Mehran University Research Journal of Engineering and Technology

https://doi.org/10.22581/muet1982.3034

2024, 43 (2) 123-132

Enhancing potato crop yield with AI-powered CNN-based leaf disease detection and tracking

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Received: 24 September 2023, Accepted: 28 March 2024, Published: 01 April 2024

KEYWORDS

Convolutional Neural Network

Plant Disease

Farming

Smart Agriculture

Hyper-Parameters

ABSTRACT

While plant diseases continue to have a severe impact on food production, farmers face a formidable challenge in trying to meet the escalating demands of a population that is expanding quickly for agricultural items like potatoes. Despite spending billions on disease management, farmers frequently struggle to effectively control disease without the aid of cutting-edge technology. The paper examines a disease diagnosis method based on deep learning. To be more precise, it uses a Convolutional Neural Network (CNN) method for the disease's detection and classification. This study examines the impact of data augmentation while conducting an extensive performance evaluation of the hyper-parameter in the setting of detecting plant diseases with a focus on potatoes. The experimental findings demonstrate the effectiveness of the suggested model's 98% accuracy. Considering growing global issues, this research aims to open new pathways for more efficient plant disease management and, eventually, increase agricultural output.

1. Introduction

Potatoes are one of the most widely cultivated crops globally and serve as a significant way to earn money for farmers. A/c to 2021 statistical report from the (FAOSTAT) which is international Food and Agriculture organization corporate statistical database, worldwide potato production reached 376 million tons and the total area which was harvested worldwide was 18,132,694 hectares [1]. In Mexico, potatoes hold a prominent place in national agriculture, being a fundamental ingredient in Mexican cuisine and various international dishes. According to a report from 2020, Mexico produces 3.76 million tons of potatoes annually [2], placing it in the top ten nations in the world for production. Through the AgriFood and MALRDFF issued a report in Mexico's AgriFood Trade the Balance, emphasizing potatoes as the first greatest exported agricultural product, with avocados holding the top spot. However, several variables can affect the output of potatoes. Crop diseases, as stated by the Food and Agricultural Organization of the United Nations (FAO), are to blame for losses of 20% to 40% of the entire potato production. These diseases can be split into two primary categories, the first of which is related to contagious microorganisms like viruses, bacteria, and fungi. If the situation is right, these diseases may quickly propagate amongst the potatoes growing in the field. The second category of illnesses is brought on by noncontagious chemical or physical components. Unfavourable environmental factors, nutritional or physiological disorders, and harm from herbicides are some of these components. In contrast with infectious diseases, non-infectious illnesses cannot spread from one potato plant onto another. However, if an entire potato crop is exposed to the same detrimental cause, these diseases can affect many plants at once [3]. Specific conditions may cause these non-infectious potato illnesses. This relationship is typically described using the conceptual model known as the sickness triangle. The three key components that interact in this model are the surroundings, the living potato plant, and any infectious agents. For the illness to appear, each of these components must be present. Potato plants can be strongly impacted by abiotic elements such as air flow, temperature, humidity, pH levels, and irrigation techniques. The infectious agent consists of organisms that can harm the potato crop, including fungi, viruses, bacteria, and others. The potato plant alone is referred to as its host in this instance. When each of these conditions is met at once, disease results. Many potato diseases have symptoms that damage the plant from the ground up, and many of them progress quickly once they have been infected.

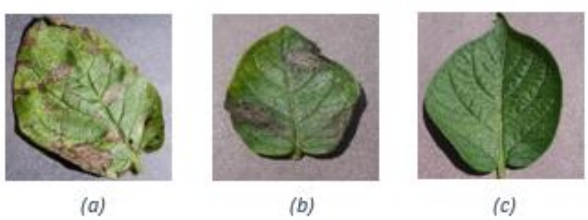

Fig. 1. Represents Some of Major Diseases In Potato Leaves Including (a): Early Blight, (b): Late Blight, (c): Healthy

