Computer Science and Information Technologies
Vol. 5, No. 1, March 2024, pp. 55~62
ISSN: 2722-3221, DOI: 10.11591/csit.v5i1.pp55-62

Deep learning technique for plant disease detection

Temitope Samson Adekunle[1], Morolake Oladayo Lawrence[2], Oluwaseyi Omotayo Alabi[3,4], Adenrele A. Afolorunso[5], Godwin Nse Ebong[6], Matthew Abiola Oladipupo[6]
[1]Department of Computer Science, Colorado State University, Fort Collins, United States
[2]Department of Computer Science, Baze University, Abuja, Nigeria
[3]Department of Mechanical Engineering, Lead City University, Ibadan, Nigeria
[4]Department of Mechanical Engineering, University of Ibadan, Ibadan, Nigeria
[5]Department of Computer Science, National Open University of Nigeria, Abuja, Nigeria
[6]Department of Data Science, University of Salford, Salford, United Kingdom

Article Info

Article history:

Received Sept 12, 2023
Revised Nov 3, 2023
Accepted Dec 25, 2023

Keywords:

Agriculture monitoring
Computer vision
Deep learning
Embedded vision
Plant disease detection

ABSTRACT

A nation's economy is primarily reliant on agricultural growth. However, several plant diseases seriously impair crop growth, both in terms of quantity and quality. Due to a lack of subject matter specialists and low contrast data, accurate diagnosis of many diseases by hand is highly difficult and time-consuming. The farm management system is therefore looking for a method for automatically detecting early illnesses. To overcome these challenges and correctly classify the different diseases, an efficient and small deep learning-based framework (E-GreenNet) is proposed. A MobileNetV3Small model is used as the foundation of our end-to-end architecture to produce finely tuned, discriminative, and noticeable features. Furthermore, the new plant composite (PC), plantvillage (PV), and data repository of leaf images (DRLI) datasets are used to independently train our proposed model, and test samples are used to evaluate its actual performance. The suggested model achieved accuracy rates of 1.00 percent, 0.96 percent, and 0.99 percent on the given datasets after a rigorous experimental study. Additionally, a comparative investigation of our proposed technique against the state-of-the-art (SOTA) reveals extremely high discriminative scores.

Corresponding Author:

Oluwaseyi Omotayo Alabi
Department of Mechanical Engineering, Faculty of Technology, Lead City University
Ibadan, Nigeria
Email: alabi.oluwaseyi@lcu.edu.ng

1. INTRODUCTION

For centuries, agriculture has played a crucial role in the domestication of the primary crops and livestock species that we rely on today. However, food insecurity remains a significant global issue, exacerbated by plant diseases. Diseases of plants can result in reduced crop yields, decreased quality, and increased food prices, all of which can negatively impact food security. Therefore, it is essential to understand and mitigate the effects of plant diseases to improve food security for current and future generations [1]. Plant infections have been shown to harm crops and drastically lower output, which leads to food shortages [2]. Based on estimates from food and agricultural organizations [3] around the world, up to 40% of the harm to agricultural productivity is caused by plant diseases and insects. Millions of people could go hungry as a result of this, and the agriculture industry could suffer greatly. Moreover, smallholder farmers contribute nearly 80% of the agricultural output in developing countries, where agriculture serves as the main source of livelihood. Roughly 50% of the global population living in poverty resides in smallholder households, making them particularly susceptible to disruptions in food supplies caused by diseases. The implementation of novel technologies for identifying plant illnesses has the potential to yield benefits, not only in terms of enhanced earnings but also by boosting food production [2].

