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Image-based Plant Disease Classification for the Management of Crop Health

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Abstract:
The classification of plant diseases is essential for ensuring agricultural production and food security. In this research, we look into two distinct methods for classifying plant diseases: Convolutional neural networks for deep learning and logistic regression (LR) for machine learning and Random Forest Classifier (RFC). Using a collection of plant pictures that represent different diseases, we train and assess LR and CNN models. The CNN model automatically learns hierarchical representations, whereas the LR model uses manually created features retrieved from the images. Our analysis indicates that both LR and CNN models can classify plant diseases with high accuracy, with CNN outperforming LR due to its capacity to recognize complicated picture patterns. The conclusions drawn from the results of this experiment show how effective machine learning and deep learning approaches are in grouping plant diseases.

Keywords: Random Foresr Classifier, CNN, Logistic Regression, machine Learning.

INTRODUCTION

Agricultural production is negatively affected by disease in plants [1] direct negative impact on food security, which could make food insecurity [2] worse. Therefore, one of the most important steps in preventing a drop in agricultural productivity is the diagnosis of the spread of plant pathogens.Food products available on demand are crucial in the identification of plant diseases. The creation of a system for accurately and effectively classifying plant diseases using image analysis processes [3] is essential for the classificationof different plant diseases based on their visible symptoms. The tool must evaluate pictures of plant leaves or other plantcomponents, properly forecasting their appearance diseases, and offer suggestions in real-time [4] for appropriate treatment or preventive measures to mitigate the spread of diseases and ensures healthy growth of plants. Traditional plant disease identification methods involve visual observation of symptoms and signs [5] exhibited by plants. These methods rely on the expertise and experience of trained plant pathologists. Symptoms such as leaf discoloration, wilting, or necrosis are observed [6], while signs like fungal spores or bacterial ooze may be visible. Microscopic examination and laboratory tests may be conducted to identify the causal pathogen. Although effective, traditional methods can be time-consuming and require specialized knowledge [7], It drove advancement of faster and more advanced techniques in recent years. Utilizing traditionalimage recognition methods for identifying plant illnesses involves several studies focusing on different crops and diseases. Dubey and Jalal [8] used K-means clustering for lesion segmentation and extracted color and texture features using GCH, CCV, LBP, and CLBP. SVM achieved 93% accuracy for three apple diseases. Chai et al. [9] investigatedtomato leaf diseases, extracting 18 parameters, and achieving94.71% and 98.32% accuracy with stepwise discriminant andBayesian discriminant PCA. Li and He [10] focused on five apple leaf diseases, achieving 92.6% accuracy using BP neural networks. Guan et al. [11] classified R diseases with

97.2% accuracy using 63 extracted parameters. Recent approaches involve CNN, achieving high accuracy in recognizing various crops and diseases [12][13]. Successful adoption relies on user-friendly tools and providing training and support to stakeholders in the agricultural sector. Image segmentation is the procedure of dividing an image into moremanageable, smaller portions. This method is used mostfrequently to identify digital components in images. There are numerous methods for partitioning images, including threshold, color-based, transform, and texture-based techniques [14]. Taking away features lessens the number ofpixels in the image, retaining only those that are most significant and eye-catching components. Image matching and search can speed up using a reduced function representation and a high envision size with this strategy. - Tagging photos in one of several defined categories is known as "image classification"[15]. controlled and uncontrolledtwo subcategories of the classifier. The purpose of this investigation is to develop an accurate and reliable plant disease classification system [16] using ML and DL models such as Random Forest Classifier (RFC), Logistic Regression(LR) and Convolution Neural Network (CNN) [17][18]. The study will involve collecting a diverse dataset of labelled images of healthy plants and various diseased conditions. Computer vision techniques will be employed to extractrelevant features. ML algorithms, such as Logistic Regression, will be utilized for initial classification. DL models such as convolutional neural networks (CNN) will betrained on the dataset to improve accuracy in disease classification. Performance metrics like accuracy, precision, recall, and F1 score [19] is going to be used to assess the models. Using the methods of Logistic Regression (LR), Random Forest Classifier (RFC), and Convolutional Neural Network (CNN) models, the project's goal is to create a classification system for plant diseases. The Plant Village Dataset, comprising over 87,000 RGB visuals of healthy anddamaged leaves, will be utilised for training and evaluating the models [20] categorized into 38 classes. The dataset willbe divided into an 80/20 ratio of training and validation sets, maintaining the original directory structure for accurate classification and validation.

