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Sigatoka and xanthomonas Banana leaf disease detection via transfer learning

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SDG.

Abstract. Plant diseases are a significant concern in agriculture, contributing to as much as 16% of global agricultural losses. This poses serious threats to food security, especially for crops like bananas, which are highly vulnerable to diseases such as Xanthomonas Wilt and Sigatoka leaf spot. These diseases have the potential to cause complete yield losses, reaching up to 100%. Addressing these challenges is crucial, and this study aims to do so by developing a robust disease detection model. Leveraging Convolutional Neural Network (CNN) algorithms, we have created a sophisticated system capable of accurately identifying and categorizing diseases in banana plants. To train our model effectively, we have gathered a meticulously curated dataset of banana plant leaf images from regions heavily affected by these diseases. This dataset has been carefully categorized into three groups: Healthy, Xanthomonas Wilt infected, and Sigatoka leaf spot infected. Employing advanced techniques such as data augmentation and transfer learning, we have fine-tuned our model using various architectures including MobileNet, EfficientNet, VGG16, VGG19, and InceptionV3. Our research findings highlight the exceptional performance of the VGG16 model, achieving an impressive classification accuracy of 81.53% during rigorous testing with independent datasets. Looking to the future, we recognize the need for further improvements in model performance. This includes acquiring a more diverse and expansive dataset and implementing automatic hyperparameter selection methods.

1. Introduction

Dessert bananas, cherished and extensively cultivated in Ethiopia, thrive across diverse regions under optimal growth conditions. With their rich cultural significance and versatile uses, bananas are not only a staple food but also a symbol of community and abundance. Their cultivation has deep-rooted socioeconomic importance, particularly in the southern and southwestern regions of Ethiopia. In these areas, bananas play pivotal roles in bolstering rural livelihoods by providing a reliable

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source of food security, generating income for local farmers, and creating employment opportunities along the entire agricultural value chain. Given that bananas cover a substantial 56.79% of Ethiopia's total fruit acreage and boast an annual production exceeding 500,000 tons, their cultivation serves as a cornerstone of agricultural sustainability and economic resilience in the country.

However, despite their economic significance, banana production faces formidable challenges, primarily from diseases such as Xanthomonas Wilt and Sigatoka leaf spot infections. These diseases not only threaten crop yields but also jeopardize food security, impacting the livelihoods of smallholder farmers and the broader ecosystem. Timely detection and effective management of plant diseases are essential to mitigate these risks and ensure the long-term sustainability of banana cultivation.

The manual detection of plant diseases presents numerous challenges due to the complexity of symptoms, variations in disease etiology, and the dynamic progression of infection. This renders naked eye detection unreliable and less efficient compared to automated systems. Automated detection methods, powered by advanced technologies such as computer vision and machine learning, offer a promising solution. These technologies provide greater precision and scalability, enabling plant pathologists, farmers, and agricultural experts to overcome obstacles in disease identification and control with enhanced efficiency and accuracy.

To address these challenges, researchers have increasingly turned to advanced technological solutions. Deep learning, a subset of machine learning, has emerged as a state-of-the-art technology with promising applications in plant disease diagnosis. By analyzing various plant parts, including leaves, stems, and fruits, deep learning algorithms can effectively detect and classify diseases with unprecedented accuracy, providing invaluable support to farmers and agricultural practitioners.

Moreover, agriculture serves as the backbone of the economy in many developing nations, including Ethiopia. A significant portion of the population relies on farming for their livelihoods, underscoring the importance of innovative solutions to enhance agricultural productivity and sustainability. In this context, the demand for technical solutions to support farmers and address agricultural challenges is particularly high.

This study contributes to addressing these challenges by leveraging cutting-edge technologies such as Convolutional Neural Network (CNN) transfer learning and data augmentation techniques. By tackling the overfitting problem associated with small datasets, these advanced methodologies enhance the accuracy and robustness of disease detection models, paving the way for future advancements in agricultural technology. The contributions of this work extend beyond academia, with practical implications for improving agricultural practices and enhancing food security in Ethiopia and beyond.