Thanks to recent technological advancements, agronomists can now utilize image-based automated process control systems to gain valuable insights into the health of plants [4]. By enabling farmers to detect diseases earlier, respond to them quickly, and lower the incidence of diseases, the adoption of autonomous detection systems enhances crop quality. Using an image processing technique, the afflicted area's size and color variations are measured. Machine learning (ML) models were initially proposed as a means of identifying and categorizing plant diseases. Support vector machines (SVMs) are one method that can be used to quickly and accurately identify crop plant diseases (SVMs) [5], decision trees (DTs) [6], random forests (RFs) [7], and K-nearest neighbors (KNNs) [8]. Due to the lengthy preprocessing and reliance on human judgment to extract and choose the proper features required to carry out the classification [9], ML-based techniques are slower because they require less training data and are simpler to implement, but they also work slowly.

Deep learning (DL)-based technologies are commonly employed in agriculture to classify plant diseases [10]. These techniques do away with time-consuming image preprocessing by automatically creating discriminative features from input data. Convolutional neural network (CNN) is a useful DL model for early plant leaf disease detection. CNN has been widely used in the most recent study to diagnose and categorize crop plants [11]. Due to this method's effective feature representation, crop-related classification tasks have shown encouraging results. Current methods for classifying plant diseases heavily rely on the computer vision's established CNN architectures, such as AlexNet [12], GoogLeNet [7], VGGNet, ResNet, and EfficientNet [13]. Various forms of study have created unique network topologies [14] to handle conditions found in the actual world, such as occlusion, dim lighting, and diverse temperature conditions. Despite recent advances, the generalization robustness and identification accuracy of DL architectures for the classification of agricultural plant diseases still need to be enhanced in order for them to function correctly on edge devices like the Jetson Nano and smartphones, among other things.

Numerous studies have been investigated using ML, they suggested using ML to categorize plant diseases [15], [16]. Gabor, gray level co-occurrence matrix (GLCM) and local binary pattern (LBP) were among the methods used to extract features from the input photographs. RF classifier, artificial neural network (ANN), KNN, and SVM are used to successfully classify plant illnesses. The best classification accuracy is achieved by Kaur's approach, which uses Gabor features, at 90.23%; nonetheless, performance still has to be improved [17]. According to El-Nabi *et al.* [18], a method was presented for the identification and categorization of diseases using weeds as a basis. Initially, the morphological opening and closing technique was used to remove noise from the dubious samples. A custom model named k-FLBPCM, a filtered LBP technique with contour masks and coefficients, was used to extract the significant features from the improved image. Using the computed key points, SVM training was carried out to classify the diseased leaf patches.

Using a method created by [19], [20] different plant leaves could have damage that could be seen and identified. In the beginning, features from the input photographs were extracted using directional local quinary patterns (DLQPs). Using the calculated key points, the SVM classifier was created to classify agricultural leaf diseases. As stated by Ajagbe and Adigun [19], this technique has a 96.50% accuracy rate. Detecting questionable images based on color and shape can further enhance detection performance. Ajagbe *et al.* [21] established a new system for classifying and identifying diseases of tea plants. The simple linear iterative cluster (SLIC) was initially used to divide the input image into many blocks, from which the features were computed using the Harris technique. Fuzzy salient areas were located using convex hulls, and GLCM was utilized to determine the feature vector. The SVM classifier was then trained utilizing the key points gathered as a final step. The framework has a 98.50% accuracy rate [22], offers more accurate crop leaf disease classification, however this approach is expensive. The methodology outlined by can be used to locate and classify a number of agricultural illnesses [23]. The suspected image was first segmented using the GrabCut method on a sample. The hue, saturation, and value (HSV) transform are used to perform feature computations on the segmented image. The earlier recovered key points were then used to train the SVM.

Plant leaf damaged areas may be correctly classified with 95% accuracy [24]. However, with noisy data, its detection accuracy decreases. Another method based on ML was used by to classify different crop diseases. First, histogram equalization (HE) was used as a preprocessing step to add more visual information to the input data [25]. While plant leaf diseases have been classified using ML and DL-based techniques, these approaches' processing times and capacity to identify various diseased leaf regions still need to be improved. The existing approaches either require extensive preprocessing or produce poor results with distorted samples. Furthermore, when unfamiliar data is introduced, they have overfitting problems.

Encouraging farmers to take timely preventive action and preventing crop damage requires precise diagnosis and classification of plant leaf diseases.

