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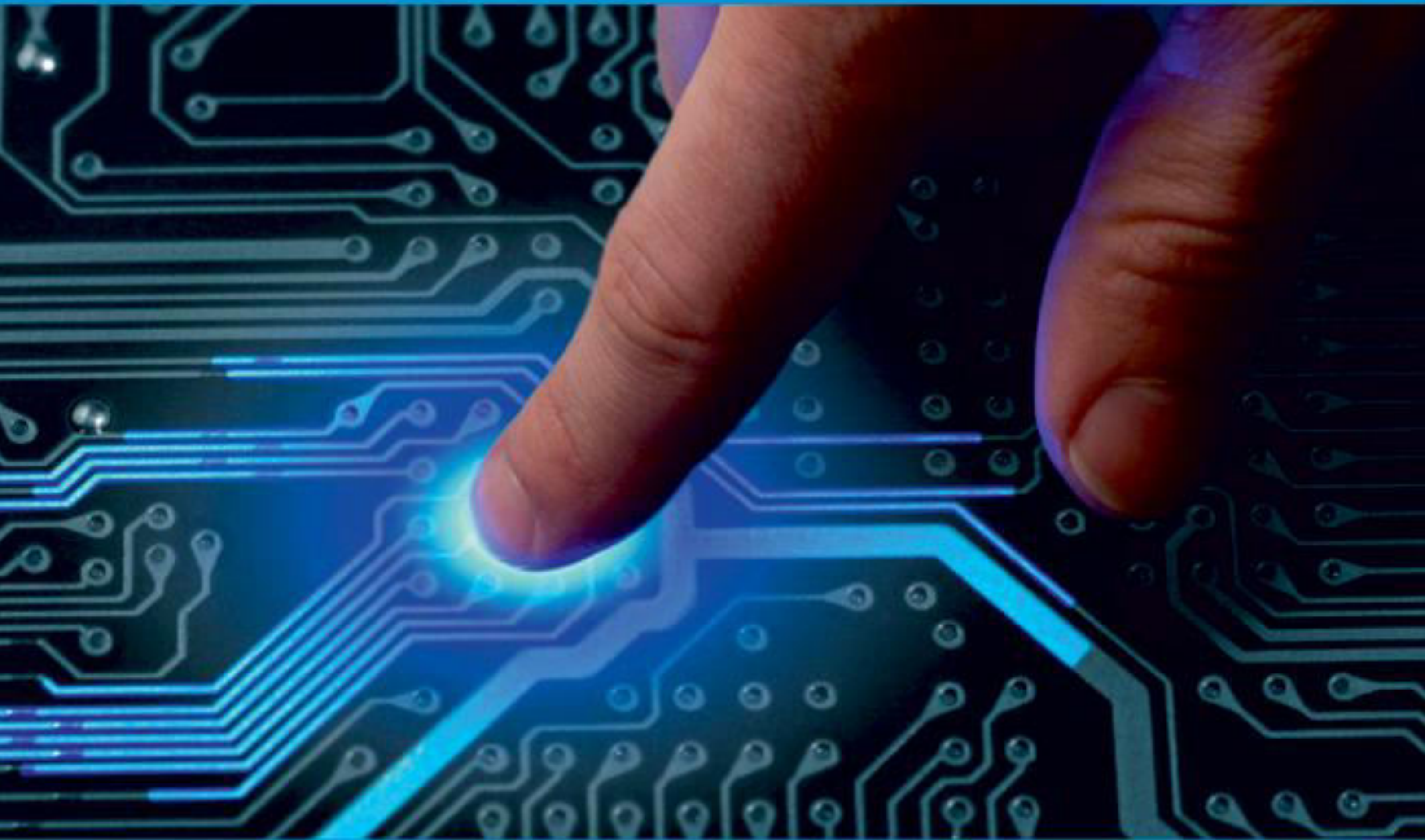

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An AI Enabled System to Detect Potato Disease

