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Image Based Plant Disease Classification Using Deep Learning Technique

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ABSTRACT- As living beings, our reliance on plants and animals for sustenance is crucial. However, the available food resources cannot sustain the global population for extended periods, as only 29% of the Earth's land is suitable for sustaining the entire ecosystem. If we didn't have plant-eating bacteria or locusts, we might have enough resources to last for years. This is where my project, Plant Disease Detection and Recognition, comes into play. The main objective of this project is to identify and diagnose the diseases affecting plants, as well as determine the most effective treatments.
By utilizing this system, we can obtain accurate information about the specific diseases afflicting plants. Additionally, we can identify the appropriate medications for eradicating these diseases completely. Plant diseases pose significant threats to the well-being of plants and trees, making it vital to detect them early in order to take appropriate measures. Understanding the type of disease before administering treatment is crucial. With a 92% accuracy rate, our system enables us to work on plants effectively, thereby extending their lifespan.
After undergoing multiple tests, this initiative has emerged as a promising boon for humankind. Farmers, who serve as the backbone of nations, play a crucial role in our survival. Ensuring that they receive fair prices for their yields is paramount, and our system will play a significant role in achieving this. By supporting agricultural sustainability and promoting healthier crops, we can create a positive impact on food production and contribute to the overall well-being of society.

KEYWORDS: Plant diseases detection; CNN; image classification; deep learning in agriculture

I. INTRODUCTION

In India, agriculture plays a vital role in the country's early development as it serves as the backbone of the nation. However, the agricultural sector is facing numerous Challenges in meeting the increasing demands of a growing global population. Additionally, it is crucial to educate the younger generation about the significance of cultivation. Food security is threatened by factors such as climate change, declining pollinators, crop pests, inadequate irrigation, and more.
Crop diseases further exacerbate the problem by reducing both the quantity and quality of food produced. Small-scale farmers, who depend on safe cultivation for their livelihoods, are particularly affected by these diseases.
One solution to this problem lies in early detection and monitoring of crop diseases. With the advent of the internet and computer vision, it has become possible to effectively address this issue. Misdiagnosing plant diseases can result in significant losses in production, time, resources, and product quality. Therefore, accurately identifying the state of the plant is crucial for successful cultivation. Various environmental anomalies, such as fungi, water scarcity, insects, and weeds, can impact crop health, requiring farmers to take preventive measures to enhance productivity.
Research in this field focuses on leveraging computer-based image processing technology to target the visual quality of crops. Artificial intelligence advancements, particularly deep learning models like Convolutional Neural Networks (CNN), enable automatic identification of plant diseases from raw images. Deep learning systems excel at extracting features from photos, allowing the neural network to learn and recognize disease symptoms.
Farmers often lack knowledge about the specific diseases affecting their plants, leading to the misuse of pesticides and insecticides, which can have negative consequences. Limited access to experts due to communication and transportation challenges further compounds the problem.
Plant diseases have a severe impact on agricultural economies, causing a significant reduction in both the quality and quantity of agricultural products. Therefore, the detection of plant diseases is a critical research topic, offering the potential to monitor large crop fields and automatically detect disease symptoms as soon as they appear on plant leaves.
By employing computer-based image processing technology, farmers can receive assistance and support despite their geographical limitations. The proposed approach consists of four main phases: creating a color, transformation structure for RGB leaf images, applying device-independent color space transformation, segmenting the images using K-Means clustering, calculating the relevant features for the infected objects, and finally, utilizing a pre-trained neural network to extract features.
The program tested five common plant diseases, including Early Scorch, Cottony Mold, Ashen Mold, Late Scorch, and Tiny Whiteness. The proposed framework successfully detected and classified these diseases with an average precision of approximately 93%, while the lowest precision value achieved was 80%. This experiment not only aids in improving

food security but also contributes to prolonging the freshness of vegetables.

Overall, the integration of image processing, deep learning, and artificial intelligence technologies offers a promising solution to the challenges faced by farmers. By accurately identifying and addressing plant diseases, this research can help mitigate the negative impact on agricultural productivity, benefiting both the farmers and the agricultural economy. Neuralsignalsarethenprocessedanddecodedusingadvancedalgorithmstoextractthe user's intended actions.