2. METHOD

There are three primary steps in the suggested structure. The gathered plant leaf photos are first preprocessed. An effective CNN model is then used to detect and classify the plant into the appropriate class using photos from the various classes. Moreover, when confronted with previously unseen data, they encounter issues related to overfitting. Accurate diagnosis and categorization of plant leaf diseases are crucial to prevent crop damage and empower farmers to take timely preventive measures. In practical terms, our technology functions by issuing warnings to the local agriculture department, enabling swift action if the identified label indicates a plant disease. In the initialization phase of Algorithm 1, the model receives a video stream (VS) and is loaded with a pre-trained plant disease detection model (PD_{DM}). After reading each frame, regions of interest (RoIs) are extracted and inspected for signs of illness. If the image appears normal, the next frame is selected. However, if a disease is detected, an alarm is triggered and relayed to the pertinent emergency teams and the agriculture department.

Algorithm 1. Plant disease detection algorithm using E-GreenNet
```
Input: Video Stream
Output: Return PlantDisease_Detected
Initialization:
PD_DM ← Load Pre-Trained Plant Disease Detection Model (PD_DM)
VS ← Acquire Video Stream
while VS do
  |    Frame ← Read (VS)
  |    RoI_S ← PD_DM (Frame)
  |    if RoI_Label is normal then
  |      |     select next Frame;              /* No action processing next frame */
  |    else
  |      |     if RoI_Label = plant disease then
  |      |       |   Send an emergency alert;      /* Call agriculture department */
  |      |    end
  |    end
end
Return: PlantDisease_Detected
```

2.1. E-GreenNet framework

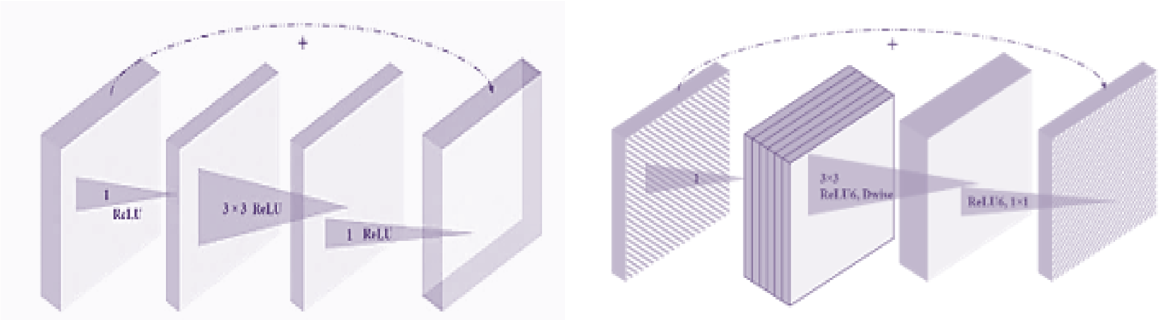
Algorithm 1 shows the plant diseases using E-GreenNet. Between 2017 and 2019, three alternative MobileNet architectures for CNN networks on mobile devices underwent continuous improvement. While creating MobileNetV1 [5], it made reference to the traditional VGG design and included depth-wise discrete convolutions. Based on that, MobileNetV2 is issued a year later, has a linear bottleneck, and an inverted residual. Through the application of network architecture search (NAS) and NetAdapt network exploration for architectural optimization, MobileNetV3 underwent significant improvement by eliminating resource-intensive layers and transitioning from ReLU to the h-swish non-linearity function by the middle of 2020. This increases both its efficiency and relative accuracy.

