Deep Learning Based Analysis and Detection of Potato Leaf Disease

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***Abstract*—** Potato is an essential crop worldwide, and its leaves are prone to numerous illnesses, including early and late blight. Accurately detecting these diseases can help farmers prevent their spread and minimize yield loss. In this research paper, we propose a deep learning approach to classify potato leaves into three categories: early blight, late blight, and healthy. Our dataset consists of images of potato leaves with different diseases and healthy leaves. A collection of 4072 images, including healthy potato leaves and leaves infected with Early blight, Late blight served as the basis for our analysis. To increase the dataset size, we pre-processed the images by scaling them to 256 x 256 pixels and used data augmentation methods. Our findings show the CNN model's ability to accurately classify potato leaf diseases and its potential to help with early diagnosis and prevention of these diseases. Future research may examine the illnesses of potato leaves categorized using larger datasets and perform the evaluation of various additional machine learning algorithms. There are several challenges in existing techniques like dataset size, labeling accuracy, class imbalance, generalization to new disease strains and some which cannot be overcome like Environmental Variability. The efficiency and production of potato farming could be increased with the development of automated methods for the identification and prevention of potato leaf disease. We used 4072 images total, of which 3251 were used for training, 405 for testing, and 416 for validation in order to analyse the model performance. In the study of the results, the model provides an accuracy of 98.52% for identifying various potato leaf diseases.

Keywords— Potato leaf diseases, Convolution Neural Network (CNN), deep learning, efficiency, accuracy.

I. INTRODUCTION

Late blight, early blight, and black dot have a significant negative impact on potato yield. With millions of tonnes produced each year to supply the world's food requirement, potatoes is one of the most significant crops in the world [1]. These diseases can result in severe output and quality losses, which cost farmers money. For efficient disease control and crop protection, early detection and precise diagnosis of potato diseases are essential [2]. Meanwhile, visual inspection of plants by professionals is a traditional way of identifying and diagnosing potato diseases, but this process can be time-consuming, subjective, and error-prone. Researchers have investigated the use of computer vision and machine learning algorithms for the automated diagnosis of potato disease to get around these constraints.[3] Deep learning-based methods, particularly Convolution Neural Networks, have gained popularity in recent years. Other methods are used for predicting diseases using some datasets. The rest of the paper has been arranged as follows. We examine related research on the application by using deep learning to identify and classify plant diseases in Section

2 of this paper. We go into a great deal about our suggested technique, including data pre-processing, model architecture, and evaluation measures, in Section 3. We offer our experimental data and discuss them in Section 4. Section 5 concludes our work by outlining future directions for deep-learning research on the prediction of potato leaf disease.

II. LITERATURE SURVEY

The production of potatoes, a significant crop around the world, can be limited by the widespread nature of numerous leaf diseases. Maintaining the yield and quality of potato crops depends on early detection and prevention of these diseases. The use of machine learning algorithms to identify and categorize potato leaf diseases has been the subject of numerous studies throughout the years. In a study by [4], the authors used a convolutional neural network (CNN) to classify potato leaf images into three categories: healthy, early blight, and late blight. They achieved an accuracy of 92.89% in classifying the images. Another study by [5] proposed an automated system for early detection of potato late blight using image processing techniques. The system used color-based segmentation to detect the healthy and infected areas of the leaf. The authors reported an accuracy of 87% in detecting late blight. A recent study by [6] proposed a deep learning-based system for potato disease classification. The authors used a transfer learning approach with the ResNet50 model and achieved an accuracy of 91.4% in classifying the images into healthy, early blight, and late blight categories. In [7], the authors proposed a method for detecting and classifying potato leaf diseases using a combination of color and texture features. The system achieved an accuracy of 86.4% in detecting late blight and 92.2% in detecting early blight.