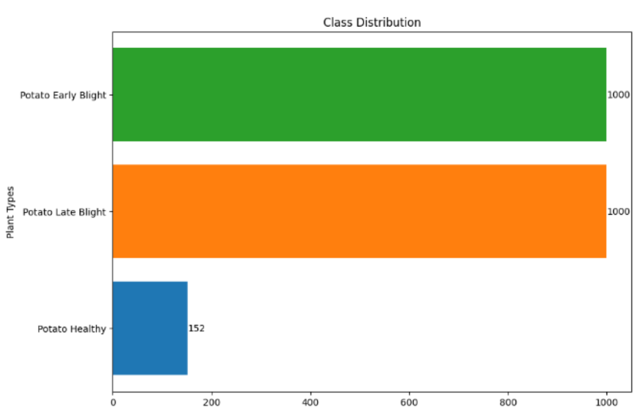

Fig. 2. Class Distribution

Continuous monitoring of potato crops is necessary to quickly spot illnesses and put in place effective countermeasures to stop the spread of them and potential production loss.

The employment of molecular, serological, and microbiological examinations is typical of traditional methods used in the diagnosis of potato illnesses. They also frequently include expert visual assessment, analysis of morphological attributes to identify infections, and expert visual assessment. Examining specific disease symptoms (like lesions, blight, galls, and tumours) or perceptible pathogen indicators is the foundation of the visual assessment approach for diagnosing potato illnesses. Emerging and inventive methods must confront the obstacles and evolving requirements set forth by the modern paradigm of potato farming, which demands heightened precision and nearly instantaneous detection.

Over recent years, diverse technologies, including image processing, pattern recognition and computer vision, have made significant strides and found practical application within potato farming, particularly in the automation of disease and pest identification procedures. Conventional models[4], [5], [6], [7], [8] encounter significant challenges, stemming from intricate pre-processing requirements and the labour-intensive design of image features, which consume both time and resources. DL technology, a branch of machine learning that is becoming more and more popular in disease diagnosis, has recently made significant strides in the field of disease detection in potato plants [9]. The availability of large datasets, improved storage capacity, and rising computer power are all responsible for this increase in popularity [10]. Convolutional Neural Networks (CNN) are one of the most widely used methods in deep learning [11], [12], [13] for tasks including semantic segmentation, object detection, and picture classification. By learning by the data present in the photos for classification, CNNs are particularly useful for identifying patterns within photographs of potato plants [14], objects, and scenes, eliminating the requirement for human feature extraction. Convolutional, pooling, and fully connected layers are some of the layers that make up CNNs, and they all work together to make it easier to learn distinct features from a variety of training data sources. In this paper we discuss different potato diseases like late blight, early blight and optimized our model with Convolutional Neural Network (CNN).

The main contributions can be summed up as follows:

1. With a particular focus on potatoes, the paper presents a novel method for diagnosing plant illnesses that makes use of the Convolutional Neural Network (CNN) method for plant disease detection and classification.

2. The study investigates how the suggested CNN-based illness detection model performs in relation to data augmentation methods and hyper-parameter optimisation. This extensive analysis offers suggestions for enhancing the diagnostic system's reliability and accuracy.

3. This study demonstrates the efficacy of the suggested methodology by identifying and categorising plant diseases with an astounding 98% accuracy rate. This high degree of accuracy suggests that the developed methodology may be useful in real-world agricultural applications, which could ultimately lead to more effective disease management.

2. Related Work

Plant disease detection has been a subject of long-standing research. The early diagnosis of plant diseases has long been studied. Numerous efforts have been made to use a variety of techniques, including classifiers that focus on characteristics like colour, texture, or the shape of potato leaves, when it comes to recognizing illnesses in potato plants. Early research efforts focused on using support vector machines, decision trees, and neural network-based classifications to identify diseases. On commercial cameras, visual spectrum images have been used to identify diseases in potato plants. Under carefully monitored lab circumstances, these images were analysed using methods such iterative multiple regression and algorithms for clustering.

An increasingly popular method for identifying illnesses in potato plants is convolution neural networks (CNNs). Some research has focused on improving feature quality by reducing obstacles brought on by variable lighting conditions and environmental complexity. Real-time models have also been developed by certain researchers to hasten the disease detection procedure for potato crops.

In Table 1: Javed Rashid et al. [15] in 2021, multi levels deep learning models developed for potato leaf detection at very first level author's model extracted potato leaves used YOLOv5 image segmentation technique, at second level deep learning technique developed with help of Convolutional Neural Network to detect early blight and late blight and the model got 99.7% of accuracy.

