Deep Learning Approaches for Potato Leaf Disease Detection and Categorization: A Review

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Abstract: **The potato (Solanum tuberosum) is one of the most important crops in the world, and sometimes productivity can get affected by a diversity of diseases, with leaf disease being one of them. The early detection and accurate diagnosis of these diseases would help in reducing their spread and thus minimize crop loss. While many approaches have been established for diagnosing and classifying the diseases of potato leaves, the demand for more accurate and timely detection is noteworthy. In this paper, we analyze and review the various methods deployed in the detection of diseases affecting potato leaves. We also propose an improved model for detection that will be covered in our futurist research.**

Keywords: **Artificial Neural Networks (ANN), Convolutional Neural Networks (CNNs), Deep Learning (DL), Genetic Algorithm (GA), K-Nearest Neighbor (KNN), Machine Learning (ML), Potato Leaf Disease Detection, Convolutional Neural Networks (CNNs), Support Vector Machines (SVM).**

I. INTRODUCTION

Potato is one of the most important staple crops worldwide. It provides food and economic stability to millions of people. But these diseases are a constant threat to potato production and can cause major reductions in crop yield and quality. Another type of disease, commonly known as leaf diseases in potatoes, is particularly harmful, as the very rapid spread of these pathogens across the potato field might compromise the whole crop. Such diseases include late blight, early blight, potato rust, and scab, which are among the most serious, leading to enormous losses in quantity and marketability. Early detection of such diseases is important for an effective control strategy while ensuring minimum use of harmful pesticides and reduced environmental impact. Traditional methods of detecting potato leaf diseases have been dependent on the visual inspection of trained professionals. These methods are inflexible, subjective, laborious, and prone to failure during the detection of early-stage diseases when interventions are most effective. To address these issues, more attention has been focused on the development of automated systems to create viable potato disease detection aimed at image processing, machine learning, and deep learning. Properly handled with state-of-the-art pattern recognition algorithms, such images could observe diseased patterns even at early stages of the infection. Moreover, innovations in machine learning techniques, including Convolutional Neural Networks (CNNs), have changed the way we approach disease detection itself. Such processes can extract relevant image features automatically and categorize them into disease classes, yielding an efficient and accurate alternative to conventional procedures. This paper aims to explore the various techniques and methods used in potato leaf disease detection, elucidating the role that imaging processing, machine learning, and deep learning played in transforming disease management. This paper highlights the integration of multiple methods and models and discusses the effectiveness of models proposed by different researchers.

II. LITERATURE REVIEW

Several prior studies that have previously set trials to detect potato leaf disease are as follows:

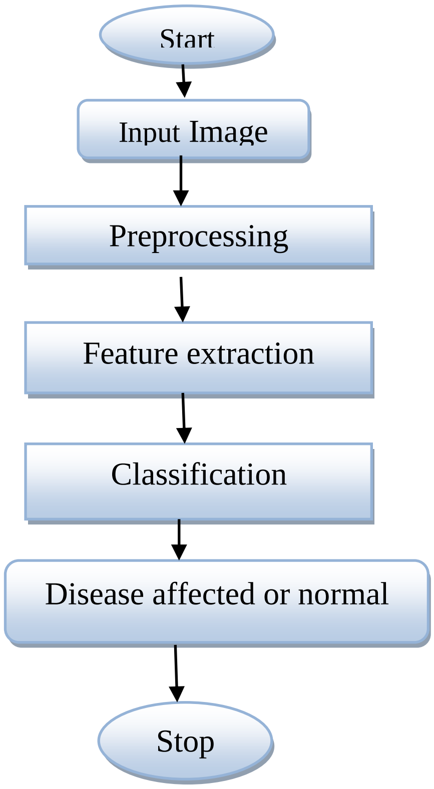
The literature survey by Utpal Barman et al. discusses the increasing use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in plant disease detection. Previous studies have shown high accuracy rates in disease classification for various crops, including banana, tomato, apple, grapevine, and cucumber. Traditional machine learning methods like Artificial Neural Networks (ANN), K-Nearest Neighbor

