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Utilizing the AlexNet and Eig(Hess)-HOG Model for Identifying and Categorizing Plant Diseases

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Abstract: Plant diseases are not only resilient but also exhibit rapid proliferation, posing a significant threat to plant health and agricultural yield. Detecting and diagnosing these diseases automatically is paramount in the field of agriculture. Many a methods have been suggested to tackle the challenge for the identification of plant diseases and diagnosis, with deep learning emerging as the favored process due to its outstanding performance. In this study, we introduce an effective methodology that leverages Machine Learning and Deep Learning a approaches. Our approach combines an AlexNet convolutional neural network (CNN) within the Hessian matrix for calculating image surface eigenvalues. Furthermore, we employ the principal component analysis (PCA) Technique for dimension reduction.

Numerous tests were conducted to assess the effectiveness of our method for classifying and detecting plant leaf diseases. We compared the production of our compare the model to other cutting-edge deep learning models, utilizing the PlantVillage dataset for model training. Our models were trained on the initial dataset and an enhanced dataset, comprising 55,448 and 61,486 images, respectively. The experimental results conclusively illustrate the excellence of our approach contrasted to current process, manifesting as improved accuracy, average precision (AP), and reduced computational complexity.

Keywords: *Eig(Hess), Machine learning , Plant diseases, HOG, AlexNet , Training precision, PCA.*

1. Introduction

Plant diseases have significant repercussions on food safety and agriculture, posing perennial challenges in the field. They lead to diminished crop quality, substantial financial burdens, and have profound impacts on sustainable agriculture, rural migration, and the overall agricultural economy [1]. Furthermore, these diseases affect rural communities, particularly those reliant on agriculture in the region. The conventional approach for disease identification involves visual inspection by experienced plant pathologists, utilizing visual examination of diseased plant leaves [2], [3]. However, the wide array of plant species, variations in disease development due to climate change, and the rapid infection transmission across regions can make accurate diagnosis difficult, even for seasoned experts. Consequently, there is a growing interest among researchers to address the issues of classifying and detecting plant diseases effectively. The quest is for a model that can deliver satisfactory results without the need for extensive preprocessing. In contemporary times, advanced technologies like artificial intelligence, machine learning, and deep learning are gaining increasing attention in agriculture due to their significant computational advancements and data processing capabilities, making them essential for efficient plant disease detection and diagnosis [4]. leading-edge plant sensing approaches often rely on a high volume of training parameters, resulting in increased prediction and training times. To counter this, machine learning methods characterized by a smaller quantity of training parameters preferred for effective plant disease detection [5]. Automatic disease detection via leaf image analysis streamlines the process and reduces costs [6]. Recent developments include novel approaches like federated distillation learning systems [7] [8] and efficient semi-supervised models [9], which simplify the classification of various tasks simultaneously. These models can be applied to improve the classification of different types of diseases in crop disease detection tasks. It has been observed that many machine learning systems struggle to provide effective occurs when dealing with extensive datasets and deep-seated lesions in different parts of plant leaves [10]. To overcome in the face of these challenges, deep learning models, particularly convolutional neural networks (CNNs), have attained prominence for immediate plant leaf disease identification.. A range numerous CNN-based structures have been presented for plant leaf disease categorization, including Xception net, DenseNet, AlexNet, ResNet, GoogleNet, Inception Net V4, VGGNet, and SoyNet, among others [11]- [33]. Additionally, more complex networks have been designed based on these classifiers for specific applications in various crops. While some researchers have proposed methods for the diagnosis of crop-specific diseases, they often lack versatility and

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struggle when applied to different crop datasets [34]. The efficiency of a plant disease classification system largely hinges on the effectiveness of attribute selection and the choice of classifiers used for training, primarily related to foliar disease symptoms. While these techniques perform well with small datasets, their performance deteriorates when confronted with large datasets. Machine learning techniques like Random Forest (RF) and Artificial Neural Network (ANN) offer improved results but require a high number of parameters and computation time, making them time-consuming and complex to process. To address these challenges, researchers are developing a novel architecture aimed at reducing complexity, avoiding excessive numerical parameters, and minimizing computational time. The proposed model has demonstrated superior performance compared to comparable advanced models via thorough simulations, offering reduced computational complexity, cost-effectiveness, and improved classification accuracy. The structure of the paper's structure is as follows: Segment 2 elaborates on prior literature, Segment 3 describes the proposed model, Segment 4 discusses simulation results, and segment 5 concludes the document.

