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SURVEY ON COMPUTERIZED POTATO PLANT DISEASE DETECTION

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Abstract: Plant diseases are a major threat to agricultural productivity worldwide, hence prompt and efficient detection techniques are required. Conventional manual inspection techniques take a lot of time, require a lot of work, and are frequently subjective. This studyexamines the latest developments in machine learning methods for plant disease diagnosis, with an emphasis on image processing, featureextraction, and classification algorithms. The assessment addresses the obstacles and potential paths forward in this subject while highlighting the technology' ability to completely transform the treatment of plant diseases.

Index Terms: Machine Learning, Image Processing, Deep Learning, Convolutional Neural Networks (CNN), SupportVector Machines (SVM).

I. INTRODUCTION

In order to meet the anticipated demand, there needs to be a minimum 50% increase in agricultural production worldwide by 2050 [1].The bulk of production now takes place in Africa and Asia, where 83% of farmers arefamily-run businesses with little to no experience in horticulture [2,3]. As a result,crop losses from pests and illnesses that exceed50% are frequent [4]. The old method of using visual inspection and human analysis to classify agricultural illnesses is no longer practical. The creation of computer vision models provides a rapid, standardized, and precise resolution to this problem. A classifier can also be used as an application after it has been trained [5]. Simple to use, all you need is a smartphone with a camera and an internet connection. The commercial app "iNaturalist" is well-known [6].

II. BASIC CONCEPTS/TECHNOLOGYUSED

Essential ideas in plant disease detectioninclude image processing, machine learning,and plant pathology. While deep learning and machine learning, particularly with regard to Convolutional Neural Networks (CNN), aid in the recognition of intricate patterns, image processing improves and analyzes images. Model performance is enhanced by data augmentation, while disease characteristics are identified by feature extraction and classification algorithms.[10] Accurate and trustworthy disease detection is ensured through model evaluation and training.

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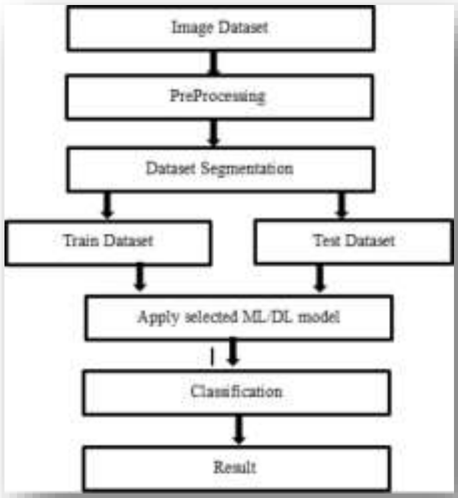

Figure 1

PRE-PROCESSING

Preprocessing is a critical step in data analysis and machine learning, transforming raw data into a clean and usable format. It involves several key steps: data cleaning, which addresses missing values, errors, and duplicates; data transformation, which scales and encodes features; data integration, which combines data from various sources; and data reduction, which simplifies the dataset without losing vital information. Techniques like normalization, one-hot encoding, and PrincipalComponent Analysis (PCA) are commonly used. Effective preprocessing ensures that the data is consistent, accurate, and ready for analysis, leading to more reliable and insightfulresults[6].

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IMAGE PROCESSING

Image processing is essential in plant disease detection, involving techniques to enhance and analyse images for meaningful information. Toboost image quality and eliminate noise, preprocessing techniques like scaling, filtering,and contrast enhancement are applied after high-quality plant part photographs have been taken.[2] Diseased regions are isolated by segmentation, and important attributes including colour, texture, and form are identified through feature extraction. These procedures enable automated, prompt, and accurate disease identification and intervention in agriculture by converting raw visual data intoactionable information[8].

