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Image-Based Plant Disease Classification Using Deep Learning Technique

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Abstract— Living organisms, including humans, heavily depend on plants and animals for sustenance. However, the current food resources confront limitations in supporting the global population over extended periods due to only 29% of the Earth's land being suitable for sustaining the entire ecosystem. Additionally, the existence of plant-eating bacteria or locusts exacerbates this challenge, further limiting the accessibility of resources for prolonged periods. This situation emphasizes the importance of our project, which centers on Plant Disease Detection and Recognition. Our primary aim is to pinpoint and diagnose diseases affecting plants while identifying the most effective treatments. Through the utilization of our system, we can obtain precise information about the specific ailments impacting plants and determine the most suitable medications to combat these diseases. The prompt recognition of plant diseases is crucial as it enables timely interventions to safeguard the welfare of plants and trees. Moreover, accurately identifying the variety of diseases before administering treatment holds paramount importance. With our system boasting an impressive 92% accuracy rate, we are equipped to efficiently address plant health concerns, thereby extending their lifespan. After undergoing rigorous testing, this endeavor has emerged as a promising asset for humanity. Farmers, who serve as the backbone of nations, play an indispensable role in our survival. Ensuring equitable treatment compensation for their harvests is of utmost importance, and our system is positioned to play a crucial role in achieving this objective. By advocating for agricultural sustainability and nurturing healthier crops, we can positively impact food production and contribute to the collective well-being of society.

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

Introduction

Agriculture plays a pivotal role in India's early development, serving as the cornerstone of the nation. However, the agricultural sector encounters myriad challenges in meeting the growing requisites of a growing global population. Educating the younger generation about the signification of cultivation is crucial as food security confronts threats from various factors such as climate change, declining pollinators, crop pests, and inadequate irrigation, among others.

The situation is further complicated by crop diseases that not only reduce the quantity but also the standard of food produced, disproportionately impacting small-scale farmers who rely on secure cultivation for their livelihoods. Tackling this challenge requires early detection and monitoring of crop diseases, facilitated by advancements in internet and computer vision technologies.

Incorrect diagnosis of the occurrence of plant diseases can lead to substantial losses in production, time, resources, and product quality. Therefore, accurately assessing the plant's condition is essential for successful cultivation. Environmental variables like fungi, water scarcity, insects, and weeds can affect crop health, prompting farmers to implement preventive measures to enhance productivity.

Research in this area focuses on leveraging computer-based image processing technology to evaluate the visual quality of crops. Artificial intelligence, particularly through advanced learning architectures such as Convolutional Neural Networks. (CNN), enables automatic identification and detection plant diseases using raw images. by extracting features from photos and learning to recognize disease symptoms.

Farmers frequently grapple with restricted knowledge about specific diseases affecting their plants, leading to the misuse of pesticides and insecticides with potential negative consequences. Additionally, limited entry to experts due to communication and transportation challenges exacerbates this issue. Plant diseases cause significant damage to agricultural economies, resulting in substantial reductions in terms of both the caliber and quantity of agricultural products.

Therefore, identifying plant diseases emerges as a critical research focus, offering the potential to monitor large crop fields and automatically identify disease symptoms as soon as they manifest on plant leaves. The integration of computer-based image processing technology assists farmers despite geographical limitations.

The proposed methodology involves developing a color conversion framework for RGB leaf images, applying deviceindependent color space transformation, segmenting images using K-Means clustering, calculating relevant features for infected objects, and utilizing a pre-trained neural network to extract features. Experimental testing on five common plant diseases resulted in successful identification and categorization with an average precision of approximately 93%, contributing not only to improved food security but also to prolonging the freshness of vegetables.

In summary, the blend of image processing, deep learning, and artificial intelligence technologies offers a promising solution to the challenges faced by farmers. Accurately identifying and addressing plant diseases through this research can help mitigate the adverse impact on agricultural productivity, benefiting both farmers and the agricultural economy.

II. LITERATURE REVIEW

Plant pathologists utilize a variety of methodologies to classify plant diseases, examining various plant components such as roots, kernels, stems, and leaves. Advanced learning models have emerged as powerful tools in this field, enabling precise disease classification. Numerous research endeavors have underscored the effectiveness of these frameworks in accurately categorizing plant diseases.

