A Review on Machine Learning Based Techniques for Leaf Blight Detection

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***Abstract*— Plant diseases like early and late blight must be promptly identified, and this requires automated blight detection. These illnesses have the potential to spread quickly and seriously harm crops. By taking timely and focused action to limit the effects, farmers can reduce crop losses and ensure food security through early detection. If left untreated, blight diseases can cause significant output losses in crops, especially in staple items like tomatoes and potatoes. Advanced technologies like machine learning and image analysis enable automated detection systems to swiftly and precisely identify disease symptoms, facilitating early intervention to prevent or minimise crop losses. Therefore, the pressing need to address the problems caused by plant diseases, encourage sustainable agricultural methods, and support international efforts to ensure food security is what motivates the need for automated blight detection. Farmers, customers, and the environment all stand to gain from the increased efficiency and precision of disease management brought about by the integration of new technologies in agriculture. This paper presents a review on the state of the art image processing and machine learning, deep learning based approaches for detection of potato leaf blight disease.**

Keywords*— *Potato Leaf Disease (blight), Deep Learning, Convolutional Neural Network, Classification Accuracy.

I. INTRODUCTION

The potato crop is a very important crop worldwide. But it is affected by blight disease. The fungus Alternaria solani is the source of early blight, a common and destructive disease that affects potato crops. On the elder leaves of the potato plant, the earliest indications of early blight appear as dark brown to black lesions with characteristic concentric rings. The afflicted leaves' demise is facilitated by these lesions, which resemble a target pattern. The illness may cause leaves to gradually turn yellow, wither, and die. Because early blight prefers to grow in warm, humid environments, it can be especially problematic in the early to mid-growing season. Crop rotation, adequate spacing, and, in extreme circumstances, the application of fungicides are examples of effective management techniques[1].

Although the potato crop is produced in large quantities in India and globally, its cost of production is increasing in recent times due to increase in cost of seeds, fertilizer and pesticides. Moreover, the production yield is reduced due to common potato crop disease such as blight. This results in large financial losses for farmers and increased crop prices for the consumers. Hence, early detection of blight is extremely important. Manual detection is both challenging due to manpower requirements and it is also time consuming Therefore, the use of technology can be used to detect potato crop blight (disease). The motivation of the proposed work is to design an automated machine learning based approach for potato crop blight (disease) .

Fig.1 Heathy, Early and Late Blight Cases.

II. EXISTING MODELS

This section presents the existing models employed thus far for potato leaf blight detection. The different processes needed are described here. Machine learning (ML) and deep learning (DL) models offer promising solutions for accurate and timely detection of potato blight [3].

Data Collection: Gathering high-quality data is essential for training robust models. In the context of potato blight detection, this involves acquiring a diverse dataset of potato plant images, including healthy and infected samples, captured under various environmental conditions.

Pre-processing: Pre-processing steps, such as image enhancement, normalization, and augmentation, play a vital role in preparing the dataset. These techniques help ensure that the model generalizes well to different scenarios and conditions [4].

Traditional Machine Learning Models: Classical ML algorithms, such as Support Vector Machines (SVM), Random Forests, or Decision Trees, can be employed for initial detection efforts. These models can leverage handcrafted features extracted from the images to identify patterns associated with potato blight.

Convolutional Neural Networks (CNNs): CNNs have demonstrated significant success in image-based tasks. For potato blight detection, a CNN can learn hierarchical features directly from the images. Transfer learning, utilizing pre-trained models like VGG16 or ResNet, can accelerate training and enhance performance, especially with limited labeled data.

Other Deep Learning Architectures: Beyond CNNs, other architectures like Recurrent Neural Networks (RNNs) or Long Short-Term Memory networks (LSTMs) can be explored, especially if temporal aspects in the progression of potato blight need to be considered. These architectures are well-suited for sequential data.

Model Evaluation and Validation: Rigorous evaluation using metrics like precision, recall, and F1 score is necessary to assess the model's performance. Cross-validation techniques help validate the model's robustness and ensure reliable predictions on unseen data [5].