ML-DL ALGORITHMS USED

Machine Learning Algorithms

An analytical approach for binary classification is called logistic regression [21]. A logistic function is used to determine the likelihood that an instance belongs to a specificclass. By maximizing the likelihood of the observed data, themodel iteratively learns the best coefficients through a process known as gradient descent. To create predictions, theRandom Forest Classifier [22] uses several different decisiontrees, which is an ensemble learning technique. On various subsets of the training data, it builds several decision trees [23], and then it averages the forecasts of all the trees to arriveat the final prediction. Tasks requiring both classification andregression [24] can be handled by Random Forest, which is proficient at handling complex interactions between features. Preprocessing the dataset, applying data augmentation to thetraining data, and, if necessary, extracting features [25] are all steps in the execution phase. By minimizing the logistic lossfunction, logistic regression calculates parameters that best suit the data, whereas random forest uses voting to join manydecision trees. Metrics including accuracy, precision, recall, and F1-score are used to assess model performance on the testing data [26]. With the use of this approach, the Plant- Village dataset [27] can be accurately separated into both healthy and unhealthy plants by logistic regression and random forest classifiers.

Deep Learning Algorithms

Convolutional neural networks, that are a type of deep learning method, were created specifically for processing and analyzing visual input [28] that is being used to implement out model. The CNNs are now the preferred method [29] for a variety of applications, including picture classification, object detection, facial recognition, and even natural language processing [30]. The arrangement of the visual cortex in both humans and animals [31] serves as the model for CNN architecture. It is made up of numerous interconnected layers that take progressively complicated features [34] from the incoming data and learn them. CNN's primary building components are convolutional layers, pooling layers, and fully linked layers. Local patterns and spatial hierarchies [32] in the input data are captured by convolutional layers. The execution procedure for a CNN, or Convolutional Neural Network [33] involves several keysteps. Firstly, the dataset is prepared by preprocessing and dividing it into training, validation, and testing sets [34]. Then, the CNN architecture is designed, considering thenumber and types of layers. The model is trained using the training dataset, optimizing the weights through backpropagation [35]. For ML model's feature extraction, a pre-trained CNN model or a trained model is utilized and extracting features [36] from a specific layer. These featurescan be fed into traditional ML models. In DL models, a CNNis specifically designed for feature extraction, trained on a large dataset, and the features are extracted from desired layers. Finally, testing is performed by evaluating the ML orDL models' performance [37] on the testing set using appropriate metrics.

METHODOLOGIES

Database Creation

The dataset is created using offline augmentation from theoriginal dataset. Obtaining the original Plant Village Datasetfrom the Kaggle website [38] consists of about 87K RGB pictures of good and diseased leaves which are categorized into 38 different classes. Out of the total dataset, we have carefully selected and utilized 70,295 images specifically fortraining and validation purposes. The number of classes and number of images per class is given in table1 below. We collected 1050 test samples apart from the training and validation images.

Table 1: Classes and Number of Images

No ofclasses	Class names	No ofimages
1	AppleApple_scab	2016
2	Apple___Black_rot	1987
3	Apple___Cedar_apple_rust	1760
4	Apple___healthy	2008
5	Blueberry___healthy	1816
6	Cherry_ (including sour)_P o w d e r y mildew	1683
7	Cherry_(including_sour)_h e a l t h y	1826
8	Corn_(maize)____Cercospora_leaf_spotGray_leaf_spot	1642
9	Corn_(maize)_C o m m o n rust_	1907
10	Corn_(maize)_N o r t h e r n__Leaf_Blight	1908
11	Corn_(maize) h e a l t h y	1859
12	Grape___Black_rot	1888
13	Grape___Esca_ (Black Measles)	1920
14	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1722
15	Grape___healthy	1692
16	Orange___Haunglongbing_(Citrus greening)	2010
17	Peach___Bacterial spot	1838
18	Peach___healthy	1728
19	Pepper, _bell____Bacterial spot	1913
20	Pepper, bell___healthy	1988
21	Potato Early blight	1939