Another contribution is Feilong Kang et al. [16] in 2022, trained a lightweight CNN model to detect potato disease like early blight and late blight and comparing them to the healthy leaves their model got 93% accuracy. They used Django platform.

Another study of Mahmudul Hassan et al.[17] in 2021 where the author proposed two methods under CNN one is VGG with RF, considered disease are late blight, rust, gray leaf spots in corn and early blight and late blight in Potato leaf meanwhile their model got 98.74%.

Study by Hassan Afzaal and Aitazaz A. et al. [18] in 2021, where they discussed about early blight disease in potato leaves with real-time database and they used three different pre-trained CNN which are GoogleNet, VGG and EfficientNet, and their model got 92% of accuracy rate.

Study of Sunayana Arya et al. [19] in 2019, Used pre-trained model of Convolutional Neural Network which is AlexNet to detect Potato and Mango leaf detection and the potato disease dataset were taken from Plant Village meanwhile Mango dataset taken from field location.

Another study of Abdul Jalil rozaqi et al. [3] in 2020, where he used to identify potato leaf disease with three types of data which are early blight, late blight and healthy in this study author identified by deep learning using convolutional Neural network. And their model obtained up to 97% of accuracy.

The next study is Wenqiang Gao et al. [20] in 2019, when he used real-time dataset of potato leaves in order to detect Early blight, Late Blight and Healthy thorough Altrous CNN-network, through which model go 9% of accuracy.

Another study of Divyansh Tiwari et al. [3] In 2020, when the author used VGG-19, pre-trained model of Convolutional Neural Network (CNN) for diagnosing potato leaf disease like late blight, early blight which directly influence quality and quantity of potatoes production and their proposed model gave accuracy upto 97.8%.

Next study is the study of Rabbia Mahum et al. [21] in 2022, used Plant Village dataset to detect potato leaves disease like blights i.e Early Blight and Late Blight, potato leaf rolls, Potato Verticillium with the help of pre-trained model Efficient DenseNet-201 and achieved accuracy of 97.2%.

The most recent Study of Mosleh Hmoud et al. [22] in 2023 used customized CNN (Convolutional Neural Network) [23] to enhance accuracy rate and to reduce computation time and information loss, author compared different machine learning and deep learning algorithm for potato blight, and their customized model got accuracy of 99%.

Table 1

Previous work on potato leaf diseases

Year	Author	Method	Datasets	Research Areas
2023	Wenqiang Gao et al. [20]	Atrous-CNN network	Real-time Database	Potato Leaf diseases
2019	Sunayana Arya et al. [19]	AlexNet	Plant Village	Potato Leaf diseases
2020	Feilong Kang et al. [16]	ResNet, Xception, MobileNet	Not mentioned	Potato Disease, Early Blight, Late Blight and Healthy
2020	Abdul Jalil Rozaqi et al. [24]	Deep Learning using CNN	Not mentioned	Potato Disease, Early Blight, Late Blight
2020	Divyansh Tiwari et al. [3]	VGG-19	Not mentioned	Potato Disease, Early Blight, Late Blight
2021	Mahmudul Hassan et al. [17]	VGG	Plant Village	Potato leaf disease
2021	Afzaal and Aitazaz A. et al. [20]	GoogleNet, VGG and EfficientNet,	Real-time Database	Potato Disease, Early Blight
2021	Javed Rashid et al. [15]	YOLOv5	Plant Village	Potato Disease, Early Blight
2022	Rabbia Mahum [21]	DenseNet	Plant Village	Potato Disease, Early Blight
2023	Mosleh Hmoud et al. [22]	Inception-v3	Plant Village	Potato Disease, Blight

3. Proposed Methodology

In this portion, we will explore the recommended architecture for potato leaves diseases detection. Our proposed architecture will take potato images as input and predict relevant labels as output. (a) Detect the type of diseases from leaves of potato or indicate them healthy, (b) the output labels are the result that obtain from our trained model, and (c) the accuracy of the model.

Fig. 3. Shows the whole process step wise that we have used for the identification of potato leaves whether their types of disease or healthy. Our algorithm has four major steps in each step we did different works like step (1) explained the steps of creating the experimental dataset, step (2) how we created our model, step (3) how we distribute the experimental dataset, and step (4) described the training process and evaluation.