One scholarly paper demonstrated the execution of numerous CNN model architectures, achieving high accuracy in plant disease grouping. This research emphasized the capability of deep learning models to precisely recognize and categorize plant diseases.

Brahimi et al. conducted an extensive analysis of 14,828 images of tomato leaves infected by nine distinct diseases. By focusing on localized diseased regions and leveraging a comprehensive dataset, their CNN model attained a remarkable level of precision of 99.18%.

Plant pests pose significant threats to crop yields, prompting Dawie et al. to explore knowledge transfer for enhanced pest identification accuracy, yielding promising results.

Singh et al. developed a classifier that achieved a 96.46% accuracy in plant disease classification, Surpassing other ML algorithms and transfer learning approaches.

Hasan et al. utilized a region-based CNN model to estimate wheat yield, achieving accuracies ranging from 88% to 94% across different wheat varieties.

Patil and Bodhe focused on sugarcane disease detection, employing shape feature extraction techniques and achieving a precision of 98.6%.

Oppenheim et al. applied CNN models for potato disease classification, successfully categorizing different classes of potato tubers.

For apple leaf disease classification, Jiang et al. suggested a real-time approach employing the VGG-Inception model and rainbow concatenation, achieving a test accuracy of 97.14%, surpassing other pre-trained models.

Atole et al. utilized a pre-trained AlexNet convolutional neural network for the rice plant classification, achieving a precision of 91.23%. A. P. Singh employed feature selection with an artificial bee colony algorithm for grape plant disease identification, achieving an accuracy of 92.14%.

Zhu et al. employed Inception V2 with batch normalization for plant species classification, outperforming Faster RCN in accuracy. M. Zhang proposed a diverse region-based CNN capable of encoding context-aware representation for plant disease classification.

Nanehkaran et al. proposed a dual-phase strategy for diagnosing plant leaf disease identification, involving image segmentation and classification using a CNN model. S. Wan and S. Goudos demonstrated accurate and faster object detection using the R-CNN deep learning model.

Rani et al. presented a deep learning-based approach, D-Leaf, for plant species identification. The D-Leaf model, employing an ANN classifier, achieved a precision of 94.88%.

Additionally, Zhao et al. proposed an image classification approach optimizing SVM model hyperparameters using an improved artificial bee colony algorithm, outperforming other methods and achieving an accuracy of 98.28%.

These studies collectively highlight the successful usage of deep learning techniques and nature-inspired optimization algorithms in plant disease classification. Deep learning frameworks show significant potential for accurate diagnosis, contributing to effective disease management strategies.

A. Image Classification ML Algorithms

In the evaluative comparison of image classification models for identifying rice and potato plant leaf diseases, a variety of algorithms were subjected to training and assessment. These encompassed Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. Amidst these methodologies, the Convolutional Neural Network (CNN) model proposed in the study demonstrated superior performance, thereby affirming its suitability for precise categorization of plant diseases.

SVM, a supervised machine learning algorithm, excels in deducing output labels, particularly with limited datasets. Leveraging a kernel method, SVM classifies non-linear data by determining a hyperplane that maximizes margins. The hyperplane equation, denoted as $y = mx + c$, defines the output label (y), parameters (m and c), and input sample (x). SVM aims to maximize classification distance by minimizing 1/2 ||w||^2, where "w" represents the weight vector. The distance (Di) between an input sample (xi) and the hyperplane is computed as |wxi + b| / ||w||. SVM's objective is to minimize 1/2 ||w||^2 while satisfying the condition y [wx + b] - 1 ⩾ 0. Hyperparameter tuning for SVM involves selecting values for parameters like c, kernel type, and gamma, accomplished through grid search, evaluating different hyperparameter configurations to choose values yielding the best cross-validation score.

The K-Nearest Neighbors (KNN) algorithm determines the Euclidean distance between the input image and every point in the dataset. By employing majority voting from the K nearest points, the algorithm classifies the image. The distance equation (d) between two points (p1 and p2) is given by d (p1, p2) = sqrt (x1 - x2) ^2 + (y1 - y2) ^2).