II. LITERATURE REVIEW

Plant pathologists employ various techniques to classify plant diseases by analyzing different parts of plants, including roots, kernels, stems, and leaves. Deep learning models have emerged as a powerful tool in this domain, enabling accurate disease classification. Several research studies have demonstrated the effectiveness of deep learning models in plant disease classification.

A paper was presented that implemented different CNN model architectures for classifying plant diseases with high accuracy. Their study showcased the potential of deep learning models in accurately identifying and classifying plant diseases.

In another study, Brahimi et al. [1] investigated 14,828 images of tomato leaves infected by nine different diseases. By focusing on localized diseased regions of the leaves and leveraging a comprehensive dataset, their CNN model achieved an impressive accuracy of 99.18%.

Plant pests pose a significant threat to crop yields, causing substantial losses for farmers. Dawie et al. [2] explored the use of transfer learning to improve the accuracy of pest identification, yielding promising results.

Singh et al. [3] proposed a classifier that achieved an accuracy of 96.46% in plant disease classification. Their model outperformed other machine learning algorithms, such as SVM, Decision Tree, Logistic Regression, and KNN, as well as transfer learning approaches like AlexNet, ResNet, VGG16, and Inception V3.

Hasan et al. [4] used a region-based CNN model to estimate wheat yield, achieving an average accuracy ranging from 88% to 94%. Their model proved useful in estimating yield production for different wheat varieties.

Patil and Bodhe et al. [5] focused on plant disease detection in sugarcane. They extracted shape features of sugarcane leaves using threshold segmentation and triangle segmentation techniques, achieving an accuracy of 98.6%.

Oppenheim et al. [6] and utilized CNN models for potato disease classification and achieved successful results in classifying different classes of potato tubers.

In apple leaf disease classification, Jiang et al. [7] proposed a real-time approach using the VGG-Inception model and rainbow concatenation. Their approach achieved a test accuracy of 97.14% and outperformed other well-known pre-trained models.

Atole et al. [8] employed a pre-trained AlexNet deep network for the classification of rice plants into three classes, achieving an accuracy of 91.23%. In grape plant disease identification, A. P. Singh [9] employed feature selection using an artificial bee colony algorithm and a support vector machine classifier. Their proposed algorithm achieved an accuracy of 92.14%.

Zhu et al. [10] applied Inception V2 with batch normalization for plant species classification and achieved higher accuracy compared to Faster RCN. M.Zhang [11] proposed a diverse region-based CNN capable of encoding context-aware representation and obtaining features for plant disease classification.

Nanehkaran et al. [12] proposed a two-step method for plant leaf disease identification, involving image segmentation based on hue, saturation, and intensity, followed by classification using a CNN model. S. Wan and S. Goudos [13] demonstrated accurate and faster object detection using the R-CNN deep learning model.

Rani et al. [14] presented a deep learning-based approach called D-Leaf for plant species identification, combining pre-trained models for feature extraction with machine learning techniques for image classification. The D-Leaf model, using an ANN classifier, achieved an accuracy of 94.88%.

Furthermore, Zhao et al. [15] proposed an image classification approach that optimized the hyperparameters of the SVM model using an improved artificial bee colony algorithm. Their approach outperformed other comparative methods for the classification of hyperspectral images, achieving an accuracy of 98.28%.

These studies highlight the successful application of deep learning methods and nature-inspired optimization algorithms in the field of plant disease classification and identification. Deep learning models have shown significant potential in accurately diagnosing plant diseases and facilitating effective disease management strategies.

A. Image Classification Machine Learning Algorithms

In the comparative analysis of image classification models for rice and potato plant leaf diseases, various algorithms were trained and evaluated, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. Among these techniques, the proposed Convolutional Neural Network (CNN) model demonstrated superior performance and suitability for plant disease classification.

SVM is a supervised machine learning algorithm that excels in inferring output labels, even with small datasets. It utilizes a kernel method to classify non-linear data by finding a hyperplane that maximizes the margins.

