An Artificial Intelligence Framework for Disease Detection in Potato Plants

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ABSTRACT

Agricultural products are a fundamental necessity for every country. When plants are afflicted with diseases, it influences the country's agricultural productivity, as well as its economic resources. Diseases are an important problem for potato plants, causing potatoes to be rejected and resulting in financial losses. Viruses and diseases in potatoes and field plants can be missed with the naked eye, particularly in the early stages of cultivation. The use of modern instruments and technology at an early stage of disease diagnosis dramatically reduces costs. This study used deep learning techniques to categorize and detect plant leaf diseases in photos taken from the Plant Village dataset. The dataset consists of 20,636 photos of plants and their diseases. This study focused on potato plants because it is the most common type of plant in the world, particularly in Pakistan. Convolutional Neural Network (CNN) methods were used to categorize plant leaf diseases into 15 classes, including three classes for healthy leaves and classes for several plant diseases such as fungal and bacterial infections, among others. The proposed models were trained and tested, achieving 98.29 and 98.029% accuracy, respectively.

Keywords-deep learning; disease classification; CNN; potato disease detection; image processing; machine vision; smart sprayer

I. INTRODUCTION

More than a billion people eat potatoes every day as a staple food, making them an important root and tuber crop on a global scale. According to the Uzbekistan State Statistics Committee, Pakistan became the main potato supplier in January 2022, making approximately 51% of all imports [1]. In 2022, the potato seeding area increased by 35% in Punjab, Pakistan, which represents more than 80% of national production, rising from 545,000 to 740,400 acres. Weather conditions were favorable for most of the crop's life cycle, and growers anticipated record production [2]. Agriculture is the foundation of all civilizations, but the emphasis is on increasing production without considering the environmental impacts that have emerged due to environmental degradation [3-4]. Plant diseases are extremely important because they can significantly affect both the quality and quantity of agricultural plants. However, as this strategy may be time-consuming, costly, and inaccurate, the detection and classification of plant diseases using Deep Learning (DL) algorithms provide a rapid and accurate solution. Images of plant infection signs are used to identify plant diseases, as well as for research, education, and analysis [5-6]. In Pakistan, potato farming has become significantly important for both customers and farmers over time. In terms of production volume, it is the fourth most important crop, providing farmers with good yields and advantageous profits. With more protein and iron than other vegetables in the typical diet, potatoes are famous for their excellent nutritional value. They also provide important sources of fiber, niacin, thiamine, and other necessary elements. The Punjab province comprises over 86% of Pakistan's potato production and sowing area.

Potatoes grow in different climates, including subtropical, temperate, and tropical ones. They are classified as a "cool-weather crop", and the temperature has a significant impact on their output. Potato germination prefers a temperature of approximately 25°C, while vegetative growth does best at approximately 20°C. On the other hand, the temperature range between 16 and 24°C is ideal for tuber production, which is severely restricted though by temperatures exceeding 30°C (86°F) or below 10°C (50°F). Typically, daily temperatures between 18 and 20°C (64 and 68°F) produce the highest yields. Potatoes are very easy to grow, but since they do best in cooler climates, it is crucial to plant them at the right time. The fall crop planting season, which makes up more than 70% of the total production, starts in early October and runs until mid-November. The spring crop can be seeded from mid-December to mid-February and represents less than 10% of the overall production. On the other hand, the summer crop, which makes up more than 15% of the overall production, is planted between early April and mid-May.

Numerous microbes, including fungi, bacteria, and viruses, are considered responsible for causing plant diseases. Experts and farmers frequently diagnose these diseases by visual inspection, without the use of specialized technology. Locally produced seed potatoes satisfy more than 99% of the need for domestic potatoes consumption in Pakistan. The country currently produces about 2.02 million MT domestically each year, of which 280,000 MT is used for seed and the remaining 1.7 million MT is accessible for consumption when post-harvest losses are taken into account. With a population of about 150 million, this translates to an average annual per capita intake of 11 Kg.

