Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 270-278, 8, 2025

**Araştırma Makalesi**

IJANSER

https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 270-278, 8, 2025

**Research Article**

# A Comprehensive Study of Deep Learning Models for Potato Leaf Blight Disease Classification

Moazam Khan[1], Muhammad Uzair [2], Muhammad Faizan [3] and Essa Khan [4]

*[1] Department of Computer systems Engineering, The University of Engineering and Technology Peshawar, Pakistan*
*[2] Department of Computer systems Engineering, The University of Engineering and Technology Peshawar, Pakistan*
*[3] Department of Computer systems Engineering, The University of Engineering and Technology Peshawar, Pakistan*
*[4] Department of Electrical Engineering University of Engineering and Technology Taxila Taxila, Pakistan*

*[1](20pwcse1927@uetpeshawar.edu.pk)*

*(Received: 22 August 2025, Accepted: 31 August 2025)*

(8th International Conference on Applied Engineering and Natural Sciences ICAENS 2025, August 22-23, 2025)

**ATIF/REFERENCE:** Khan, M., Uzair, M., Faizan, M. & Khan, E. (2025). A Comprehensive Study of Deep Learning Models for Potato Leaf Blight Disease Classification, *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(8), 270-278.

***Abstract –*** Accurately classifying plant diseases is essential to agricultural research because it maintains crop health and ensures food security. Because potatoes are a staple crop with global importance, this paper focuses on the specific classification of potato illnesses, including late blight, early blight, and healthy plants.Employing Convolutional Neural Networks (CNNs), we introduce two classification models: one, developed iteratively through a trial-and-error approach, custom CNN model achieves a notable accuracy of 98.04%, while the other harnesses a pre-trained DenseNet169 architecture, surpassing its predecessor with an impressive 99.92% accuracy rate. These models leverage high-resolution images of potato leaves to effectively distinguish between healthy and diseased plants, providing a foundation for timely disease management strategies.The implications of this research extend to agriculture, with a potential to minimize crop losses and promote sustainable potato cultivation practices.

*Keywords – Plant disease classification, potato diseases, late blight, early blight, healthy plants, Convolutional Neural Networks (CNNs), DenseNet169, agricultural research, image analysis, disease management.*

## I. Introduction

One exceptional crop is the potato (Solanum tuberous.), which has global significance, underpinning the diets of approximately 1.5 billion people and standing as a cornerstone of modern agriculture. Originating in the Andean highlands of South America, the potato has transcended continents and climates, becoming a critical component of the world's food supply. In 2009, its annual yield exceeded a staggering 329 million metric tons, solidifying its position as the most important non grain agricultural product in the world's food chain [1]. But the path from its Andean origins to international renown has not been without danger.Numerous fungal infections can have a detrimental effect on potato quality, productivity, and crop health.tubers' quality.Early blight (Alternaria solani) and late blight (Phytophthora infestans) are the two most harmful of these adversaries.Two of these enemies are especially dangerous: early blight (Alternaria solani) and late blight (Phytophthora infestans).The Irish Potato Famine in the 19th century was caused by late blight, a worldwide threat to food security that is estimated to result in yield losses of $6.7 billion an nually [2] [3]. Just as cunning, early blight infects older potato leaves and causes significant output losses because of its characteristic "bull's eye spot" effect on leaves [5,6]. With our growing understanding of numerous potato ailments, the urgency to develop novel strategies for timely detection and control of crop diseases is accelerating. Traditional visual scouting remains inconsistent, labor-demanding, and vulnerable to observer bias. By contrast, the emergence of digital agriculture marks a decisive shift. Rapid progress in imaging modalities—such as hyperspectral sensing, RGB camera systems, and smartphone-based acquisition prepared with advances in machine learning and artificial intelligence, is creating powerful opportunities to reimagine plant disease diagnostics [4][5]. Focusing on the challenges posed by early and late blight in potato production, this study harnesses these technologies to build an effective solution. Our goal is to deliver a dependable, efficient pipeline for sensitive and accurate early-stage detection of these diseases. To this end, we utilize leading deep learning architectures, including VGG16, VGG19, ResNet-50, and Mobile Net. Owing to their well-established ability to learn rich hierarchical features and capture intricate patterns in data, these models hold strong promise for substantially improving disease classification accuracy. [6] [7]. We employ a thorough technique that includes exacting model evaluation and parameter adjustment in order to achieve this goal. By using this method, we hope to advance disease categorization in relation to potato harvests. By contrasting our results with those of previous studies and benchmark datasets, we aim to show how much more effective and efficient our suggested model is. By doing this, our research advances the cause of sustainable agriculture in the face of these powerful enemies while also supporting the continuing global efforts to protect potato crop harvests. [8] [9] The details of our methodology are covered in detail in the sections that follow. By embracing the potential of advanced technology, we aim to empower farmers and agricultural stakeholders with the tools they need to protect this vital crop and secure global food supplies. [10] Wajiro higashietal.The purpose of thestudy was to evaluate how well VegeCare, a tool, classified the primary leaf diseases affecting potato crops.Three distn ct classifications were included in the dataset utilized for the investigation.The tool was trained and tested across several epochs to gauge accuracy.According to the results, the VegeCare tool classified potato illns ses with an accuracy rate of above 96%. The model demonstrated state-of-the-art performance on both private and public datasets.