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ABSTRACT: Potato, a globally consumed vegetable, holds a prominent position in agriculture, recognized as the primary vegetable worldwide. Despite their widespread cultivation, potatoes face a significant threat from various diseases, including early blight, late blight, and septoria blight. These diseases can inflict severe damage if not addressed promptly, leading to substantial economic losses for farmers. To mitigate these challenges, a proposed model in this research employs advanced image processing methods to detect and identify diseases affecting potato leaves. Among the various Machine Learning algorithms, the Convolutional Neural Network (CNN) emerges as a preferred choice for its effectiveness in image classification.The proposed research methodology involves analyzing images of both normal and disease-affected potato leaves. Through meticulous algorithmic scrutiny, the model accurately labels potato plant leaves as either diseased or normal. This approach aims to empower farmers by enabling early detection of diseases, facilitating timely intervention, and ultimately safeguarding against significant economic losses.

KEYWORDS: extraction, logistic regression, convolutional neural network, deep learning

I. INTRODUCTION

Potato is a vital food crop in India, serving as a crucial source of carbohydrates. However, the potato's production faces significant challenges due to various diseases, Protecting crops involves dealing with weather, diseases, and threats from animals. While we can take measures against animal risks, we can't control the weather, which makes agricultural outcomes unpredictable.

Another major aspect is to consider how diseases affect crop growth, especially for important foods like potatoes, which are a staple for most of India's population. Diseases like late blight (PhytophthoraInfestans) and early blight (AlternariaSolani) are serious threats. Identifying and classifying these diseases quickly is crucial to avoid losing crops and facing financial losses.

To address this issue, efficient disease detection becomes imperative. Traditional methods, relying on naked-eye observations by farmers or local experts, prove inadequate due to time constraints and a lack of expertise. Consequently, an automatic leaf disease detection system is essential.

Using digital solutions, especially image analysis, is a more efficient way to monitor and identify plant diseases. We can look at visible patterns on plant leaves using different image processing methods. The patterns we find are then compared with historical data, and machine learning helps classify the diseases.

In nutshell combining image processing and machine learning is a powerful strategy to accurately identify and classify agricultural diseases. This approach helps improve crop protection and promotes sustainable agricultural practices..

II. RELATED WORK

Identifying diseases in plants during their initial stages is a significant priority in the field of agriculture. Numerous researchers are actively addressing the challenge of early detection and diagnosis of plant diseases. The outcomes of their research efforts in this area include the following results

Monzurul Islamel et. at. [1] have developed a method to diagnose plant diseases, specifically potato diseases, that incorporates image processing and machine learning. Employing image analysis on publicly available images from 'Plant Village,' their system efficiently categorizes diseases in potato plants and distinguishes healthy leaves. Utilizing a segmentation process and employing support vector machine (SVM) methodology for classification, the proposed model demonstrated a noteworthy accuracy of approximately 95% when classifying around 300 images. The implementation of multiclass SVM image segmentation contributes to the development of an automated and user-friendly system. This system successfully identifies major potato diseases, including Late Blight and Early Blight, with minimal computational effort. In essence, this methodology presents a scalable and efficient solution for the automated

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diagnosis of plant diseases, offering farmers a reliable and time-saving approach to identifying and mitigating issues in their crops.

Sardoganel at.[2]have explored the utilization of transfer learning and diverse pre-trained models on a dataset of potato leaf images. Their findings indicated that VGG 19 exhibited the highest accuracy, reaching 97.8%. This outperformed the accuracy of a back propagation neural network, which achieved 92%, and a support vector machine, which achieved 95%. The research highlights the efficacy of VGG 19 in accurately classifying potato leaf diseases, showcasing its superior performance compared to alternative models in the experimental setup.