TABLE I. SHARES OF SEASONAL POTATO PRODUCTION

Crop Production	Planting	Harvesting	Share
Winter	Jan-Feb	Apr-May	7.1 %
Summer	Mar-May	Aug-Oct	15-20%
Autumn	Sept-Oct	Jan-Feb	70-75%

This study aims to use DL and computer image processing to develop a quick and accurate disease detection system. DL approaches are good at classifying plant diseases [7]. An artificial infection detection method can help new gardeners and experienced plant pathologists identify plant diseases based on visual cues on plant traits. [8-9]. A CNN-based machine learning approach was used for the identification and classification of plant diseases. The dataset used consists of various plant species collected from a global data archive called "Plant Village". However, this study mainly focused on several potato plants varieties due to their importance and widespread cultivation, especially in Pakistan [10]. In [11], Artificial Intelligence (AI) was reported to offer the potential to improve crop productivity through soil and weather data analysis, helping to optimize irrigation and fertilization approaches. Furthermore, AI enables early detection of plant diseases and monitoring of plant health, facilitating prompt interventions and minimizing crop damage. Additionally, AI applications in automating farm machinery not only streamline operations but also result in cost savings and improved operational efficiency. Finally, seed potato generation allows diseases to spread quickly, as one seed potato produces about ten tubers.

In Japan, there are about 12 viruses that affect potato production [12], making disease management measures necessary for the yields to be increased. The Japanese government created a three-stage propagation system for seed potato production and distribution to encourage consistent potato production and provide disease-free and high-quality seed potatoes. The seed potato yield increased 10 times at every stage of propagation. As a result, today Japan has one of the highest potato yields per unit of land worldwide. However, healthy and disease-free seed potatoes can suffer during multiplication. Inspections utilizing various detection techniques are carried out along the propagation chain to spot and remove damaged seed potatoes and ensure their quality. Polymerase Chain Reaction (PCR), electron microscopy, and enzyme-linked immunosorbent assays (ELISA) are some of the examination techniques used [13].

To design a functional and field-ready system, it is crucial to incorporate the specialized knowledge of field workers. As a result, this study included on-site consultations with experts in unusual plant identification [14]. The experts found and considered a few factors throughout these conversations, entailing:

- Plants with abnormalities can be identified in their early development.
- Compared to the early development stage, when plants are in their mid-growth stage, their neighboring plant leaves may overlap, making it harder to spot abnormal plants. Abnormal plants can be found by comparing them with nearby healthy plants.
- Leaves that show disease symptoms were taken into account during detection. A plant is considered odd if it has unusual leaves and disease symptoms.

Based on these inputs, a system that can be employed in the field was designed on the following:

- Image processing usage to identify abnormal potato plants in their early development stages. Each plant is then obtained and classified utilizing a newly created explainable deep classification model.
- Utilization of a specially designed pipeline to compare unusual potato plants with nearby plants to identify them in the mid-growth period.
- During the middle stage of growth, identifying unusual potato leaves involves engaging an existing deep learning model for leaf detection in conjunction with the proposed explainable deep classification model to categorize the identified leaves. This study developed algorithms to identify unusual potato plants, evaluated their accuracy, and examined their effectiveness under diverse field light circumstances. The DL models were developed and validated on certain datasets.

In [15], a method was proposed to recognize and classify tomato leaf diseases, using the LeNet architecture, which is a CNN variant. This architecture was used to classify images of tomato plant leaves based on the obvious symptoms of diseases and present a decision-making strategy that relies on exact judgment and scientific methodologies. Deep residual learning and transfer learning were used to train the CNN on a portion of the Plant Village dataset that contained photos of tomato plant leaves. The results showed that the proposed method was computationally economical and beat VGG models pre-trained on the ImageNet dataset in terms of accuracy and retraining time [16].

In [17], 20 agrochemicals are often uniformly administered throughout a growing season, ignoring the geographical diversity of disease infestations within a potato crop. To improve potato production, growers have augmented the uniform application of agrochemicals by 150% in the last 20 years, increasing production costs and environmental degradation. This study also discussed the benefits of effective crop management, which can be achieved by precisely applying agrochemicals. These benefits could include improved potato quality, increased tuber production, as well as financial and environmental gains [18]. The creation of intelligent sprayers that can recognize spatially variable weed and disease distribution within potato fields can allow for the targeted administration of agrochemicals only in the affected areas. Precision agriculture techniques are still in their early stages in Pakistan, although they are steadily gaining acceptance in other parts of the world. By maximizing pesticide use and supporting sustainable practices, these artificial sprayers application could revolutionize agricultural practices.

