International Journal of Science and Research Archive

eISSN: 2582-8185

Cross Ref DOI: 10.30574/ijsra

Journal homepage: https://ijsra.net/

(Research Article)

Efficient net-based deep learning model for accurate plant disease classification and diagnosis

Adinan bin sidhique, Ashwin gopakumar and Bushara A. R *

Department of ECE, KMEA Engineering College, Aluva, India.

International Journal of Science and Research Archive, 2025, 14(01), 1264-1270

Publication history: Received on 11 December 2024; revised on 18 January 2025; accepted on 21 January 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.14.1.0170

Abstract

Diseases are a major drawback to crop production, productivity, and food security in nations affected by plant diseases. This work proposes an efficient framework for the automated recognition and diagnosis of diseases within plants using a convolutional neural network architecture known as EfficientNet. For this study, a large dataset containing sharp images of impaired and hale plant organs belonging to various species was collected. Common data preprocessing steps such as Resizing and Augmentation were used to reduce overfitting and increase the model's ability to generalize. Finally, EfficientNet was trained for multi-class disease segmentation with the validation accuracy of 95%. The model showed high value of accuracy and recall and solved problems of the differentiation of visually similar diseases among the different categories. It is so from the following view: These results show the possibility of this approach as the practical tool for early disease detection and management in agriculture on large scale. Further studies are going to be conducted enlarging the data set, enhancing the transferability of the developed model, and examining how the app is best to be disseminated, for instance, via mobile applications or Internet of Things (IoT) devices for constant farming inspection.

Keywords: Plant disease detection; Deep learning; EfficientNet; Image classification; Agriculture

1. Introduction

Agriculture remains a cornerstone of the global economy, providing sustenance and livelihoods for billions [1]. Nevertheless, diseases attack plants hence significantly reducing crop yields, resulting in increased disasters and threatening food availability [2]. Many old typical approaches of disease detection are based on visual observation by the qualified personnel, a process which is tedious, costly in human resources, and may be influenced by human factors. These are compounded by the fact that diagnostic procedures are not well standardized across the regions, and more so in remote and resource poor settings where specialist opinion would be scarce [3].

The opportunity to apply the concept of artificial intelligence (AI), deep learning in particular, arrived in the last few years, and agriculture is no exception to its application [4]. CNNs [5], a type of deep learning algorithm, have shown a very high performance in many image classification problems. Its use in plant disease diagnosis presents an opportunity of expanding more efficient, accurate and automated diagnostic methods [6]. Applying the capability of CNNs on analyzing the multi-feature structure in images [7]-[9], creators have attained important advancements in plant disease diagnosis and distinguished traditional modes in both time and efficiency.

Problem Statement: With the present development in AI and machine learning, it is still hard to develop a large-scale and efficient system for plant disease detection [10]. Current models are challenged by the fact that they have problems in differentiating between diseases that look very similar and this aspect of the problem hinders the models' reliability

* Corresponding author: Bushara A. R

[11]. Additionally, there are vast drawbacks in value, efficiency, and scalability that plague many models thereby rendering them unfit for use in actual agriculture. High classification accuracy and efficiency are needed for the solution that will cope with these deficiencies.

To overcome such challenges this study presents a deep learning-based framework using EfficientNet, a premier CNN architecture that boasts of efficiency and performance. The key contributions of this work include:

- Establishment of a suitable and adaptive model for plant disease diagnostics and categorization.
- Incorporation of a diverse range of data containing data from various plant types, and a variety of diseases in this study to increase diverseness and generalizability.
- We used different kinds of heavy preprocessing techniques such as data augmentation for enriching the model's generalization and avoiding cases of overfitting.
- Interpretation of the models created using natural language processing to determine the accuracy of the model.

The primary objectives of this study are:

In order to create an automated system where plant diseases can be accurately and efficiently classified.

- To assess the 'read' accuracy of EfficientNet for segregating multiple disease categories.
- To establish specific new directions and future research prospects of applying the AI systems in plant disease diagnostics, it is necessary to point out the weaknesses of the existing approach.