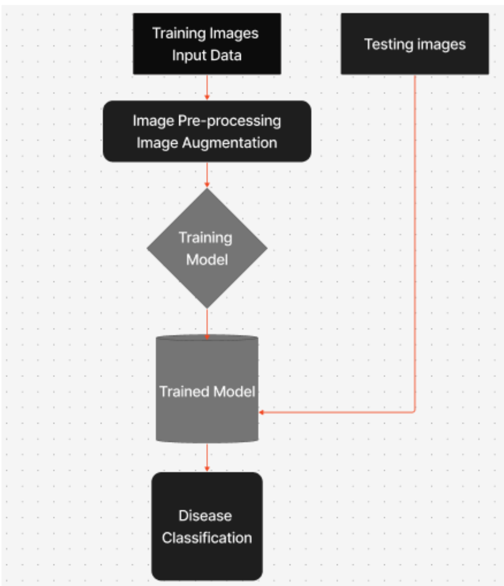


Fig.1.Flow chart of the proposed methodology.

In 2022, Kolenda Kashyap Chakraborty et al. [11] applied deep learning to automatically identify early and late blight in potato foliage from optical imagery. They trained four convolutional networks—VGG16, VGG19, MobileNet, and ResNet50—on the Plant Village dataset, with VGG16 achieving the top baseline accuracy of 92.69%. After fine-tuning VGG16 (via parameter adjustments), performance improved markedly, reaching 97.89% accuracy in distinguishing healthy leaves from early and late blight. The study presents the optimized VGG16 architecture with accompanying loss and validation accuracy curves, and comparative benchmarks indicate the method's superiority over existing approaches for potato disease classification.

## II. METHODOLOGY

Our research project's classification of potato leaf diseases is organized into six separate stages. figure 1 provides a graphic representation of these consecutive steps.

Step A: Gathering the dataset.
Step B: Preparing the data.
Step C: Augmenting the data.
Step D: Data splitting is step.
Step E: Model Training.
Step F: The models are evaluated.

### *A. Gathering datasets*

Our suggested approach to treating plant diseases makes use of deep learning methods. The main obj active is to use a variety of deep learning models to classify multiple plant diseases with the maximum possible accuracy. For this reason, Plant village offers publicly accessible datasets of potato leaves. Figure 2

### *B. Preparing the data*

The first stage of computer vision and image analysis is picture pre-processing, in which unprocessed image data is carefully transformed to improve the visual input's quality and optimize it for further computational processes. This preliminary processing


Figure 2: Three typical Plant Village Dataset photos of potato leaves.