According to [19], early blight, a prevalent potato disease caused by Alternaria Solani Sorauer, is common throughout Pakistan. Like other plant leaf diseases, it first affects older, less productive leaves before advancing up the plant canopy and triggering leaf senescence. The first symptoms of this disease are small black or brown lesions of 1-2 mm that grow into dark-pigmented concentric rings in a favorable environment [20]. In [21], early blight was controlled by applying fungicides indiscriminately without considering its geographical distribution. This method has an adverse effect on the environment in addition to raising production costs. An intelligent classification system that can discriminate between diseased and healthy plants and allow targeted fungicide administration is required to support economic and environmental sustainability. Implementing a precise and immediate disease detection system could accelerate the localization of affordable crop protection strategies and improve global food security. Additionally, site-specific pesticide administration can depend on accurate disease identification utilizing machine vision and DL.

In [22], a neural network-based disease detection approach was presented, subjecting a series of low-resolution photographs to principal components analysis and then introducing them into a neural network to detect plant diseases. A disease identification approach based on thresholding and picture segmentation was also proposed in [23], applying threshold levels to identify sickness in each block of sick leaf grayscale photos. In [24], a novel image segmentation technique was introduced for disease quantification, transferring color images to the I1I2I3 color space before converting them to HSV to effectively quantify diseases in various plant species. In [25], an unsupervised color-based disease-qualifying approach was used, showing greater accuracy compared to previous methods. The images were divided into many classes, and then a deterministic supervised learning technique was utilized to train each class. However, many of these technologies are not suitable for real-time application of agrochemicals because of the lengthy inference time required for image processing, despite the breakthroughs in disease identification algorithms. Fortunately, recent developments in GPU-embedded processors have resulted in a large increase in the number of applications using AI, making possible the development and implementation of novel methods and models, in particular DL techniques [26]. The sector of agriculture and crop protection may undergo a revolution due to promising DL models for faster and more effective disease identification.

GPU-based parallel computing has significantly helped the creation and deployment of CNNs across numerous applications. In [27], different CNNs were shown to have good accuracy levels on sizable datasets with a variety of image classes. CNNs have been one of the most effective DL methods for image processing in recent years. CNNs often consist of numerous layers, such as fully linked, conventional, and pooling layers. Convolution is a crucial linear action in the conventional layer since it is one of the multiple mathematical operations that are essential to CNNs [28]. According to [29], the conventional layer, which manages the significant computational load, is an essential component of a CNN. To reduce the stress on the spatial computational parameters, pooling layers are usually positioned between subsequent conventional layers. The fully connected layers have activation functions that pull the results from CNN, such as object classification. Data are kept in the form of two-dimensional grids, or arrays, in digital images. A kernel is a small unit of an array. The Rectified Linear Unit (ReLU), which converts negative pixel values to zeros to speed up the calculation and make it easier to identify targets, is one of the most widely used activation functions.

Color segmentation is applied to capture a picture of a sick leaf, and the results produce HSV characteristics. The Artificial Neural Network (ANN) is trained to distinguish between samples with and without disease. ANN classification performs 80% better than previous techniques, showing a significant gain in accuracy. On the other hand, such methods have approximately 80% accuracy, which is relatively low and causes certain detection errors. To solve this problem, in [30], a CNN method was proposed, which used leaf pictures to differentiate healthy from infected cucumbers. The CNN was used to identify two serious viral infections, Zucchini Yellow Mosaic Virus (ZYMV) and Melon Yellow Spot Virus (MYSV). The dataset utilized consisted of 800 photographs of cucumber leaves, of which 200 showed ZYMV, 300 showed MYSV, and 300 showed healthy leaves. Rotational modifications were made to expand the dataset. A CNN structure with 96 Ms, three convolutional layers, three pooling layers, and three normalization layers was suggested for the multiclassification challenge, and ReLU was employed as the activation function. This method achieved a precision score of 94.9%. Furthermore, in [31], it was shown that climate change impacts potato yield in Prince Edward Island, Canada.

As the most important thing is to detect diseases and pests in low time and cost, DL and ML are the most feasible to use. Additionally, this study highlighted the enormous influence of GPU usage on the exponential rise of AI applications. Intelligent sprayers can recognize the spatially varied distributions of weeds and diseases in potato fields. Inference times should be estimated to determine the suitability of CNNs in a smart sprayer for on-demand fungicide treatment. The addition of disease detection utilizing CNN and machine vision, as well as the investigation of the viability and practicality of integrating them into a smart sprayer, gives a sense of creativity and originality to this study. However, this study involved pre-trained inception-v3-based transfer learning weights to obtain a high-performance classification. The model was expanded by training it on the ImageNet dataset, which increases the new Inception-v3 model's learning efficiency. This method shares the learned model parameters with the new model to improve detection performance through transfer learning.