Deployment and Monitoring: Once a model is trained and validated, it can be deployed for real-time monitoring. Continuous monitoring and periodic updates are essential to adapt the model to changing environmental conditions and evolving strains of potato blight. Implementing a comprehensive approach that combines data quality, model selection, and ongoing refinement is crucial for developing effective ML and DL models for potato blight detection in agriculture

III. LITERATURE REVIEW

This section presents the related work done in this domain. The methods used along with the salient features and findings are presented in a tabular form for ease of analysis

Table I.
Review of Existing Literature

S.No.	Paper Title	Authors	Reference	Findings
1	A Convolutional Neural Network Based Potato Leaf Diseases Detection Using Sequential Model	Bonik et al.	[6]	CNN model used for potato leaf blight detection. Accuracy of 94.2% achieved.
2	Hybrid Feature-Based Disease Detection in Plant Leaf Using Convolutional Neural Network, Bayesian Optimized SVM, and Random Forest Classifier.	Singh et al.	[7]	Blight Detection in Tomato Leaves, using different algorithms. CNN achieves: 94.07% accuracy. Support Vector Machine (SVM) achieves 92.2% accuracy. Random Forests (RF) achieves 96.1% accuracy.
3	Potato plant leaves disease detection and classification using machine learning methodologies	A. Singh et al.	[8]	Blight Detection in Tomato Leaves, using K-Means Clustering and SVP. Proposed Approach attains a classification accuracy of 95.9% accuracy.
4	Detection of a potato disease (early blight) using artificial intelligence	Afzal et al.	[9]	GoogleNet, VGGNet, and EfficientNet used for classifying potato blight with an F-Score of 0.84–0.98, 0.79–0.94 and 6.8–8. respectively
5	Detection of potato disease using image segmentation and machine learning	Tiwari et al.	[10]	Feature extraction followed by classification using the Random Forest algorithm. Classification Accuracy of 97% achieved.
6	Potato Leaf Diseases Detection Using Deep Learning	Iqbal et al.	[11]	VGG-19 for feature extraction followed by Logistic Regression rendered an accuracy of 97.7%.
7	Potato disease detection using machine learning	Tariq et al.	[12]	Image processing followed by Convolutional Neural Networks used to obtain an accuracy of 99%.
8	Transfer learning on VGG16 for the Classification of Potato Leaves Infected by Blight Diseases.	Akther at al.	[13]	Transfer learning through the VGG16 deep learning model to obtain an accuracy of 96.88%.

IV. METHODOLOGY

The methodology of the paper is explained in this section. It is necessary to process the raw potato leaf images before the training process. Each of the sub-processes is described here:

Illumination Correction: For blight detection, illumination correction is an essential step in the processing of UAV-captured photos. High-resolution photos of agricultural fields are frequently taken by unmanned aerial vehicles (UAVs), which provide useful information for precision farming applications. Variations in illumination during the process of acquiring images, however, may present difficulties for precise analysis. The goal of illumination correction techniques is to improve the quality and dependability of the acquired images so that precision agricultural decision-making and interpretation are more accurate.

The lighting conditions of UAV-captured photos can vary depending on several factors like the time of day, weather, and vegetation shadows. These variances may result in uneven lighting throughout the photos, which makes it challenging to gather useful data for crop monitoring and analysis. Correcting for illumination becomes necessary to lessen [14].

Segmentation: The ability to precisely identify and localise diseased zones within potato crops is made possible by image segmentation, which is critical to the detection of potato blight. Compared to conventional picture classification techniques, our method offers a more thorough and precise analysis. The goal of image segmentation is to divide an image into discrete parts so that specified areas can be analysed specifically. This is especially crucial for identifying the early symptoms of potato blight.

Within the potato crop, image segmentation enables accurate localization of afflicted areas. For focused actions like the application of pesticides or the removal of sick plants, this localization is crucial. Segmentation helps stop the disease from spreading and maximises agricultural resource use by precisely defining the borders of impacted areas [15].

Classification:

The Convolutional Neural Networks (CNNs) can automatically extract hierarchical characteristics from images, they have become the mainstay for image classification applications. These neural networks perform exceptionally well in applications like picture identification because they are specifically made for processing organised grid data.

Convolutional, pooling, and fully linked layers are among the layers that make up a CNN's architecture. Convolutional layers identify patterns in the input image by applying filters, hence identifying local features. By reducing spatial dimensions, pooling layers preserve significant information. High-level features are integrated for categorization in fully connected layers [16].

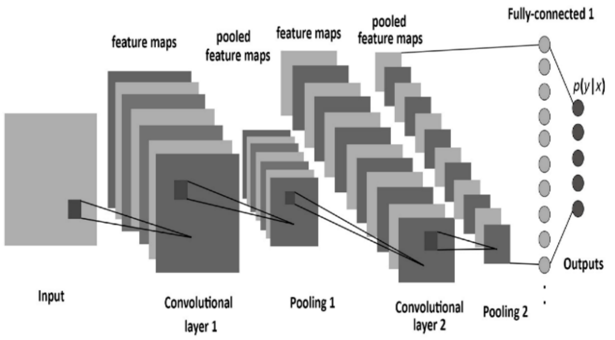

Fig.2 The CNN Model

The convolution operation is given by equation 1:

$$x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau \qquad (1)$$

Here,
x(t) is the input
h(t) is the system under consideration.
y is the output
*is the convolution operation in continuous domain
For a discrete or digital counterpart of the data sequence, the convolution is computed using equation 2:

$$y(n) = \sum_{-\infty}^{\infty} x(k)h(n-k) \qquad (2)$$

Here
x(n) is the input
h(n) is the system under consideration.
y is the output
*is the convolution operation in discrete domain