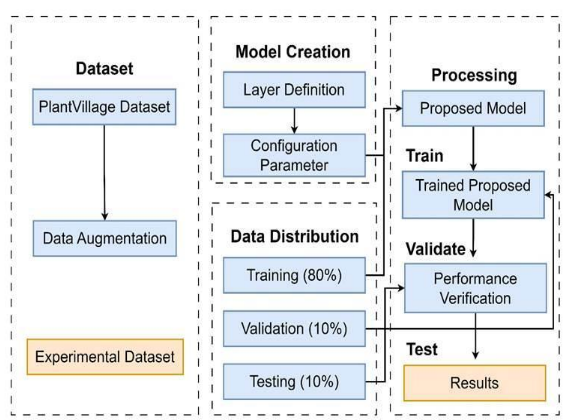

Fig. 3. Visual Representation of Proposed Model to Detect Potato Leaf Diseases

3.1 Dataset

We used Plant Village [25] dataset which have 14 different crops from which we extracted healthy potato leaves and their two diseases late blight and early blight [26]. Total 2150 images.

Deep neural network models [27], [28] can sometimes run into a challenge known as overfitting during training. This means that a highly capable model can basically "memorize" the dataset, which is not what we want. To tackle this issue, we employ a technique called data augmentation, which is widely used across various fields. The primary aim of data augmentation is to expand the dataset's size. Data augmentation is typically carried out through two different approaches. The first is the usual approach, which aims to create new images that carry the same features and characteristics but lack the ability to simplify. Data augmentation has various techniques like rotation, flipping vertically and horizontally, adjusting brightness, Gaussian noise, blurring, scaling images [29] and many more. However, these techniques can sometimes produce lower-quality and less diverse results.

We can also use Generative Adversarial Networks (GANs) as another approach. GANs are a Deep Learning [30], [31] approach used for generative modelling. This method uses techniques like Convolutional Neural Networks (CNNs) [32] to create fake samples that closely look like the features of the original images. GAN models typically consist of two key sections one is generator and the second is discriminator. The generator network takes arbitrary noise as input and creates images based on that noise. Alternatively, the discriminator network is responsible for deciding whether the input image is "real" (from the original dataset) or "fake" (created by the generator). This approach helps us avoid overfitting issues.

In our specific case, to create our experimental dataset, we opted for the data augmentation method to mitigate the risk of overfitting. In setting up data augmentation, we used a few techniques such as rotation, flip vertical and horizontal, Gaussian blur, salt and paper dots and scaling.

3.2 Model Creation

In Fig. 3, we illustrate the CNN architecture designed for classifying diseases in potato plants. This network takes 256 × 256 colour images as input, and we normalize their pixel values to a range of (0, 1) for processing. Our proposed convolutional network consists of six layers, each employing filters with varying capacities: 4, 8, 16, 32, 64, and 128, in that order. We chose this sequence because layers nearer to the model's start tend to learn convolutional features less effectively than those closer to the output. Additionally, we used a 3 × 3 kernel size for the 2D convolution window, a value commonly recommended for the number of filters. To activate each node in the convolutional layers, we employed the rectified linear unit (ReLU) as our activation function. Following the convolutional layers, we introduced a max-pooling layer to use the feature map then reduces the most significant features into smaller patches. This technique is applied to all convolutional layers specified in the architecture [33], [34], [35]. The outcome of the final MaxPooling layer is pass by ta MaxAveragePooling layer, transforming it into a vector. This vector is then linked to a dense layer with 3 output nodes, each representing one of the 3 categories. We use “softmax” activation in this dense layer, which assigns a probability to each category for the analysed image.

For a detailed overview of our model's layer structure, please refer to Table 1, which provides comprehensive information.