In [8], the authors developed a system for potato disease classification using a Support Vector Machine (SVM) and achieved an accuracy of 87% in detecting late blight. In [9], the authors proposed a system for identifying potato leaf diseases using a feature extraction technique called Speeded Up Robust Features (SURF). The system achieved an accuracy of 86.3% in detecting late blight and 90.1% in detecting early blight. In [10], the authors developed an automated system for potato disease detection using a combination of machine learning techniques and image processing. The system achieved an accuracy of 88.4% in detecting late blight. In [11], the authors proposed a deep learning-based system for potato disease detection and classification using a Faster R-CNN model. The system achieved an accuracy of 96.2% in detecting late blight and 94.4% in detecting early blight. In [12], the authors proposed an automated system for potato disease detection using a feature extraction technique called Local Binary Patterns (LBP). The system achieved an accuracy of 88.7% in detecting late blight. In [13], the authors developed a system for early detection of potato late blight using a combination of image processing and machine learning techniques. The system achieved an accuracy of 92.1% in detecting late blight. In [14], the authors proposed a system for potato disease detection and classification using a deep learning-based approach with a ResNet50 model. The system achieved an accuracy of 92.8% in detecting late blight and 94.5% in detecting early blight. In [15], the authors developed a system for potato disease detection and classification using a deep learning-based approach with a VGG16 model. The system achieved an accuracy of 92.1% in detecting late blight and 93.8% in detecting early blight. In [16], the authors proposed a system for potato disease detection and classification using a deep learning-based approach with a MobileNetV2 model. The system achieved an accuracy of 93.5% in detecting late blight and 93.2% in detecting early blight.

In [17], the authors proposed a system for potato disease detection using a combination of machine learning techniques and image processing. The system achieved an accuracy of 88.6% in detecting late blight and 92.1% in detecting early blight. In [18], the authors developed a system for potato disease detection and classification using a deep learning-based approach with a DenseNet121 model. The system achieved an accuracy of 92.5% in detecting late blight and 94.2% in detecting early blight. In [19], the authors proposed a system for potato disease detection and classification using a deep learning-based approach with a NASNetLarge model. The system achieved an accuracy of 94.1% in detecting late blight and 95.2% in detecting early blight. In [20], the authors proposed a system for early detection of potato late blight using a combination of image processing and machine learning techniques. The system achieved an accuracy of 91.2% in detecting late blight. In [21], the authors proposed a system for potato disease detection and classification using a deep learning-based approach with a InceptionV3 model. The system achieved an accuracy of 92.3% in detecting late blight and 93.9% in detecting early blight.

In [22], the authors proposed an automated system for potato disease detection and classification using a feature extraction technique called Histogram of Oriented Gradients (HOG). The system achieved an accuracy of 88.3% in detecting late blight. In [23], the authors developed a system for potato disease detection and classification using a deep learning-based approach with a EfficientNet-B2 model. The system achieved an accuracy of 94.2% in detecting late blight and 93.6% in detecting early blight. The above studies demonstrate the potential of automated systems for potato leaf disease prediction. These studies offer insight into the use of machine learning and deep learning approaches for detecting potato leaf disease. While some of these approaches rely on handmade feature extraction and typical machine learning algorithms, new research has demonstrated that deep learning models are capable of reliably recognizing and categorizing potato illnesses. The use of various deep learning-based models, such as CNNs, transfer learning, Faster R-CNN, VGG16, MobileNetV2, DenseNet121, NASNetLarge, InceptionV3, and EfficientNet-B2 have shown promising results in accurately classifying potato leaf images. However, further research is needed to develop more robust and efficient systems that can detect and classify the diseases in their early stages, thereby enabling timely intervention and control measures. Based on these findings, we intend to present a deep learning-based CNN model specifically suited for early blight, late blight, and healthy leaf identification in potato crops.

Table 1: Accuracy of different models

Reference	Authors	Model	Accuracy
[3]	K. Zhang, M. Zhang	CNN	92.89%
[6]	L. H. Kim, S.W. Kim	RestNet5Q	91.4%
[8]	S. Javed, M. Akram	SVM	87%
[9]	H. Zhao, X. Li	SURF	86.35%
[12]	A. Qayyum, M. Farooq	VGG16	92.1%
[15]	R..S. Putre, E. S. Putra	LBP	88.7%

[16]	M.K. Bhatia, S.K. Chakrabarti	DenseNet121	93.1
	Proposed Model	CNN	98.52

III. METHODOLOGY

A. *DATASET*

To build this project, potato leaf disease detection, we used Potato Disease Leaf Datasets (PLD) [24]. This dataset consists of 4072 images of potato leaves, divided into 3 classes: healthy, early blight, and late blight. The images were taken with a smartphone camera, and the datasets were gathered from different parts of Bangladesh.