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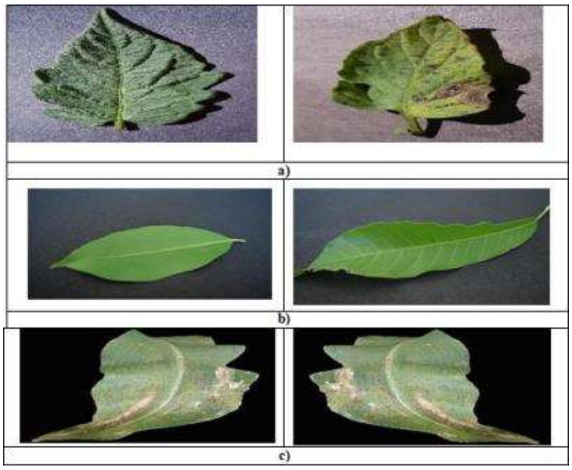
DATA SEGMENTATION

Data segmentation in plant disease detection involves a series of steps to accurately isolate diseased regions in plant images. It starts with image acquisition using high-resolutioncameras, followed by preprocessing to enhanceimage quality through noise reduction and contrast adjustment. The core segmentation techniques include thresholding, edge detection, clustering, and deep learningmethods like Convolutional Neural Networks (CNNs), each serving to partition the image into meaningful segments. Post-processing techniques like morphological operations further refine these segments. Finally, feature extraction identifies key characteristics such ascolour, texture, and shape from the segmented regions, enabling precise disease classification and analysis.



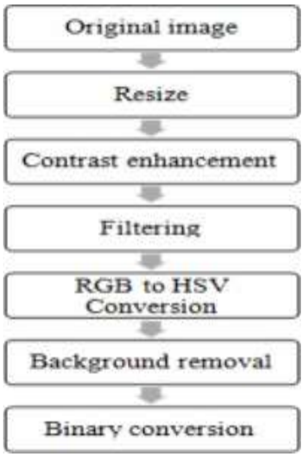


Figure 2 Figure 3

FEATURE EXTRACTIION

Feature extraction is a crucial step in plantdisease detection that involves identifying and quantifying key characteristics from segmentedimages. These characteristics, which include colour, texture, and shape, provide valuableinformation about the regions of interest[9]. Forexample, colour features may involve theaverage RGB or HSV values, while texturefeatures might use Gray-level co-occurrencematrices (GLCM) or Local Binary Patterns (LBP) to capture surface patterns[11]. Shape features could include geometric properties likearea, perimeter, and aspect ratio. By transforming raw image data into a set of informative features, feature extraction enablesmore accurate and efficient classification of plant health[8].

III. STUDY OF RELATED WORK

DISEASES OF POTATO PLANT

Our dataset lists several potato diseases, along with symptoms and preventative strategies. Wart, Charcoal Rot, Soft Rot, Bacterial Wilt, Black Scurf, Common Scab, Dry Rot, LateBlight, Early Blight, Potato Leafroll Virus, andPotato Mosaics are some of the important diseases. Warty growths, decaying tubers, and leaf withering and discoloration are some of the symptoms. The use of disease-free seed tubers,crop rotation, appropriate watering, andfungicide sprays are the main components of control measures. In order to manage thesediseases and reduce crop losses, preventive methods including preserving soil conditions
and avoiding injuries during harvest are essential.

PRE-PROCESSING

Since different datasets are used, preprocessingis critical as the images may differ in resolutionand background. The preprocessing techniquesused in this research are illustrated in Figure 3.The utilization of preprocessing techniques, namely resizing images to 227x227x3, applying an edge threshold of 0.75 for contrastenhancement, and applying the strel function for edge sharpening, effectively improves image quality and highlights features. By simplifying the images through background separation and binary conversion, significant features can be easily identified for additional

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examination. These preprocessing steps are crucial for preparing images for deep learningmodels, as they improve data consistency and clarity[11].

Rotation of healthy images for data augmentation successfully tackled class imbalance by boosting the quantity of healthy images from 152 to 1000. After augmenting thedataset, it was divided into training, validation,and test sets and handled with the Keras libraryusing different batch sizes and image dimensions in order to improve model performance. Preprocessing and augmentation techniques greatly enhanced dataset balance and quality, resulting in improved accuracy in classifying potato leaves using a deep learning model. Transfer learning using the pretrained MobileNet model helped create a strong classifier that can accurately identify plant diseases[12].