Malvika Ranjanel et.al [3] have presented an intricately designed disease detection system tailored for cotton plants. The methodology involves the capture of images depicting disease-affected cotton leaves. Subsequently, a sophisticated integration of diverse image processing techniques and Artificial Neural Network (ANN) methodologies is employed for the purpose of distinguishing between healthy and diseased samples. Notably, the ANN classification process demonstrated an accuracy level of 80%. This research signifies a systematic and technologically advanced approach to plant disease detection, particularly in the context of cotton crops.

Prajwala TM el at.[4] have presented a novel approach for detecting and identifying diseases in tomato leaves. Their work utilized a modified Convolutional Neural Network (CNN) model known as LeNet. The neural network incorporated an automatic feature extraction technique, enhancing its ability to classify various diseases affecting tomato plants. The proposed system demonstrated a noteworthy average accuracy ranging from 94% to 95% in effectively identifying and detecting diseased leaves. This achievement underscores the practicality and effectiveness of employing neural networks for automated plant disease diagnosis.

In their groundbreaking 2016 research, Waghmare and Kokare[5] have introduced a novel plant disease detection method for grape leaves. Utilizing image capture and meticulous segmentation, the approach employs a high-pass filter to extract unique diseased leaf textures. Locally based fractal features ensure texture pattern invariance, facilitating multiclass SVM for disease identification. With a remarkable 96.6% accuracy, the system automates Decision Support Systems, aiding farmers in promptly addressing prevalent grape diseases like downy mildew and black rot.

Wang et al.[6] have introduced an innovative method for disease discrimination in wheat and grapevines, utilizing K-means segmentation and extracting a comprehensive set of 50 features. This sophisticated approach enhances accuracy by analyzing color, shape, and texture characteristics. The formalization of these techniques contributes valuable insights into image processing applications for agricultural crop disease discrimination.

Namrata R. Bhimte et al. have rigorously classified cotton leaf diseases, as documented in [7]. Their methodology involves employing K-means segmentation, a color-based technique, to isolate the disease-affected portion of a leaf image. The classification process hinges on extracting pertinent features, notably the color and texture, from the segmented image region. Remarkably, their classification model achieves an impressive accuracy rating of up to 98.46%.

Damian Bienkowski et al.[8] have Potato disease detection using non-imaging spectrometry analyzed the visible and near-infrared spectrum, achieving 84.6% accuracy for foliar symptoms. Distinguishing healthy and pre-symptomatic leaves reached 92%, but field trials showed lower accuracy in whole-plant readings ($r2$: 0.66 for late blight, 0.31 for blackleg, 0.41 for healthy foliage). The models struggled with subtle foliar impacts. Despite impractical broad-acre spectrometer deployment, hyper spectral imaging holds promise for precision agriculture and Integrated Pest Management in potato disease management. Methodology used: VGG19 for fine-tuning (transfer learning) with Logistic regression.

The study, authored by Farabee Islam et al.[9], focuses on advancing potato disease detection using leaf images and transfer learning. With a goal to enhance potato production and minimize farmer costs, the authors implemented a transfer learning technique, leveraging pre-trained deep learning models to detect diseases early. The experiments, encompassing 152 healthy leaves, 1000 late blight leaves, and 1000 early blight leaves, achieved an impressive 99.43% accuracy in testing (20% test data, 80% train data). The research compared sequential deep learning models with various pre-trained models, highlighting the superiority of transfer learning. This approach demonstrated exceptional performance, surpassing all existing works in potato disease detection. Methodology used transfer learning.

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Potato, a globally significant crop, faces hindrances to proper growth due to diseases, notably Early Blight (EB) and Late Blight (LB). M D AsifIqbalel at.[10] have proposed an image processing and machine learning-based system utilizing seven classifiers, with the Random Forest achieving 97% accuracy. By analyzing 450 images from a public plant village database, the approach paves the way for automatic plant leaf disease detection, promising improved potato cultivation practices using Random Forest Classifier.