The CNN has the following layers [17]:

Convolutional Layers: In feature extraction, convolutional layers are essential. In order to identify patterns like edges, textures, and forms, filters, also known as kernels, convolve across the input image. Through weight sharing and parameter sharing, convolutional processes enable the network to learn complicated representations by capturing spatial hierarchies.

Pooling Layers: In order to down sample feature maps, pooling layers come after convolutional layers. Max pooling and average pooling are two popular pooling techniques that minimise spatial dimensions without sacrificing significant information. This procedure improves translation invariance and aids in the management of computational complexity.

Fully Connected Layers: Fully connected layers combine high-level features for classification and come after convolutional and pooling layers. A dense network is created when all of the neurons in one layer connect to all of the neurons in the layer above. The last completely connected layer generates probability outputs for the final classification through the use of an activation function logic.

Final Classification: By introducing non-linearity, activation functions allow the network to discover intricate correlations within the data. Rectified Linear Unit, or ReLU, is a popular CNN activation function that creates non-linearity by outputting the input for positive values and zero for negative values.

CNN training entails gradient descent and backpropagation to optimise weights and biases. The discrepancy between expected and actual values is measured using loss functions. Well-known optimisation techniques, such as Adam and RMSprop, modify weights in order to reduce loss. To avoid overfitting, data augmentation and dropout are frequently employed [18].

The performance metrics are:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (3)$$

$$Sensitivity\ or\ Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$Specificity = \frac{TN}{TN+FP} \qquad (5)$$

$$Precisiosn = \frac{TP}{TP+FP} \qquad (6)$$

$$F-Measure = \frac{2.Precision.Recall}{Precision+Recall} \qquad (7)$$

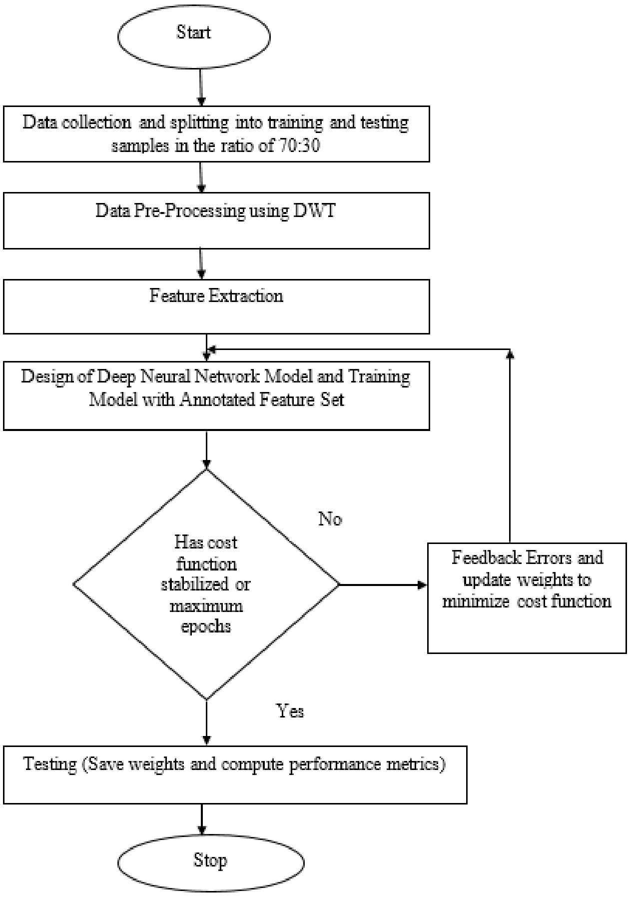

Fig.3 Flowchart of Proposed System

The aim of any designed approach is to attain high values of accuracy of classification along with other associated parameters.

V. CONCLUSION

It can be concluded that potato crop is a very important crop which is affected by blight disease. Early detection of blight is necessary to stop the crops from damage. Artificial Intelligence and Machine Learning tools are being used to detect potato leaf blight as this will allow automated detection, and need less manpower. However accurate classification is challenging due to different capturing angles, lighting conditions and variability in crops. The background and review presented in this paper can serve as an underpinning for further research in the domain. The review focusses on the image pre-processing, segmentation, feature extraction and classification stages. The parameters which must be computed to evaluate the system performance is also presented in this paper.

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