phase is essential to data improvement and refinement since it provides a variety of advanced methods designed to tackle certain issues with digital images. An essential component of image pre-processing, image scaling plays a fundamental function in computer vision. This process entails resizing images—adjusting their width and height—to optimize them for downstream model training. By converting raw inputs into a standardized, more tractable representation, training can be accelerated. In general, models train more efficiently on smaller images than on very large ones because computational cost scales with the number of pixels (approximately with the square of the linear dimension), so larger inputs substantially increase training time. This emphasizes how crucial it is to skillfully resize photos as a tactical tool to speed up the machine learning process. Our approach to image scaling involves transforming the original images into a standard 256 x 256-pixel size, with both the width and height set to 256 pixels throughout the Kerasimplemented Deep Learning architecture pipeline's picture loading phase. We use DenseNet-169 as the backbone, which expects input tensors of size 256×256×3. Accordingly, all images are resized to 256 pixels in height and width and kept as three-channel (RGB) inputs to meet the network's specifications and ensure compatibility during training and inference. Pictures are complex pixel-value compositions. Black-and-white, or monochromatic, pictures can be contained in single pixel matrices, while their color counterparts require different arrays for each of the three-color channels (red, green, and blue). Pixel values that fall between 0 and 255 are commonly represented as unsigned integers that describe color depth or pixel intensity. Although it is possible to feed raw photos straight into our models, doing so can provide difficulties in the modeling stage, thereby reducing training effectiveness and adding complications. A popular tactic to lessen these difficulties is to scale the pixel values to a range between 0 and 1 in order to normalize them before model input. Dividing each pixel value by 255 is a useful method that produces a matrix with all pixel values falling between 0 and 1. This ideal normalizing procedure improves training and overall performance while guaranteeing that the model can handle picture input well.

### *C. Data augmentation:*

By applying various changes to preexisting images, image augmentation creates more training instances. This calculated tactic is used to increase the training dataset's heterogeneity and diversity, which eventually improves the model's ability to generalize and navigate a variety of situations. We use the "Image Data Generator" function from Kera's package to do picture augmentation, a crucial preprocessing method, in the context of our study. This procedure methodically adding controlled modifications to the photos in our training dataset, so enhancing the data's diversity and resilience. In computer vision research, this augmentation is an essential phase where the caliber and variety of the training dataset have a big influence on how well the model generalizes. To introduce variations of up to 30 degrees, we randomly apply rotations to the photos. This enables the model to identify things from various angles, which is an essential ability for practical uses. The model can accommodate changes in object size and position thanks to the use of random zooming. Pictures are enlarged by 20% or more. 3) Horizontal and Vertical Flipping: By flipping photos both horizontally and vertically, we create mirroring effects. This helps handle orientation variances by adding mirror images to the dataset. In machine learning and data analysis, data splitting is an essential step, especially when working with datasets for tasks like model evaluation and training. It entails splitting a dataset into discrete subsets forces.

### *D. Data Splitting*

Data splitting's main objective is to guarantee that machine learning models are successfully trained, verified, and tested while avoiding problems like overfitting and data leakage. Using the Image Data Generator and validation split parameter, we are configuring data splitting for testing, validation, and training. An effective tool for preprocessing and data augmentation in computer vision tasks is the ImageDataGenerator. As previously indicated, the machine learning model is trained using 80% of the dataset. Here, the data is used to teach the model new features and patterns. During training, a lower percentage (10%) is set aside for validation. Without being utilized for training, this validation set aids in fine-tuning hyperparameters and tracking the model's performance. Ten percent of the data are set aside for testing. To determine how effectively the model generalizes to new data, you can test its performance on this designated subset after training is finished.

