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Advancing Crop Protection through Convolutional Neural Networks: A Multi-Plant Disease Classification Study

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Abstract – Agriculture plays a pivotal role in sustaining human life by serving as the primary source of food, yet its vulnerability to diseases poses a significant threat to global food security. The effective management of these diseases is paramount to ensuring crop productivity and safeguarding the stability of food systems worldwide. This study introduces a novel approach based on convolutional neural networks (CNNs), leveraging the robust DenseNet169 architecture, for disease classification across four distinct plant species: potato (Solanum tuberosum), tomato (Solanum lycopersicum), grapes (Vitis vinifera), and apple (Malus domestica).The classification task encompasses identifying late blight, early blight, and healthy states for potato and tomato; black rot, leaf blight, and healthy states for grapes; and apple scab, black rot, and healthy states for apple. Remarkably, the proposed model demonstrates exceptional performance, achieving an impressive accuracy rate of 99.5% on the classification task. This significant outcome underscores the transformative potential of deep learning techniques in revolutionizing precision agriculture practices. By automating disease diagnosis through advanced machine learning algorithms, such as CNNs, this study pioneers a paradigm shifts in agricultural management. The implementation of automated disease detection enables timely interventions, mitigating crop losses and enhancing overall agricultural sustainability. This research not only showcases the efficacy of deep learning methodologies but also underscores their instrumental role in addressing critical challenges faced by the agricultural sector.

Keywords – Plant Disease Classifications, Convolutional Neural Networks (CNNs), Densenet169, Precision Agriculture, Food Security, Disease Diagnosis.

I. INTRODUCTION

Plant disease poses a critical threat to agricultural production, and failure to address it in a timely manner can result in escalating food insecurity. Addressing this issue is imperative to bolster grain harvest yields and support Pakistan's economy, where agriculture contributes to 18.9% of the GDP (Gross Domestic Product) and provides employment for 47% of the population. Many diseases can affect plants, and this is especially true in Pakistan and other parts of the world. Plant diseases can arise and spread due to a variety of circumstances, such as weather patterns, the quality of the soil, and the presence of pests and pathogens

[1]. Traditional methods alone are insufficient, highlighting the need to harness advanced Artificial Intelligence techniques like Machine Learning and Deep Learning for accurate and efficient plant disease classification. By leveraging these technologies, researchers can contribute to improving crop management practices and safeguarding agricultural productivity, ultimately benefiting both farmers and consumers.

However, the journey from its Andean roots to global prominence has not been without its perils. Potato plants are susceptible to a range of fungal pathogens that can wreak havoc on crop health, yield, and the quality of the tubers. Among these adversaries, late blight (Phytophthora infestans) and early blight (Alternaria solani) are particularly menacing. Late blight, infamous for triggering the Irish Potato Famine in the 19th century, remains a global threat to food security, causing annual yield losses estimated at $6.7 billion [2] [3]. Early blight, with its characteristic "bull's eye spot" effect on leaves, is no less insidious, affecting older potato leaves and contributing to significant yield losses.

As our understanding of these plants diseases has deepened, so too has the urgency to develop innovative solutions for their early detection and management. Traditional methods of disease screening, reliant on manual visual inspections, have proven to be resource-intensive, subjective, and prone to human bias. However, in the era of digital agriculture, a promising frontier has emerged. Recent advances in imaging technologies, including hyperspectral cameras, RGB imaging systems, and smartphone applications, combined with the remarkable capabilities of machine learning (ML) and artificial intelligence (AI), have opened new possibilities for revolutionizing disease diagnosis in agriculture [4][5].

This research paper embarks on a journey to harness these emerging technologies and confront the challenges posed by late blight and early blight in potato cultivation. The primary objective is to develop a robust and efficient solution for the accurate and early diagnosis of these devastating diseases. To achieve this, we turn to deep learning models, including VGG16, VGG19, ResNet50, and MobileNet. These models, renowned for their ability to learn intricate patterns from data, hold immense potential for significantly enhancing disease classification [6][7].

In 2019 Sammy V. Militante et al [8] offer an effective method for identifying several diseases in a range of plant kinds. The apple, corn, grape, potato, sugarcane, and tomato plants are among the crops for which the system is intended to identify and diagnose diseases. Three hundred and fifty thousand photos, representing both disease-free and healthy plant leaves, make up the training dataset. The researchers trained the algorithm to precisely identify the particular plant variety and detect and classify plant diseases by using deep learning models. The system showed remarkable efficiency in identifying and detecting the type of diseases present as well as the plant species, and the trained model attained a high degree of accuracy.