- Inverted residual: ReLU layers are replaced by bottleneck layers as a better, more efficient way to extract all the information. There is also an expansion layer within the bottleneck block. Additionally, the mobile network is better equipped to transfer gradients between layers via direct routes around bottlenecks, preventing gradient loss and layer explosion. A residual block is a key component of many DL architectures, as shown in Figure 1(a). Residual blocks and inverted residual blocks function nearly equally well despite having substantially lower memory costs as shown in Figure 1(b). To better illustrate the primary distinction between the two types of blocks, a visual representation is shown in Figure 1.
- NAS: we use reinforcement learning and recurrent neural networks (RNNs) to determine the ideal MobileNetV3 architecture on a hardware platform with limitations. It systematically converges towards the optimal configuration of a neural network model tailored to a particular purpose by effectively exploring diverse hierarchical search spaces through reinforcement learning. As an illustration, the extension layer of MobileNetV3 has been modified, building upon the initial design of MobileNetV2.
- Swish function: higher accuracy levels are achieved by substituting the new and unique activation function swish for the ReLU function. This function is defined as (1):

$$swish(x) = x.\sigma(x) \quad (1)$$

Due to the complexity of the sigmoid function in the swish formula, mobile edge devices may need to have a high computing power need. A solution to this issue is provided by MobileNetV3, which approximates sigmoid functions in swish using ReLU6 functions. This is referred to as h-swish and is described as (2):

$$h - swish[x] = x\frac{ReLU6(x+3)}{6} \quad (2)$$



(a) (b)

Figure 1. A pictorial representation of (a) residual block and (b) inverted residual block

3. RESULTS AND DISCUSSION

This section examines the dataset, assessment metrics, and evaluation metrics. The experimental setup and performance measures are first given, then the datasets are discussed and the findings are assessed. All models, including the proposed E-GreenNet, underwent training comprising a total of 10 epochs, employing a moderate learning rate to preserve the bulk of previously acquired knowledge. This section delves into the evaluation metrics, assessment dataset, and graphical findings. Following a thorough examination of the datasets and an analysis of the outcomes, the experimental design and performance metrics are elucidated. The recommended E-GreenNet was specifically trained for 10 epochs at a modest learning rate to ensure retention of the majority of previously acquired data. The experiments were executed on an NVIDIA RTX 3070 Super GPU with 32 GB of onboard memory, utilizing TensorFlow as the backend and the Keras DL framework. The effectiveness of the suggested model was evaluated using a variety of evaluation measures, such as accuracy, precision, recall, and F1-score, as stated in the equations below.

3.1. Evaluation metrics

The definition of accuracy in the classification problem is the number of correct predictions the model makes across all types of predictions.

$$Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \quad (3)$$

The percentage of the dataset that is actually affected by the disease that has been identified as a plant disease is measured by precision. The photos having a disease scenario are TP, and the anticipated positives (images predicted to be disease are TP and FP).

$$Precision = \left(\frac{TP}{TP+FP}\right) \quad (4)$$

$$Recall = \left(\frac{TP}{TP+FN}\right) \quad (5)$$

$$F1 - score = 2 \times \left(\frac{Precision \times Recall}{Precision+Recall}\right) \quad (6)$$

3.2. Datasets

To evaluate the performance of the proposed E-GreenNet model, we used the benchmark datasets plantvillage (PV) and data repository of leaf images (DRLI). To further evaluate the robustness of the suggested model, a new dataset called the plant composite (PC) dataset was also created by combining the two original datasets. The aggregate statistics of the datasets that are included are shown in Table 1.

Table 1. Overall statistics of the included benchmark datasets i.e., PV, DRLI, and a newly created

S/N	Dataset	Training	Testing	Validation	Total Images
1	PV	39110	107961	4434	54415
2	DRLI	3341	912	358	4602
3	PC	43141	116962	4814	59707

3.2.1. Plant village dataset

Furthermore, in order to evaluate the robustness of the suggested model even further, two datasets were combined to create a new dataset known as the PC dataset. The aggregate statistics for all the datasets are shown in Table 1. On this dataset, which contains images of plants with various ailments, we ran a number of experiments to evaluate the suggested strategy's classification accuracy. In greater detail, there are a total of 38 classes in the PV dataset, which includes 54,415 photos from 14 different plant species. Of the 38 classes, 26 were taken from sick plants and 12 from healthy plants. Images from the PV dataset are used to represent tomatoes, strawberries, grapes, and mangoes. The dataset used in the study displays a range of image quality aberrations, including noise, blurring, and color fluctuations, in addition to samples with varying sizes, colors, and lighting. Consequently, it provides a range of challenging information for the identification and categorization of affected plant leaf areas. A few samples from the PC dataset are displayed in Figure 2. The plant leaves in the top row exhibit a state of health, whereas those in the bottom row manifest signs of disease. Each row consists of four leaves for comparison.