This study employed Convolutional Neural Network (CNN) transfer learning and data augmentation techniques to address the overfitting issue stemming from small datasets. The contributions of this research are outlined as follows:

- A total of 1982 banana leaf images were collected from Arbaminch Zuria Woreda Lante and Chano kebele, as well as the Gamugofa zone Mierab Abaya Woreda Omolante kebele. These images were meticulously categorized and cross-checked by two plant pathologists to ensure accuracy;
- Eight data augmentation parameters were utilized to artificially expand the dataset. This augmentation process resulted in a notable increase in the model's detection accuracy;
- Comparative analysis revealed that employing data augmentation with CNN pretrained models (VGG16, VGG19, MobileNet, EfficientNet, and InceptionV3) for banana disease classification significantly enhanced performance when compared to developing a model from scratch;
- Experimental findings demonstrate that leveraging data augmentation via pretrained models substantially improves the performance of the proposed model. The remarkable outcomes of the experiments underscore the efficacy of transfer learning and data augmentation in enhancing the proposed model's performance.

The rest of the paper is compiled as follows. Section 2 explains the similar works of the other scholars. Section 3 explains the system architecture of the proposed model, Section 4 describes the algorithm used to build the disease detection model, and Section 5 explains the source of the dataset, experimental scenario, hyperparameter selection methods, result, and discussion. In the end, the article concludes the summary in Section 6.

2. Related works

Research in banana disease detection has witnessed significant advancements in recent years, driven by the urgent need to address threats posed by diseases such as Xanthomonas Wilt and Sigatoka leaf spot. Various studies have explored innovative approaches, including neural network-based methods and deep learning algorithms, to improve the accuracy and efficiency of disease detection in banana leaves and fruits. This section highlights several noteworthy contributions in this domain, ranging from traditional image processing techniques to the integration of CNNs and transfer learning for enhanced disease diagnosis. Additionally, advancements such as transfer learning and the exploration of machine learning for crop prediction have furthered our understanding of banana disease detection. By combining cutting-edge technologies with comprehensive reviews of the field, researchers are making significant strides toward safeguarding banana crops and ensuring global food security. This section encompasses a review of related works by various authors focusing on plant disease detection employing diverse techniques.

Saranya et al. [1] introduced a neural network-based approach for detecting diseases in banana leaves and fruits. The experimentation utilized a dataset consisting of 60 images, including 25 leaf disease images, 25 fruit disease images, 5 healthy leaf images, and 5 healthy fruit images. The researchers employed traditional image processing techniques, encompassing image acquisition, preprocessing, segmentation, feature extraction, and classification using an Artificial Neural Network (ANN). Image preprocessing involved tasks such as conversion to JPG format, resizing, and color conversion. Fuzzy C-means and histogram-based equalization were utilized for image segmentation, followed by pattern recognition for feature extraction. Classification was performed using a feed-forward back-propagation neural network.

Amara et al. applied a deep learning-based approach to classify banana diseases [2]. The process involved image acquisition, processing, feature extraction, and classification. The dataset comprised 3700 labeled images categorized into three classes: Healthy, Black Sigatoka, and Black Speckle. Preprocessing included conversion to grayscale and resizing to 60×60 pixels. The LeNet architecture of CNN facilitated automatic feature extraction and classification. The authors conducted experiments under various scenarios, including different image formats and dataset partitioning percentages, to optimize model performance, evaluated using classification accuracy metrics.

Sinshaw et al. conducted a systematic literature review on computer vision and machine learning in plant disease detection [3]. They proposed a CNN-based model for potato light blight detection, employing transfer learning and data augmentation techniques [4]. Eunice et al. conducted an extensive review of plant disease detection using deep learning, highlighting the need for improved robustness in models capable of accommodating diverse datasets [5].

In another study, the focus was on enhancing the efficiency of plant disease identification using CNN-based pre-trained models [6]. The researchers refined hyperparameters of established models such as DenseNet-121, ResNet-50, VGG-16, and InceptionV4, using the PlantVillage dataset. DenseNet-121 achieved superior classification accuracy, surpassing state-of-the-art models. Liu et al. proposed YOLOX-ASSANano, an improved lightweight real-time model for apple leaf disease detection based on YOLOX-Nano [7].

Table 1. Summary of related works.

Ref. no.	$DS(\geq !K)$	DA	RD	TL	CNN	ACC
[7]	✓	✓	✓	–	✓	97.8
[8]	–	✓	✓	–	✓	86
[9]	✓	✓	–	✓	✓	90
[10]	–	–	–	✓	✓	98.2
[11]	✓	–	✓	✓	✓	99
[12]	–	✓	✓	–	–	96
[16]	–	–	–	–	–	

1 K=1000; DA=Data Augmentation; RD=Real Dataset; TL=Transfer Learning; Acc=Accuracy.

De Silva and Brown combine CNNs and Vision Transformers (ViTs) for plant disease detection [8]. The highest accuracy achieved by their proposed model is 90.1%. Aggarwal et al. [9] and Simhadri et al. [10] developed a model for rice leaf disease detection They used federated transfer learning and got 99% accuracy for rice leaf. The researcher used machine learning for crop prediction [11] with an accuracy of 99.59%. A comprehensive review is done by Domingues et al. on the use of machine learning for plant disease detection. The authors suggested combining computer vision and machine learning for the detection and classification of plant diseases [12]. The summary of the literature review is presented in Table 1.