The Random Forest algorithm utilizes ensemble learning, which involves combining multiple decision trees for image classification purposes. Every judgment tree functions autonomously to make predictions, and the final classification is determined by majority voting among the trees.

In conclusion, the CNN model suggested in the study outperformed SVM, KNN, Decision Tree, and Random Forest Precisely categorizing rice leaf ailments and potato plant leaf conditions. This highlights the effectiveness and appropriateness of the CNN model for this particular task.

III. DATASET AND PROPOSED CNN MODEL

A. Data collection

The research paper employs specialized datasets tailored to rice and potatoes, utilizing an 80:20 split configuration to ensure effective evaluation. Under this arrangement, 80% of the images are allocated for the training phase, while the remaining 20% are reserved for thorough testing.

The Rice dataset, comprising a sum of 5932 images, is extensive and encompasses four distinct varieties of rice leaf diseases: Bacterial blight, Blast, Brown Spot, and a Tungro, as illustrated in Figure 1. For the training phase, 3785 images are utilized, with 947 images specifically earmarked for testing, adhering to the 80:20 test-train split. This meticulous division ensures that a substantial portion of the dataset is dedicated to training the models, while a separate and distinct subset is set aside for the comprehensive evaluation of 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 dataset comprising 1500 images of potato leaves. Within this dataset, 1200 images are allocated for the combined purposes of training and validation, while the remaining 300 images are exclusively reserved for testing. Figure 2 provides a visual representation of the dataset, illustrating three distinct classes of potato leaves: early blight, late blight, and healthy. Additionally, Table 1 outlines the dispersion of images for both the training and validation phases 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 dispersion of training and validation 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 adjusted to 128 X 128 pixels. Train: X (1200, 128, 128, 3), y= (900) Test: X (300, 128, 128, 3), y = (300).

B . Novel CNN Proposal

This research introduces an innovative CNN framework, specifically tailored for the precise classification of potato and rice plant leaves, as depicted in Figure 3. The main goal is to differentiate between healthy leaves and those affected by diseases.

The investigation extends to encompass an exhaustive comparative examination that incorporates traditional machine learning techniques, juxtaposed with the advanced CNN model. Challenges inherent in image-based computer vision tasks often arise from the need for demanding memory and computational resources. Managing extensive data, where input feature dimensions can scale up to 49152 for a 128x128x3 image, can pose significant computational hurdles.

The CNN model adeptly addresses these challenges by drawing inspiration from biological models of human visual perception. It employs layered architectures meticulously designed to discern pertinent features from images efficiently. The model incorporates various components, including convolutional layers, rectified linear units (ReLU) layers, pooling layers, dropout layers, and fully connected layers. These elements work synergistically to capture spatial and temporal dependencies, mitigate computational demands, and preserve crucial features necessary for making accurate predictions.

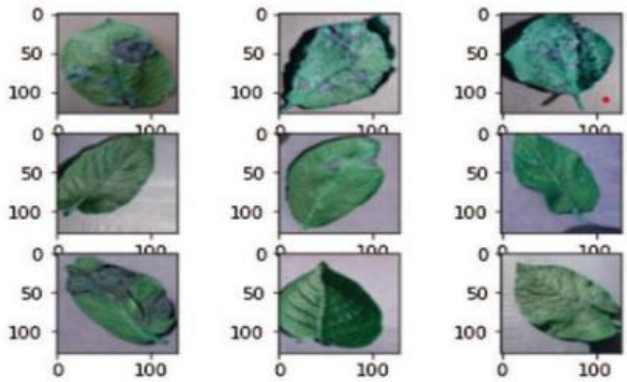

Figure 3: Resized potato leaf dataset

Convolutional layers within a neural network excel in identifying high-level features or uncovering concealed patterns by employing a group of filters that extract valuable information from an image. Following the operation of these filter kernels, the data undergoes processing through the ReLU (Rectified Linear Unit) sub-layer. In this ReLU sub-layer, each negative value in the convolved matrix is set to zero, preserving positive values through the utilize of the maximum function (max(a, 0)).