Figure 2. Exemplary images from the benchmark datasets

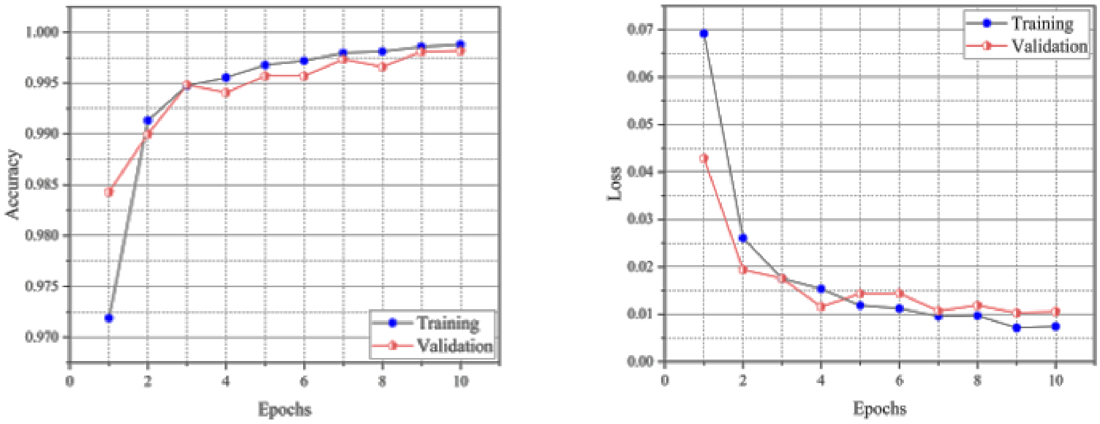
3.3. Performance comparison with state-of-the-art

In this study, various pre-trained CNN-based methods were assessed alongside the proposed model for diagnosing plant diseases. The evaluation included a comparison of the models based on parameters count, accuracy, precision, recall, and F1-score. The proposed E-GreenNet model was pitted against several pre-trained CNN-based methods for plant disease identification, showcasing superior performance. Notably, the E-GreenNet model outshines previous state-of-the-art (SOTA) models by using the fewest parameters while achieving impressive accuracy rates of 100%, 96%, and 100% across the three datasets. Additionally, when compared to MobileNetV1, despite both models' computational efficiency, E-GreenNet exhibits superior performance across all datasets with almost half the parameters.

The findings of MobileNetV1 and the suggested model are comparable, according to a comparison between the two models. With 3.23 million parameters in MobileNetV1 compared to 1.53 million in E-GreenNet, the difference is more significant. A summary of the comparison between the input size and network training parameters of the suggested E-GreenNet and the SOTA models is given in Table 2, which also discusses the performance of the pre-trained models. It is demonstrated that the pre-trained models perform well with low false alarm rates. Nonetheless, there needs to be an increase in the false prediction rate because it is still quite high. Thus, this study examined the precision and imprecise forecast of a trained and optimized CNN (E-GreenNet). The training accuracy and training loss graphs are shown in Figure 3, with the total number of epochs displayed on the horizontal axis and accuracy and loss indicated on the vertical axis. It is clear from Figure 3(a) that E-GreenNet can be used to diagnose plant illnesses. As the number of training and validation process iterations increases, the model's training and validation accuracy line graph varies, as seen in Figure 3(b).