In 2020, Mohit Agarwal et al. [9] a simplified CNN model with 8 hidden layers is proposed in this paper. The proposed model outperforms both traditional machine learning approaches and pretrained models in terms of disease identification. Evaluation using the PlantVillage dataset, which includes diverse crops including 10 classes specific to tomato diseases, demonstrates the efficacy of the proposed model. Additionally, image pre-processing techniques, such as random brightness adjustment and augmentation, are employed to further enhance CNN’s performance. The proposed model also exhibits robust performance on other datasets, showcasing its potential for accurate and efficient tomato disease identification.

In 2021, Farah Saeed et al. [10] use computer vision techniques to enhance plant disease detection and recognition in 2021. They will specifically concentrate on the effects of illnesses on agricultural food production and quality. Using a pre-trained VGG19 convolutional neural network model, the suggested method extracts deep features from plant photos. A parallel fusion technique based on partial least squares (PLS) regression is then employed. A PLS projection technique is then used to choose the most pertinent and discriminative features. Lastly, for disease recognition, an ensemble baggage tree classifier is used. Three distinct crops from the Plant Village dataset—potato, corn, and tomato are used to evaluate the system, and the results show an average accuracy of about 90.1%. According to the results, combining PLS-based fusion and selection strategies improves recognition accuracy while cutting down on computational time, which makes it a viable strategy for crop disease management and early detection in real-world agricultural settings.

In 2021, M N Ahil et al. [11] focused on classifying leaf diseases in apples and grapes using machine learning approaches. The dataset that the author used was sourced from the Plant Village dataset on Kaggle. It included roughly 3171 photos of apple leaf disease and 4062 images of grape leaf disease. Convolutional neural networks (CNN) and multilayer perceptrons (MLP) were the techniques used to complete the classification challenge. After pre-processing the dataset to make it more suitable for the classifiers, leaf disease classification was carried out. In order to determine how well the classifiers classified apple and grape leaf diseases, the author compared and evaluated their accuracy as well as their performance metrics.

In our pursuit of this goal, we follow a comprehensive methodology that involves rigorous model evaluation and parameter optimization. Through this approach, we aim to push the boundaries of disease classification in the context of potato crops. By comparing our findings to existing research and benchmark datasets, we endeavor to demonstrate the superior efficiency and efficacy of our proposed model. In doing so, our research not only contributes to the ongoing global efforts to safeguard potato crop yields but also advances the cause of sustainable agriculture in the face of these formidable adversaries [12] [13].

Wajiro-higashi et al. [14] The author conducted a study to assess the performance of a tool called VegeCare in classifying the main leaf diseases of potato crops. The dataset used in the study had three different classes. To measure accuracy, the tool was trained and validated over multiple epochs. Results showed that the VegeCare tool performed well, with an accuracy rate of over 96% in classifying potato diseases. The model achieved cutting-edge performance on both custom and public datasets.

The research [15] developed an improved algorithm for identifying apple leaf diseases and attained an accuracy rating of 96.23% by utilizing MobileNetV2. Several models were used in the study [4] to detect tomato leaf illnesses. MobileNet achieved the highest accuracy rate of 94%, followed by Xception at 95.32%, VGG16 at 93.35%, ResNet50 at 96.03%, DenseNet121 at 96.3%, and EfficientNetB5 at 99.07%.

The accuracy of the study [16] was 99.22%.Three CNN-based models for the classification of tomato leaf diseases were proposed in this work: VGG-16, ResNet-152, and EfficientNet-B4. According to the study, the models' accuracy was 93.75%, 97.27%, and 98%, in that order. The research [17] identified tomato illnesses with a 99.9% classification accuracy by using a DenseNet model.

II. MATERIALS AND METHOD

The classification of plants leaf diseases in our research project is structured into six distinct phases. A visual depiction of these sequential steps is illustrated in Figure 1.

- Step A: Dataset collection.
- Step B: Data pre-processing.
- Step C: Data augmentation.
- Step D: Data splitting.
- Step E: Training Models.
- Step F: Evaluation of the models.