3. System architecture

Because it performed incredibly well in numerous challenges and research articles, the deep CNN technique was selected to build the model. In the paper [13], the author has proven the algorithm's superior performance for image identification and classification problems. Furthermore, the technique has several advantages over other traditional machine learning techniques, one of which is automatic feature selection for categorizing or identifying images, which makes the neural network robust.

The system architecture begins with the preparation of training and validation set with the support of a banana plant pathologist. Following that, data preparation was done to make the data usable. Several tasks were employed in this step, as shown in the diagram. Having followed that, the prepared data was input into the CNN algorithm, and the model built was tested using evaluation metrics. Finally, after the validation of the model, the trained model was tested with unseen data to check its performance. The proposed system architecture is depicted in Figure 1 and the proposed model is presented in Figure 2.

During training, the CNN algorithm was used to extract the leaf's features. This is referred to as training the model. The model's performance is evaluated using validation data while it is training. In short, the validation set is used to assess the model's performance during the training phase. Then, the pre-trained models (VGG16, VGG19, MobileNet, EfficientNet, and InceptionV3) were tested to obtain the top-performing model, and the top-performing model was saved based on the model evaluation. Finally, the top-performing model was evaluated with unseen and unlabeled data throughout the testing phase.

4. Algorithm selection

The major objects involved in training a neural network are layers or the algorithm's model, input data and corresponding targets, loss function which defines the feedback signal used for learning, and optimizer which determines how learning is processed. Figure 3 depicts the interaction of the previously mentioned objects [14]. In this paper, the deep CNN algorithm and several CNN pretrained models were experimented to build a robust banana disease classification via transfer learning. Deep CNN is one of the most famous deep learning algorithms because it is a multilayered, feedforward ANN. This type of neural network has been widely used in developing applications for computer vision, natural language processing, and other fields. The algorithm is a "biologically-inspired variant of the Multi Layered Perception (MLP) neural network that has been designed to emulate the multilayered visual cortex of the human visual system" [15]. The four major components of the algorithm are explained in the next subsection.

4.1. Conv layer

The Conv(•) is a dot product of the input image I, and the convolution kernel, K. The output is a convolved feature map, f_c. Mathematically, the f_c operation is

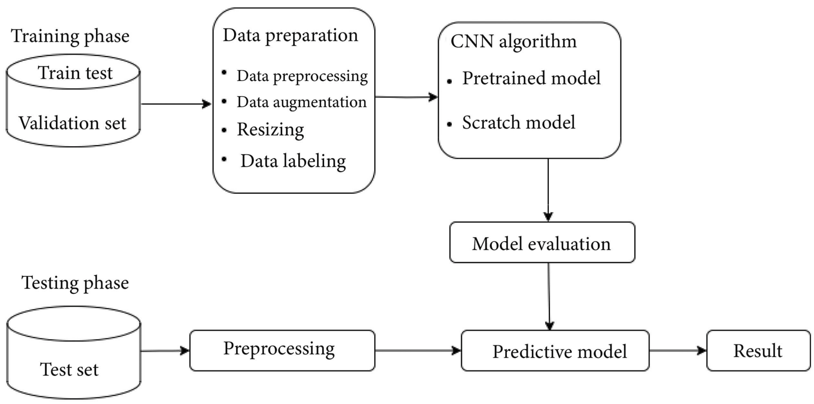

Figure 1. System architecture.