(KNN), Support Vector Machine (SVM), and Decision Trees have also been used. The paper highlights the challenges of traditional methods, such as reliance on expert knowledge, and the importance of imbalanced datasets in plant disease detection. The survey highlights the benefits of using deep learning over traditional techniques in plant disease detection. The SBCNN demonstrated high validation and training accuracy, with a validation accuracy of 96.98% in the non-augmented dataset and 96.75% in the augmented dataset, and no overfitting in the augmented dataset, making it a promising precision farming tool [1]. The paper's literature survey by Abdul Jalil Rozaqi et al. aims to provide a comprehensive understanding of the research topic. It reviews existing research, identifying gaps and evaluating methodologies used in previous studies. The survey also discusses theoretical frameworks used in related studies, providing insights into the research problem. Key findings from previous studies are summarized, contextualizing the current research within the existing body of knowledge. The survey also identifies relevant trends and developments in the field, helping to understand the evolution of the subject matter and future research directions. The survey includes a comprehensive list of references, ensuring credit to original authors and in-depth information [2]. This paper by YANG ZHANG et al. used various methods for detecting and classifying potato leaf diseases, including segmentation techniques and machine learning algorithms. Key techniques include K Means Clustering, Support Vector Machines (SVM), and Artificial Neural Networks (ANN). The paper compares these methods and finds that the proposed model achieves a higher classification accuracy of 97.8%, demonstrating the effectiveness of transfer learning and logistic regression in disease classification. The paper concludes that logistic regression provides a state-of-the-art solution for classifying potato leaf diseases, outperforming models like KNN and SVM. This comprehensive literature survey highlights advancements in plant disease detection through machine learning techniques. The Faster RCNN model outperformed the original model in detecting tomato leaf diseases, with 2.71% higher recognition accuracy. The k-means clustering algorithm effectively analyzed bounding box sizes [3]. As per Divyansh Tiwari and his colleagues, a study has been done for various methods used in plant disease detection, particularly for potato leaves. Traditional techniques like local binary patterns and K-means clustering were found to be insufficient for detecting leaf diseases. However, recent advancements have seen the adoption of deep learning models, such as LeafNet, which are combined with a bag of visual words model for tea leaf classification. Faster R-CNN and transfer learning have also been explored for image identification and classification. The paper proposes a novel deep learning model that achieves a classification accuracy of 97.8% for potato leaf diseases, highlighting the growing importance of automated systems in plant disease detection. The proposed model achieved 97.8% classification accuracy on a 2152 image dataset, with logistic regression as the best classifier. The model used transfer learning and pre-trained models, with VGG19 providing optimal results [4]. As per Kaiming He and colleagues, it presents a significant advancement in deep learning, particularly for image recognition tasks. It discusses the use of VLAD and Fisher Vector as effective shallow representations for image retrieval and classification, highlighting the importance of residual representations in improving performance. The paper also discusses the multigrid method, which reformulates problems into subproblems at multiple scales, emphasizing the role of residual solutions in optimization. The paper also highlights the historical context of shortcut connections in neural networks and the advantages of training deep networks with residual connections. The authors present results from the ImageNet dataset and CIFAR-10, demonstrating their effectiveness across different datasets. The paper introduces a residual learning framework for training deeper networks, achieving better optimization results. It shows increased depth increases accuracy, with a training error of less than 0.1% and a test error of 7.93% [5]. Christian Szegedy et al. provide an overview of the evolution and significance of Convolutional Neural Networks (CNNs) in computer vision, focusing on the Inception architecture. The paper highlights the success of AlexNet in the 2012 ImageNet competition, which led to further research on deeper and more efficient networks like VGGNet and GoogLeNet. The authors emphasize the importance of architectural design in the effectiveness of CNNs. The Inception architecture, particularly GoogLeNet, is noted for its efficiency, utilizing fewer parameters than AlexNet and VGGNet. However, the complexity of the Inception architecture poses challenges for modifications and scaling. The authors propose design principles for scaling up convolutional networks efficiently. The paper presents a top-1 error of 17.3% and a top-5 error of 3.5% using four models and a single frame evaluation of 21.2% and 5.6%, highlighting significant improvements over the state of the art in the ILSVRC 2012 classification challenge [6]. Purnawarman Musa et al. examine the principles of image processing, its developments, embedded system difficulties, and biometric applications. It emphasizes how crucial segmentation, object detection, color imbalance correction, and image restoration