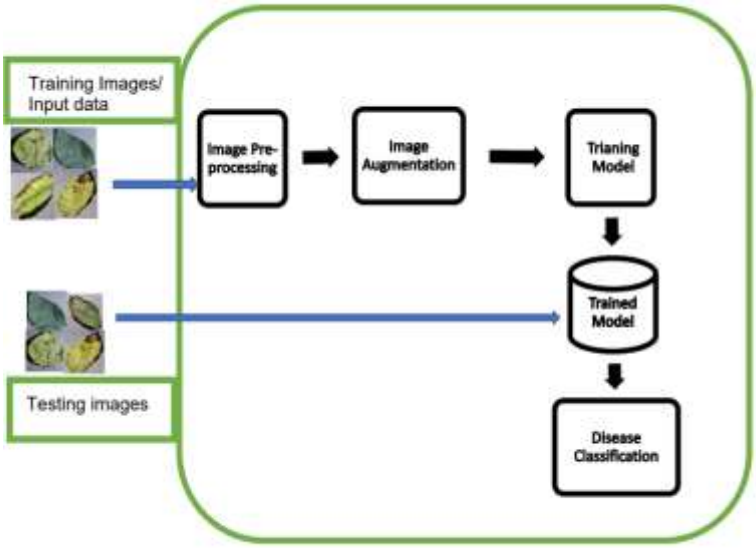

Figure 1. Flowchart of the proposed methodology

A. Dataset Collection

Our proposed method for addressing plants diseases involves using deep learning techniques. The primary goal is to classify multiple plants diseases by employing deep learning models to achieve the highest accuracy. Publicly available datasets of plants leaves can be obtained from Plantvillage for this purpose Figure 2.

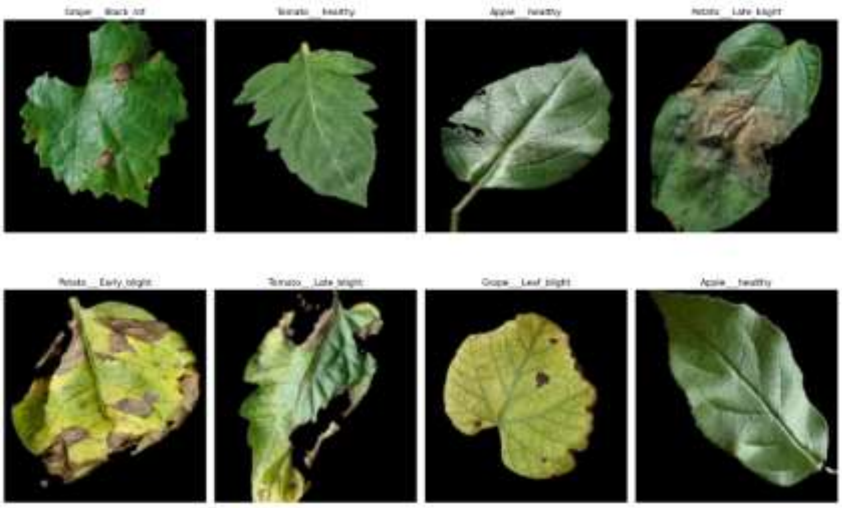

Figure 2. Leaf images from Plant Village Dataset

B. Data Pre-Processing

Image pre-processing serves as the foundational step in computer vision and image analysis, where raw image data undergoes a meticulous transformation process aimed at elevating the quality of the visual input and optimizing it for subsequent computational procedures. This pre-processing phase plays a pivotal role in data refinement and enhancement, offering a range of sophisticated techniques tailored to address specific challenges inherent in digital imagery.

1) *Image resizing*

Image resizing is a pivotal aspect of image pre-processing, holding a foundational role in the field of computer vision. It encompasses the modification of an image's dimensions, specifically its width and height, with the primary aim of optimizing the data for subsequent model training. In essence, this practice involves adapting the original image into a more manageable format, facilitating accelerated model training. Notably, machine learning models exhibit enhanced training efficiency when exposed to smaller images, as opposed to those with significantly larger dimensions. In the case of larger images, the neural network is burdened with the task of processing an exponentially greater number of pixels, thereby prolonging the training duration. This underscores the critical importance of adeptly resizing images as a strategic measure to expedite the machine learning workflow.