The equation of the hyperplane separating classes can be represented as $y = mx + c$, where y represents the output label, m and c are parameters, and x is the input sample. SVM aims to maximize the classification distance, which can be achieved by minimizing $1/2 \|w\|^2$, where w is the weight vector.

The distance, Di, between an input sample xi and the hyperplane can be calculated as $Di = |wxi + b| / \|w\|$. The objective of SVM is to minimize $1/2 \|w\|^2$ while satisfying the condition $y [wx + b] - 1 \geq 0$.

Hyperparameter tuning for SVM involves selecting values for parameters such as c, kernel type, and gamma. This tuning process can be performed using the grid search algorithm, where different combinations of hyperparameters are evaluated, and the values yielding the best cross-validation score are selected.

K-Nearest Neighbors (KNN) algorithm calculates the Euclidean distance between the input image and every other point in the dataset. It then utilizes majority voting from the K minimum distance points to classify the image. The general equation for calculating the distance between two points, p1 and p2, is given by d (p1, p2) = sqrt (x1 - x2) ^2 + (y1 - y2) ^2).

The Random Forest algorithm employs ensemble learning by combining multiple decision trees to classify input images. Each decision tree in the ensemble independently makes a prediction, and the final classification is determined by majority voting among the trees.

Overall, the proposed CNN model outperformed SVM, KNN, Decision Tree, and Random Forest in the classification of rice and potato plant leaf diseases, demonstrating its effectiveness and suitability for this task.

III. DATASET AND PROPOSED CNN MODEL

A. Data Acquisition

The paper utilizes rice and potato datasets, which are divided into an 80:20 split configuration. In this configuration, 80% of the images are allocated for training purposes, while the remaining 20% are reserved for testing.

The Rice dataset comprises a total of 5932 images, encompassing four different varieties of rice leaf diseases, As shown in Fig. (1), namely Bacterial blight, Blast, Brown Spot, and Tungro. For the training phase, 3785 images are used, while 947 images are employed for testing, adhering to the 80:20 test-train split. This approach ensures that a substantial portion of the dataset is dedicated to training the models, while a separate subset is reserved for evaluating their performance.

(a) (b) (c) (d)

Figure 1**:** Sample images of rice leaf image dataset (a) bacterial blight (b) blast (c) brown spot (d) tungro

The study utilizes a potato leaf dataset consisting of 1500 images. Out of these, 1200 images are utilized for training and validation, while the remaining 300 images are reserved for testing. As shown in Fig. (2), The dataset encompasses three distinct classes of potato leaves: early blight, late blight, and healthy. provides a sample illustration of the potato leaves,Table 1 presents the distribution of training and testing images within the dataset.

(a) (b) (c)

Figure 2: Sample images of potato leaf image dataset (a) early blight (b) late blight c) healthy

Table 1: The distribution of training and testing images within the dataset.

Image dataset	Total images	Training images	Testing images	Classes
Rice dataset	5932	3785	947	04
Potato leaf dataset	1500	1200	300	03

During the preprocessing stage, all the images are resized to 128 X 128 pixels.

Train: X (1200, 128, 128, 3), y= (900) Test: X(300, 128, 128, 3), y = (300)

B. Proposed Convolution Neural Network

This paper proposes a deep learning-based Convolutional Neural Network (CNN) model for accurate image classification of potato and rice plant leaves, Fig (3), specifically focusing on distinguishing between healthy and diseased leaves.

The study also includes a comparative analysis of traditional machine learning techniques alongside the CNN model.

Image-based computer vision problems typically demand high memory and computational resources. With input feature dimensions reaching up to 49152 for an image of size 128x128x3, handling such extensive data can pose computational challenges.

CNN, inspired by biological models of human visual perception, effectively addresses this issue by utilizing layered architectures to extract relevant features from images. The CNN model employs convolutional layers, ReLU layers, pooling layers, dropout layers, and fully connected layers to capture spatial and temporal dependencies, reduce computational requirements, and retain essential features for accurate predictions.

