi: 10.1007/978-981-99-3485-0_61.

[18] E. Moupojou et al, "FieldPlant: ADataset of Field Plant Disease Detection and Classification with Deep Learning," IEEE Open Acess Journal, vol. 11,pp. 35398-35410, 2023, dio:10.1109/ACCESS.2023.3263042.

[19] Theodora Sanida, Argyrios Sideris, Maria V. Sanida, and Minas Dasygenis, "Tomato leaf disease identification via Two–stage Transfer Learning Approach," Smart Agricultural Technology, vol. 5, 100275, ISSN 2772-3755, 2023, doi: 10.1016/j.atech.2023.100275.

[20] W. Xu, W. Li, and L. Wang, and M. F. Pompelli, "Enhancing Corn Pest and Disease Recognition through Deep Learning: A Comprehensive Analysis," Agronomy 13, 2023, doi: 10.3390/agronomy13092242.

[21] G. Smaranjit, Corn or maize leaf disease dataset, Kaggle, 2020. https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset?select=data.

[22] R. Devi, V. Kumar, and P. Sivakumar, "EfficientNetV2 Model for Plant Disease Classification and Pest Recognition," Computer Systems Science & Engineering, vol. 45, no. 2, 2023, doi: 10.32604/csse.2023.032231.

[23] N. Kumar, M. Rathee, N. Chandran, D. Gupta, A. Rastogi, and R. Sharma, "CrypTFlow: Secure TensorFlow Inference," 2020 IEEE Symposium on Security and Privacy (SP), pp. 336–353, 2020, doi: 10.1109/SP40000.2020.00092.

[24] K., Simonyan, and A. Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition," 3rd International Conference on Learning Representations (ICLR 2015), Computational and Biological Learning Society, 2015, pp. 1–14, dio: 10.48550/arXiv.1512.03385.

[25] A. Paymode, V. Malode,"Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG," Artificial Intelligence in Agriculture, vol. 6, pp. 23-33, 2022, doi: 10.1016/j.aiia.2021.12.002.

[26] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

[27] Y. G, R. B, K. M and S. R, "Efficient Plant Disease Detection using K-Means clustering and DenseNet-based Classification," 2025 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2025, pp. 1197-1204, doi: 10.1109/ICEARS64219.2025.10941165.

[28] M. Tan, and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," Proceedings of the 36 th International Conference on Machine Learning, Long Beach, California, PMLR 97, 2019, doi:10.48550/arXiv.1905.11946.

[29] R. Devi, V. Kumar, and P. Sivakumar, "EfficientNetV2 Model for Plant Disease Classification and Pest Recognition," Computer Systems Science & Engineering, vol.45, no.2, 2023, doi: 10.32604/csse.2023.032231.

[30] W. Shafk, A. Tufail, C. Liyanage, and R. Apong, "Using transfer learning-based plant disease classifcation and detection for sustainable agriculture," BMC Plant Biology, no. 136, 2024, dio: 10.1186/s12870-024-04825-y.

[31] I. Khan, S. Sohail, D. Madsen, and B. Khare, "Deep transfer learning for fine-grained maize leaf disease classification," Journal of Agriculture and Food Research, vol. 16, 2024, doi: 10.1016/j.jafr.2024.101148.

[32] C. Szegedy, S. Loffe, V. Vanhoucke, and A. Alemi, "Inception-v4, inception-ResNet and the impact of residual connections on learning," AAA1'17: Proceeding of the Thirty-First AAAI Conference on Artificial Intelligence, 04 February 2017, pp. 4278 -4284, doi: 10.5555/3298023.

[33] T.-H Nguyen, T.-N Nguyen, and B.-V Ngo, "A VGG-19 Model with Transfer Learning and Image Segmentation for Classification of Tomato Leaf Disease," AgriEngineering, no. 4, pp. 871-887, 2022, doi: 10.3390/agriengineering4040056.

[34] Ira P. Saril , Budi Warsito ,and Oky D. Nurhayati, "Automated Classification of Parasitic Worm Eggs Based on Transfer Learning and Fine-Tuned CNN Models," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 16, no. 5, 2025. doi: 10.14569/IJACSA.2025.0160511.

[35] A. Darwish, D. Ezzat, and A. E. Hassanien, "An optimized model based on convolutional neural networks and orthogonal learning particle swarm optimization algorithm for plant diseases diagnosis," Swarm and Evolutionary Computation, vol. 52, 2022, doi: 10.1016/j.swevo.2019.100616.

[36] A. Septiarini, R. Saputra, A. Tejawati, M. Wati, and H. Hamdani, "Pattern Recognition of Sarong Fabric using Machine Learning Approach Based on Computer vision for Cultural Preservation," International Journal of Intelligent Engineering and Systems, vol. 15, no. 5, pp. 284–295, Oct. 2022, doi: 10.22266/ijies2022.1031.26.