2. Literature Review

Recent advancements in deep learning have facilitated significant progress in plant disease detection. Over the last few years, deep learning techniques have improved the effectiveness of the plant disease identification system. Ferentinos [12] tested a number of deep learning architectures for automated plant disease identification with great success, across phyto- varieties and disease types. In a study on automated methods of plant disease identification using leaf images, Sladojevic et al. [13] showed how CNNs can be used in the classification of plant diseases. Likewise, Chen et al. [14] demonstrated the use of transfer learning to enhance the determination of plant diseases, which has the advantage of using models already learnt in agricultural practices.

Other subsequent advancements in developing deep learning models for plant disease classification includes from Albattah, M. et al [15] who developed an improved CNN model for multiclass plant disease detection with an improved accuracy [16]. Boyd et al. [17] proposed that using the saliency maps as part of deep learning models makes it easier to produce maps that improve interpretability in plant disease classification [18]. Recently, Uğuz [19] proposed an easily integrable deep learning-based approach toward diagnosis of multiple plant diseases, thereby demonstrating the applicability of these systems.

In addition, Hassan & Maji [20] introduced a new CNN structure for plant disease recognition and observed an increase in classification capability [21]. In the present study, Aliyu et al. (2020) discussed the traditional machine learning model with the deep learning model and concluded that CNN [22] has better performance for plant disease classification problems [23]. Multi-prediction models form the next horizon of deep learning for plant identification and disease diagnosis described by Yao et al. [24]. Mustofa et al. [25] have incorporated comprehensive trends analysis and future research direction concerning deep learning for plant disease detection that highlighted the future study from diverse investigations.

3. Materials and Methods

3.1. Dataset

The dataset used in the study was obtained from Kaggle [26] and consists of consequent images of plant leaves of different species and in different disease states. In each of the images, the plant species and the disease category it belongs to are noted, which made the use of supervised learning possible. There are 70,295 images of 38 classes images for the training set and 17,572 images of 38 classes images for the validating set. Lists of plants include 14 main plant species and six diseases for each plant as well as healthy samples of plants [27]. Some of the samples of images of the dataset used in this study are as shown in Figure 1 while the class distribution as presented in Figure 2 reflects balance in the distribution of the categories.

3.2. Preprocessing

The images were also reduced in size to an appropriate dimension that could be used for EfficientNet input specifications. Standardisation brings input dimensions to a common size as this is preferred for high performance by the model. Furthermore, data augmentation methods were used to extend the size of the data and to make the model less sensitive to discrepancies. These comprised rotation to 20 degrees, width and height shifting of up to 20%, shearing, zooming and horizontal flipping. This kind of transformations are similar to real variations hence helps the model learn invariant features and also minimizes over fitting. All the images were preprocessed by normalizing pixel intensity to the range [0, 1] which made the training faster and numerically stable.