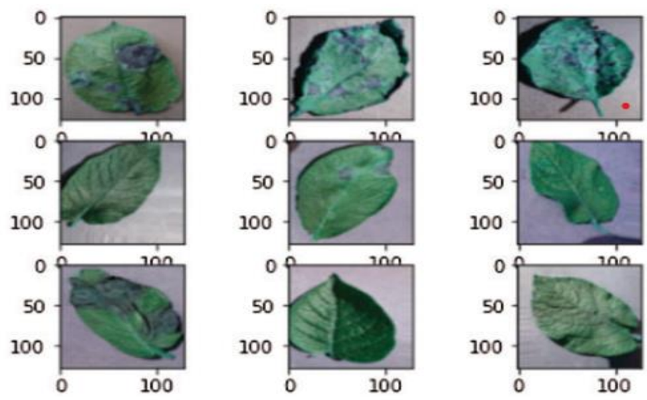

Figure 3**:** Resized potato leaf dataset

Convolution layers prize high-position features(descry hidden patterns) by operation of a set of pollutants that prize useful information from an image. After the operation of pollutants kernels, the data is passed from the ReLU subcaste. ReLU sets each negative value of the convolved matrix to zero and retains positive values by using the maximum (a, 0) function.

The reused data is inputted into another subcaste called the pooling subcaste. The pooling subcaste reduces the size of the inputs and pets up processing. Different hyperactive-parameters at the pooling subcaste of the CNN model are sludge size, stride, maximum, or average pooling. There can be n number of complications and pooling layers in a CNN model. Completely connected layers are present at the end of a CNN model.

Each knot is connected to every knot in the former subcaste is completely connected layers. Completely connected layers are heavy data- driven layers of the CNN model. A completely connected subcaste performs the task of bracketing the image into different classes in the affair subcaste. The completely connected layers are also called thick layers of the CNN model to perform the task of image bracket.

The powerhouse subcaste is used to help the neural network from over fitting. Power house is an important regularization (42) fashion for neural networks. The SoftMax activation Function is used at the affair subcaste which produces a vector that represents the probability distribution of the possible affair classes.

IV. PROBLEM STATEMENT

Agriculture is a vital component of the Indian economy, employing a significant portion of the workforce. India holds the distinction of being the world's largest producer of various agricultural products. The economic growth of farmers relies on the quality of their crops, which is directly influenced by plant growth and yield. Consequently, the identification of diseases in plants plays a crucial role in the agricultural sector.

Plant diseases can impede plant development and disrupt the ecological balance for farmers. Early detection of plant diseases through automated techniques is highly advantageous. Manual diagnosis of plant diseases using leaf photographs is a time-consuming process. Therefore, the development of computational methods to automate the detection and classification of diseases using leaf images is essential.

V. EXISTING SYSTEM

The prevailing method of plant disease detection involves manual observation by plant experts, relying on their visual assessment skills to identify diseases. However, this approach becomes challenging when dealing with extensive crop fields. Moreover, in certain countries, farmers may lack access to proper facilities or be unaware of the possibility of consulting with experts.

This not only makes consulting experts costly but also time-consuming. In such situations, the proposed technique for monitoring a large number of plants would be highly beneficial. By automating the process through advanced technology, it would enable efficient and cost-effective monitoring of plant diseases, alleviating the need for extensive human intervention and reducing the burden on farmers.

A. Disadvantages of Existing System

- Only humans are capable of predicting diseases.
- The procedure is extremely slow.
- Consumption of time and space is also very high.
- The price is also high.

VI. PROPOSED SOLUTION

This study focuses on the accurate identification of plant diseases through the implementation of segmentation, feature extraction, and classification techniques. The process involves capturing images of leaves from different plant species using a digital camera or a similar device. These images are then utilized to classify the affected regions within the leaves. To detect plant diseases effectively, the proposed framework incorporates Convolutional Neural Networks (CNN) and Deep Neural Networks (DNN).

The framework is designed to utilize low-cost and open-source software, ensuring a reliable and cost-effective approach to plant disease detection. By leveraging these advanced techniques, the study aims to enhance the accuracy and efficiency of disease identification, ultimately contributing to improved agricultural practices and crop management.

Advantages

- The system detects relevant images using an inexpensive camera and the OpenCV software.
- Open CV helps in analyzing images and videos effectively.