### *E. Training Models*

A pre-trained DenseNet169 design serves as the foundation for the model architecture, which is the next step. To improve and categorize photos, layers are applied on top of the underlying model. These extra layers have a number of uses. To lower the chance of overfitting, dropout layers are incorporated for regularization. By normalizing the activations of the preceding layers, batch normalization layers stabilize the training procedure. The model can learn complex features thanks to its tightly connected layers. Lastly, there are three units in the output layer, each of which represents one of the three classes. SoftMax activation is used to classify several classes. Model compilation is the following stage once the model architecture has been established. Important configurations are made during this stage. Choosing the objective function is critical; for this multi-class task we adopt categorical cross-entropy, which penalizes the divergence between the ground-truth label distribution and the model's predicted class probabilities. Model discrimination is monitored using the Area Under the ROC Curve (AUC), a threshold-independent metric that summarizes how well the classifier separates classes. To efficiently minimize the loss and promote stable convergence, we optimize with Adam. To control the step size during gradient descent, a learning rate of 0.001 is set. The training phase starts as soon as the model is put together. Over 50 epochs, the model is trained using the fit approach. The model uses the computed loss and AUC values to determine and update its weights at each epoch. After every epoch, the verbose training process offers progress updates. The model's weights are adjusted during training to improve image classification; improvements are indicated by variations in loss and AUC values.

The model architecture is defined using TensorFlow and Keras It includes a preprocessing pipeline that resizes and rescales input photos to a uniform size and range in order to standardize them. In order to add diversity and lessen overfitting, data augmentation is also used. Max-pooling layers come after convolutional layers, which make up the model's core. The purpose of these layers is to extract patterns and significant information from the input photos. Max-pooling layers minimize spatial dimensions for computational efficiency, while convolutional layers use filters to search images for pertinent features.. Multiple layers are stacked to create a deep network. Following the convolutional layers, fully connected (dense) layers are employed to classify the extracted features. These layers learn to make predictions based on the features detected in the earlier layers. The output layer, using the softmax activation function, comprises three units, each corresponding toone of the three potato classes, enabling multi-class classification. The model is then compiled, specifying the optimizer (in this case, Adam) to adjust model weights during training to minimize the loss function (categorical cross-entropy). The goal of training is to reduce the loss and enhance accuracy.During training,which spansmultiple epochs (in this instance , 50 epochs), the model is exposed to the training data, computes predictions, and updates weights based on the loss function.Shuffling the training data set helps prevent the model from learning data order.Additionally, validation data is utilizedduring training to monitor performance on previously unseen data and detect overfitting.

F. Evaluation:

Evaluation of the models Finally, after the model is trained and validated, it undergoes testing on a separate test dataset that it has not encountered during training or validation. This evaluation phase assesses themodel' sability to generalizeand classify previously unseen data , providing valuable information about its real-world performance.

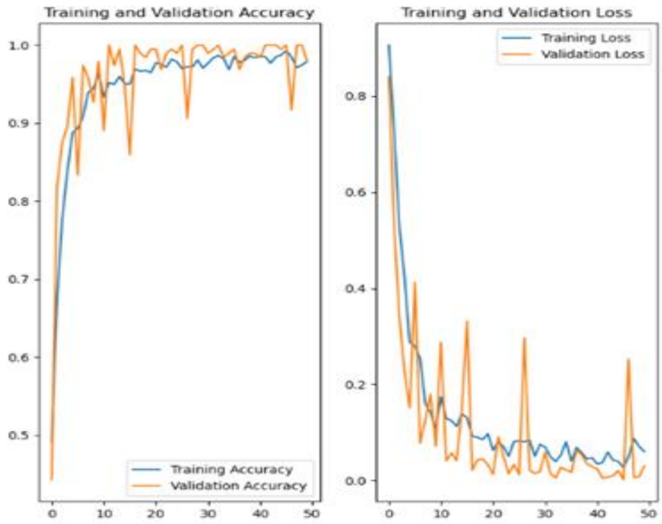


Fig.3. CustomCNNmodelaccuracyandloss.