2. Related Works

The traditional method of visually diagnosing plant diseases is a time-consuming process, labor concentrated, costly, and personal. These drawbacks have motivated researchers to explore alternative, more efficient methods. Various machine learning methods have been offered to address this issue with great precision, cost decrease, and reduced subjectivity.

Yanli.et al. [35] highlighted the benefits of lightweight models, which offer faster disease identification and require less memory space. They introduced the HLNet deep learning prototype, found on a featherweight convolutional neural network (CNN), designed for rapid and powerful disease recognition.

In another study by [36], the diagnosis of cotton leaf disease was examined. They proposed a deep meta-learning-based model capable of identifying various crop diseases. The dataset consisted of 2,385 healthy and diseased leaf images, and the model achieved an impressive precision of 98.53%.

An innovative approach to vegetation image identification found on deep learning procedures using sheet vein patterns were created [37]. This method successfully classified three legume species (white haricot ,kidney bean, and soy) utilize 3 to 6 levels of CNN technical solutions.

Furthermore, deep learning examples were educated and evaluated on the Plant Village data pool in reference [38]. The study assessed the achievement of double well-known CNN structures, GoogLeNet and AlexNet, in three scenarios (color, grayscale, and segmentation). The results revealed that GoogLeNet outperformed AlexNet, achieving an precision rate of 99.35% on the test set.

To identify the symptoms of four gherkin diseases, In [39] utilized a deep CNN, achieving a recognition precision of 93.4%. In [40] also presented a CNN-based system to identify cucumber leaf diseases with an a precision of 94.9%.

In [41] employed deep learning methods for identifying leaf diseases in plants and antecedents. They used nine neural network structures for feature extraction, with subsequent classification by support vector machines (SVM), extreme learning machines (ELM), and k-nearest neighbor methods. The highest accuracy, reaching 97.86%, was achieved using the SVM classifier and model ResNet 50, though the limitation of this approach was the use of a very limited dataset consisting of solely 1965 images of eight another foliar crop diseases.

In [42] introduced a deep CNN structure for recognizing and categorizing eight different types of soy stress. Their approach included a clarification mechanism and forecasts through high-resolution top-K property card, allowing for the identification, classification, and quantification of stress intensity. It also enabled the autonomous detection of visual indicators when expert annotations were lacking.

Additionally, other innovative techniques involve the use of lesions and stains for disease identification [43], [44]. These approaches offer the advantage of identifying multiple diseases on the same leaf and enhancing data by dividing leaf images Into different sub images.

In [45] employed the GoogLeNet model for differentiating 79 health issues in 14 types of vegetation under demanding experimental environments. The exactness percentage for a sole lesion and territory was 94%, surpassing the 82% accuracy for the entire image.

For wheat plant illness identification, in [46] used Mask-RCNN with either ResNet50 or ResNet101 as the feature extraction network. the average precision on the test dataset was 92.01%.

Huang et al. [47] introduced approaches that self-train the necessary determining the depth of neural network for plant leaf disease identification using neural structure search technique. The model achieved a recognition precision of 98.96% and 99.01% on unbalanced and balanced datasets, sequentially. Though, the precision declined to 95.40% when the image's gray equilibrium was not rectified.

To diagnose camellia leaf diseases, Long et al. [48] explored two training methods: training from scratch and transfer learning from ImageNet. The results indicate that transfer learning significantly improved the categorization effectiveness and convergence rapidity, achieving a classification precision of 96.53%.