are to face recognition. The constraints of embedded systems, especially camera sensors, in implementing facial recognition technologies are also covered in the article. The CLAHE approach, which is suggested to enhance facial recognition in different lighting circumstances, is also covered in the paper. The outcomes demonstrate that CLAHE can effectively identify and detect faces, which makes it essential for practical uses. The research showcases face detection and recognition using the LBPH method in indoor and outdoor settings, highlighting challenges in recognizing twins' faces. The CLAHE method improves recognition accuracy in varying lighting conditions and proposes biometric applications [7]. As per Priyadarshini Patil and colleagues, examine various methods and findings related to automated disease management in potato crops, focusing on detecting blight diseases using image processing and machine learning techniques. Key findings include the use of neural networks for disease detection, Support Vector Machines (SVM) for late blight disease detection, image processing techniques for identifying disease-affected areas, clustering techniques for cotton disease detection, and a method combining Discrete Cosine Transform (DCT) with SVM. The authors argue that their proposed system is robust, performing well with real-time data from various regions. Classifier performance analysis shows that Artificial Neural Network (ANN) outperforms SVM and Random Forest (RF) in detecting potato diseases, achieving 92% accuracy. The proposed system detects early and late blight diseases in potato crops using leaf images and FCM clustering. Testing 500 images, it identified 4842 defected regions and trained SVM, RF, and ANN classifiers, with ANN achieving 92% accuracy [8]. This paper discusses the impact of plant diseases on global crop yield loss and the growing application of artificial intelligence (AI) and machine learning in agriculture. It highlights the importance of early detection and diagnosis in mitigating the adverse effects of plant diseases. Previous research on disease detection has utilized various neural network architectures, such as BRBFNN, AlexNet, and LeNet. The paper also focuses on tomato diseases, with studies achieving 98.8% accuracy using a pre-trained CNN-based architecture. The Muhammad E. H. Chowdhury et al. emphasize the importance of segmentation for improving disease detection models. The U-Net architecture is proposed for image segmentation, particularly in biomedical applications. The proposed methods outperform existing state-of-the-art works in plant disease detection, particularly in tomato leaves. The EfficientNet-B7 model outperformed existing literature in the binary classification of healthy and diseased tomato leaves using segmented images. It achieved 99.12% accuracy in 6-class classification and 99.89% accuracy in 10-class classification. The modified U-net segmentation model achieved 98.66%, 98.5%, and 98.73% accuracy [9]. The literature survey by Kazi Naimur Rahman et al. on plant disease detection highlights significant contributions in the field of deep learning and image processing techniques. Key findings include the use of Convolutional Neural Networks (CNNs), comprehensive approaches, innovative models, performance evaluations, data augmentation and transfer learning, and machine learning techniques. CNNs have become the standard for image classification tasks, and comprehensive approaches have been developed. Innovative models have been introduced for specific crops, and performance evaluations have shown high accuracy rates in detecting diseases in potato plants. However, further research is needed to optimize model architectures and integrate various techniques for improved accuracy and efficiency. The research achieved high plant disease detection accuracy rates with a custom CNN model, reaching 95.62% in leaf classification. The model's robustness was enhanced using a comprehensive dataset of 30,945 images across eight plant species [10]. As per Asif Raza et al., the importance of early detection of plant diseases, particularly in potato crops, is discussed. Previous research has proposed various methodologies, including image processing techniques and open-source algorithms. Pre-trained models like VGG19 and VGG16 have shown high accuracy in classifying potato leaf diseases. Challenges in disease detection require expertise, and automated systems are needed to alleviate the burden on agricultural experts. Advancements in machine learning, particularly Convolutional Neural Networks, have led to improved disease detection accuracy. An ensemble learning model combining predictions from multiple models is proposed for addressing common potato diseases. These advanced detection systems can transform industrial agriculture, contributing to food security and sustainable practices. The proposed framework for detecting potato diseases achieved 84% accuracy using CNN and LVQ algorithms. It integrated a Gaussian filter, improved data accuracy, and used automated hyperparameter tuning. The lightweight deep convolutional model improved processing rates [11]. Aria Dolatabadian and colleagues highlight the impact of machine vision on agriculture, highlighting the economic impact of crop diseases, which can cost $220 billion annually. The paper also discusses imaging technologies like smartphones, drones, and satellites, as well as machine learning approaches like Convolutional Neural Networks and Recurrent Neural Networks. Sensor technologies like infrared thermal devices, multispectral, and hyperspectral cameras are also discussed. The paper