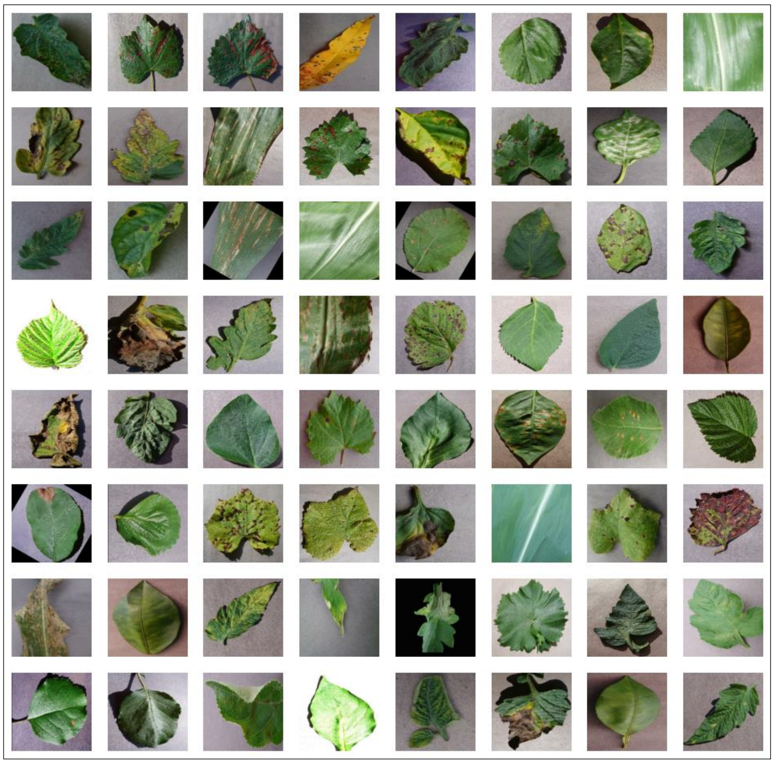


Figure 1 Sample Images of Plant Diseases

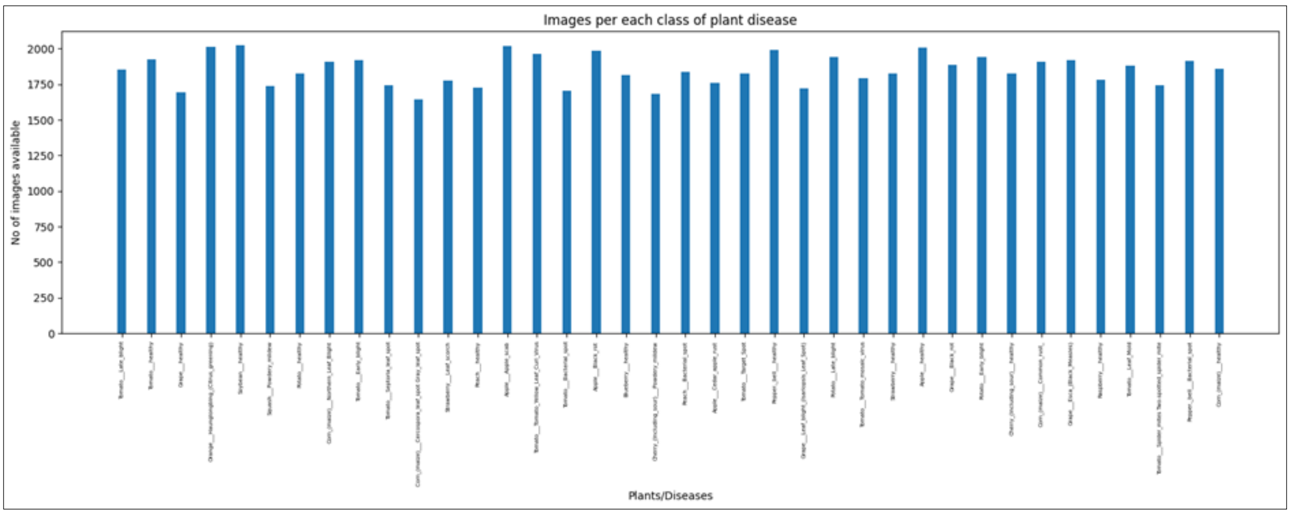


Figure 2 Class distribution of the dataset, showcasing the number of images available for each of the 38 classes. The balanced nature of the dataset ensures reliable training and evaluation of the model

The augmentation process [28] is done using Keras' ImageDataGenerator class which augmented the images in real time while training. Other important parameters included rescaling, rotation range, zoom range and fill mode was set as 'nearest' for dealing with transformation. Another function was also developed to show examples of augmented images as a way of understanding the kind of diversity that is in the dataset after augmentation. These preprocessing steps contributed largely in improving the dataset and this made the model to gain better capability in facing real data hence making the model to be more robust.