In our methodology for image resizing, we have transformed the original images into a standardized size of 256 x 256 pixels, where the height and width are both set to 256 pixels, during the image loading phase within the Deep Learning architecture pipeline implemented with Keras. This resizing aligns with our use of the DenseNet169 pre-trained model as the central component of our architecture, which requires input images of dimensions (256 x 256 x 3). Here, the height and width dimensions remain at 256 pixels, while the third-dimension accounts for the three colour channels, ensuring compatibility with the model's input specifications.

2) *Image normalization*

Images serve as intricate compositions of pixel values. Monochromatic, or black-and-white, images can be encapsulated as single pixel matrices, whereas their colour counterparts necessitate separate arrays for distinct colour channels, such as red, green, and blue. Frequently, pixel values are denoted as unsigned integers, residing within the 0 to 255 range, characterizing pixel intensity or colour depth. While it is feasible to ingest unprocessed images directly into our models, this approach can pose challenges during the modelling phase, potentially impeding training efficiency and introducing complexities.

To mitigate these challenges, a common strategy is to standardize the pixel values prior to model input by scaling them to a range between 0 and 1. An effective approach is to divide each pixel value by 255, resulting in a matrix where all pixel values are situated within the 0 to 1 range. This normalization process is considered optimal, ensuring that the model can efficiently handle image data while enhancing training and overall performance.

C. Data Augmentation

Image augmentation entails the generation of additional training instances by subjecting existing images to a range of transformations. This strategic approach is employed to amplify the diversity and variability of the training dataset, ultimately enhancing the model's capacity for generalization and its adeptness in navigating diverse scenarios.

In the context of our research, we employ the `ImageDataGenerator` tool from the Keras library to carry out image augmentation, a vital preprocessing technique. This process involves systematically introducing controlled variations into our training dataset images, which, in turn, bolsters the robustness and diversity of the data. This augmentation serves as a crucial step in computer vision research, where the quality and diversity of the training dataset significantly impact the model's ability to generalize effectively.Key aspects of our image augmentation process include:

1) *Rotation*

We randomly apply rotations to the images, introducing variations of up to 30 degrees. This allows the model to recognize objects from different perspectives, a vital skill for real-world applications.

2) *Horizontal and Vertical Flipping*

We introduce mirroring effects by flipping images horizontally and vertically. This augments the dataset with mirror images, aiding in handling orientation variations.

3) *Zooming*

Random zooming is employed, enabling the model to handle variations in object size and position. Images are magnified within a range of 20%.

D. *Data Splitting*

Data splitting is a crucial step in machine learning and data analysis, particularly when dealing with datasets for tasks like training and evaluating models. It involves dividing a dataset into distinct subsets for specific purposes. The primary goal of data splitting is to ensure that machine learning models are trained, validated, and tested effectively while avoiding issues like overfitting and data leakage.

we are setting up data splitting for training, validation, and testing using the ImageDataGenerator and validation split parameter. The ImageDataGenerator is a powerful tool for data augmentation and preprocessing in computer vision tasks. Data splitting is a critical step in machine learning, where the dataset is divided into distinct subsets for different purposes:

1) *Training Data*

As mentioned earlier, the majority of the dataset (80%) is used for training the machine learning model. This is where the model learns patterns and features from the data.

2) *Validation Data*

A smaller portion (10%) is reserved for validation during training. This validation set helps in tuning hyperparameters and monitoring the model's performance without actually being used for training.

3) *Testing Data*

The 10% of the data is reserved for testing. After training is complete, you can evaluate the model's performance on this reserved subset to assess how well it generalizes to unseen data.

E. Training Models.

Moving on to the model architecture, it is built using a pre-trained DenseNet169 architecture as the base model. Layers are added on top of the base model to fine-tune and classify images. These additional layers serve various purposes. Dropout layers are included for regularization, reducing the risk of overfitting. Batch normalization layers stabilize the training process by normalizing the activations of the previous layers. Dense, densely connected layers provide the model with the capacity to learn complex features. Finally, the output layer consists of twelve units, each corresponding to one of the twelve classes. It uses softmax activation for multi-class classification.