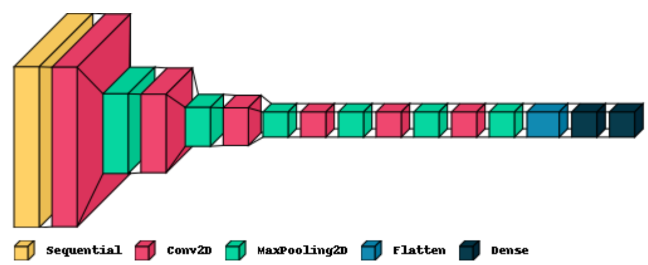

Fig. 4: CNN Visual Representation

Table 2

Convolutional Neural Network Layers

Layers	Parameters
Conv2D	Kernel (3,3), Strides (1,1), input shape (32, 256, 256, 3), output shape (32, 254, 254, 32), Activation = ‘ReLu’
MaxPooling2D	Pool Size (2,2)
Conv2D	Kernel (3,3), Strides (1,1), input shape (32, 256, 256, 3), output shape (32, 254, 254, 32), Activation = ‘ReLu’
MaxPooling2D	Pool Size (2,2)
Conv2D	Kernel (3,3), Strides (1,1), input shape (32, 256, 256, 3), output shape (32, 254, 254, 32), Activation = ‘ReLu’
MaxPooling2D	Pool Size (2,2)

Conv2D	Kernel (3,3), Strides (1,1), input shape (32, 256, 256, 3), output shape (32, 254, 254, 32), Activation = 'ReLu'
MaxPooling2D	Pool Size (2,2)
Conv2D	Kernel (3,3), Strides (1,1), input shape (32, 256, 256, 3), output shape (32, 254, 254, 32), Activation = 'ReLu'
MaxPooling2D	Pool Size (2,2)
Flatten	Output Shape (32, 256), Activation = 'ReLu'
Dense	Output Shape (32, 64), Activation = 'ReLu'
Dense	Output Shape (32, 10), Activation = 'Softmax'

3.3 Data Distribution

A popular method for dividing a dataset into sets for training and validation is by allocating percentages, such as 70:30 or 80:20. High validation accuracy may not necessarily indicate a good model, which is one of the issues that may occur with this approach. It is possible that this split will produce biased findings if some information is missing from the data that were not used for training. We use a k-fold cross-validation method to assess the model's performance. The k-folds approach seeks to make sure that both the training and validation phases include all the dataset's features. The dataset is split into smaller subsets using the k-fold cross-validation approach. As a result, k times of the cross-validation approach are repeated. K = 3, K = 5, and K = 10 are typical values in machine learning. To achieve a reasonable balance between cheap computation cost and low bias for a calculation of model performance, we use k = 5.

In training process, we used Adam as optimizer and the loss function, we used Sparse Categorical entropy with batch size of 32 along with 50 epochs while the dropout we set was 0.2 as shown in Table 3.

Table 3

Parameters used in Proposed CNN Model

Parameter	Value
Optimizer	Adam
Loss Function	Sparse Categorical Crossentropy
Batch Size	32
Epochs	50
Dropout	0.2
Verbose	1

4. Result and Discussion

It has been noted that the Plant Village dataset was used in most of the research. As a result, the classifications' nature and outcome are extremely similar. After the DL model and optimization technique were shown to be the most efficient duo, the collection of photos of potato leaves underwent a varied class illnesses classification. To distinguish between leaves with late blight, early blight, and healthy leaves, we collected photos of potato diseased leaves.