22	Potato Late blight	1939
23	Potato healthy	1824
24	Raspberry healthy	1781
25	Soybean healthy	2022
26	Squash Powdery mildew	1736
27	Strawberry Leaf scorch	1774
28	Strawberry healthy	1824
29	Tomato Bacterial spot	1702
30	Tomato Early blight	1920
31	Tomato Late blight	1939
32	Tomato Leaf Mold	1882
33	Tomato Septoria_leaf_spot	1745
34	Tomato Spider_mites_Two- spotted_spider_mite	1741
35	Tomato Target Spot	1827
36	Tomato Tomato_Yellow_Leaf_Curl_Virus	1961
37	Tomato Tomato_mosaic_virus	1790
38	Tomato healthy	1926

Data Augmentation

To improve the generalization and performance of the models for logistic regression and random forest classifiers [39], data augmentation techniques can be applied. Data augmentation [40] involves applying transformations to the existing dataset, creating new samples with diverse variations. This increases the quantity and diversity of the training data, leading to improved model performance.

Image Preprocessing

To increase the quality and usability of images for analysis or further processing, image preprocessingtechniques [41] are used. These methods include operations like cropping, rotation, flipping, edge detection, thresholding, normalization, noise reduction, contrast enhancement, and filtering [42]. Resizing, scaling, and noise reduction procedures change the size of an image while reducing pixel values' random fluctuations. Methods for increasing contrast boost visual quality, whereas normalization [43] uniformizes pixel value ranges. Color space conversion makes visual representation easier [44] while cropping concentrates attention on areas of significance. Correct alignment or orientation by rotation and flipping. While thresholding converts images to binary format [45] for segmentation, edgedetection highlights boundaries. To enhance or reduce certain picture aspects, filtering employs specialized filters [46]. The Sample image before resizing is given in the following image Fig 1 below.

Fig 1: Sample Image Before Resizing

The image as shown in Fig 2 is the resized image of the same image as Fig 1. The image shown below in Fig 3 is an image that's being created because of a thresholding technique called Binary Inverse [47] on plant images. It converts the images into a binary representation where foreground pixels are set to 0 and background pixels are set to the maximum value of 255. This method is useful for segmenting objects of interest from the background [48], allowing further analysis or processing on the extracted plant regions.