Subsequently, the processed data advances to another sub-layer known as the pooling sub-layer. This pooling sub-layer serves a dual purpose of reducing input size and expediting processing. Various hyperparameters, including kernel size, stride, and the choice between maximum or average pooling, can be adjusted within the pooling sub-layer of the CNN model. It's common for multiple convolutional and pooling stages to exist in a CNN framework.

The final layers in a CNN framework consist of the fully connected stages. In these layers, every node forms links with every node in the preceding sub-layer. dense layers, also referred to as dense layers, are data-intensive components of the CNN model, playing a pivotal role in categorizing the image into different categories within the output sub-layer.

To mitigate overfitting, a regularization technique known as the dropout sub-layer is employed. Dropout functions as a vital regularization technique for neural networks, aiding in enhancing generalization performance.

The output sub-layer utilizes the SoftMax activation function, producing a vector that represents the probability distribution across potential output classes. This SoftMax activation assists in determining the probability of different classes, thereby facilitating accurate classification within the output sub-layer.

IV. PROBLEM STATEMENT

Agriculture plays a foundational function in the Indian economy, providing substantial employment opportunities to a substantial element of the workforce. India boasts the contrast of being the world's leading producer of various agricultural commodities. The well-being of agriculturists and the nation's economic prosperity are intricately tied to the excellence of their crops, which directly impacts plant growth and yield. Therefore, timely detection of diseases affecting plants is of maximum significance in the farming sector.

The occurrence of plant conditions not only stunts plant growth but also disrupts the delicate ecological balance crucial for farmers' livelihoods. Early identification of plant diseases, facilitated by automated techniques, offers considerable advantages. Manual diagnosis of plant conditions based on leaf photographs is a time-consuming task. Thus, there exists a pressing need to develop computational methods capable of automating the recognition and categorization of diseases using leaf images, representing a significant advancement in agricultural innovation.

V. CURRENT APPROACH

The current approach to detecting plant diseases relies heavily on manual observations conducted by plant experts who utilize their visual assessment abilities to identify various ailments. However, this method encounters challenges when implemented in large crop fields. Additionally, in certain regions, farmers may face difficulties accessing appropriate facilities or may not be aware of the opportunity to seek advice from experts.

Relying on expert consultation not only entails significant costs but also proves to be a time-consuming process. In such situations, the proposed method for monitoring a large population of plants emerges as a highly advantageous alternative. By introducing automation through advanced technology, this approach strives to streamline and cost-effectively manage the surveillance of plant diseases. This would reduce the requirement for extensive human involvement, thereby alleviating the burden on farmers.

A. Limitations of the Current System

- Disease prediction relies solely on human capabilities.
- The process is exceptionally sluggish.
- High consumption of time and space.
- Elevated costs associated with the existing system.

VI. PROPOSED RESOLUTION

This research focuses on achieving accurate plant disease identification by strategically applying segmentation, feature extraction, and classification methodologies. The workflow involves capturing images of leaves from various plant species using a digital camera or similar device. These acquired images form the basis for identifying and classifying affected regions within the leaves. To ensure effective plant disease detection, the proposed framework integrates advanced technologies, specifically CNN and DNN.

Significantly, the framework is meticulously designed to capitalize on the capabilities of low-cost and open-source software, establishing a reliable and cost-effective approach to plant disease detection. By incorporating these cutting-edge techniques, the study aims to enhance the accuracy and effectiveness of disease identification, ultimately resulting in advancements in agricultural practices and improved crop management.

Advantages:

- The system adeptly identifies pertinent images using a cost-effective camera and the OpenCV software.
- OpenCV facilitates effective analysis of both images and videos.

VII. MODULE CATALOG

- Image capture.
- Preliminary image processing.
- Image augmentation.
- Segmentation of images.
- Comprehensive image scrutiny.
- Extraction of distinctive features.
- Classification of diseases.

A. Image capture.

To commence the data-gathering phase, the initial phase involves accessing a publicly available repository containing relevant information. This entails compiling images that will serve as input data for subsequent processing stages.