Athanikar el at.[11],have presented a neural network-based method for detecting and classifying potato leaf samples, employing K-Means Clustering segmentation. The developed algorithms extract 24 features, encompassing color, texture, and area, from single leaf images. Utilizing a Back Propagation Neural Network (BPNN), the system identifies and classifies leaves as healthy or diseased, providing disease descriptions. The features, including color, texture, and area, contribute to training the neural network achieving over 92% accuracy, the trained network successfully classifies both healthy and diseased leaves, showcasing the effectiveness of multi-feature extraction. Methodology used gray level co-occurrence matrix (GLCM),A back Propagation Neural Network (BPNN).

MalvikaRanjan el at.[12], focuses on the analysis and classification of PhyllanthusElegans Wall leaves, particularly assessing their potential in breast cancer treatment. The research aims to offer an alternative to conventional treatments like chemotherapy. It involves image acquisition, processing, and classification, emphasizing segmentation using HSV for color transformation from RGB. Leaf disease analysis considers color and shape, employing a feed-forward Neural Network with Back-propagation for classification. Comparative results between Multi-layer Perceptron (MLP) and Radial Basis Function (RBF) highlight the Neural Network's superior accuracy. The methodology is based on MLP and RBF algorithms, with the advantage of applicability to various plant types. Methodology Used Multi-layer Perceptron (MLP) and Radial Basis Function (RBF).

Addressing the challenges in paddy production due to diseases, paper[13] introduces an automated system for diagnosing common paddy leaf diseases—Brown spot, Leaf blast, and Bacterial blight. Farmers in remote areas often struggle with disease identification, prompting the need for an efficient solution. K-means clustering is used to isolate affected parts in paddy leaf images and visual features like color, texture, and shape are utilized for disease classification. The Support Vector Machine (SVM) classifier recognizes the type of paddy leaf diseases. Following identification, the system recommends pesticides/fertilizers based on disease severity, aiding agricultural decision-making. Study by Yao Q et al[14] introduces image processing techniques and Support Vector Machine (SVM) for early and accurate detection of rice diseases. Employing SVM, rice disease spots are segmented, and their shape and texture features are extracted. The method is applied to classify rice bacterial leaf blight, rice sheath blight, and rice blast, achieving an impressive accuracy of 97.2%. The SVM approach proves effective in detecting and classifying these disease spots.

The research in [15] focuses on identifying leaf spot, a prevalent crop disease, through a four-stage process: image acquisition, K-means clustering-based image segmentation, feature extraction (Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, and Variance), and classification using a Neural Network (NN) classifier. The proposed system achieves impressive accuracies, with bacterial leaf spot and target spot of cotton leaf diseases reaching 90% and 80%, respectively. For tomato leaf diseases septoria leaf spot and leaf mold—the accuracy is an outstanding 100%. Methodology used is K-means and KNN.

III. METHODS FOR DISEASE DETECTION

The outcome of literature review indicates the application of following methods that support the early disease detection in potato crop.

2.1 Convolution Neural Networks (CNNs)

Deep Convolutional Neural Networks (CNNs) have revolutionized leaf disease detection by automatically extracting intricate features from images without manual intervention. Their advantages span various applications, including precision agriculture [6].

Convolutional Layer: This initial layer applies convolution operations using kernels to produce feature maps, capturing essential lower-level features from leaf images.

Pooling Layer: The down sample feature maps will reduce the complexity and overfitting. Max pooling, a common technique, retains important information while reducing data size.

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Fully Connected Layer: Positioned at the network's end, these layers transform flattened feature maps into 1-D data for final predictions, employing both linear and non-linear transformations.

Optimal weights, obtained through techniques like gradient descent and the Adam algorithm, will play a crucial role in enhancing model performance and minimizing loss. The seamless integration of these layers enables deep CNNs to effectively detect and classify leaf diseases, aiding in agricultural decision-making.