With the model architecture defined, the next step is model compilation. During this phase, key configurations are set. The choice of loss function is crucial, and for this multi-class classification task, Categorical Cross-Entropy is chosen as the appropriate loss function. This function quantifies the difference between predicted and actual class probabilities. To monitor the model's performance, the Area Under the ROC Curve (AUC) metric is used. This metric assesses the model's ability to distinguish between classes effectively. Finally, the optimizer, in this case, Adam, is employed to minimize the loss function. A learning rate of 0.001 is specified to regulate the step size during gradient descent.

Once the model is compiled, the training process begins. The model is trained using the fit method over 150 epochs. During each epoch, the model computes and updates its weights based on the calculated loss and AUC values. The training process is verbose, meaning that it provides progress updates after each epoch. Throughout training, the model's weights are fine-tuned to better classify images, with changes in loss and AUC values indicating progress.

F. Evaluation Of The Models

After completion of the training and validation phases, the model undergoes rigorous testing on an independent dataset that remains unseen during both training and validation processes. This evaluation phase serves to gauge the model's capacity for generalization and its efficacy in accurately classifying previously unseen data, thereby providing crucial insights into its real-world performance.

The following formula, where TP stands for True Positives, TN for True Negatives, FP for False Positives, and FN for False Negatives, is used to calculate the accuracy of the model:

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

This statistic, which represents the percentage of correctly classified examples compared to the total number of instances evaluated during testing, functions as a basic indicator of the model's overall performance.

Table 1. Model Performance And Configuration

Model	Optimizer	Loss Function	Epochs	Classification Accuracy (%)
DensNet169	Adam	Categorical CE	150	99.5

III. RESULTS

Training progress, including loss and accuracy metrics, is printed for each epoch to monitor the model's convergence. After training, the model is evaluated using a separate test dataset to assess its generalization to new, unseen data. Evaluation metrics such as loss and accuracy are computed and displayed. Throughout and after training, various visualizations, such as loss and accuracy curves across epochs, are generated to provide insights into the model's performance and convergence. Fig 3 and Fig 4

In summary, the training process aims to optimize the model's weights to accurately classify potato images into their respective classes. Architectural choices, data augmentation techniques, and training parameters significantly influence the model's performance and its ability to generalize to novel data.