Our methodology is customized to accommodate an assortment of image formats, including .bmp, .jpg, and .gif, encompassing the most prevalent image domains. For real-time data collection, pictures are directly obtained from a camera feed. To ensure accurate segmentation, a white background is utilized, considering that the color of most leaves varies from red to green.

This deliberate selection of a white background not only assists further examination but also improves visibility, enabling seamless examination of the images. When capturing cotton images, a specialized image-capturing system is employed to minimize distortion.

Stringent measures are in place to avoid direct sunlight during the photography process, as its presence can potentially distort the captured images, thereby preserving the integrity of the collected data.

B. Preliminary image handling

Image pre-processing entails employing computational algorithms to manipulate. perform various manipulations on digital images. In our context, the primary objective is to recognize plants by thoroughly analyzing the provided images using a specialized algorithm. The approach for both image processing and detection remains consistent, employing a customized algorithm customized for the particular assignment at hand.

However, it is crucial to emphasize the importance of image quality throughout this process. The productivity of the method relies heavily on the clarity and quality of the image being processed. If the image lacks clarity or fails to provide sufficient visual information, the utilization of the method becomes impractical.

Therefore, it is essential to ensure that the images are clear and high-quality, as depicted in Fig. (4), to facilitate precise plant detection through the meticulous analysis conducted by thealgorithm.

Figure 4: Infected Tomato Leaf

C. Image augmentation

Image enhancement involves the manipulation of digital images to optimize them for display or subsequent processing. This transformative process encompasses the usage of various techniques aimed at improving visual quality or isolating specific features within the images. Several effective methods are employed for image enhancement, including:

- Histogram Equalization: This method redistributes the pixel intensities in an image, augmenting overall contrast and enhancing visibility.
- Noise Removal using Filters: Filtering techniques are implemented to diminish or eradicate unwanted noise, yielding in a more pristine and aesthetically pleasing image.
- Unsharp Mask Filtering: This approach enhances image details by emphasizing high-frequency components, ultimately improving the overall sharpness.
- Decorrelation Stretch: By independently adjusting the color channels of an image, this technique heightens color contrast and unveils concealed information.

D. Segmentation of images.

Image segmentation involves the intricate process of dividing a digital image into multiple segments or sets of pixels, often mentioned to as image objects, as depicted in Fig. (5). This technique is invaluable for image identification and analysis as it dissects the picture into distinct parts, allowing for the examination of each segment individually.

Characteristic features commonly utilized for image segmentation include color, texture, and intensity. The segmentation of the image into segments not only facilitates a more detailed analysis but also enhances the comprehension of various elements present within the picture.

The significance of picture partitioning lies in its capability to derive significant insights from the. image, contribute to object recognition, and enable targeted analysis of specific areas of curiosity. It plays a crucial role in various computer vision tasks, including object detection, image classification, and comprehensive image understanding.