emphasizes the importance of integrating contextual data to enhance disease detection models. Challenges include the need for tailored models for specific regions and crops and the potential for real-time monitoring and autonomous crop disease management. The study shows that a model using SVM outperformed other methods in fruit disease detection, achieving an average F1 score of 92.06% and classification accuracy of 99%, aiding in early disease detection and treatment monitoring [12]. The study by Abhisek Saha et al. examines various methods and models for detecting plant diseases, particularly focusing on potato leaves. Traditional methods rely on visual inspection, which is time-consuming and impractical in remote areas. Advancements in technology, such as spectrometers and DNA extraction methods, are complex and costly. Artificial intelligence plays a significant role in automating and improving the accuracy of leaf disease detection. Existing models have achieved accuracies of 97.65% and 98.34%, while others have achieved 98% accuracy. However, most existing methods use transfer learning models, which can be computationally complex. The paper identifies a gap in the need for efficient, lightweight models for crop leaf disease detection in resource-constrained environments. The proposed model achieved over 99% precision and effectively categorized potato leaves into three groups [13]. The study Md. Jalal Uddin Chowdhury and colleagues discuss the importance of early detection of plant leaf diseases, which significantly impact agricultural productivity. The review explores various machine learning algorithms, including Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Random Forest, with SVM achieving the highest accuracy of 98%. The paper also discusses the application of deep learning models, particularly Convolutional Neural Networks (CNNs), in image classification tasks. The paper emphasizes the need for robust datasets for training models and the effectiveness of the Decision Tree algorithm in disease classification. Future directions include enhancing accuracy and generalization across different plant species and environmental conditions. The CNN model, trained on 17,430 images, achieved an accuracy of 85.31% in detecting and classifying 14 plant leaf diseases, demonstrating the potential of deep learning techniques for crop disease management [14]. In their article, Vikash Sawan et al. discussed image segmentation techniques, such as neural network-based segmentation, which are essential for accurate diagnosis. Challenges in tomato farming, such as climate change and pollution, necessitate improved diagnostic methods. Deep learning applications are explored, but further enhancement is needed. Architectures like DenseNet and ResNet are discussed, along with machine learning and computer vision techniques for early diagnosis. Current techniques face limitations, and emerging research areas include integrating genetic algorithms with convolutional neural networks for hyperparameter tuning. Future directions include real-time detection, multidisease detection, and IoT devices. The CNN and GA model achieved 98.3% accuracy in predicting potato leaf diseases, demonstrating high precision and effectiveness. It distinguished early and late blight conditions, optimized hyperparameters, and reduced manual labor [15]. Muhammad Ahtsam Naeem and colleagues present an automated method for detecting early and late blight diseases in potato plants, achieving a high accuracy of 99% in late blight detection, a crucial step for improving crop yield. The proposed method uses SVM for 99% accuracy in selecting 550 features, with C-SVM achieving 99.6% and Q-SVM showing second-best accuracy in distinguishing late blight occurrences, emphasizing early detection for potato crop yield [16]. A study by Charanpreet Singh and colleagues using deep learning models, including EfficientNet, VGGNet-19, DenseNet-201, and ResNet-101, successfully identified potato virus Y-infected plants with an accuracy of 85%, highlighting the importance of early detection for disease management and crop yield improvement. The study demonstrated 85% accuracy in distinguishing healthy and PVY-infected potato plants, even with mild symptoms. It underscores the potential of deep learning models for real-time disease detection in agriculture and emphasizes the importance of accurate strain identification [17]. The study by JAYASHREE PASALKAR et al. presents a CNN-based method for predicting potato leaf diseases, achieving 97.4% accuracy. It uses transfer learning and a pre-trained CNN on a potato leaf image dataset. The approach is user-friendly, contributing to sustainable agriculture and food security. The CNN model outperformed traditional hard coding techniques in predicting potato leaf diseases, with 97.4% accuracy. It effectively differentiates between healthy and diseased leaves, reducing crop losses. The CNN-based method shows potential for improving crop productivity and disease management [18]. The article by Natnael Tilahun Sinshaw et al. reviews AI and machine learning techniques for detecting potato diseases, identifying major ones like late blight and bacterial wilt. It highlights deep learning's effectiveness over classical methods and categorizes 39 primary studies for future research. The review identified 39 studies on potato disease detection using deep learning algorithms, revealing their effectiveness over classical machine learning methods. The study identified open research problems and highlighted the importance of AI and machine learning in improving plant disease detection techniques [19].