Table 2. Evaluation of the proposed model E-GreenNet against the SOTA models utilizing the benchmark datasets

Model	Class	PV				DRLI				PC			
		Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy
VGG19	Healthy	0.99	0.97	0.99	1	0.95	0.96	0.87	0.95	1	0.98	1	0.99
	Infected	0.97	0.98	1		0.98	0.94	0.94		0.96	0.99	1	
VGG16	Healthy	1	1	0.97	0.98	0.97	0.97	0.95	0.94	0.97	1	1	1
	Infected	0.99	0.98	0.98		0.94	0.95	0.94		0.95	0.99	0.99	
MobileN	Healthy	0.99	1	0.99	0.99	0.96	0.97	0.96	0.96	0.96	1	1	1
etV1	Infected	1.0	0.99	0.98		0.97	0.96	0.98		0.98	0.94	0.99	
Efficient	Healthy	0.99	0.99	1	0.99	0.98	0.79	0.91	0.91	1	0.96	0.95	1
NetB0	Infected	0.99	0.98	0.99		0.84	0.97	0.88		1	0.98	1	
E-	Healthy	0.99	0.99	1.	1.00	0.95	1	0.98	1	0.98	1	1	1
GreenNet	Infected	0.98	1.00	0.99		0.98	0.96	0.97		1	0.99	0.99	



(a) (b)

Figure 3. The training (a) model accuracy and (b) model loss

4. CONCLUSION

In this research, we introduced E-GreenNet, a novel model designed for the detection of plant diseases, inspired by the architecture of MobileNetV3Small. To align with our specific objective of identifying plant diseases, we fine-tuned the existing model. The proposed E-GreenNet effectively utilizes the DRLI dataset, the PV dataset, and a newly introduced dataset named the PC dataset, enabling accurate detection and categorization of infected plant leaves. This study leverages MobileNetV3Small, referred to as E-GreenNet, in an enhanced and refined configuration. Employing an end-to-end training architecture and E-GreenNet, deep key points are computed and categorized into their respective classes. Performance evaluation was conducted using the novel PC dataset, comprising images from diverse classes, alongside publicly available benchmark datasets such as PV and DRLI. The maximum accuracy achieved was 99.89%, with a precision of 99.4%, and a recall of 99.4%. Our approach demonstrated superior reliability and efficiency compared to current methods, showcasing promising results within a shorter time frame. Looking ahead, our future endeavors include developing a new model incorporating an attention mechanism and subjecting our approach to testing with challenging datasets.

ACKNOWLEDGEMENTS

Our families and friends were amazing, supporting us every step of the way. We're so grateful to everyone who played a part in this research-big or small.

REFERENCES

[1] O. O. Alabi, S. A. Ajagbe, O. A. Adeaga, and M. O. Adigun, "Investigating Fuel Adulteration Using Arduino as an Engine Protection Device (EPD)," *Journal of Hunan University Natural Sciences*, vol. 50, no. 9, pp. 106–113, 2023, doi: 10.55463/issn.1674-2974.50.9.11.

[2] S. Gouda, R. G. Kerry, G. Das, S. Paramithiotis, H.-S. Shin, and J. K. Patra, "Revitalization of plant growth promoting rhizobacteria for sustainable development in agriculture," *Microbiological Research*, vol. 206, pp. 131–140, 2018, doi:

10.1016/j.micres.2017.08.016.
[3] D. Shafiei, S. A. Mostafavi, and S. J. Mehrabadi, "Geometrical optimization of city gate station's water bath indirect heater to minimization of fuel consumption," *Journal of Thermal Engineering*, vol. 9, no. 4, pp. 841–860, 2023, doi: 10.18186/thermal.1325287.
[4] O. O. Alabi, O. A. Adeaga, S. A. Ajagbe, T. S. Adekunle, and M. O. Adigun, "Performance of the Solar PV Module of the Dual Solar Axis Tracker of a Smart Home Monitoring System," *Journal of Hunan University Natural Sciences*, vol. 50, no. 9, pp. 21–29, 2023, doi: 10.55463/issn.1674-2974.50.9.3.
[5] K. Elangovan and S. Nalini, "Plant Disease Classification Using Image Segmentation and SVM Techniques," *International Journal of Computational Intelligence Research*, vol. 13, no. 7, pp. 1821–1828, 2017.
[6] H. Benhar, A. Idri, and J. L. Fernández-Alemán, "Data preprocessing for heart disease classification: A systematic literature review," *Computer Methods and Programs in Biomedicine*, vol. 195, 2020, doi: 10.1016/j.cmpb.2020.105635.
[7] B. Darwin, P. Dharmaraj, S. Prince, D. E. Popescu, and D. J. Hemanth, "Recognition of Bloom/Yield in Crop Images Using Deep Learning Models for Smart Agriculture: A Review," *Agronomy*, vol. 11, no. 4, pp. 1–22, 2021, doi: 10.3390/agronomy11040646.
[8] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A Survey of Deep Learning and Its Applications: A New Paradigm to Machine Learning," *Archives of Computational Methods in Engineering*, vol. 27, no. 4, pp. 1071–1092, 2020, doi: 10.1007/s11831-019-09344-w.
[9] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artificial Intelligence in Agriculture*, vol. 4, pp. 58–73, 2020, doi: 10.1016/j.aiia.2020.04.002.
[10] L. Li, S. Zhang, and B. Wang, "Plant Disease Detection and Classification by Deep Learning - A Review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.
[11] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network," *Procedia Computer Science*, vol. 167, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225.
[12] N. K. Trivedi *et al.*, "Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network," *Sensors*, vol. 21, no. 23, pp. 1–15, 2021, doi: 10.3390/s21237987.
[13] K. Sathya and M. Rajalakshmi, "RDA-CNN: Enhanced Super Resolution Method for Rice Plant Disease Classification," *Computer Systems Science and Engineering*, vol. 42, no. 1, pp. 33–47, 2022, doi: 10.32604/CSSE.2022.022206.
[14] H. Alaeddine and M. Jihene, "Plant leaf disease classification using Wide Residual Networks," *Multimedia Tools and Applications*, vol. 82, no. 26, pp. 40953–40965, 2023, doi: 10.1007/s11042-023-15226-y.
[15] T. S. Adekunle *et al.*, "A Framework for Robust Attack Detection and Classification using Rap-Densenet," *ParadigmPlus*, vol. 4, no. 2, pp. 1–17, 2023, doi: 10.55969/paradigmplus.v4n2a1.
[16] S. Parez, N. Dilshad, T. M. Alanazi, and J. Weon Lee, "Towards Sustainable Agricultural Systems: A Lightweight Deep Learning Model for Plant Disease Detection," *Computer Systems Science and Engineering*, vol. 47, no. 1, pp. 515–536, 2023, doi: 10.32604/csse.2023.037992.
[17] F. W. Ipeayeda, M. O. Oyediran, S. A. Ajagbe, J. O. Jooda, and M. O. Adigun, "Optimized gravitational search algorithm for feature fusion in a multimodal biometric system," *Results in Engineering*, vol. 20, pp. 1–8, 2023, doi: 10.1016/j.rineng.2023.101572.
[18] S. A. El-Nabi, W. El-Shafai, E.-S. M. El-Rabaie, K. F. Ramadan, F. E. Abd El-Samie, and S. Mohsen, "Machine learning and deep learning techniques for driver fatigue and drowsiness detection: a review," *Multimedia Tools and Applications*, pp. 1–37, 2023, doi: 10.1007/s11042-023-15054-0.
[19] S. A. Ajagbe and M. O. Adigun, "Deep learning techniques for detection and prediction of pandemic diseases: a systematic literature review," *Multimedia Tools and Applications*, pp. 1–35, 2023, doi: 10.1007/s11042-023-15805-z.
[20] Y. Wu, D. Wei, and J. Feng, "Network attacks detection methods based on deep learning techniques: A survey," *Security and Communication Networks*, vol. 2020, pp. 1–17, 2020, doi: 10.1155/2020/8872923.
[21] S. A. Ajagbe, A. A. Adegun, A. B. Olanrewaju, J. B. Oladosu, and M. O. Adigun, "Performance investigation of two-stage detection techniques using traffic light detection dataset," *IAES International Journal of Artificial Intelligence*, vol. 12, no. 4, pp. 1909–1919, 2023, doi: 10.11591/ijai.v12.i4.pp1909-1919.
[22] D. Gümüşbaş, T. Yıldırım, A. Genovese, and F. Scotti, "A comprehensive survey of databases and deep learning methods for cybersecurity and intrusion detection systems," *IEEE Systems Journal*, vol. 15, no. 2, pp. 1717–1731, 2021, doi: 10.1109/JSYST.2020.2992966.
[23] H. Aldawood and G. Skinner, "Educating and Raising Awareness on Cyber Security Social Engineering: A Literature Review," in *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*, 2018, pp. 62–68, doi: 10.1109/TALE.2018.8615162.
[24] B. Tugrul, E. Elfatimi, and R. Eryigit, "Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review," *Agriculture*, vol. 12, no. 8, pp. 1–21, 2022, doi: 10.3390/agriculture12081192.
[25] E. C. Too, L. Yujian, S. Njuki, and 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.