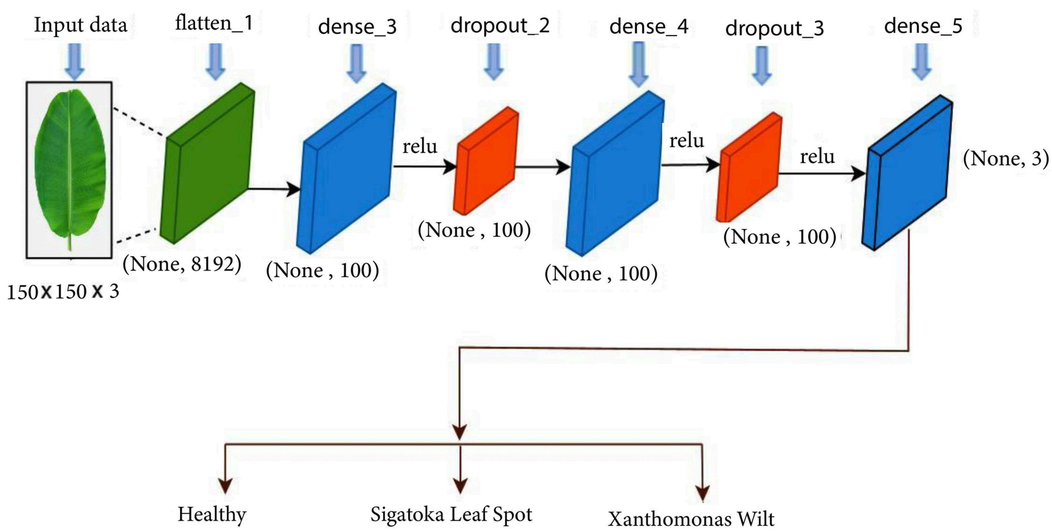

Figure 2. The proposed model.

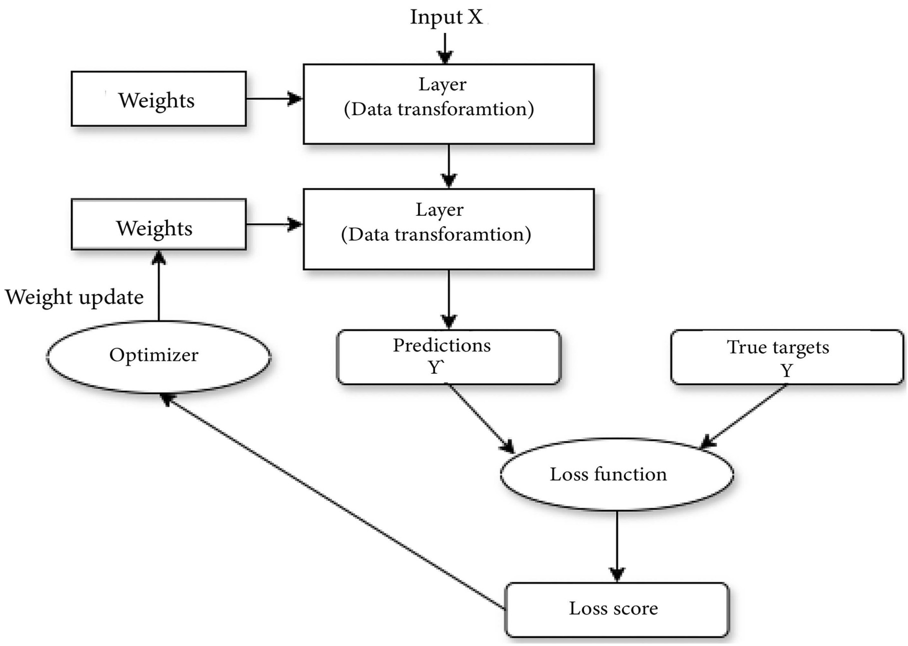

Figure 3. The relationships of NN objects [19].

defined as:

$$f_c = conv(i,j) = (I \otimes K)(i,j)$$
$$= \sum_m \sum_n I(m,n) K(i-m.j-n), \quad (1)$$

where $\otimes$ represents a 2D discrete conv operator.

4.2. Pooling layer

The pooling layer is the second layer after the convolutional layer operation. This layer provides a typical down-sampling operation which reduces the in-plane dimensionality of feature maps to introduce translation invariance to a small shift and distortion and decreases the number of subsequent learnable parameters. After an operation is performed in the convolution layer, a feature map is generated as an output. The output of the Convolutional layer feature map will be reduced in the pooling layer. Different filter sizes are used in the pooling layer. Usually, a 2×2 size filter is used, and several functions like max pooling, average pooling, and sum pooling are used [16].

4.3. AF

One of the hyperparameters in the deep CNN algorithm is an activation function. It is used as a decision function and helps to learn different complex patterns from given data [17]. In a neural network, the activation function handles a distinct and complex task, such as image detection and classification. The activation function for a convolved feature map is mathematically defined as follows:

$$T_l^k = g_a(f_l^k). \quad (2)$$

The equation is described f_l^k as the output of a Conv operation, which is assigned to AF $g_a(\cdots)$ that adds non-linearity and returns a transformed output T_l^k for lth layer [12].

ReLU (Rectified Linear Unit) AF: The ReLU activation function is one of the most commonly used activation functions. Mathematically defined as:

$$f(x) = \max(0, x), \quad (3)$$

where x is the input to a neuron.