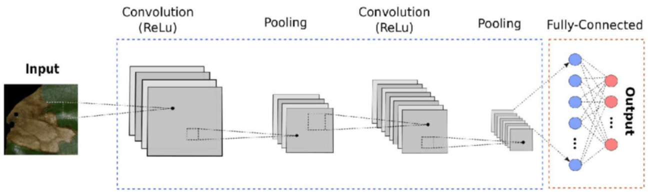

Fig 1. CNN model for disease detection

1.2 VGG Model

This model involves assembling a diverse array of plant images and sorting them into healthy foliage and disease categories. The VGG model, trained on the ImageNet dataset, serves as the foundation, with its convolutional layers extracting patterns indicative of plant health.

The VGG model undergoes customization to detect disease markers within plant imagery, refining its proficiency in plant health interpretation. Training refines its ability to correlate visual cues with plant health, guided by loss and accuracy metrics.

Validation and testing ensure the model's efficacy, with adjustments for dynamic evolution. Once validated, the model transitions to practical use, providing automated, image-based diagnoses for farmers.

By leveraging pre-trained models, this approach amalgamates deep learning and transfer learning to safeguard plant health effectively, symbolizing the convergence of technology and agriculture for a sustainable future.

The process involves assembling plant images, training the VGG model, refining its abilities through training and validation, and deploying it for automated diagnoses.

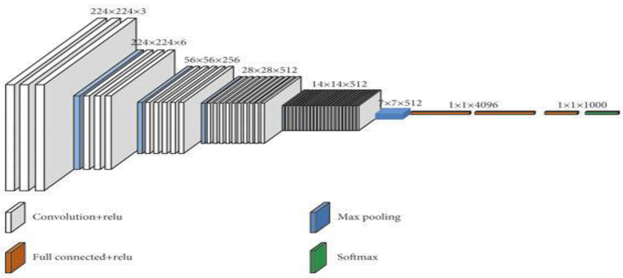

Fig 2. VGG Model

1.3 VGG19

Utilizing the VGG19 model for plant disease identification is a meticulous process. Initially, a dataset of labeled plant images is curated, each tagged based on its health status. These images undergo thorough preprocessing, including resizing and pixel value normalization to meet VGG19's input requirements.

VGG19's deep architecture, with 16 convolutional layers and 3 dense layers, excels in extracting intricate features from images. Fine-tuning the model may be necessary to capture the nuances of plant disease patterns effectively.

During training, the model is trained comprehensively or selectively, with adjustments made for optimal performance. Validation and testing validate the model's accuracy, fine-tuning hyperparameters as needed.

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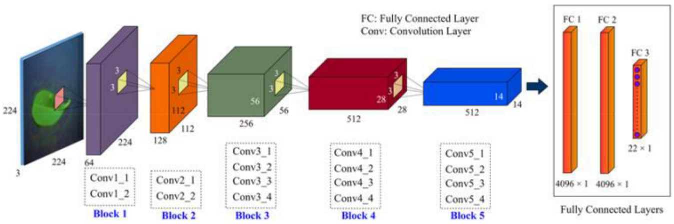
Once achieving satisfactory results, the model transitions to real-world applications, aiding agricultural professionals in automating plant health classification. This technology facilitates early disease detection and management, leveraging VGG19's advanced feature extraction and tailored fine-tuning to address plant disease identification challenges.



1.4 SUPERVISED LEARNING

In the realm of plant disease detection, supervised learning is crucial, utilizing meticulously labeled datasets to train models in distinguishing healthy and diseased plants. The journey begins with assembling and preprocessing comprehensive datasets, ensuring uniformity and quality. Various feature extraction methods, from color histograms to pre-trained CNNs, capture plant health essence.
In the data preparation phase, algorithms like Support Vector Machines, Decision Trees, Random Forests, and CNNs are tested. They are trained meticulously to refine parameters and predict plant health accurately.
Hyperparameter tuning and cross-validation enhance performance and guard against overfitting. Deployed models offer prompt diagnosis, minimizing crop damage, and bolstering agricultural productivity.
This fusion of supervised learning with agriculture offers automated tools for disease diagnosis, advancing sustainable farming practices and global food security.