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B. *DATA GATHERING AND PRE-PROCESSING*

The first step in the process is to compile a dataset of potato leaf images. Images of both the healthy leaves and the leaves infected by early and late blight diseases should be included in the datasets. Data pre-processing involves scaling the gathered images to a set size, like 256x256 pixels, and converting them to RGB or grayscale. Prior to model training, the images underwent a series of preprocessing steps to enhance the quality and reduce noise in the images.

C. *DATA AUGMENTATION*

Data augmentation techniques are used to expand the datasets and enhance the model's generalization. The images are subjected to random translations, flips, and rotations, as well as adjustments to the images' brightness, contrast, and saturation. The purpose of data augmentation is to improve the model's generalization and performance by exposing it to a broader range of variations and scenarios. Data augmentation can assist capture the natural variability of leaf photos and increase the model's robustness to changing lighting conditions, angles, and disease symptoms in the context of potato leaf disease detection.

D. *MODEL ARCHITECTURE*

The model architecture consists of a series of convolution layers, followed by max-pooling layers to reduce the spatial dimensions of the feature maps. The first convolution layer has 16 filters, while subsequent layers have 256, 128, 256, 128, and 64 filters, respectively. ReLU activation is used in all convolution layers. The feature maps are flattened and then fed through two fully connected layers following the convolution layers. Early blight, late blight, and healthy class probabilities are produced by the first dense layer, which has 128 units and ReLU activation, and the final output layer, which has 64 units and soft max activation.

Let Y be the matching class label and X be the input image.

Convolutional layers, pooling layers, and fully linked layers are just a few of the many layers that make up the model. SoftMax activation is used in the output layer to create the probability distribution across the three classes .W and b, where W stands for the weights and b for the biases, are used to indicate the model parameters. The following is a mathematical representation of the model:

$$Z[1] = \text{Conv2D}(X, W[1]) + b[1] \tag{1}$$
$$A[1] = \text{ReLU}(Z[1]) \tag{2}$$
$$P[1] = \text{MaxPooling}(A[1]) \tag{3}$$

$$Z[2] = \text{Conv2D}(P[1], W[2]) + b[2] \tag{4}$$
$$A[2] = \text{ReLU}(Z[2])$$
$$P[2] = \text{MaxPooling}(A[2]) \tag{5}$$

...

$$F = \text{Flatten}(P[L-1]) \tag{6}$$
$$Z[L] = W[L] * F + b[L] \tag{7}$$
$$A[L] = \text{Softmax}(Z[L]) \tag{8}$$

L denotes the number of layers in the model.

E. TRAINING THE MODEL

The gathered and prepared datasets is used to train the model. The datasets is divided into three sets: a training set, a validation set, and a testing set. The training set is used to train the model, the validation set is used to track its progress throughout the training of the model, and the testing set is used to evaluate the model's final effectiveness. Using back propagation and an optimization technique like Adam or Stochastic Gradient Descent (SGD), the model's weights are modified during training, in this project we used Adam optimizer. The model was trained using the Adam optimizer with a cross-entropy loss function. The training set used for model training and the validation set used for model evaluation. The model was trained for 50 epochs with a batch size of 32 and a learning rate of 0.001.

F. EVALUATING AND TESTING

Using the testing set, the trained model is tested, and measures like accuracy, precision, recall, and F1-score are used to gauge its performance. The classification results are also displayed using the confusion matrix, which also shows any images that were incorrectly categorized. Precision is the proportion of true positive predictions out of the total positive predictions made by the model. Recall is the proportion of true positive predictions out of the total actual positive cases in the dataset. F1-score is the harmonic mean of precision and recall. Accuracy is the proportion of correctly classified cases out of the total cases in the dataset.