Other techniques, such as the use of saliency maps [49], segmentation, and edge mapping [50], were utilized to identify plant diseases. Brahimi et al. [51] introduced a new deep learning model network to identify disease spots, which offered a clearer visualization impact compared to traditional disease treatment approaches.

In another study, J Arun Pandian offer a 14-tier deep Convolutional Neural Network (CNN) model for leaf disease screening using sheet images. The model achieved an precision of 99.96% and outperformed existing learning approaches.

Waleed albattah [53] introduced a custom CentreNet framework with DenseNet-77 as the backbone network. The approach taken a tripartite strategy, including the extraction of the targeted region , key point abstraction using CentreNet, and disease categorization.

In a comprehensive review [54], C. Jackulin et al. evaluated diverse ML and DL methods for diagnosis of plant diseases, comparing their performance and utilization in diverse studies. Additionally, Dahiya et al. [55] discussed the deep learning architecture and diverse parameters related to CNN and element affecting the performance of DL models in detecting plant leaf diseases.

3. Materials and Methods

3.1. Montage expérimental

To address the current limitations and improve upon existing plant disease detection methods, we present the entire process of our proposed approach in this section. We conduct a comprehensive experimental analysis using precision average and recall criteria to evaluate the effectiveness of our proposed descriptor.

Our proposed algorithm is implemented and executed within the Anaconda software on a computer system equipped with 12 GB of DDR 1600 MHz RAM, Intel HD Graphics 5000 with 15366 MB memory, an Intel Core i5 processor, and a central processing unit running at 2.2 GHz.

Figure 1 illustrates the schematic of our proposed technique. The process begins with reading and resizing images to dimensions of 227 × 227 × 3 using MATLAB with bicubic interpolation. These images are then simultaneously processed by a deep feature generator, an enhanced AlexNet CNN, as well as the Eig(Hess)-HOG algorithm. The enhanced AlexNet CNN analyzes the images, recognizes patterns, and generates a feature vector of dimension 1 × 64 [56]. Concurrently, the Eig(Hess)-HOG algorithm extracts features. Subsequently, the PCA algorithm is applied to reduce the dimensions of the features produced by the Eig(Hess)-HOG descriptor.

In our approach, to ensure that the Eig(Hess)-HOG descriptor and the enhanced AlexNet CNN have equal contributions to the last characteristic attribute, the aspects of the Eig(Hess)-HOG descriptor are reduced to 1 × 59 using the PCA algorithm. Following this dimension reduction step, the feature vectors Eig(Hess)-HOG-PCA, the learned feature vector, and the feature vector Eig(Hess)-HOG-PCA are combined, resulting in an effective image feature with a dimension of 1 × 128.

For clarity, a brief description of AlexNet CNN, Eig(Hess)-HOG, and PCA is provided as follows:

- The PCA (Principal Component Analysis) algorithm serves as a dimensionality-reduction technique commonly applied to large datasets. Its primary purpose is to transform a set of numerous variables into a smaller set while preserving the significant information contained in the original dataset. PCA is employed for various purposes, including reducing computational demands, shortening training times, and simplifying models [57].
- The AlexNet CNN architecture consists of 25 layers, and for our enhanced AlexNet model, the last three layers from the original AlexNet CNN are removed, while the remaining layers are retained. Subsequently, we add a fully connected (FC) layer with dimensions 1 × 64 to the end of the adapted AlexNet CNN. This improved AlexNet CNN not only reduces the total number of parameters and the proportion of parameters in the fully connected layer but also enhances the automatic detection of critical and high-level features without human intervention [56].
- The Eig(Hess)-HOG algorithm is a modification of the original HOG (Histogram of Oriented Gradients) algorithm that focuses on the gradient calculation step. This method initially calculates the Hessian matrix of the image. Then, it computes the eigenvalues $\lambda 1$ and $\lambda 2$ of the Hessian matrix. A key characteristic of Hessian eigenvalues is their invariance under rotation, which makes the Eig(Hess)-HOG algorithm rotation-invariant. This algorithm, utilizing the magnitude of eigenvalues, achieves more stable and precise classification results and exhibits continuous rotation invariance, further enhancing its performance [56].