TRANSFER LEARNING

The dataset was split in a 7:3 ratio for training,and AlexNet was employed with 25 layers andmodified output layers to differentiate betweenhealthy and diseased plants. The model was trained with a learning rate of 0.1 for 25 epochs, involving 10,000 iterations and validationevery 10 iterations. The tailored design of AlexNet and carefully planned training regimensignificantly improved the model's accuracy inidentifying plant health. The method enabled effective learning and strong disease identification[11].

Class imbalance and model adaptation are effectively addressed by this study's preprocessing and transfer learning methods. The preprocessing steps improved the quality and balance of the dataset by performing imagesegmentation and data augmentation, making itmore suitable for training adeep learning model.[12]

OPTIMISATION TECHNIQUE

The Adaptive Gradient Algorithm (AdaGrad), Root Mean Square Propagation (RMSProp),and Adaptive Moment Estimation (Adam) wereamong the optimization algorithms compared. Adam was found to be the most efficient, with a learning rate of 0.0001, and it performedbetter than stochastic gradient descent.

The model's refinement was significantly aidedby the selection of loss functions and optimization algorithms. Adam outperformed other algorithms thanks to its carefully selectedlearning rate, makingtraining more efficient[12].

Ref no:	Research Work/Paper	Author / Year	Techniques	Experiments/ Observations	Remarks
[1]	"Detection and Classification of Plant Leaf Diseases Using Image processing Techniques: A Review"	Savita N. Ghaiwat	Various techniques such as Artificial neural network, Probabilistic Neural Network, Genetic Algorithm, k-Nearest Neighbor, Principal Component Analysis and Fuzzy logic.	Neural networks and SVMs arehighlighted for their strengths in handling specific types of data and noise, but also for their complexity.	suitable for a particular application by evaluatingthe strengthsand weaknesses of various techniques.
[2]	"Automatic Detection and Classification of Plant Disease through Image Processing"	Mr. Pramod and S. landge	An image processing based software methodology for plant diseases detection and classification	an image processing based software methodology forplant diseases detection and classification	will reduce cost, chemical testing procedure, time and
					enhance productivity.

[3]	"Automatically identify plant diseasesby analyzing lesion spots on leaves usingdeep learning techniques"	SP Adarsha	Deep Convolutional Neural Networks (CNN): A CNN model istrained on a dataset ofleaf images with labeleddiseases. This model learns to recognize patterns in the lesion spots that correspond to different diseases.	The study highlights the potential of deep learning in agricultural applications, particularly in disease detectionand management.	Accurate and timely disease identification can significantly contribute to improving crop yields and reducing economic losses in agriculture.
[4]	"Identification of plant-leaf diseases using CNN andtransfer-learning approach"	Sk Mahmudul Hassan	Depthwise Separable Convolution: This technique is integrated to significantly reduce the number of parameters and computational cost without compromisingaccuracy.	The MobileNetV2 architecture, with its optimized parameters, is compatible with mobile devices, suggesting potential for real-time disease detection in agricultural settings.	While achievinghigh accuracy, the generalizabili ty of the model todiverse plant species and disease typesmight necessitate further investigation.
[5]	"Digital image processing techniques for detecting, quantifying and classifying plant diseases"	J. G. A. Barbedo	Deriving meaningful information from segmented images, such as color, texture, and shape characteristics.	The paper provides a thorough overview of digital image processing techniques applicable to plant disease detection.	The effectiveness of traditional image processing techniques might be constrained by compl exdisease symptoms and varyin gplant conditions.
[6]	"Plant disease detection using deep convolutional neuralnetwork"	J Arun Pandian	Fine-tuning of learningrate, batch size, and optimizer to maximize model performance.	The proposed 14-DCNN achieved impressive training and validation accuracies of 99.993%and 99.985%, respectively.	Exploring the model's performance on real-world, uncontrolled image conditions would be valuable for