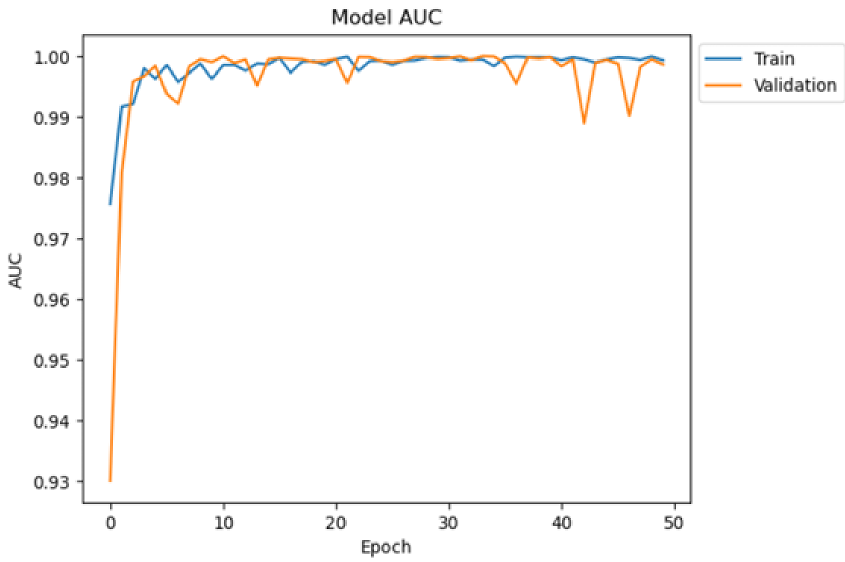


Fig.4. Training and validation accuracy of Densnet169 model.

•

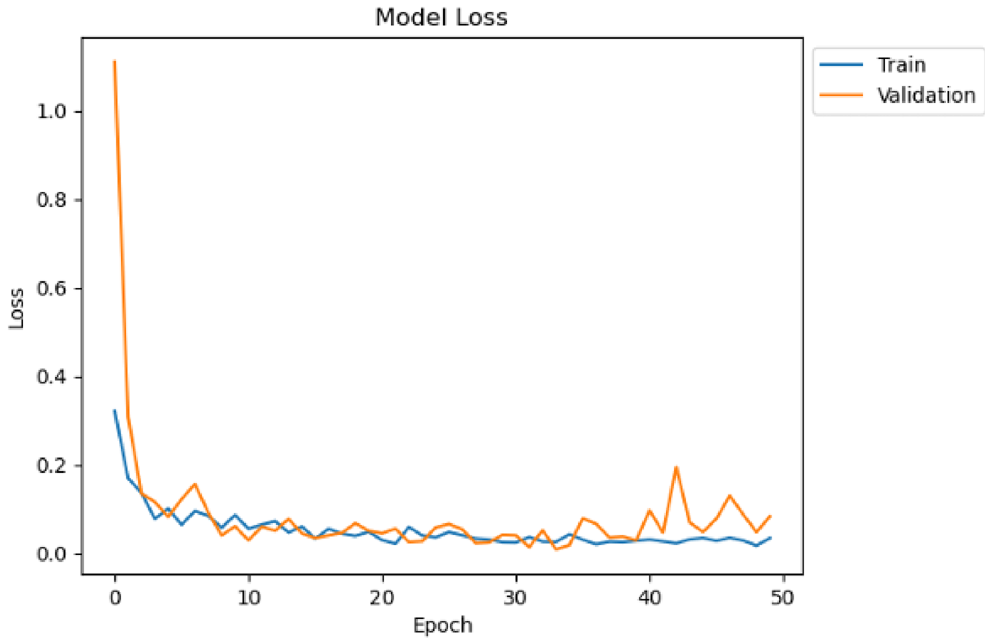


Fig.5. DenseNet-169 training–validation loss profile.