Support Vector Machines (SVM), Decision Trees, Random Forests, and sophisticated deep learning models like Convolutional Neural Networks (CNNs) are utilized .
SVM, K-NN, and CNNs are used for plant leaf disease detection, showcasing the effectiveness of machine learning approaches
Plant disease classification involves dataset creation, preprocessing, and the utilization of machine learning algorithms like SVM, K-NN, and CNNs.

IV. PROPOSED SYSTEM

In light of the review made the following steps are used to detect disease in potato crop applying machine learning strategy.

1.Data Collection: Gather a comprehensive dataset of potato crop images showing both healthy plants and various disease symptoms. This dataset should cover different potato varieties, growth stages, and environmental conditions.
2.Data Preprocessing: Clean and pre process the collected data, including image normalization, resizing, and augmentation to ensure uniformity and enhance model generalization.
3.Model Selection: Choose an appropriate deep learning architecture, such as convolutional neural networks (CNNs), for image classification tasks. Consider pre-trained models like ResNet, VGG-16 and VGG-19, or Inception, which can be fine-tuned on the potato disease dataset to leverage their learned features.
4. Model Training: Train the selected model on the pre processed dataset using techniques like transfer learning to adapt the model's parameters to the specific task of potato disease classification. Use techniques such as batch normalization, dropout, and early stopping to improve model performance and prevent overfitting.
5. Model Evaluation: Evaluate the trained model's performance using metrics like accuracy, precision, recall, and F1 score on a separate validation dataset. Adjust hyper parameters and model architecture as needed to optimize performance.
6. Deployment and Integration: Deploy the trained model into a user-friendly application or web interface accessible to farmers. Integrate the model with remote sensing technologies, if applicable, to enable real-time disease monitoring and prediction.
7. Continuous Improvement: Continuously collect feedback from users and stakeholders to improve the model's performance and usability. Incorporate new data and updates to keep the model relevant and effective in detecting emerging disease patterns.

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8. Collaboration and Knowledge Sharing: Foster collaboration with agricultural experts, researchers, and farmers to exchange knowledge, validate model predictions, and ensure alignment with real-world agricultural practices.

V. RESULTS AND DISSUSION

The AI-based web app achieved promising results in detecting potato leaf diseases using the VGG-19 algorithm. The model exhibited high accuracy, precision, recall, and F1-score in classifying various diseases such as early blight, late blight, and healthy. The app's interface allowed users
to upload images of potato leaves, which were then processed by the model to provide real-time disease identification. Plant village and Potato disease dataset consists of 1500 image files of 3 different classes, namely early blight, late blight, and healthy. We have used 100 early blight,100 late blight and 100 healthy images of leaf.

Disease	Accuracy rate
Early Blight	97.02
Late Blight	96.08
Healthy	98.01

The successful implementation of the VGG-19 algorithm in the web app demonstrates the effectiveness of deep learning in potato disease detection. The app's user-friendly interface and real-time processing capabilities make it a valuable tool for farmers and researchers. However, further improvements can be made to enhance the app's performance, such as integrating additional deep learning models for improved accuracy and expanding the dataset to include more diverse images for training. Overall, the web app shows great potential in revolutionizing the way potato diseases are detected and managed in agriculture.

VI. CONCLUSION

In today's agricultural landscape, early disease detection in plants is paramount for optimizing productivity and ensuring high-quality yields. Given the expertise required for disease diagnosis, implementing a smartphone-based detection system holds immense promise. By enabling farmers to simply capture images of affected leaves and transmit them to a server, this technology streamlines the process. The server, equipped with advanced algorithms, swiftly analyzes the images, identifies the specific disease, and recommends tailored treatment solutions. This seamless integration of smartphone technology with disease detection not only empowers farmers with timely insights but also fosters enhanced crop management practices, ultimately contributing to a sustainable and prosperous agricultural ecosystem.

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