VII. LIST OF MODULES

- Image acquisition.
- Image pre-processing.
- Image enhancement.
- Image segmentation.
- Image analysis
- Feature extraction.
- Disease classification

A. Image Acquisition

To initiate the data collection process, the first step involves accessing a publicly available repository containing relevant information. This includes gathering images that serve as the input for subsequent processing.

Our approach is designed to accommodate various image formats such as .bmp, .jpg, and .gif, encompassing the most common image domains. Real-time images are acquired directly from a camera feed. To ensure accurate segmentation, as the color of most leaves' ranges from red to green, a white background is provided.

This facilitates further study, enhances visibility, and enables easy analysis of the images. For capturing cotton images, a specialized image capturing system is utilized, ensuring minimal distortion.

Care is taken to avoid direct sunlight during the photography process, as it has the potential to distort the captured images.

B. Image Pre-processing:

Image pre-processing refers to the application of computer algorithms for performing various manipulations on digital images. In our context, the specific objective is to detect plants by analyzing the provided images using a dedicated algorithm.

A similar approach is adopted for both image processing and detection, employing a specific algorithm tailored to the task. However, it is crucial to emphasize that the quality of the image plays a vital role in this process.
If the image is not clear or lacks sufficient clarity, it becomes impractical to apply the algorithm effectively.
Therefore, ensuring clear and high-quality images Fig. (4), is imperative to facilitate accurate plant detection through algorithmic analysis.

Figure 4: Infected Tomato Leaf

C. *Image Enhancement:*

Image enhancement refers to the manipulation of digital images to make them more suitable for display or further processing. This process involves applying various techniques to improve the visual quality or extract specific features from the images. Several methods can be employed to enhance an image effectively, including:

- Histogram Equalization: This technique redistributes the pixel intensities in an image to enhance the overall contrast and improve visibility.
- Noise removal using filters: Filtering techniques are applied to reduce or eliminate unwanted noise from the image, resulting in a cleaner and more visually pleasing output.
- Unsharp mask filtering: This method enhances image details by accentuating high-frequency components, thereby improving overall sharpness.
- Decorrelation stretch: By adjusting the colour channels of an image independently, this technique enhances colour contrast and reveals hidden information.

D. *Image Segmentations:*

Image segmentation refers to the process of dividing a digital image into multiple segments or sets of pixels, often referred to as image objects, Fig. (5), This technique is employed to facilitate image identification and analysis by breaking down the image into distinct parts and examining each segment individually.
Common characteristics utilized for segmenting images include color, texture, and intensity. By partitioning the image into segments, it becomes easier to analyze and understand the different elements within the image.
Image segmentation enables the extraction of meaningful information from the image, aids in object recognition, and allows for targeted analysis of specific regions of interest. It plays a vital role in various computer vision tasks, such as object detection, image classification, and image understanding.

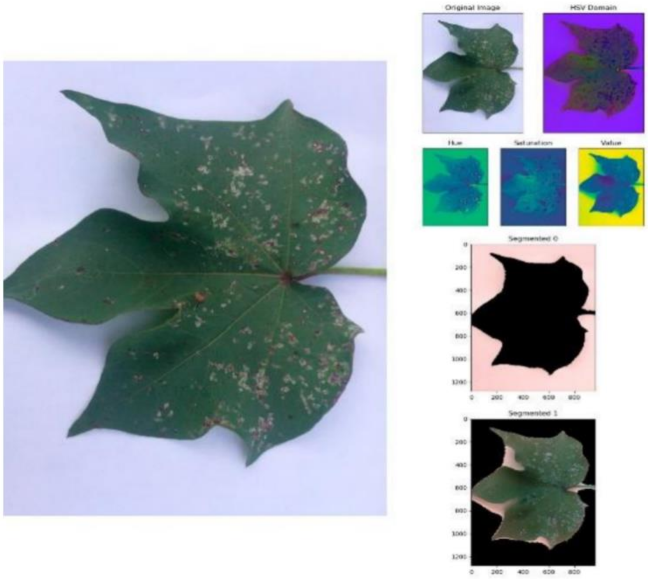

Figure 5: Image Segmentation of a Leaf

E. *Image Analysis:*

The next step involves utilizing image segmentation to identify the region of interest within the image. In this process, a region-based segmentation technique is employed, primarily focusing on distinguishing between healthy and diseased regions of the plant leaf based on their color.
By analyzing the color information, the segmentation algorithm separates the leaf into distinct regions, allowing for the identification of areas that exhibit signs of disease or damage. This region-based approach enables the differentiation of healthy and affected portions of the leaf, providing valuable insights into the overall health and condition of the plant. By accurately delineating the regions of interest, this segmentation technique serves as a crucial component in plant leaf analysis and aids in diagnosing and monitoring plant diseases effectively.