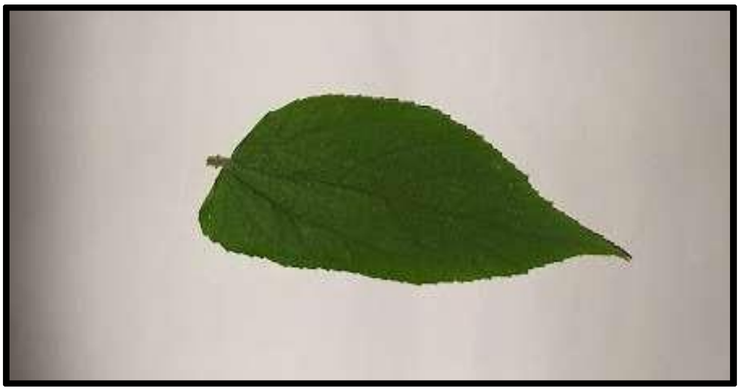

Fig 2: Sample Image after Resizing

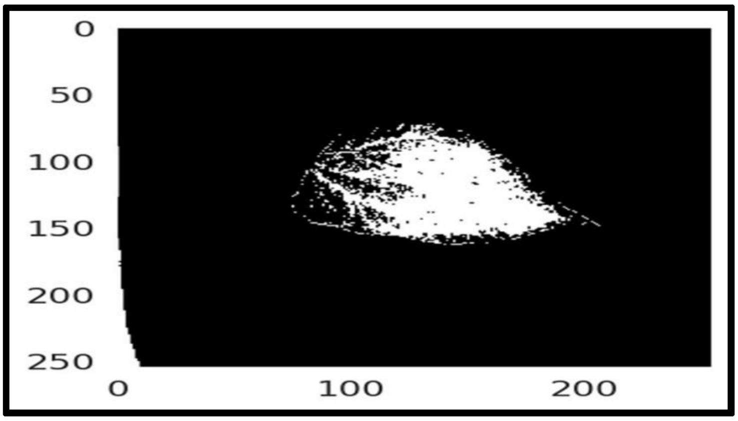

Fig 3: Original Image before LBP Feature Extraction

Feature Extraction

Local Binary Patterns (LBP) feature extraction [49] is a widely used technique in computer vision for texture analysis. LBP captures local patterns in an image by comparing the intensity [50] between an inner pixel and the neighbouring pixels. These comparisons are encoded into binary patterns that represent the local texturing info. Different machine learning approaches, notably the Random Forest classifier, Convolutional Neural Networks (CNN), and Logistic Regression, can use LBP features [51]. In Random Forest, LBP features can contribute to decision-making based on texture information. In CNN, LBP features can be used as input channels or concatenated with other features toenhance [52] texture representation. In Logistic Regression, LBP features can help model the relationship between the texture patterns and the target variable [53], enabling classification based on texture characteristics. The Image before LBP feature extraction is given in Fig 4 below.

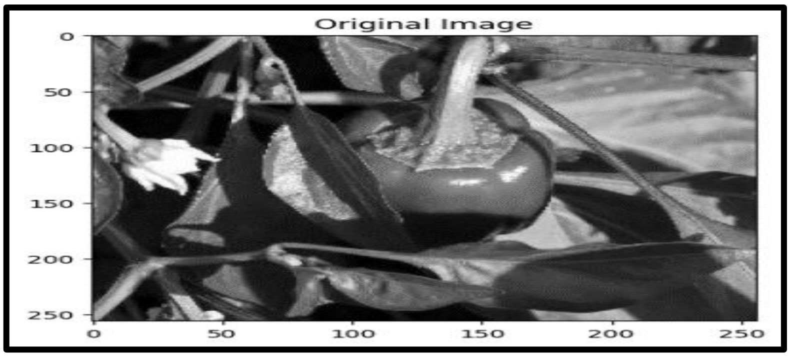

Fig 4: Original Image after LBP Feature Extraction

In the above Fig 5 the image that is being obtained afterfeature extraction is given.

Training

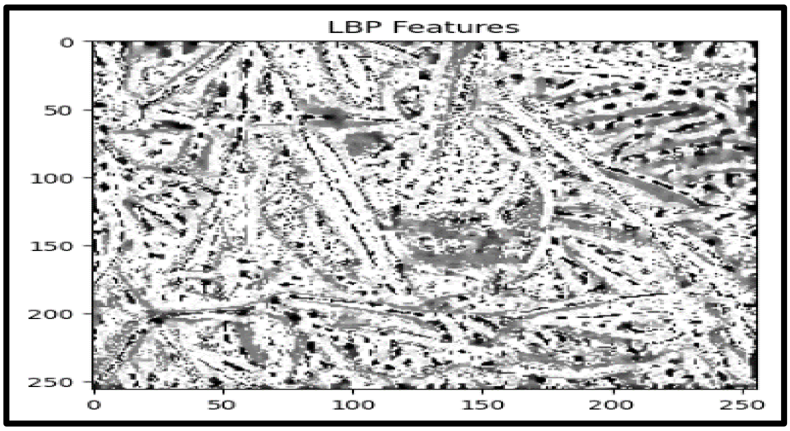

Fig 5: Original Image after LBP Feature Extraction

In the experiment, a total of 70,295 images were trained using the specified hardware and software components. To leverage the computational power of the GPU, the CUDA toolkit [54] was installed, facilitating more effective computation for deep and machine learning models. The training procedure was made simpler by the experimental platform's use of a combination of hardware and software resources. The details of the experimental setup, including the specific components and configurations, are provided in Table 2, showcasing the environment where the training of the images took place.