REFERENCES	MODEL	ADVANTAGES
Mahum et al.	Dense net 201	Reduces dimension through the use of transition layers.
Ghosh et al.	ResNet50	Deeper architecture along with a high degree of feature learning
Tiwari et al.	Logistic Regression	Achieved 97.8% accuracy, greater other classifiers.
Ghosh et al.	Proposed CNN Models	Improved generalization via augmenting data
Tiwari et al.	VGG19	97.8% detection accuracy for potato disease was accomplished by transfer learning.
Vikash Sawan et al.	CNN Using Genetic Algorithm (GA).	Achieved an impressive accuracy of 98.3% after optimization using a genetic algorithm.

III. PROPOSED METHODOLOGY

The proposed arrangement consists of several key steps:-



Data collection

We used a publicly available collection of potato leaf photos for this investigation. Images of both healthy and diseased potato leaves can be found in the dataset. The diseases include leaf curl, late blight, and early blight [15]. There are 892 photos in our dataset. Images have been gathered from various sources. Three hundred photos are taken from the publicly accessible "Plant Village" database. We have gathered photos with the assistance of specialists from the University of Agricultural Sciences' plant pathology department in Dharwad, India. Additionally, we took pictures of both healthy and diseased potato leaves from a countryside and a plant station. The photographs were captured from various distances and angles. There are 430 photos of diseased leaves and 462 photos of normal leaves [8].

Data preprocessing

Before applying machine learning algorithms to picture datasets, it is crucial to preprocess them, namely by shrinking images and standardizing pixel values. Photos should be resized to the same dimensions (a width/height of 256 pixels in this instance), standardizing the size of the images throughout the dataset [10].

All visuals are rescaled to size 512 * 512. This reduces the computation and processing complexity. Additionally, this evenly scales the dataset to enable precise feature extraction. HSV pictures are created from the original photographs. Here, we work in HSV color space to use the intensity information for feature extraction and classification [8]. We pre-processed the dataset by randomly rotating, flipping, and zooming the photos before training the CNN model. We also divided the dataset into three parts: testing, validation, and training. 80% of the total was made up of each component [15].

Feature Extraction

The next stage is to extract features from the leaf HSV image after identifying the defective region. These characteristics will be applied to the classification process. Since texture features are effective in classifying HSV images, we use them here. We make use of texture characteristics that are taken from every linked component. Using a matrix of gray level co-occurrence from the hue component of the region of interest derived from related components in the HSV color space, seven textures are recovered.

Homogeneity, contrast, inverse difference, difference variance, uniformity, maximum probability, and diagonal are some of the different texture characteristics. Classification is done using the features that were extracted [8]. CNNs identify diseases by extracting pertinent information from photos of potato leaves, including color, texture, and shape [15].

Classification

The challenge of classifying is determining which set a new observation falls into. We employ classification in our study to determine whether a picture of a potato leaf is normal or diseased. Three well-known machine learning classifiers—SVM, RF, and ANN—are compared for performance. Additionally, we select the classifier that performs the best on our dataset. In essence, SVM is a kernel-based machine learning approach designed for linear separation. RF is an ensemble learning technique that builds a large number of decision trees. Even when data contains noise and randomness, it still performs well. An artificial neural network (ANN) is a computational model in which data moves across network node levels. Here, the seven texture characteristics serve as the inputs for an ANN with a seven-node input layer. There are fifteen nodes in the hidden layer, and the output layer is the third layer [11].

IV. CONCLUSION

Consequently, automated, image-based disease detection systems based on machine learning and deep learning technologies are experiencing more attention. The use of advanced image processing methods, including digital imaging, hyperspectral, and multispectral analysis, has shown promise in detecting disease symptoms on potato leaves. Based on photographs of leaves, machine learning algorithms—in particular, Convolutional Neural Networks, or CNNs—have shown remarkable accuracy in classifying various diseases. These AI-based models are very useful for widespread implementation in agricultural practices since they can automatically learn features from enormous data sets.

Improving model performance, creating more durable systems that can function in a variety of field scenarios, and integrating real-time disease monitoring into decision support systems are the keys to the future of potato leaf disease detection. In addition to lowering the need for pesticides, this will promote sustainable agricultural methods, strengthen crop health, and increase food security. Automated systems for detecting potato diseases will develop into vital resources for farmers through further innovation, ultimately enhancing the productivity and sustainability of potato production globally.

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