F. *Feature Extraction:*

Feature extraction plays a crucial role in machine learning as part of the dimensionality reduction process. It involves dividing and condensing a large set of raw data into smaller, more manageable classes. This step becomes particularly important when dealing with substantial amounts of data, as it aims to minimize resource usage while avoiding potential errors.
Feature extraction serves as a critical step in this scenario, as it enables the extraction of the most relevant features from large datasets by selecting and combining variables into meaningful functions.
By identifying and extracting the most informative attributes, feature extraction aids in reducing the dimensionality of the data, which not only simplifies subsequent analysis but also enhances the overall performance and efficiency of machine

learning algorithms. Thus, feature extraction acts as a vital technique for optimizing resource utilization and ensuring accurate modeling and analysis of complex datasets.

G. Disease Classifications:

The proposed approach involves utilizing a sophisticated deep learning model to accurately identify plant diseases. To begin the process, a digital camera or a similar system captures an image of the affected leaf on a plant. This image is then scanned using OpenCV, a popular computer vision library.

The primary objective of this step is to determine the type of plant depicted in the image. Once the plant species is identified, the deep learning model analyzes the image further to detect and classify the specific disease afflicting the plant.

By leveraging advanced algorithms and techniques, the model can accurately diagnose the disease based on visual patterns and characteristics exhibited in the image. This method enables efficient and reliable identification of plant diseases, aiding in timely intervention and appropriate treatment to mitigate crop losses.

VIII. CONCLUSION

The agricultural sector plays a vital role in providing food to people worldwide, and the early detection and recognition of plant diseases are crucial for its success. In this paper, we have presented an overview of deep learning and reviewed recent research on plant leaf disease recognition using deep learning techniques. With sufficient training data, deep learning methods have shown high accuracy in identifying plant leaf diseases.

We emphasized the importance of collecting large and diverse datasets, employing data augmentation, transfer learning, and visualizing convolutional neural network (CNN) activation maps to improve classification accuracy. Additionally, we discussed the significance of detecting plant leaf diseases with limited samples and highlighted the importance of hyper-spectral imaging for early disease detection.

However, there are some limitations to be addressed. Many deep learning models proposed in the literature perform well on specific datasets but lack robustness when tested on different datasets, indicating the need for more robust models capable of adapting to various disease datasets. Most studies have relied on the Plant Village dataset for evaluating DL model performance, but since it was collected in a lab setting, there is a need to establish a large dataset of plant diseases under real field conditions.

While some researchers have utilized hyperspectral images of diseased leaves and applied DL frameworks for early disease detection, challenges related to obtaining labeled datasets for early disease stages and accurately identifying invisible disease symptoms persist.

This paper also presents a survey of different disease classification techniques applicable to plant leaf disease detection, with a focus on an algorithm for image segmentation that enables automatic detection and classification of plant leaf diseases. Various plant species such as Jute, Grape, Paddy, and Okra were used to test the algorithms and methods. The results demonstrate the effectiveness of the algorithm in efficiently recognizing and classifying leaf diseases with minimal computational effort.

Furthermore, to enhance the recognition rate during the classification process, Artificial Neural Network, Bayes Classifier, mathematical logic, and hybrid algorithms can also be employed.

In conclusion, this paper provides a comprehensive review of deep learning-based approaches for plant leaf disease recognition. It highlights the importance of data collection, augmentation, transfer learning, and visualization techniques in improving accuracy. It also emphasizes the challenges of obtaining labeled datasets for early disease detection and the potential of hyperspectral imaging. Finally, the paper presents an algorithm for image segmentation and discusses the possibility of using additional classification techniques to enhance disease recognition.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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