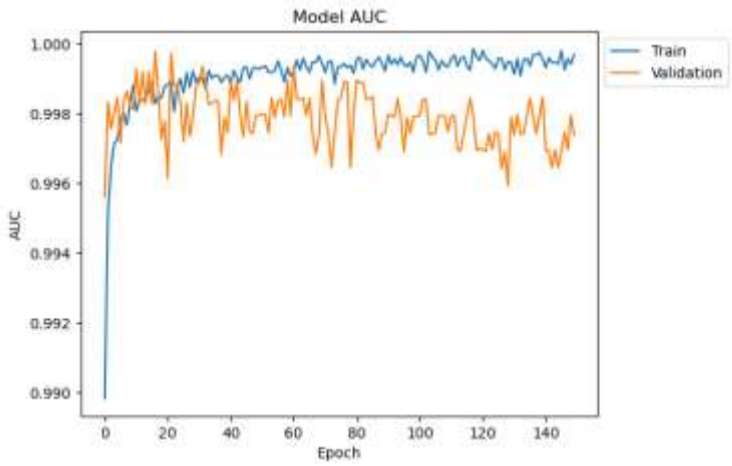

Figure 3. Training and validation accuracy of Densnet169 model for 150 epochs

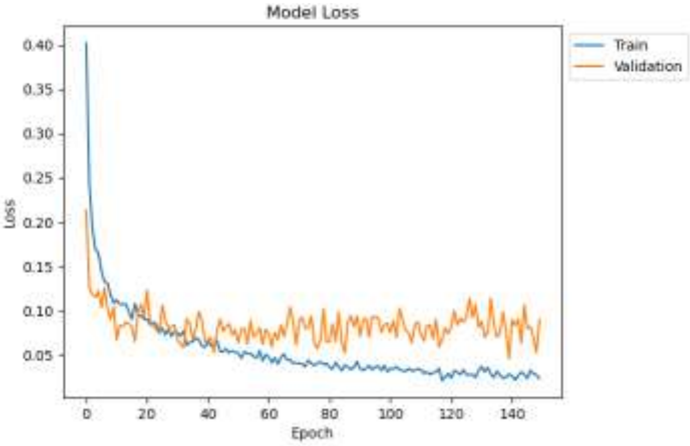

Figure 4. Training and validation loss of Densnet169 model for 150 epochs

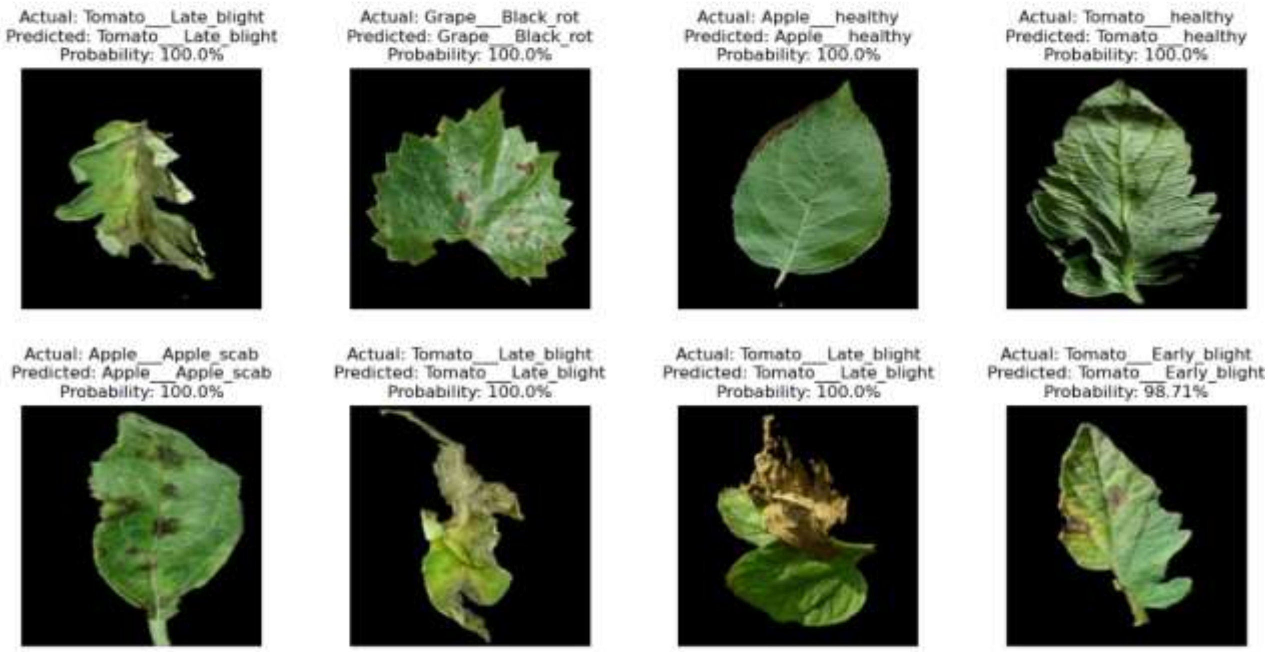

Figure 5. Prediction of DenseNet169 model.

IV. DISCUSSION

A comprehensive overview of the current research in this domain reveals challenges when comparing with existing models. This difficulty arises due to several factors, including limited access to researchers' generated datasets and the unavailability of model parameters for replication. However, our comparative assessment is grounded in an examination of methodologies and outputs using the respective datasets of these studies.

Notably, the studies utilized the PlantVillage dataset, and our proposed approach outperformed all these methods. Conversely, other works relied on their own generated datasets, which unfortunately are not publicly accessible.

V. CONCLUSION

This study introduces a 12-class classification system aimed at identifying potato (Solanum tuberosum), tomato (Solanum lycopersicum), grapes (Vitis vinifera), and apple (Malus domestica). The diseases considered for classification are late blight, early blight, and healthy state for potato and tomato; black rot, leaf blight, and healthy state for grapes; and apple scab, black rot, and healthy state for apple. The initial step involves data augmentation for the class with a limited number of images . Subsequently, the augmented data is aggregated for training across CNN model, (DensNet169). Performance assessment reveals that DensNet169 outperforms other models, achieving a test accuracy of 95.5%. Following this, fine-tuning enhances the model, resulting in an impressive test accuracy of 99.5%. The successful detection and classification of multi plant leaves affected by these diseases make the automated system valuable for farmers, contributing significantly to improving crop yield in the agricultural sector. While this research provides valuable insights into the automatic detection of potato leaves with early and late blight, it is essential to note that all experiments were conducted on a benchmark dataset. Future work will focus on testing the model on real-time images to assess its consistency in practical applications.