4.4. Logistic function

Also known as a Sigmoid AF. It is traditionally a very popular activation function. The function takes an input and transforms between 0 and 1. Similarly, the input value of more than 1 transformed to 1, and a value smaller than 0 snapped to 0.

$$G(z) = \frac{1}{(1+e^{-z})}, \quad (4)$$

where $G(z)$=Sigmoid function, and e=Euler's number.

4.5. FC Layer

The FC layer is a simple feed-forward neural network. Its input is the output of the final pooling or Conv layer, which is flattened and becomes an input to the FC layer. The term 'flattening' is used to describe the process of converting the three-dimensional matrix output of a pooling or Conv layer into a one-dimensional array. Figure 4 demonstrates the process of converting a 3D matrix to a 1D array.

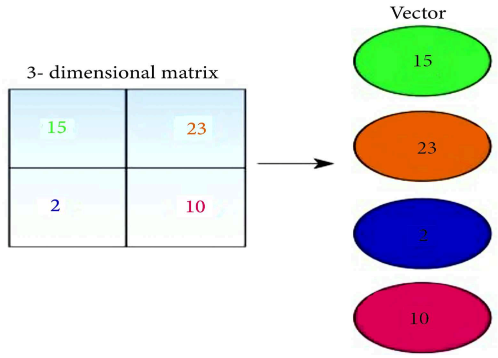

Figure 4. FC layer operation.

5. Experimental and results

The authors implemented the proposed model All the algorithms are implemented in Python, which uses a local workstation and cloud-based Google Colab platform with GPU. Visual Code editor is used on the local platform, and Jupiter Notebook is only supported in Colab. All the implemented models are compiled and run with Python 3 compilers. The models are built with the support of Pandas, Keras, Sci-kit Learn, TensorFlow, and the mathplotlib library of Python. The local workstation contains an 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80 GHz processor and RAM of size 16.0 GB (15.8 GB usable). Cloud-based Google Colab consists of a System RAM of 0.9/12.7 GB, a disk of 26.2/107.7 GB, and a T4 GPU. The implementation of the dataset is available publicly in Banana Leaf Disease Images - Mendeley Data. A sample of the dataset is presented in Figure 5.

5.1. Dataset source

To develop the CNN detection model, a banana image dataset was prepared, with images collected from the SNNPR Arbaminch Zuria Woreda Lante Kebele and Chano Kebele and Gamugofa Zone Mierab Abaya Woreda Omolante Kebele, each banana leaf image acquired by a smartphone. A total of 1982 photos were prepared from the local farm dataset. The collected images were categorized under three categories 'Healthy', 'Xanthomonas Wilt', and 'Sigatoka' infected leaf. The local dataset prepared was available for other researchers.

*DatasetLink.: *hailu, yordanos (2021), "Banana Leaf Disease Images", Mendeley Data, V1, doi: 10.17632/rjykr62kdh.1*

5.2. Experimental Scenarios

VGG16, VGG19, MobileNet, EfficientNet, and InceptionV3 were utilized in experiments to train pretrained models. During the training of the neural network, the activation function of the model, learning rate, optimization algorithm, loss function, and batch size were all examined. The model was also tested using model evaluation metrics. Finally, the performance of the model was assessed using previously unseen data.

5.2.1. Hyperparameters settings

Hyperparameters are machine learning parameters that govern the learning process of the model. Due to that, the performance of the machine learning algorithm highly depends on an optimal configuration of hyperparameters. Recent neural networks highly depend on different types of optimal hyperparameter value selection. Some of the hyperparameters of a neural network are the network's architecture, regularization, learning rate, number of layers, and optimization algorithm [18,19].

Different hyperparameters have different domains, for instance, a learning rate has a real value, the number of layers has an integer value, whether to use an early stopping or not has a binary value, and the choice of optimizer has a categorical value. For integer and real-valued hyperparameters, the domains are mostly bounded for practical reasons, with only a few exceptions [20–22].