4.1 Validation of Proposed Model

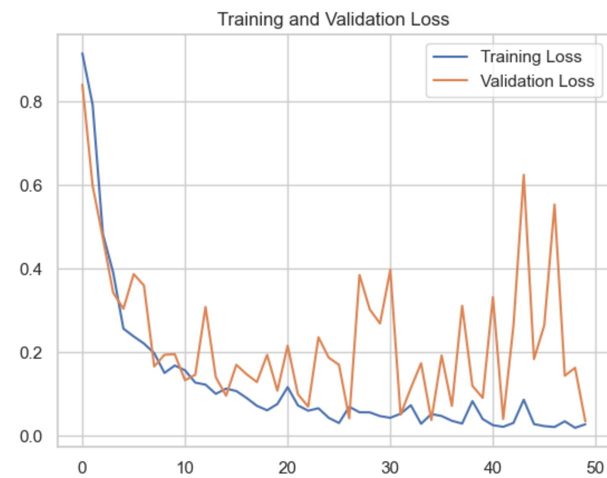

Fig. 5(a). Training and Validation Loss

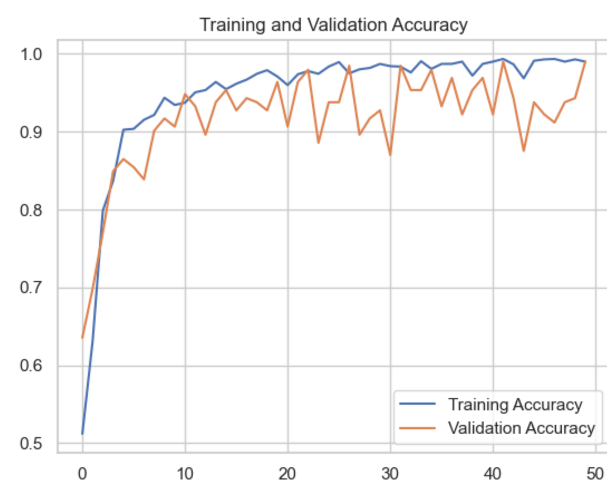

Fig. 5(b). Training and Validation Accuracy

Fig. 5(a) and 5(b) represent the training and validation of accuracy and loss. We achieved training and validation 98.44% accuracy. We ran 50 epochs which took almost 2 hours, we used python language to train and evaluate. Jupyter as environment.

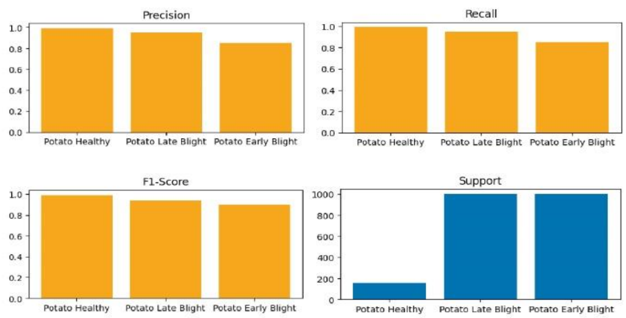

Fig. 6: Classification Report of Our Proposed Model

Fig. 6 is the representation of Classification Report of our proposed model. This fig. reflects the precision, recall, F1-score, and Support for each class.