II. PROPOSED MODEL'S CNN ARCHITECTURE

Deep learning is a strong ML algorithm entailed in speech recognition, picture analysis, and image restoration. It varies from conventional ML since it employs multiple closely connected layers. This allows the output of one layer to be used as the input for the following layer. DL automatically gathers and optimizes features during the model training process, in contrast to conventional methods that necessitate feature engineering. Unsupervised, supervised, or semi-supervised learning environments can be engaged. The convolutional layer, the pooling layer, the activation function layer, and the fully connected layer make up the structure of a CNN, as shown in Figure 2. CNNs are quite effective in applications like object identification and image categorization. CNNs were utilized for DL in the plant disease recognition project to obtain accurate plant disease recognition.

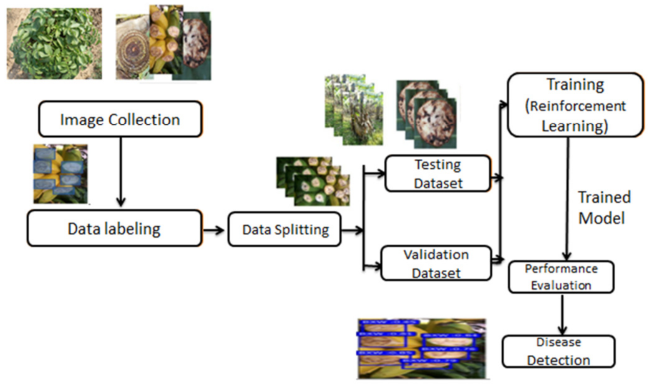

Fig. 1. The proposed method's CNN architecture.

A. Study Site and Data Collection

In Pakistan, summer typically lasts longer than the short winter. The country had completely relied on imported seed varieties until recently because there were no locally prepared potato seed variants. Four or five diseases out of a total of 18 or 19 threaten Pakistani potato crops, creating problems for the crop. Numerous diseases might be caused by using potassium and calcium fertilizers in insufficient amounts. One of the main regions in Pakistan for potato production is the one around the districts of Okara, Sahiwal, Kasur, and Pakpattan. The Sahiwal-based Potato Research Institute (PRI) has taken steps to create seven seeds. Pakistan imports seed potatoes from Germany and the Netherlands and exports potatoes to countries such as Afghanistan, Russia, the Middle East, and Germany.

Canon PowerShot SX540 and Logitech C270 HD digital cameras were used to capture pictures of healthy and diseased potato plants (Russet Burbank variety) in collaboration with a local plant pathologist to identify the visual symptoms of early blight. The observations were consistent with Kemmit's classification of blight disease early stages during the potato growing season. Photographs of the early, middle, and late phases of the disease in potato leaves were taken based on the visual symptoms observed. Early July, or around 35 Days After Planting (DAP), is when visual symptoms of early blight, such as pale, yellow-colored leaves, first appear. Around 65 DAP, the disease enters its mid-stage, which is shown by brown concentric circles on the leaves of potato plants. Finally, the disease enters its late stage around 80 DAP. These stages are shown in Figures 2-4. Since there are no effective treatments for the disease, it is essential to identify it accurately as soon as possible to minimize damage. It is important to note that because the data points in the captured frames depend on how severe the disease is, they can change in real-time. If a plant has a more severe disease than another, there may be more disease data points. Due to its development, the disease also tends to show itself in potato plants as patches.

Fig. 2. Pictures for identifying early blight disease stages on potatoes, showing the disease's early-stage leaves as being pale yellow.

Fig. 3. Mid-stage concentric brown circles in the leaves.

Fig. 4. Senescence of leaves during the disease's final stage.

III. RESULTS AND DISCUSSION

The images were captured in 2023 from 9:00 a.m. to 4:00 p.m., in natural sunshine, at a height of around 140 cm. The collected photos were resized to 1280×720 pixels using a specially created Python application to speed up processing. The 1280×720-pixel resolution was chosen expressly to improve the model suitability for real-time applications. This resolution was also chosen to determine whether it would be possible to build a smart variable rate sprayer that utilizes a live camera signal by combining the proposed CNN model with hardware.