REFERENCES

[1] Bastas, K. K. (2022). Impact of climate change on food security and plant disease. In K. K. Bastas (Ed.), Microbial Biocontrol: Food Security and Post Harvest Management: Volume 2 (pp. 1-22).

[2] Sharma, R. K., Patel, J. K., Patel, D. R., & Patel, R. N. (2020). Management of Early Blight of Potato (Solanum tuberosum L.) caused by Alternaria solani [(Ellis & Martin) Jones & Grout] through Fungicides and its Impact on Yield. Int. J. Curr. Microbiol. App. Sci, 9(3), 1683-1693.

[3] Nolte, P., Miller, J., Duellman, K. M., Gevens, A. J., & Banks, E. (2020). Disease management. In Potato Production Systems (pp. 203-257).

[4] Aksoy, E., Demirel, U., Bakhsh, A., Zia, M. A. B., Naeem, M., Saeed, F., Çalışkan, S., & Çalışkan, M. E. (2021). 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).

[5] Fones, H. N., Bebber, D. P., Chaloner, T. M., Kay, W. T., Steinberg, G., & Gurr, S. J. (2020). Threats to global food security from emerging fungal and oomycete crop pathogens. Nature Food, 1(6), 332-342.

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

[7] Nowicki, M., Foolad, M. R., Nowakowska, M., & Kozik, E. U. (2012). Potato and tomato late blight caused by Phytophthora infestans: an overview of pathology and resistance breeding. Plant Disease, 96(1), 4-17. https://doi.org/10.1094/PDIS-05-11-0458.

[8] Militante, S. V., Gerardo, B. D., & Dionisio, N. V. (2019). Plant leaf detection and disease recognition using deep learning. In 2019 IEEE Eurasia Conference on IoT, Communication and Engineering (ECICE) (pp. 579-582). IEEE.

[9] Agarwal, M., Gupta, S. K., & Biswas, K. K. (2020). Development of efficient CNN model for tomato crop disease identification. Sustainable Computing: Informatics and Systems, 28, 100407. https://doi.org/10.1016/j.suscom.2020.100407

[10] Saeed, F., Khan, M. A., Sharif, M., Mittal, M., Goyal, L. M., & Roy, S. (2021). Deep neural network features fusion and selection based on PLS regression with an application for crops diseases classification. Applied Soft Computing, 103, 107164. https://doi.org/10.1016/j.asoc.2021.107164

[11] Ahil, M. N., Vanitha, V., & Rajathi, N. (2021). Apple and grape leaf disease classification using MLP and CNN. In 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA) (pp. 1-4). IEEE.

[12] Najdabbasi, N., Mirmajlessi, S. M., Dewitte, K., Landschoot, S., Mänd, M., Audenaert, K., Ameye, M., & Haesaert, G. (2020). Biocidal activity of plant-derived compounds against Phytophthora infestans: An alternative approach to late blight management. Crop Protection, 138, 105315. https://doi.org/10.1016/j.cropro.2020.105315

[13] Abuley, I. K., & Hansen, J. G. (2021). An epidemiological analysis of the dilemma of plant age and late blight (Phytophthora infestans) susceptibility in potatoes. European Journal of Plant Pathology, 161(3), 645-663. https://doi.org/10.1007/s10658-021-02306-7

[14] Ruedeeniraman, N., Ikeda, M., & Barolli, L. (2021). 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) 23 (pp. 470-478). Springer.

[15] Liu, S., Bai, H., Li, F., Wang, D., Zheng, Y., Jiang, Q., & Sun, F. (2023). An apple leaf disease identification model for safeguarding apple food safety. Food Science and Technology, 43, e104322. SciELO Brasil.

[16] Khalid, A., Akbar, S., Hassan, S. A., Firdous, S., & Gull, S. (2023). Detection of tomato leaf disease using deep convolutional neural networks. In 2023 4th International Conference on Advancements in Computational Sciences (ICACS) (pp. 1-6). IEEE.

[17] Bouni, M., Hssina, B., Douzi, K., Douzi, S., & others. (2023). Impact of pretrained deep neural networks for tomato leaf disease prediction. Journal of Electrical and Computer Engineering, 2023. Hindawi.