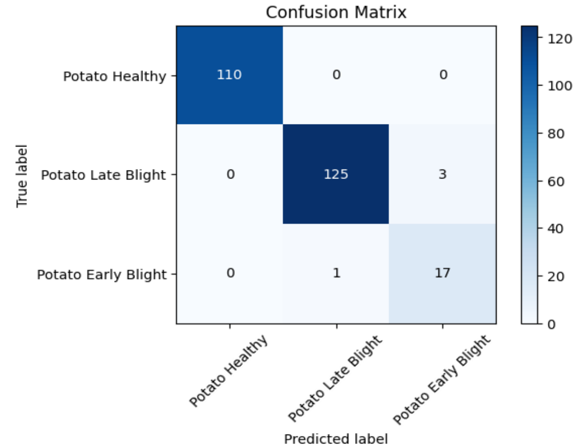

Fig. 7: Confusion Matrix of Proposed Model

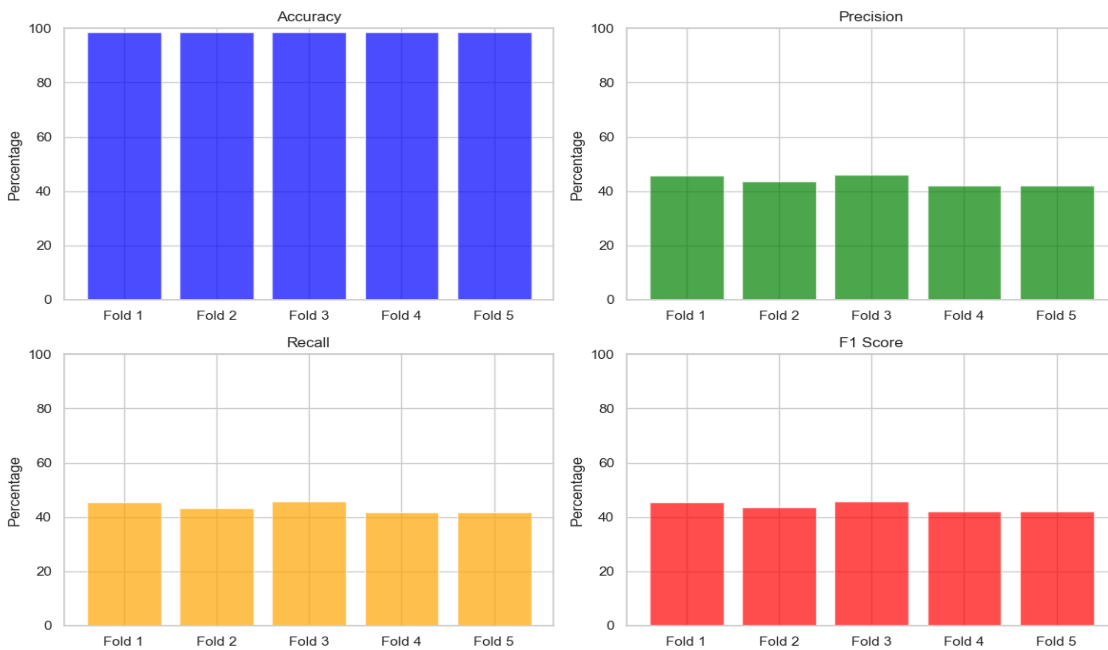

Fig. 8. Report Obtained from K Folds

Fig. 7 is the Confusion Matrix obtained from the evaluation of our proposed model which represents True Positive, True Negative, False Positive, and False Negative values for each class separately.

Fig. 8 shows the report of the 5 folds obtained from k fold library of python scikit learn and we evaluated this Fig. from test dataset, and you can see the consistency and stability of the accuracy is same in 5 folds while precision, recall, and F1-score are also almost same and have stability in 5 folds.

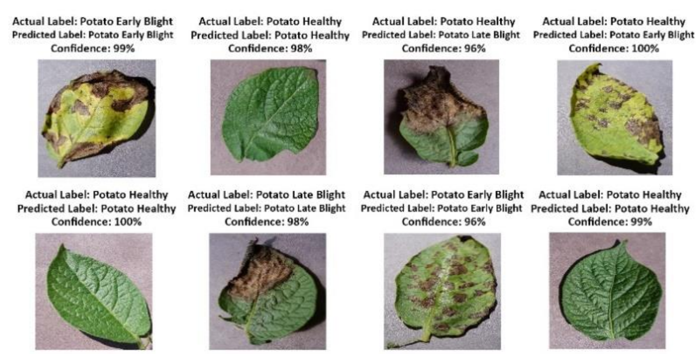

Fig. 9. Result Obtained from Our Proposed Model

Fig. 9 shows the result obtained from our proposed model. You can see all predictions are accurate with almost 100% confidence. There you can see the actual label, predicted label and confidence in percentage.

5. Conclusion

The agriculture sector has a difficult task in satisfying the rising demand for food supply due to the fast-expanding world population and the ongoing threat of plant diseases. The efficiency of disease control remains a major problem for farmers despite huge investments in disease management. By allowing early identification of plant pathogens via adaptive algorithms, the application of DL approaches offers a possible option. Convolutional Neural Networks (CNNs) have emerged as one of these methods that is particularly useful for classifying and identifying plant diseases. The primary focus of this study's performance examination was on the leaves of the potato plant. The CNN model has proven to be superior through thorough testing and research with an extensive number of hyper-parameters, like activation functions, optimizers, and dropout rates, holding the potential to revolutionize farming practices. The CNN model assists in more effective farming practices, ensuring increased agricultural yield by speeding up crucial disease control choices. For this study, Plant Village dataset was used to collect images of potato plant disease which is related to Leaf Blights like Early Blight and Late Blight. These images, which were separated into the beginning, middle, and end stages, provided crucial training data for CNN models employing transfer learning techniques. The mini-batch size, epochs, and data augmentation were among the hyper-parameters whose effects were also investigated in the study. A few performance metrics were investigated as part of the study, including classification accuracy, F1-score, precision, recall, and ROC curves were carefully evaluated and provided illuminating information about the model's performance. Thanks to this study, the practice of recognizing plant diseases using CNNs has evolved, however there are still other areas that require additional research and development: A bigger, more diversified dataset with a wider variety of plant species and disease types will help this model's ability to generalize.

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