					practical applications.
[7]	"Plant DiseaseDetection Using CNN"	NishantShelar	The core of the model, CNNs are employed for image processing and classification.	The core of the model, CNNs are employed for image processing and classification.	The research focuses on a specific dataset and might not generalize well to otherplant speciesor disease types.
[8]	"Color Transform Based Approach for Disease Spot Detectionon Plant Leaf"	Piyush Chaudhary, Anand K. Chaudhari, Dr. A. N. Cheeranand Sharda Godara	Otsu method of threshold calculation is applied to detect diseasespot on color component. Various"Dicot" and "Monocot" family plants leaves were analyzed in both noisy and noise free (white) background	In this paper,effect of HSI, CIELAB color and YCbCrspaces comparison has been done for spot detection	Developed algorithm is independent of disease s spot color, plant type and background noise.
[9]	Transfer learning- based deep ensemble neural network for plant leaf disease detection	Sasikala Vallabhajos yula, Venkatrama phanikumar Sistla, and Venkata Krishna Kishore Kolli	Pre-trained models are fine-tuned on a plant leafdisease dataset to adapt to the specific task.	Leveraging pre-trained models accelerated training and improved accuracy.	Exploring different ensemble combination methods and hyperparame ter optimization could further enhance performance.
[10]	Deep learning system for plant disease detection andclassification	Amritha Haridasan, Jeena Thomas, and Ebin Deni Raj.	A convolutional neural network (CNN) architecture is employed for disease detection andclassification.	The proposed CNN model demonstrated high accuracy in classifying paddy plant diseases.	Exploring advanced CNN architecturesor incorporating transfer learningcould potentially enhance performance.
[11]	"Plant DiseaseDetection Over Multiple DatasetsUsing AlexNet"	Palika Jajoo, Mayank Kumar Jain, SarlaJangir	Pre-processing, image processing, transferlearning	Data augmentation, specifically rotating healthy images, effectively addressed class imbalance by increasing the	By enhancing feature visibility and simplifying the dataset, the methods contribute to more

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				number of healthy images from 152 to 1000.	accurate and efficient plant disease detection.
[12]	"Application of MobileNet-v1 for Potato Plant Disease Detection Using Transfer Learning",	Anshuman Singh, Sumita Mishra, Vineet Singh	Optimisation technique, transfer learning	The model's refinement was significantly aidedby the selection of loss functions and optimization algorithms	Adam was found to bethe most efficient, with a learning rateof 0.0001

Table of comparison of all concepts

IV. CHALLENGES FACED IN EXSISTINGSYSTEM

- **Varied Morphological Features:** Plant diseases present diverse and complex morphological features, making it challenging to select a classification method that can accurately differentiate between various diseasepatterns. Each method has its strengths andweaknesses, and no single method is universally effective.

- **Time Complexity:** Methods like k-Nearest Neighbor (k-NN) are straightforward and easy to implement but are computationally intensive.They require significant time to makepredictions, especially with large datasets, as they calculate the distance to every trainingsample for classification.

- **Complex Algorithm Structure:** Artificial Neural Networks (ANN) are highly effective for classification tasks but come with a complexand often opaque algorithm structure. Understanding and tuning neural networks require significant expertise and computationalresources, making them difficult to deploy andmaintain.

- **Parameter Optimization:** Support VectorMachines (SVM) are excellent for handlinghigh-dimensional data and provide robust performance. However, finding the optimal parameters (such as the kernel type andregularization parameters) for training SVMs on non-linear data is a difficult and time- consuming task, which complicates their implementation.

- **Noise Tolerance:** While ANN can handle noisyinput data well due to their inherent robustness,other techniques may not perform as well in thepresence of noise. This can lead to decreased accuracy and reliability in real-world applications where data is often imperfect.

- **Computational Complexity:** Techniques like SVM involve quadratic optimization processes that are computationally intensive. This high computational demand can limit the scalabilityand efficiency of SVMs, especially when applied to large datasets or complex classification problems.

- **Lack of Generalization:** Some classification techniques may perform exceptionally well on specific datasets but fail to generalize across different plant species, environments, or conditions. This lack of robustness and adaptability can limit the applicability of these models in diverse agricultural settings.