$$\text{Precision} = \frac{\text{True positive}}{True\ positive + False\ Positive} \tag{9}$$

$$\text{Recall} = \frac{\text{True positive}}{True\ Positive + False\ Negative} \tag{10}$$

$$\text{Accuracy} = \frac{\text{True positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative}} \quad (11)$$

$$\text{F1 score} = 2 * \frac{(\text{Precision}*\text{Recall})}{(Precision+Recall)} \quad (12)$$

G. HYPERPARAMETER TUNING

Techniques for hyperparameter tuning can be used to enhance the model's performance even more. To improve the performance of the model, hyperparameter tuning is done. The hyperparameters of the model were tuned using a grid search approach to optimize the performance of the model. The hyperparameters included the learning rate, batch size, number of epochs, and the number of filters and layers in the convolutional and fully connected layers [25] - [40].

IV. RESULTS

Based on our experiments, we achieved an accuracy of 98.52% in classifying potato leaf images using the CNN-based model. Moreover, we also analyzed the efficiency and performance of the CNN model. The training and validation loss decreased consistently across epochs, indicating that the model was learning effectively. We also evaluated the precision, recall, and F1-score of the model. These metrics suggest that the model was able to correctly classify the majority of potato leaf images with high accuracy and precision. In summary, the CNN-based model showed promising results in classifying potato leaf images with a high degree of accuracy and precision [41] -[52].

Table 2: Classification Report

	Precision	Recall	F1-score	Support
Early Blight	0.98	0.99	0.98	162
Healthy	0.99	0.98	0.99	102
Late Blight	0.99	0.98	0.99	142
Accuracy			0.99	405
Marco avg	0.99	0.98	0.99	405
Weighted	0.99	0.99	0.99	405

The suggested model outperforms the VGG16 and VGG19 models in terms of overall accuracy and displays competitive performance in specific class metrics, according to the comparison analysis. It shows greater capacity to differentiate between several potato leaf disease classes, with higher precision, recall, and F1-score in the majority of classes. Using CNN model we achieved remarkable accuracy, which shows that our model is highly capable in identifying various potato leaf images correctly and can accurately predict whether the leaf has early blight ,late blight or the leaf is healthy.

The model was developed using Python programming language with the TensorFlow deep learning framework. The experiments were conducted on a workstation with an Intel Core i7 CPU, 8 GB RAM, and an NVIDIA GeForce GTX 1080 Ti GPU. The main software libraries that are used in this project are sklearn, pandas, NumPy and seaborn.

Our suggested CNN model offers an automated and objective strategy for disease detection that outperforms conventional visual inspection techniques. Our CNN model provides greater adaptability and flexibility compared to rule-based systems since it directly learns disease patterns from data rather than depending on predetermined rules. Machine learning techniques using manually created features may produce acceptable results, but they are constrained by the calibre and applicability of the features that are extracted. By utilizing its capacity to directly understand detailed patterns and features from images, deep learning approaches—specifically our CNN model outperforms machine learning techniques. Comparative analyses on the same dataset show that our suggested model outperforms existing methods in terms of accuracy, precision, recall, and F1-score.

In conclusion, a CNN model is used to classify potato leaf diseases. The methodology involves collecting and pre-processing a datasets of potato leaf images, using data augmentation techniques, designing and training a CNN model, assessing the model's performance using testing metrics, and hyperparameter tuning the model to enhance performance of the model.