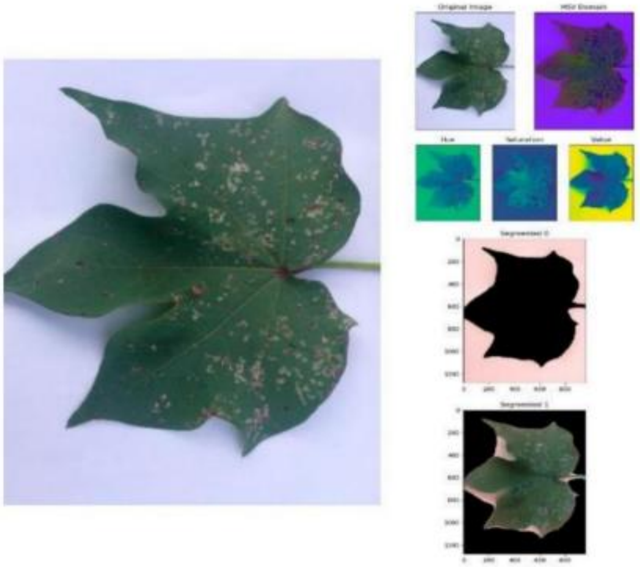

Figure 5: Image Segmentation of a Leaf

E.Comprehensive image scrutiny

The subsequent stage involves utilizing image segmentation to pinpoint the area of interest within the picture. Employing a region-based segmentation technique, the main goal is to differentiate between healthy and diseased segments of the plant leaf, primarily built upon their color. Through a Thorough examination of color information, the segmentation algorithm partitions the leaf into distinct regions, facilitating the identification of areas displaying signs of disease or damage. This region-based approach enables clear differentiation between healthy and affected portions of the leaf, offering valuable views on the overall health and condition of the plant. By accurately delineating these areas of interest, this segmentation technique plays a central significance in plant leaf analysis, significantly contributing to the efficient diagnosis and monitoring of plant diseases.

F. Extraction of distinctive features

Feature extraction plays a vital role in ML as part of the dimensionality reduction process. It involves breaking down and condensing a large set of raw data into more manageable classes. This step becomes particularly important when handling with extensive datasets, aiming to minimize resource usage while avoiding potential errors.

In this regard, feature extraction becomes a critical step, facilitating the extraction of the predominant relevant features from vast datasets by selecting and combining variables into meaningful functions. By identifying and extracting the most enlightening attributes, this process helps diminish the intricacy of the data. This not only simplifies subsequent analyses but also enhances the comprehensive performance and productivity of ML algorithms. Thus, feature extraction emerges as a vital technique for optimizing resource utilization, ensuring accurate modeling, and facilitating the analysis of complex datasets.

G. Classification of diseases

The proposed methodology involves the deployment of a sophisticated DL framework for accurate plant disease identification. The process begins with capturing an image of the affected leaf on a plant using a digital camera or a comparable system. Subsequently, the image undergoes analysis using OpenCV, a widely used computer vision library.

The main goal of this stage is to ascertain the plant type depicted in the picture. Once the plant species is identified, the DL framework further examines the image to recognize and classify the specific disease affecting the plant. Leveraging advanced algorithms and techniques, the model proficiently diagnoses the disease derived from discernible visual patterns and characteristics observed in the picture. This approach facilitates efficient and reliable identification of plant diseases, enabling timely intervention and the execution of appropriate treatments to mitigate crop losses.

VIII. CONCLUSION

The agricultural sector acts as a cornerstone in global food provision, emphasizing the crucial need for timely identification and acknowledgment of plant diseases. This paper provides an insightful examination of DL methodologies, particularly focusing on recent research regarding the recognition of plant leaf diseases through deep learning approaches. With sufficient training data, deep learning techniques demonstrate notable accuracy in identifying plant leaf diseases.

We emphasize the significance of compiling extensive and diverse datasets, incorporating data augmentation techniques, utilizing transfer learning strategies, and visualizing CNN activation maps to enhance classification accuracy. Furthermore, we highlight the significance of detecting plant leaf diseases even with limited samples and discuss the capability of hyperspectral imaging for early disease detection.

However, certain limitations need addressing. While many DL frameworks proposed in the literature excel on specific datasets, they may lack robustness when tested on diverse datasets. This underscores the necessity for more adaptable models capable of accommodating various disease datasets. Additionally, while the Plant Village dataset is commonly used to assess DL framework performance, its origin in a controlled lab setting highlights the essential for a substantial dataset encompassing plant diseases under authentic field conditions.

This document also presents a survey of diverse disease classification techniques applicable to plant leaf disease detection, focusing on a technique for image segmentation that facilitates automatic detection and classification of plant leaf diseases. Trials involving various plant species, such as Jute, Grape, Paddy, and Okra, demonstrate the algorithm's efficacy in proficiently recognizing and classifying leaf diseases with minimal computational effort. Moreover, to enhance recognition rates during the classification process, Artificial Neural Networks, Bayes Classifiers, mathematical logic, and hybrid algorithms are explored as viable options.

In essence, this paper provides an extensive summary of deep learning-centric strategies for plant leaf disease recognition. It underscores the significanse of data-related processes, visualization techniques, and challenges associated with obtaining labeled datasets for early disease detection. Additionally, the capability of hyperspectral imaging is contemplated, and an algorithm for image segmentation is proposed, pioneering a discussion on the augmentation of disease recognition through additional classification techniques.

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