V. CONCLUSION

The study highlights developments in computerized plant disease identification through the use of deep learning, machinelearning, and image processing methods. According to the paper, classification models such as Convolutional Neural Networks (CNNs) and AlexNet have an accuracy range of 95–98%, particularly when preprocessing and transfer learning techniques are used to improve them.

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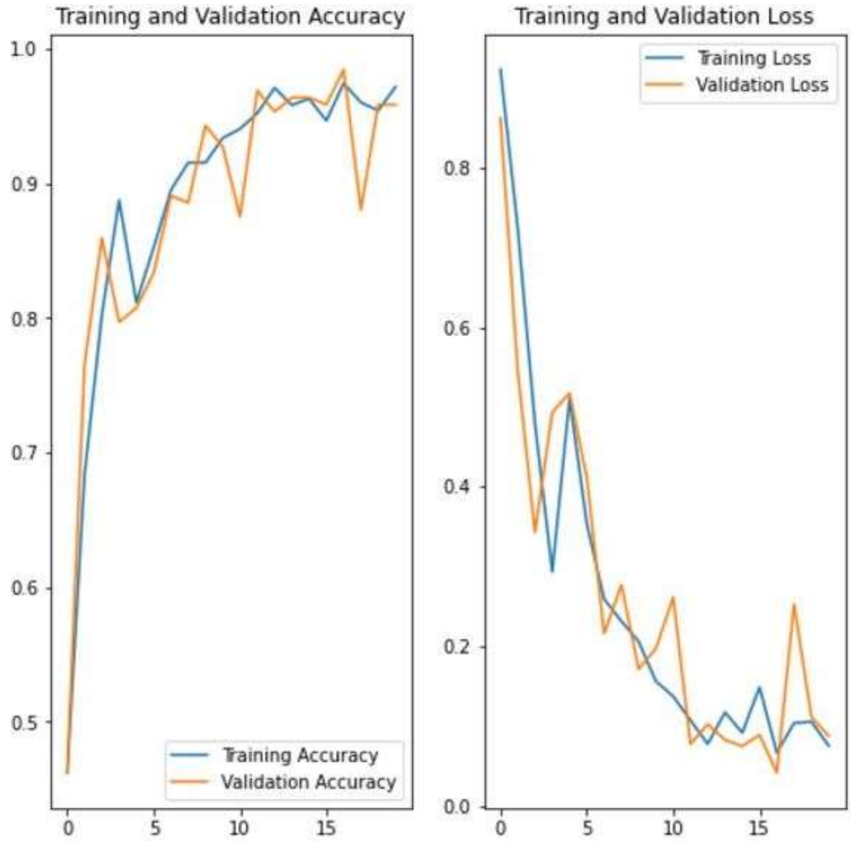

We are currently in the development phase of our project, where we are assessing andderiving conclusions from different methods toidentify the most efficient way to detect plant diseases. By using various preprocessing techniques like resizing images, applying edge thresholds for contrast enhancement, and usingedge sharpening functions, we have observed notable enhancements in image quality and feature highlighting.

After reviewing approaches in different studies,we found that Convolutional Neural Networks (CNNs), when used alongside data augmentation and transfer learning methods,typically deliver improved precision and resilience in identifying diseases. An example isthe promising results shown in potato plantdisease detection using MobileNet-v1 with transfer learning. Likewise, AlexNet has been successfully employed across various datasets for identifying plant diseases. Although Support Vector Machines (SVMs) offered useful insights, they were not as effective as CNNs.

Our continuous evaluation shows that preprocessing steps such as background separation and binary conversion are essential in boosting the visibility of important features, thereby enhancing the overall performance of the model. Our objective is to find a thorough and effective way to accurately detect plantdiseases by improving our methods and using more advanced techniques.

Additional studies will concentrate on enlarging the dataset, integrating differentdisease types, and investigating hybrid models to enhance detection abilities. Ongoing progress in machine learning and computer vision is anticipated to lead to more advanced

and automated agricultural solutions, ultimatelyresulting in improved crop health and higher agricultural productivity.

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