TABLE III Performance summary and training configuration

| SI. NO | Architecture | Optimization algorithm | Objective function | Number of Epochs | Classification Accuracy (%) | Loss value |
|---|---|---|---|---|---|---|
| 1 | Custom CNN Model | Adam | Categorical CE | 50 | 98 | 0.039 |
| 2 | DensNet169 | Adam | Categorical CE | 50 | 99.92 | 0.056 |

TABLE IV COMPARISON WITH EXISTING WORK

| SI. NO | Reference | Methodology used | Bench Dataset used | Accuracy achieved | Outcomes |
|---|---|---|---|---|---|
| 1 | [11] | Deep learning with VGG16, VGG19,resNet50, MobileNet and VGG16finetuned | PlantVillagedataset | 97.89% | 3 Class problem |
| 2 | [12] | Conventional MLmethods including GraphCut,SVM,k-NN,ANNandRF | AI Challenger Global AIContestdataset | 97.40% | 5 Class problem |
| 3 | [13] | Conventionalmachinelearningsuchas RandomForest | Owngenerateddataset of450images | 97% | 2 Class problem |
| 4 | [14] | MaskRegion-basedconvolutionalneural network (MaskR–CNN) architecture,withresidualnetworkasthebackbone | Owngenerateddataset | 81.40% | 2 Class problem |
| 5 | [15] | GoogleNet,VGGNet,andEfficientNet | Owngenerateddataset | - | 2,4 and 6 class |
| 6 | [16] | VGG16andVGG19 | PlantVillagedataset | 91% | 3 class problem |
| 7 | [17] | Conventionalmachinelearningsuchas K-Mean,Graylevelco-occurrencematrix | PlantVillagedataset | 95.99% | - |
| 8 | Proposed | DensNet169andCustomCNNmodel | PlantVillagedataset | 99.92% | 3 class problem |

## III. DISCUSSION

A thorough summary of all the works that are currently available in this particular domain is given in table iv. A number of issues make comparing with current models difficult, including the inaccessibility of the generated datasets that researchers use and the lack of replication model parameters. Our comparative evaluation is predicated on their approaches and results using their own datasets, albeit these challenges. The plant village dataset was the subject of three noteworthy research, and our suggested strategy outperforms them all. The remaining pieces made use of their own created datasets, which are regrettably private.

## IV. CONCLUSION

In order to distinguish between normal, early, and late blights on potato leaves, this study presents a three-class classification system.Data augmentation for the class with a restricted number of photos (healthypotato) is the first stage.Following that, two CNN models—DensNet169 and Custom CNNmodel—are trained using the combined enhanced data. With a test accuracy of 92.69%, DensNet169 performs better than other models, according to performance evaluation. After then, the model is improved through fine tweaking, yielding an astounding 99.92% test accuracy.The automated system's ability to successfully identify and categorize potato leaves afflicted by various diseases makes it useful for farmers and greatly increases crop production in the agricultural industry. It is important to remember that all of the tests in this study were carried out on a benchmark dataset, even though it offers insightful information about the automatic identification of potato leaves with early and late blight. In order to evaluate the model's consistency in real-world applications, future research will concentrate on testing it on live images.

## REFERENCES


[1] A. Chandrasekara, T. Josheph Kumar *et al.*, "Roots and tuber crops as functional foods: a review on phytochemical constituents and their potential health benefits," *International Journal of Food Science*, vol. 2016, 2016.

[2] R. Sharma, J. Patel, D. Patel, and R. Patel, "Management of early blight of potato (*Solanum tuberosum* L.) caused by *Alternaria solani* [(Ellis & Martin) Jones & Grout] through fungicides and its impact on yield," *International Journal of Current Microbiology and Applied Sciences*, vol. 9, no. 3, pp. 1683–1693, 2020.

[3] P. Nolte, J. Miller, K. M. Duellman, A. J. Gevens, and E. Banks, "Disease management," in *Potato Production Systems*, pp. 203–257, 2020.

[4] E. Aksoy, U. Demirel, A. Bakhsh, M. A. B. Zia, M. Naeem, F. Saeed, S. Çalışkan, and M. E. Çalışkan, "Recent advances in potato (*Solanum tuberosum* L.) breeding," in *Advances in Plant Breeding Strategies: Vegetable Crops: Volume 8: Bulbs, Roots and Tubers*, pp. 409–487, 2021.

[5] H. N. Fones, D. P. Bebber, T. M. Chaloner, W. T. Kay, G. Steinberg, and S. J. Gurr, "Threats to global food security from emerging fungal and oomycete crop pathogens," *Nature Food*, vol. 1, no. 6, pp. 332–342, 2020.