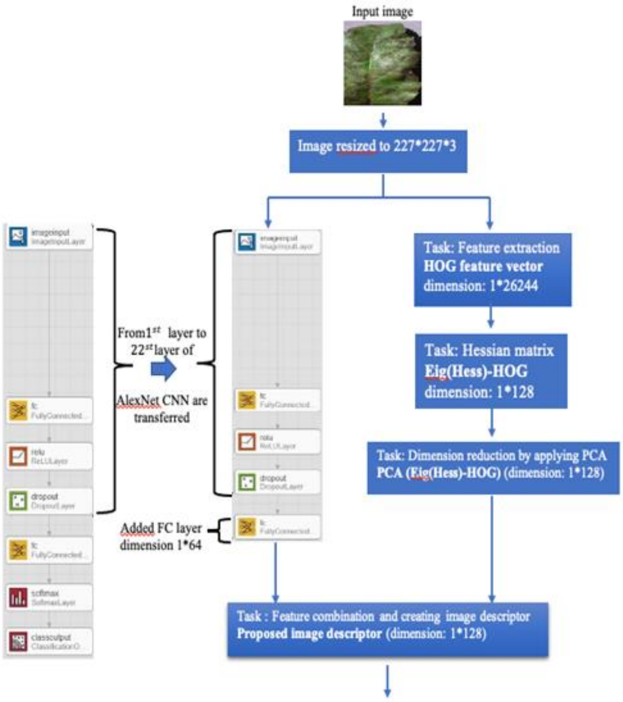

Fig. 1. Proposed method

3.2. Plant village Dataset

In our study, we utilize the PlantVillage dataset, containing a comprehensive number of 54,305 images distributed across 38 categories. These classes encompass 14 different plant species, with 12 classes representing healthy plants and 26 classes corresponding to diseased plants [59]. The dataset comprises colored images of varying sizes, and it includes an additional class for identifying 1,143 background images. Therefore, the dataset's overall image count reaches 55,448. In Figure 2, you can observe representations of the 38 distinct leaf types from the dataset.

Fig 2. Images from the PlantVillage dataset

3.3. Plant Disease Dataset

We recreated this dataset through offline augmentation based on the original dataset, which is accessible on this GitHub repository. The augmented dataset comprises approximately 87,000 RGB images featuring both healthy and diseased crop leaves, categorized into 38 distinct classes. The entire dataset is partitioned into a training set and a validation set, maintaining an 80/20 ratio, while preserving the directory structure.

Fig 2. Images from the PlantDisease dataset

3.4. Performance indictors

Evaluating the performance of the proposed method involves assessing correct detections (true positives), detection errors (false negatives), accurate negatives, and erroneous positives. Various metrics and signs, such as precision, sensitivity, and particularity, are utilized to gauge the method's effectiveness, as expressed in the ensuing mathematical formulas.

$$\text{Precision} = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

$$\text{Sensitivity} = TP/(TP + FN) \quad (2)$$

$$\text{Specificity} = TN/(FP + TN) \quad (3)$$

These metrics are calculated based on the following indices:

True Positives (TP): The count of instances that truly belong to class C and are correctly identified by the classifier.

True Negatives (TN): The count of instances that do not belong to class C in reality and are correctly identified as such.

False Positives (FP): The count of instances that do not belong to class C but are erroneously classified as such.

False Negatives (FN): The count of instances that belong to class C but are inaccurately classified as something else.

4. Results and discussions

To evaluate the performance of our proposed approach, we conducted experiments using two databases, namely Plantvillage and PlantDisease. The testing accuracy of our approach is summarized in Table 1. As shown in Table 1, after 10 epochs of training on the Plantvillage database, the proposed approach achieved a validation accuracy of

92.3%, a training accuracy of 94.96% and a loss of 0.1875. Similarly, after 30 training epochs, the validation accuracy remained at 93.5%, while the training accuracy increased to 98.64%, with a constant loss of 0.0623 and a Validation loss of 0 ,2016. In the case of PlantDisease database, the proposed approach also achieved validation accuracy of Additionally, the validate the efficiency of our offered solution, we conducted comparative experiments involving five influential CNN architectures, namely DenseNet,

83.11%, training accuracy of 82.25% and loss of 0.3247 after 10 training epochs and for 30 training epochs the proposed approach achieved validation accuracy of 87.26%, training accuracy of 85.43% and loss of 0.1543 and Validation loss of 0.2803.