The Hyperparameters Parameter Optimization (HPO) problems are defined as follows. Let A represent a machine learning algorithm with hyperparameters, and the domain of the nth hyperparameter is represented by Λ_n. The overall hyperparameter configuration space as $\Lambda = \Lambda_1 \times \Lambda_2 \times ...\Lambda_N$. A vector of hyperparameters is denoted by $\lambda \in \Lambda$, and with

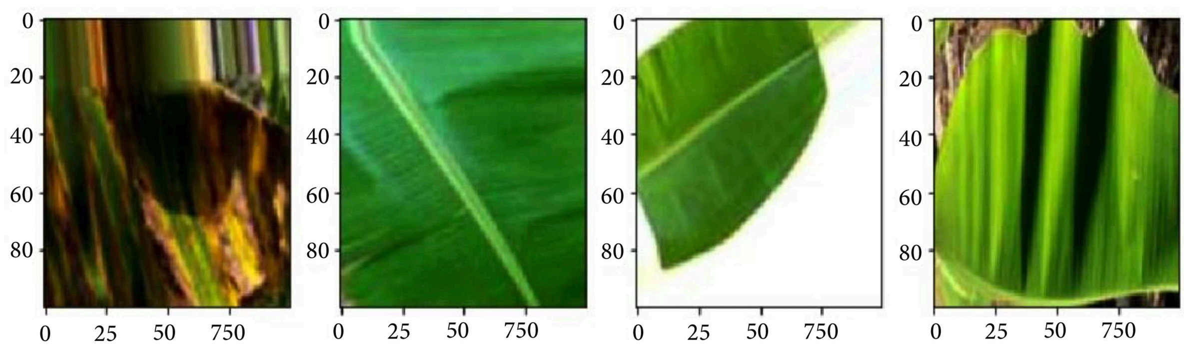

Figure 5. Sample dataset.

Table 2. Hyperparameters of the experimentation.

Hyperparameters	Value
Activation function (Last layer)	Softmax
Learning rate	0.0001
Epoch	30
Dropout	0.5
Optimization algorithm	RMSprop

its hyperparameters instantiated to λ is denoted by A_λ [18].

In some previous work, the Keras Tuner framework was used in order to select the optimal hyperparameter. The framework helps to automate the manual-based hyperparameter searching process, which saves time and resources consumed in the process. The framework has three built-in hyperparameter optimization algorithms (Bayesian Optimization, Hyperband, and Random Search) [23]. However, in this work due to a lack of computational resources, a manual-based hyperparameter search process was used.

Table 2 presents the hyperparameters and values used in the experiment. Each hyperparameter value was tested with random values, and the best performance value was used.

5.2.2. Model evaluation

Model evaluation is a significant process that determines how effectively a model performs. The assessment metrics accuracy, precision, recall, and F1-score are used in computational problems like classification and detection to forecast which class instance belongs to which class.

Table 3 presents the evaluation metrics used to compare the models, and mathematically defined as:

$$Accuracy = \frac{TP + FP}{TP + TN + FP + FN}, \tag{5}$$

$$Precision = \frac{TP}{TP + FP}, \tag{6}$$

$$Recall = \frac{TP}{TP + FN}, \tag{7}$$

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall}, \tag{8}$$

where TP is the True Positive; FP the False Positive; FP the False Positive, and FN the False Negative.

Table 4. Layer details of the model.

Layer (type)	Output shape	Param #
Flatten 1 (Flatten)	(None, 8192)	0
Dense 3 (Dense)	(None, 100)	819300
Dropout 2 (Dropout)	(None, 100)	0
Dense 4 (Dense)	(None, 50)	5050
Dropout 3 (Dropout)	(None, 50)	0
Dense 5 (Dense)	(None, 3)	153
Total params: 824,503		

5.3. *Proposed model*

As depicted in, the proposed model is developed for the classification task by freezing the layers (Table 4) of all VGG16 pretrained models and adjusting the activation function, dropout, and other hyperparameters using the model from the flattening layer.

5.4. *Results and discussions*

The best hyperparameter configurations for the pretrained models include a learning rate of 0.001, a batch size of 64, a categorical CE loss function, an optimization approach of RMSprop, and a Softmax last layer activation function, as determined by the values of the hyperparameters. The analysis of various classes is given in Table 5.

Figure 6 Training accuracy of the VGG16 model presents the VGG16 pretrained model's performance, and it has roughly similar values for training and validation accuracy, indicating that the pretrained model has no overfitting or underfitting concerns. Additionally, Figure 7 illustrates the comparison of the

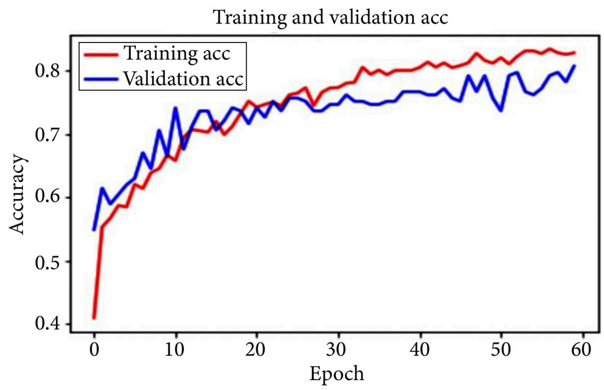

Figure 6. Training accuracy of VGG16 model.