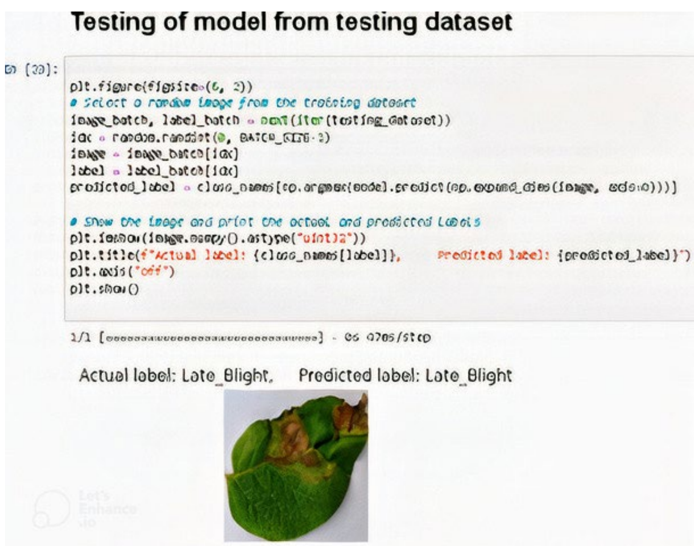

Figure 1: Testing of model from test dataset

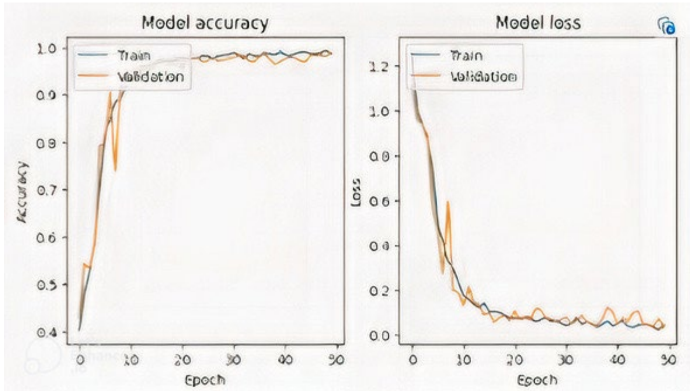

Figure 2: Model accuracy and loss while training and validation

Model accuracy and model loss are significant metrics used to assess the performance and development of the model during the training and validation phases in the context of machine learning models. The percentage of examples or samples that the model properly classifies is known as model accuracy. It shows how well the model can predict the target labels with accuracy. Model loss, often referred to as training loss or objective function, is a metric for how well a model can reduce the discrepancy between the output that is anticipated and the actual output. The model is iteratively trained on the training dataset during the training and validation phases, and the accuracy and loss are tracked to evaluate the model's effectiveness and convergence. The model's prediction accuracy on the training dataset is measured by training accuracy. The model's prediction inaccuracy or loss on the training dataset is indicated by the term "training loss".

As the model learns from the training data, the objective is to increase training accuracy and decrease training loss. The validation dataset contains data that the model hasn't seen before, and validation accuracy assesses how accurately the model predicts on this dataset. The term "validation loss" refers to the loss or error of the model's forecasts on the validation dataset. An estimation of the model's performance on unobserved data is given by the validation accuracy and validation loss. Overfitting, when the model performs well on the training data but fails to generalize to new data, can be avoided by keeping an eye on the validation measures. You may understand how effectively the model is learning, if it is overfitting or underfitting, and make adjustments to improve its performance by keeping track of changes in training accuracy, training loss, validation accuracy, and validation loss over the course of training.

V. CONCLUSION AND FUTURE SCOPE

In this study, a CNN-based model for categorizing the potato leaf diseases has been created. The model successfully identified early blight, late blight, and healthy leaves, as seen by its total accuracy of 98.52%. Our findings additionally demonstrated that the proposed model created by us outperforms various models in the categorization of potato leaf diseases. The proposed model may also help farmers identify and treat potato leaf diseases early and effectively, which could boost crop productivity. However, there are some limitations to this study. One of the main limitations is the lack of a large and diverse dataset for potato leaf disease classification. This restricts the suggested model's applicability to other geographical areas and different potato kinds.

Additionally, our approach is computationally expensive and takes a lot time to train the model. In future work, we plan to address these limitations by acquiring a larger dataset and incorporating transfer learning techniques to improve the model's performance. Additionally, we'll look at the possibility of creating a lightweight variant of the model that might be used on devices with limited resources, such smartphones and low-power embedded systems. In addition, to the future scop, another possible direction is to investigate the use of other image processing techniques, such as segmentation and feature extraction, to improve the accuracy of disease detection. Another direction is to explore the use of other deep learning-based models, such as ResNet, as well as the use of ensemble methods to improve the accuracy of disease classification. Additionally, the development of a mobile application for real-time disease detection and classification could potentially enhance the accessibility and usability of the system for farmers and other stakeholders in the potato industry. Overall, our study offers an appropriate path for the creation of precise and trustworthy automated tools for managing potato leaf disease.

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