[6] D. E. Cooke, L. M. Cano, S. Raffaele, R. A. Bain, L. R. Cooke, G. J. Etherington, K. L. Deahl, R. A. Farrer, E. M. Gilroy, E. M. Goss *et al.*, "Genome analyses of an aggressive and invasive lineage of the Irish potato famine pathogen," 2012.

[7] M. Nowicki, M. R. Foolad, M. Nowakowska, and E. U. Kozik, "Potato and tomato late blight caused by *Phytophthora infestans*: an overview of pathology and resistance breeding," *Plant Disease*, vol. 96, no. 1, pp. 4–17, 2012.

[8] N. Najdabbasi, S. M. Mirmajlessi, K. Dewitte, S. Landschoot, M. Mänd, K. Audenaert, M. Ameye, and G. Haesaert, "Biocidal activity of plant-derived compounds against *Phytophthora infestans*: An alternative approach to late blight management," *Crop Protection*, vol. 138, p. 105315, 2020.

[9] I. K. Abuley and J. G. Hansen, "An epidemiological analysis of the dilemma of plant age and late blight (*Phytophthora infestans*) susceptibility in potatoes," *European Journal of Plant Pathology*, vol. 161, no. 3, pp. 645–663, 2021.

[10] N. Ruedeeniraman, M. Ikeda, and L. Barolli, "Performance evaluation of VegeCare tool for potato disease classification," in *Advances in Networked-Based Information Systems: The 23rd International Conference on Network-Based Information Systems (NBiS-2020)*, Springer, 2021, pp. 470–478.

[11] K. K. Chakraborty, R. Mukherjee, C. Chakroborty, and K. Bora, "Automated recognition of optical image based potato leaf blight diseases using deep learning," *Physiological and Molecular Plant Pathology*, vol. 117, p. 101781, 2022.

[12] C. Hou, J. Zhuang, Y. Tang, Y. He, A. Miao, H. Huang, and S. Luo, "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation," *Journal of Agriculture and Food Research*, vol. 5, p. 100154, 2021.

[13] M. A. Iqbal and K. H. Talukder, "Detection of potato disease using image segmentation and machine learning," in *Proc. 2020 Int. Conf. on Wireless Communications Signal Processing and Networking (WiSPNET)*, IEEE, 2020, pp. 43–47.

[14] J. Johnson, G. Sharma, S. Srinivasan, S. K. Masakapalli, S. Sharma, J. Sharma, and V. K. Dua, "Enhanced field-based detection of potato blight in complex backgrounds using deep learning," *Plant Phenomics*, 2021.
[15] H. Afzaal, A. A. Farooque, A. W. Schumann, N. Hussain, A. McKenzie Gopsill, T. Esau, F. Abbas, and B. Acharya, "Detection of a potato disease (early blight) using artificial intelligence," *Remote Sensing*, vol. 13, no. 3, p. 411, 2021.
[16] R. A. Sholihati, I. A. Sulistijono, A. Risnumawan, and E. Kusumawati, "Potato leaf disease classification using deep learning approach," in *Proc. 2020 Int. Electronics Symposium (IES)*, IEEE, 2020, pp. 392–397.
[17] V. Singh and A. K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques," *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41–49, 2017.
[18] A. Alptekin and M. Yakar, "Determination of pond volume with using an unmanned aerial vehicle," *Mersin Photogrammetry Journal*, vol. 2, no. 2, pp. 59–63, 2020.
[19] L. Karataş, A. Alptekin, and M. Yakar, "Mardin historical Kuyumcular (Jewelers) Bazaar restoration evaluation," in *Proc. Advanced Engineering Days (AED)*, vol. 5, pp. 15–17, 2022.
[20] D. F. Maune, *Digital Elevation Model Technologies and Applications: The DEM User Manual*, The American Society for Photogrammetry and Remote Sensing, 2001. ISBN: 1-57083-064-9.