BIOGRAPHIES OF AUTHORS

Temitope Samson Adekunle is a Ph.D. student at the Department of Computer Science, Colorado State University, Fort Collins, United State. His major research focus is in the aspect of artificial intelligent and machine learning, fluid dynamics, mathematics modelling, data engineering, simulation and modeling, and big data mining. He can be contacted at email: temitope.adekunle@colostate.edu.

Morolake Oladayo Lawrence is a lecturer at the Department of Computer Science, Baze University, Abuja, Nigeria. Her teaching and research expertise is in data structures, computer architecture, machine learning, artificial intelligence, bioinformatics, algorithms, the internet of things, and data science. She can be contacted at email: morolake.lawrence@bazeuniversity.edu.ng.

Oluwaseyi Omotayo Alabi is a lecturer in the Department of Mechanical Engineering, Lead City University Ibadan, Nigeria. His major research focus is in the aspect of applied artificial intelligent, energy system, heat transfer, HVAC, simulation and modeling, aerodynamic, and computational thermal fluids. He has about 30 papers to his credit in reputable journals. He can be contacted at email: alabi.oluwaseyi@lcu.edu.ng or oalabi4330@stu.ui.edu.ng.

Adenrele A. Afolorunso is a lecturer at the Department of Computer Science, National Open University of Nigeria (NOUN), Abuja and a faculty member of Afircan Centre of Excellence for Technology Enhanced Learning. From 2007-2010, she was the head of unit of Computer Science and Information Technology at NOUN. She received her Ph.D. in Computer Science, specialising in cyber security, from the University of Lagos, Nigeria in 2017, and prior to that taught at Cetep City University, Lagos, Nigeria and Olabisi Onabanjo University, Ago-Iwoye, Nigeria. She has been a joint recipient of grant from DSTN (France), senate research grant, NOUN. She has supervised several M.Sc. and B.Sc. projects. She majorly publishes in the areas of cyber security, machine learning, software engineering solutions to life issues, had developed several course materials and instructional videos on diverse courses in computer science for NOUN. She can be contacted at email: aafolorunsho@noun.edu.ng.

Godwin Nse Ebong is an expert in cloud engineering, data engineering, and data analysis. with a bachelor of science in Engineering and a masters in Data Science, both in the UK. He can be contacted at email: g.n.ebong@edu.salford.ac.uk.

Matthew Abiola Oladipupo obtained B.Tech. Electronic and Electrical from LAUTECH, Nigeria and M.Sc. Data Science, University of Salford, UK. His research interest includes data science and AI just to mention but view. He is a Ph.D. student at the Department of Data Science, University of Salford, UK. He can be contacted at email: m.a.oladipupo@edu.salford.ac.uk.