VGGNe, Inception V3, and ResNet. The examination precision for these various methods are detailed within Table .

As depicted in the table, our offered solution performs better than other leading methods examined on the public dataset, even when employing the best classifiers. The primary think for this superior performance lies in our approach's utilization of a combination of Alexnet pretrained with Eig(Hess)-HOG, which harnesses the strengths of both techniques.

When considering the validation accuracy values obtained after 30 epochs by the various approaches, our proposed method achieved an accuracy of 98.64%. In comparison,

respectively.

Regarding validation precision values, our proposed method exhibited the best performance with a precision of 93.5%, followed by INC-VGGN with 91.83%, Inception V3 with 85%, DenseNet-201 with 79.00%, VGGNet-19 with 74.83%, and ResNet-50 with 69.67%.

5. Conclusions

Plant diseases have long been a pressing issue in agriculture, posing a significant threat to food

Table 1. Precision and loss of approach proposed after 30 training periods for the two databases

		Training precision %	Validation precision %	Training loss	Loss of validation
Plantvillage database	10 Iterations	94.96	92,3	0,1875	
	30 Iterations	98,64	93,5	0,0623	0,2016
PlantDisease Dataset	10 Iterations	82,25	83,11	0.3247	
	30 Iterations	85,43	87,26	0.1543	0.2803

DenseNet-201, ResNet-50, Inception V3, VGGNet-19, and INC-VGGN obtained validation accuracy values of 84.13%, 70.41%, 92.14%, 74.20%, and 97.57%,

manufacturing security. in extreme instances, these illness can result in complete crop failure. There is a compelling need for early detection of plant diseases within the realm

Table 2. Perforance and error of various methods after 30 training sessions.

	10 Iterations			30 Iterations			
	Training precision %	Validation precision %	Training loss	Training precision %	Validation precision %	Training loss	Validation loss
DenseNet-201	80,27	76,3	0 ,5726	84,2	79	0,4451	0,4987
ResNet-50	65,2	64,7	1,0028	70,4	69,7	0,8338	0,8442
Inception V3	85,6	82,3	0,4087	92,1	85	0,2576	0,3717
VGGNet-19	65,2	66,7	1,1640	74,2	74,8	0.,9162	0,9026
INC-VGGN	93,9	90,2	0,2122	97,6	91,8	0 ,0856	0,2409
Proposed method	94.96	92,3	0,1875	98,64	93,5	0,0623	0,2016

of agricultural information. Presently, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have displayed remarkable capabilities in addressing the myriad challenges associated with disease detection. This paper introduces an innovative approach that amalgamates a Convolutional Neural Network (CNN) known as AlexNet with the Hessian matrix to compute eigenvalues of the image surface. Additionally, the Principal Component Analysis (PCA) algorithm is harnessed for dimensionality reduction in the context of image-based plant disease identification, mitigating practical limitations.

Our experimental results affirm the efficacy of the proposed descriptor, with a remarkable detection accuracy of 91.83% on the PlantDisease dataset and an impressive accuracy of 93.67% on the Plantvillage dataset. These findings lead us to the conclusion that our approach surpasses other existing methods in this domain.

For our future endeavors, we aspire to adapt our approach for deployment on mobile devices to enable automated monitoring and identification of a wider spectrum of plant diseases, with a specific focus on disease detection at diverse locations within the plant and at different stages of disease development. Simultaneously, we aim to extend the application of our approach to real-world scenarios, including computer-aided diagnosis (CAD), thereby contributing to advancements in agricultural information systems.

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