Table 3. Evaluation metrics and interpretation.

Metrics	Meaning
Accuracy	How often the model predicts the classes correctly
Precision	How often positive value predicted correctly
Recall	How sensitive is the classifier while detecting positive instances
F1-score	Is a harmonic mean of precision and recall

Table 5. Assessment analysis of various classes.

	Precision	Recall	F1-score	Support
Healthy	0.90	0.60	0.72	43
Sigatoka	0.83	0.78	0.81	51
Xanthomonas	0.81	0.90	0.85	103
Samples avg	0.81	0.81	0.81	197

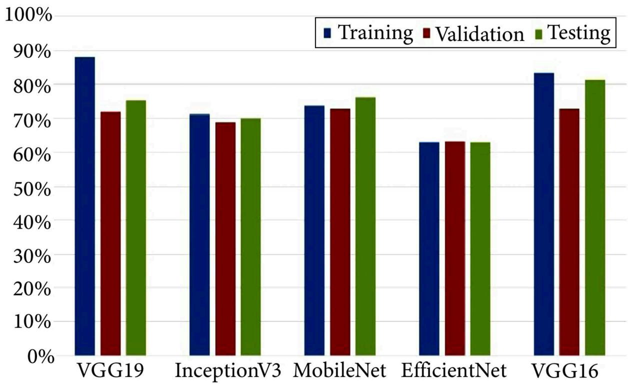

Figure 7. Comparing the model's performance.

pre-trained model experimented, and according to the bar chart, the VGG16 scored a promising result.

6. Conclusion

Farmers face formidable challenges stemming from diseases such as banana Xanthomonas Wilt and Sigatoka leaf spot, which pose imminent threats to agricultural productivity by swiftly decimating entire fields if left unchecked. Recognizing the urgent need to combat these threats, we embarked on a mission to develop a cutting-edge deep-learning algorithm specifically tailored to detect and classify these debilitating illnesses in banana plants. Our research journey involved rigorous experimentation with a diverse array of pre-trained models, including VGG16, VGG19, MobileNet, EfficientNet, and InceptionV3. Among these models, the VGG16 pretrained model emerged as a standout performer, showcasing remarkable accuracy of 81.53% in effectively distinguishing healthy banana leaves from those afflicted with Xanthomonas Wilt or Sigatoka leaf spot. These promising results signify a significant step forward in our quest to revolutionize plant disease detection methodologies, offering newfound hope for enhancing agricultural resilience and sustainability on a global scale. Moving forward, our future work will focus on refining our deep-learning algorithm by incorporating additional datasets, including ones from different geographic locations and environmental conditions. Additionally, we plan to explore methods for optimizing the deep learning model to make it lightweight, ensuring efficient deployment in resource-constrained environments while maintaining high performance and accuracy. This holistic approach aims to address the pressing challenges of plant disease detection in banana cultivation, ultimately contributing to the long-term stability of global food production.

References

1. Saranya, N., Pavithra, L., Kanthimathi, N., et al. "Detection of banana leaf and fruit diseases using neural networks", *2nd Int. Conf. on Inve. Res. Com., App.*, **202**, pp. 493–499 (2020). DOI: 10.1109/ICIRCA48905.2020.9183006

2. Amara, J., Bouaziz, B., and Algergawy, A. "A deep learning-based approach for banana leaf diseases classification", *Datenbanksysteme für Business, Technologie und Web (BTW 2017) - Workshopband. Bonn: Gesellschaft für Informatik e.V.. PISSN: 1617-5468*, ISBN: 978-3-88579-660-2. pp. 79-88. Workshop Big (and small) Data in Science and Humanities (BigDS17). Stuttgart. 6.-10. März 2017.