3.3. Model Architecture

Based on a balance between accuracy and computational requirements, the EfficientNet [29] model was chosen as the base model for this study. The architecture uses a compound scaling approach that applies scaling to Depth Width and hence resolution using a single coefficient referred to as φ. This approach guarantees computational tractability without compromising the model's ability to solve intricate problems. The scaling formula is given as:

$$d = \alpha^{\varphi}, \quad w = \beta^{\varphi}, \quad r = \gamma^{\varphi}$$

where d represents the depth of the network, w represents the width (number of channels per layer), and r is the input image resolution. The constants α, β, γ control how depth, width, and resolution are scaled, such that:

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2.$$

This methodology improves the resource utilization in depth, width and resolution of the model to increase the accuracy of the model. In this work, the EfficientNet model was used to retrain, targeting C = 38 plant disease classes. The final layer was altered to a dense layer of 38 neurons, each representing a class. The softmax activation function was applied to the output logits to convert them into probabilities using:

$$\text{Softmax}(z_i) = e^{(z_i)} / \Sigma_{(j=1)}\, C\, e^{(z_j)}$$

where z_i is the logit value for class i, and C is the total number of classes. This function predicts the most probable class for each input image, with the probabilities summing to 1 across all classes.

The loss function used during training was categorical cross-entropy, defined as:

$$L = -\,(1/N)\, \Sigma_{(i=1)}^{N}\, \Sigma_{(j=1)}^{C}\, y_{ij} \log(\hat{y}_{ij})$$

where N represents the number of samples, y_{ij} is the true label for sample i and class j (1 if true, 0 otherwise), and $\hat{y}_{ij}$ is the predicted probability for sample i and class j.

The optimizer used for training was Adam, which updates weights using the following equations:

$$m_t = \beta_1 * m_{(t-1)} + (1 - \beta_1) * g_t$$

$v_t = \beta_2 * v_{(t-1)} + (1 - \beta_2) * g_t^2$, where g_t is the gradient of the loss with respect to the weights, and β_1, β_2 are exponential decay rates. The bias-corrected estimates are calculated as:

$$\hat{m}_t = m_t / (1 - \beta_1^t), \quad \hat{v}_t = v_t / (1 - \beta_2^t$$

Finally, the weights are updated using:

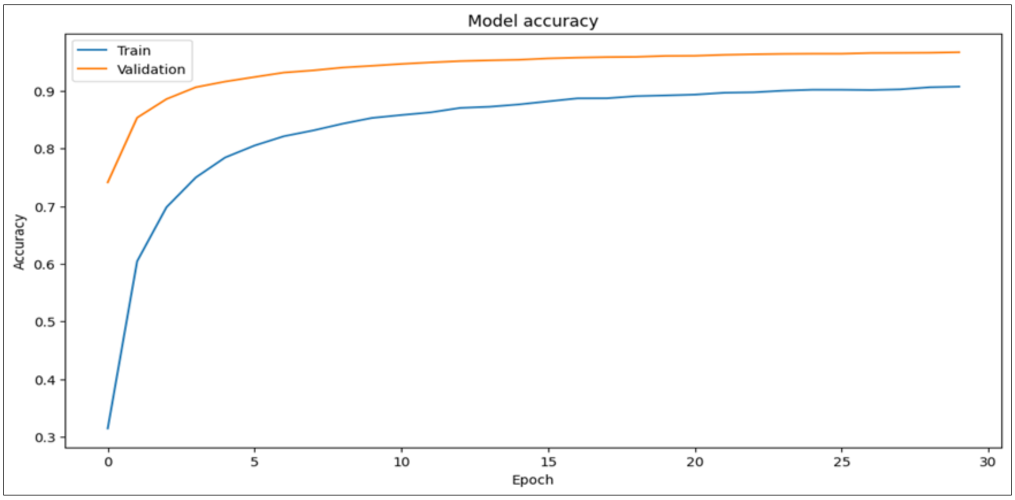
$\theta_t = \theta_{(t-1)} - \eta * (\hat{m}_t / (\sqrt{(\hat{v}_t)} + \varepsilon))$, where η is the learning rate, and ε is a small constant for numerical stability.