TABLE II. ACCURACY IN EACH CLASS AND OVERALL ACCURACY IN THE TRAINING AND TESTING PHASES

Plant disease	CNN training accuracy	CNN testing accuracy
Pepper bell bacterial	99.5	98.6
Pepper bell healthy	98.1	98.9
Potato early blight	97.6	98.9
Potato healthy	99.1	94.1
Potato late blight	96.3	98.9
Tomato target spot	95.7	94.1
Tomato mosaic virus	98.5	98.9
Tomato yellow leaf curl virus	97.7	99.1
Tomato bacterial spot	99.3	98.9
Tomato early blight	97.1	97.3
Tomato healthy	98.5	98.9
Tomato late blight	98.6	97.1
Tomato leaf mold	98.5	98.9
Tomato septoria leaf spot	98.1	98.2
Tomato spider mites	98.9	99.1
Overall accuracy	98.29	98.029

Photos were collected throughout the potato growing season to identify the disease stages. Various CNN models were trained using pictures of the diseases at each step, as well as pictures of the symptoms associated with each stage. Table II provides a summary of the accuracy achieved for each class throughout the test and examination phases, as well as the overall accuracy for all classes during both phases.

A. *Evaluation of the Proposed Method Compared to Previous Works*

1) *CNNs of Two, Four, and Six Classes*

During the initial early blight detection training, the validation accuracy values for each CNN ranged from 0.95 to 0.97. Compared to VGG Net and Efficient Net, GoogleNet showed a lower validation accuracy. However, as illustrated in Table III, for midstage early blight detection, all CNNs demonstrated higher validation accuracy, ranging from 0.99 to 1.00. Similarly, all CNNs' validation accuracy ranged between 0.99 and 1.00 at the final stage of early blight. The validation accuracy of the 4-class CNNs was 0.92. As shown in Table III, the validation accuracy of the joint stages (initial+mid) was somewhat worse than that of the individual stages (initial, mid, and late). The validation accuracy for the mid-to-final early blight disease stage ranged from 0.84 to 0.86. Based on the narrow accuracy range, all CNNs behaved similarly. Additionally, the initial and terminal phases of the early blight disease had a classification accuracy ranging from 0.92 to 0.94. In 4-class CNNs, the validation accuracy for the beginning and the final stages of the disease was somewhat higher than for the initial+mid and mid+last phases. On the other hand, the validation accuracy for the initial, intermediate, and terminal disease stages varied from 0.81 to 0.85 for the 6-class CNN. The 6-Class CNN suffered relatively significant training and validation losses due to the large number of identical classes, which reduced validation accuracy scores.

A Dell Latitude 5580 was used to measure the three CNNs' inference times, which varied from 121 to 145 ms. The inference time values for the CNNs in all classes fell within a similar range, showing that it had little to no impact on the different CNN classes. The VGG Net showed the fastest inference time among the three CNNs, with values ranging from 398 to 458 ms. This was mostly due to its ability to learn more parameters in a single forward pass than GoogleNet and Efficient Net. The inference speed of EfficientNet ranged from 5.95 to 6.53 fps. Compared to other CNNs, GoogleNet had the shortest inference time. The detection accuracy of GoogleNet was found to be significantly lower compared to other CNNs. On the other hand, the F1-score, recall, and precision of the VGG Net demonstrated promising results in terms of disease detection accuracy, but it is less effective for real-time applications due to its longer inference time. GoogleNet and EfficientNet offer a good balance between accuracy and inference speed, making them stronger competitors for the creation of real-time smart sprayers when both accuracy and inference speed are essential. The CNNs examined had considerably varied inference times, while GoogleNet and EfficientNet had the smallest disparities. GoogleNet and VGG Net revealed comparable inference time ranges [32]. In conclusion, the accuracy findings and statistical measurements obtained for different CNN architectures, along with the analysis of inference time, showed that EfficientNet exhibits promise for implementation and integration into a smart sprayer for targeted fungicide treatment in potato fields. The EfficientNet is an excellent selection for further processing integration into a variable-rate smart sprayer due to its disease detection accuracy during various stages of disease evolution, as indicated by statistical measures such as recall, precision, and F1-score, as well as its relatively quicker inference time. Through this integration, fungicide applications in potato fields will be precise and effective.