3. Sinshaw, N.T., Assefa, B.G., Mohapatra, S.K., et al. "Applications of computer vision on automatic potato plant disease detection: A systematic literature review", *Computational Intelligence and Neuroscience*, **2022**(1) (2022): Article ID 7186687. https://doi.org/10.1155/2022/7186687

4. Sinshaw, N.T., Assefa, B.G., and Mohapatra, S.K. "Transfer learning and data augmentation based CNN model for potato late blight disease detection", Inter. *Conf. on. Info. and. Comm. Tech. for. Deve. for. Afri.* (2021). http://dx.doi.org/10.1109/ICT4DA53266.2021.9672243

5. Eunice, J., Popescu, D.E., Chowdary, M.K., et al. "Deep learning-based leaf disease detection in crops using Images for agricultural applications", *Agro.*, **12**, p. 2395 (2022). https://doi.org/10.3390/agronomy12102395

6. Li, L., Zhang, S., and Wang, B. "Plant disease detection and classification by deep learning-A review", *IEEE. Acc.*, **9**, pp. 56683–56698 (2021). http://dx.doi.org/10.1109/ACCESS.2021.3069646

7. Liu, S., Qiao, Y,. Li, J., et al. "An improved lightweight network for real-time detection of apple leaf diseases in natural scenes", *Agro.*, **12**, p. 2363 (2022). https://doi.org/10.3390/agronomy12102363

8. De Silva, M. and Brown, D. "Multispectral plant disease detection with vision transformer-convolutional neural network hybrid approaches", *Sens.*, **23**(20), p. 8531 (2023). https://doi.org/10.3390/s23208531

9. Aggarwal, M., Khullar, V., Goyal, N., et al. "Federated transfer learning for rice-leaf disease classification across multiclient cross-silo datasets", *Agro.*, **13**(10), p. 2483 (2023) http://dx.doi.org/10.3390/agronomy13102483.

10. Simhadri, C.G. and Kondaveeti, H.K. "Automatic recognition of rice leaf diseases using transfer

learning", *Agro.*, **13**(4), p. 961 (2023). http://dx.doi.org/10.3390/agronomy13040961

11. Elbasi, E., Zaki, C., Topcu, A.E., et al. "Crop prediction model using machine learning algorithms", *App. Sci.*, **13**(16), p. 9288 (2023). http://dx.doi.org/10.3390/app13169288
12. Domingues, T., Brandão, T. and Ferreira, J.C. "Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey", *Agri.*, **12**(9), p. 1350 (2022). http://dx.doi.org/10.3390/agriculture12091350
13. Ferentinos, K.P. "Deep learning models for plant disease detection and diagnosis", *Comp. and Elec. in Agri.*, **145**, pp. 311–318 (2018). http://dx.doi.org/10.1016/j.compag.2018.01.009
14. Chollet, F. "Deep learning mit python und keras: das praxis-handbuch vom entwickler der keras-bibliothek", *MITP.Ver. GmbH. and Co. KG.*, (2018).
15. Teow, M.Y. "Understanding convolutional neural networks using a minimal model for handwritten digit recognition", *2nd. Inter. Conf. on Auto. Cont. and Inte. Syst.*, pp. 167–172 (2017). http://dx.doi.org/10.1109/I2CACIS.2017.8239052.
16. Patil, A. and Rane, M. "Convolutional neural networks: An overview and its applications in pattern recognition", *Inter. Conf. on Infor. and Comm. Tech. for Inte. Sys. Sprin.*, pp. 21–30 (2020). http://dx.doi.org/10.1007/978-981-15-7078-0-3
17. Khan, A., Sohail, A., Zahoora, U., et al. "A survey of the recent architectures of deep convolutional neural networks", *Artif. Intel. Rev.*, **53**(8), pp. 5455–5516 (2020). http://dx.doi.org/10.1007/s10462-020-09825-6
18. Feurer, M. and Hutter, F. "Hyperparameter optimization", In Automated Machine Learning: Methods, Systems, Challenges, pp. 3–33 (2019). https://doi.org/10.1007/978-3-030- 05318-5_1
19. Li, L., Jamieson, K., DeSalvo, G., et al. "Hyperband: A novel bandit-based approach to hyperparameter optimization", *J. of Mach. L. Res.*, **18**(185), pp. 1–52 (2017).
20. Bergstra, J., Bardenet, R., Bengio, Y., et al. "Algorithms for hyper-parameter optimization", *Advances in Neural Information Processing Systems*, **24**, pp. 2546–2554 (2011). https://proceedings.neurips.cc/paper/2011
21. Nguyen, V., Gupta, S., Rana, S., et al. "Filtering bayesian optimization approach in weakly specified search space", *K. and Info. Sys.*, **60**, pp. 385–413 (2019). http://dx.doi.org/10.1007/s10115- 018-1238-2
22. Shahriari, B., Bouchard-Côté, A., and Freitas, N. "Unbounded bayesian optimization via regularization", In *Arti. Intel. and St.*, pp. 1168–1176 (2016).
23. O'Malley, T., Bursztein, E., Long, Chollet.F., et al., "Kerastuner," (2019). https://github.com/keras-team/keras -tuner. (2019).

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