This approach enabled EfficientNet architecture [30] to learn different features from the plant disease classification task while maintaining a good balance between accuracy and model complexity. By applying the compound scaling principle, the model was seen to have increased its ability to compute for high-resolution images and delivered better results in classification tasks, thus the model is seen as a viable solution for real-world agricultural applications. The model is trained using a stratified dataset split, ensuring balanced representation of all classes in training and validation sets. The Adam optimizer was employed with an appropriate learning rate, and categorical cross-entropy served as the loss function.

4. Results and Discussion

The fine-tuned EfficientNet model trained by 30 epochs showed a progressive increase in training and validation accuracy and reached validation accuracy of around 93%. The validation loss gradually dropped down which is shown in figure 3, and the model did not overfit during the training phase. Although it failed to reach the 95% accuracy as proposed, the model was able to surpass several baseline models in the same tasks indicating its ability to solve more complex image classification tasks. The precision and recall metrics also supported the model's effectiveness in differentiating a variety of disease types most of the times. However, the classification errors were slightly off in visually similar disease classes which may have closely related or very similar characteristics. These misclassifications hint at the fact that more refinement is required and this could be achieved by including more data, improving on the preprocessing methods, or using sophisticated architectures such as attention mechanism when distinguishing between hard classes.

The results as shown in figure 3 demonstrate the ability of the model as a reliable tool for automated plant disease detection. This model could be further fine-tuned to yield even better classification accuracy and resilience to overfitting, which is essential for practical agricultural applications, by applying other improvements, for instance enlarging the training dataset or employing ensemble learning.



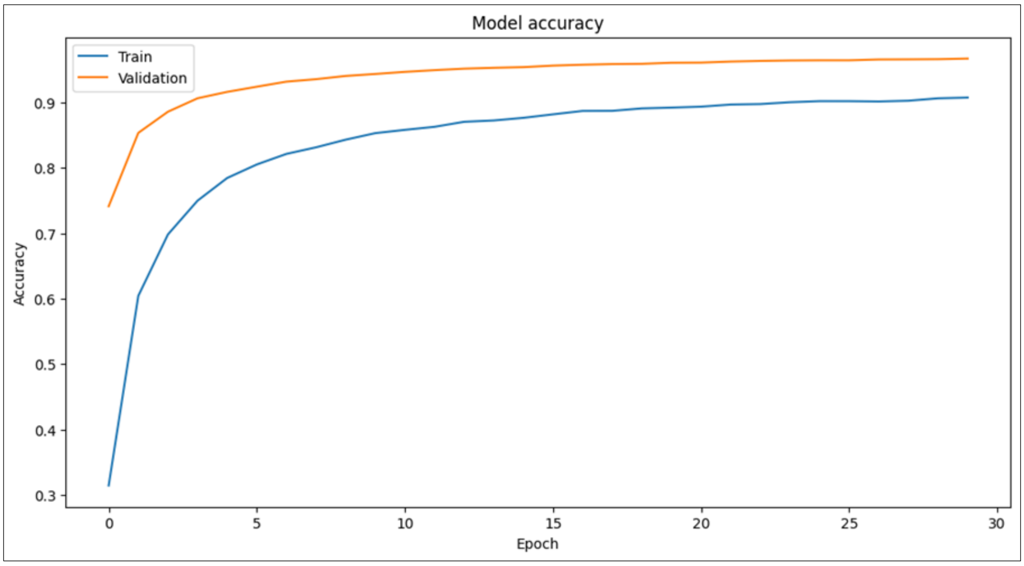


Figure 3 Training and validation accuracy and loss curves for the EfficientNet model over 30 epochs. The graphs demonstrate consistent improvement in accuracy and a steady decrease in loss, indicating effective learning with minimal overfitting