TABLE III. TRAINING AND STATISTICAL ANALYSIS OF THE TWO, FOUR, AND SIX-CLASS CNNS FOR THE POTATO PRODUCTION SYSTEM IN CLASSIFYING THE EARLY BLIGHT DISEASE STAGES

Class	Model	Growth Stage	1 Val Acc	2 Val Loss	3 Tr Loss	Precision	Recall
Two-class CNNs	GoogleNet	Beginning	0.96	0.33	0.01	0.8	0.91
		Middle	1.00	0.03	0.01	0.92	0.94
		Final	1.00	0.00	0.00	0.83	0.87
	VGGNet	Beginning	0.96	0.61	0.00	0.88	0.87
		Middle	0.99	0.04	0.01	0.97	0.95
		Final	0.99	0.06	0.00	0.88	0.9
	EfficientNet	Beginning	0.96	0.08	0.02	0.90	0.90
		Middle	0.98	0.03	0.10	0.98	0.89
		Final	0.99	0.02	0.10	0.90	0.90
Four-class CNNs	GoogleNet	Beginning + Middle	0.93	0.29	0.10	0.90	0.86
		Middle + Final	0.90	0.59	0.29	0.87	0.89
		Beginning + Final	0.93	0.10	0.10	0.95	0.95
	VGGNet	Beginning + Middle	0.92	0.27	0.01	0.84	0.85
		Middle + Final	0.86	0.13	0.07	0.79	0.78
		Beginning + Final	0.93	0.25	0.12	0.88	0.88
	EfficientNet	Beginning + Middle	0.92	0.01	0.01	0.88	0.88
		Middle + Final	0.84	0.79	0.30	0.85	0.85
		Beginning + Final	0.89	0.09	0.10	0.99	0.98
Six-class CNNs	GoogleNet	Beginning + Middle + Final	0.81	0.21	0.08	0.74	0.74
	VGGNet	Beginning + Middle + Final	0.82	0.32	0.12	0.73	0.72
	EfficientNet	Beginning + Middle + Final	0.85	0.12	0.02	0.74	0.75

1 Val acc = validation accuracy; 2 Val Loss = validation loss; 3 Tr loss = training loss.

2) *CNN and Deep Learning Frameworks*

CNNs may now be operated more easily due to advances made in DL and machine vision. Multiple frameworks have been developed to improve computational efficiency for a variety of applications, including Caffe, Torch, Theano, and others. Large and complicated computational models may be built using DL frameworks, while they also make it easier to calculate gradient losses, which reduces the discrepancy between projected and real-world data. Given the intensive processing requirements of CNNs, the use of a GPU-enabled workstation speeds up images training and validation utilizing DL frameworks. Some frameworks integrate networking between the CPU, GPU, and memory with DL libraries. This study chose the PyTorch framework for all CNN-related tasks, including training, validation, and testing, due to its accessibility to resources, GPU support, and simplicity [33-34]. This research examined three CNNs, VGGNet, EfficientNet, and GoogleNet, for early blight disease identification at different stages, based on their suitability for commercial applications, real-time performance, and accuracy. Among these models, GoogleNet was considered the one with the most precise predictions, as it successfully identified plant diseases and parts in [35-36]. The VGG Net design employs three convolutional filters to increase accuracy and eliminate overfitting issues [37]. This architecture provides a few choices with varying layer levels, including Vgg-11, Vgg-13, and Vgg-16. This study evaluated the efficiency of the most recent version, VGGNet-16, in classifying diseases at various stages. EfficientNet was created using a methodical approach to network depth, breadth, and resolution [38]. Based on the compound scaling technique, EfficientNet is said to be a light and accurate model. This study used the lightweight EfficientNet model B0, which is renowned for its accurate performance according to picture results.

IV. CONCLUSIONS AND FUTURE WORK

Agriculture plays a vital role in the development of any country economy [39]. This study investigated several dataset combinations with various CNNs to identify and categorize early blight disease in potato production. All CNNs examined demonstrated the ability to distinguish between damaged and healthy plants with varied degrees of accuracy, precision, recall, and F1-score. The outcomes showed that, at different stages of disease identification, EfficientNet and VGGNet both outperformed GoogleNet. In contrast to EfficientNet and VGGNet, GoogleNet had the shortest inference time. Applying fungicides to sick parts of potato crops with a machine vision and DL-based sprayer has a great potential to reduce agrochemicals in agricultural fields. It is interesting to investigate the integration of these models in Variable Rate Sprayers (VRS) to manage and monitor potato crops in real-time. However, it is important to anticipate potential challenges, such as conflicting detection signals encountered by the sprayer nozzle due to various factors, such as multiple diseases, diverse potato plant species, and different ground surface covers. This paper focused on early blight, the predominant potato disease in Pattoki, Punjab, Pakistan. Future research involves broadening this study to encompass a broader spectrum of diseases, diverse potato varieties, and alternative farming approaches.

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