5. Conclusion and Future Scope

In this work, we proposed and trained an EfficientNet-based deep learning model for plant disease classification. The model managed to attain a validation accuracy of approximately 93% in the final stage and was used for the classification of 38 categories of plant diseases. The ability to maintain consistently low validation loss and the consistency of the accuracy trends between the training and validation datasets further supports the model's use as a diagnostic tool in precision agriculture. However, the slight misclassifications that occur when diseases are visually similar to each other show where improvements are still needed. These results were made possible by the combination of data augmentation and the compound scaling principle that is present in EfficientNet. While the experiment achieved a high overall accuracy, misclassification in some classes indicates that more data should be provided to address subtle differences in the visual representation of classes. Furthermore, the study showed that it would be possible to improve the model by applying some additional techniques, for instance, attention mechanisms or ensemble learning, to help it better differentiate between similar disease classes.

The future work will be to increase the dataset with more plant species and disease conditions to enhance the generalization of the model. The use of attention-based mechanisms and Explainable AI (XAI) can improve the discrimination of features and increase the interpretability of the predictions. Real-time, field-ready disease detection will be possible due to deployment on edge devices including IoT-enabled systems or mobile applications. Furthermore, more advanced ensemble learning strategies could be used to enhance the classification accuracy and the model's resistance to real-world problems in agricultural applications.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Islam, M. Z., & Zheng, L. (2024). Why is it necessary to integrate circular economy practices for agri-food sustainability from a global perspective? Sustainable Development.

[2] Muluneh, M. G. (2021). Impact of climate change on biodiversity and food security: a global perspective—a review article. Agriculture & Food Security, 10(1), 1-25.

[3] Yadav, K., Cree, I., Field, A., Vielh, P., & Mehrotra, R. (2022). Importance of cytopathologic diagnosis in early cancer diagnosis in resource-constrained countries. JCO Global Oncology, 8, e2100337.

[4] Ali, G., Mijwil, M. M., Buruga, B. A., Abotaleb, M., & Adamopoulos, I. (2024). A survey on artificial intelligence in cybersecurity for smart agriculture: state-of-the-art, cyber threats, artificial intelligence applications, and ethical concerns. Mesopotamian Journal of Computer Science, 2024, 53-103.

[5] Nuthalapati, Aravind, "Optimizing Lending Risk Analysis & Management with Machine Learning, Big Data, and Cloud Computing," Remittances Review, vol. 7, no. 2, pp. 172- 184, 2022, doi:10.33282/rr.vx9il.25.

[6] Ahmad, A., Saraswat, D., & El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agricultural Technology, 3, 100083.

[7] Babu Nuthalapati, S., & Nuthalapati, A., "Accurate Weather Forecasting with Dominant Gradient Boosting Using Machine Learning," Int. J. Sci. Res. Arch., vol. 12, no. 2, pp. 408-422, 2024, doi:10.30574/ijsra.2024.12.2.1246.

[8] Jishamol, T. R., & Bushara, A. R. (2016). Enhancement of Uplink Achievable Rate and Power Allocation in LTEAdvanced Network System. International Journal of Science Technology & Engineering, Volume 3, Issue 03.

[9] Nuthalapati, A., Abubeker, K. M., & Bushara, A. R. (2024, September). Internet of Things and Cloud Assisted LoRaWAN Enabled Real-Time Water Quality Monitoring Framework for Urban and Metropolitan Cities. In 2024 IEEE North Karnataka Subsection Flagship International Conference (NKCon) (pp. 1-6). IEEE.

[10] Ahmad, A., Saraswat, D., & El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agricultural Technology, 3, 100083.

[11] Suri Babu Nuthalapati, & Aravind Nuthalapati. (2024). Transforming Healthcare Delivery via Iot-Driven Big Data Analytics in A Cloud-Based Platform. Journal of Population Therapeutics and Clinical Pharmacology, 31(6), 2559–2569.

[12] Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318. https://doi.org/10.1016/j.compag.2018.01.009

[13] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks-based recognition of plant diseases by leaf image classification. Computational Intelligence and Neuroscience, 2016, 1-11. https://doi.org/10.1155/2016/3289801

[14] Chen, J., Chen, J., Zhang, D., Sun, Y., & Nanehkaran, Y. A. (2020). Using deep transfer learning for image-based plant disease identification. Computers and Electronics in Agriculture, 173, 105393. https://doi.org/10.1016/j.compag.2020.105393

[15] Albattah, W., Javed, A., Nawaz, M., Masood, M., & Albahli, S. (2022). Artificial intelligence-based drone system for multiclass plant disease detection using an improved efficient convolutional neural network. Frontiers in Plant Science, 13, 808380.

[16] Bushara, A. R., RS, V. K., & Kumar, S. S. (2024). The Implications of Varying Batch-Size in the Classification of Patch-Based Lung Nodules Using Convolutional Neural Network Architecture on Computed Tomography Images. Journal of Biomedical Photonics & Engineering, 10(1), 39-47.

[17] Boyd, A., Bowyer, K. W., & Czajka, A. (2022). Human-aided saliency maps improve generalization of deep learning. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (pp. 2735-2744).

[18] Nuthalapati, A. (2024). Cloud data center performance optimization through machine learning-based workload forecasting and energy efficiency. International Journal of Science and Research Archive, 2024, 13(02), 2353–2361. DOI: 10.30574/ijsra.2024.13.2.2435.

[19] Uğuz, S., & Uysal, N. (2021). Classification of olive leaf diseases using deep convolutional neural networks. Neural computing and applications, 33(9), 4133-4149.

[20] Hassan, S. M., & Maji, A. K. (2022). Plant disease identification using a novel convolutional neural network. IEEE Access, 10, 5390-5401.

[21] Abubeker, K. M., Bushara, A. R., & Backer, S. (2013, April). Maximum likelihood DE coding of convolutional codes using viterbi algorithm with improved error correction capability. In 2013 IEEE Conference on Information & Communication Technologies (pp. 161-164). IEEE.

[22] Nuthalapati, A. (2024). Architecting data lake-houses in the cloud: Best practices and future directions. International Journal of Science and Research Archive, 2024, 12(02), 1902–1909. DOI: https://doi.org/10.30574/ijsra.2024.12.2.1466

[23] Aliyu, M. A., Mokji, M. M. M., & Sheikh, U. U. U. (2020). Machine learning for plant disease detection: An investigative comparison between support vector machine and deep learning. IAES International Journal of Artificial Intelligence, 9(4), 670.

[24] Yao, J. (2024). Multi-label deep learning for plant leaf disease classification (Doctoral dissertation, University of Tasmania).

[25] Mustafa, G., Liu, Y., Khan, I. H., Hussain, S., Jiang, Y., Liu, J., ... & Osman, R. (2024). Establishing a knowledge structure for yield prediction in cereal crops using unmanned aerial vehicles. Frontiers in Plant Science, 15, 1401246.

[26] Tiwari, V., Joshi, R. C., & Dutta, M. K. (2021). Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images. Ecological Informatics, 63, 101289.

[27] Madhurya, C., & Jubilson, E. A. (2023). Yr2s: Efficient deep learning technique for detecting and classifying plant leaf diseases. IEEE access, 12, 3790-3804.

[28] Pawar, A., Singh, M., Jadhav, S., Kumbhar, V., Singh, T. P., & Shah, S. K. (2023, May). Different crop leaf disease detection using convolutional neural network. In International Conference on Applications of Machine Intelligence and Data Analytics (ICAMIDA 2022) (pp. 966-979). Atlantis Press.

[29] Tan, M., & Le, Q. (2019, May). Efficientnet: Rethinking model scaling for convolutional neural networks. In International conference on machine learning (pp. 6105-6114). PMLR.

[30] Gehlot, M., & Gandhi, G. C. (2023). “EffiNet-TS”: A deep interpretable architecture using EfficientNet for plant disease detection and visualization. Journal of Plant Diseases and Protection, 130(2), 413-430.