Table 2: Details of Experimental Platform

Hardware Platform		Software Platform	
CPU	Intel(R) Core (TM) i5-6500 CPU @ 3.20GHz 3.19 GHz	OS	Windows 1164-bit
GPU	Nvidia Geforce GTX1650 Ti	Framework	Logistic Regression, Random Forest Classifier, Convolution Neural Network
RAM	8GB	Programming	ATLAB o2020a o64-bit

Testing

To get the prediction scores for each class, the test data isused to evaluate the previously acquired data model. The bestguess of the test data's class will be determined by the class with the greatest prediction score. The test dataset is utilized to assess how well the trained model performs on unobserved data. Based on the characteristics found in the test data the model forecasts the likelihood scores for each class. These prediction scores represent the model's level of assurance in classifying each data point. The best guess for that particular data point is the class with the highest prediction score. By comparing the prediction scores between classes, the model can determine the most likely class for each instance of test data, enabling accurate classification and decision-making.

RESULTS AND DISCUSSIONS

The testing process produced the results displayed in table 2.

Table 2: Results of ML Algorithms

	Random Forest Classifier	Logistic Regression
Accuracy	67%	58.63%
F1-Score	66%	32%
recall	67%	56%
precision	68%	82%

The table displays the accuracy, F1-score, recall, and precision values [55] for two different classifiers: Random Forest and Logistic Regression. Random Forest Classifier achieved an accuracy of 67% and a relatively highF1-score of 66%, indicating a balanced performance. Logistic Regression had a lower accuracy of 58.63% and A 32% F1- score indicates overall performance. The highest accuracy was achieved by CNN (99.39%), demonstrating its superior case-classification abilities accurately. When comparingthe results obtained from logistic regression (58.63%accuracy), random forest classifier (67% accuracy), and CNN (99.39% accuracy) in plant disease classification, it's clear that the CNN method performs better than the conventional picture recognition methods cited in the literature. Previous research has used techniques like K-means clustering, SVM, stepwise discriminant analysis, Bayesian discriminant PCA, BP neural networks, and feature extraction techniques such as GCH, CCV, LBP, and CLBP. These studies achieved accuracies ranging from 92.6% to 98.32% for specific crop diseases. However, the recent approach using CNN has shown remarkable accuracy in recognizing various crops anddiseases, surpassing the traditional techniques mentioned in the literature.

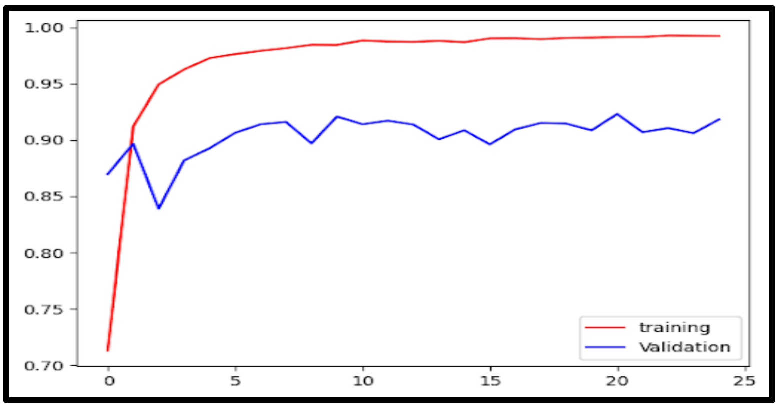

Fig 6: Accuracy curve

The accuracy curve for training and validation visuals is shown in Fig. 6. It displays the model's accuracy performance for a classification job with 37 classes during training and validation. The curve demonstrates the model's learning progress and potential overfitting or underfitting.

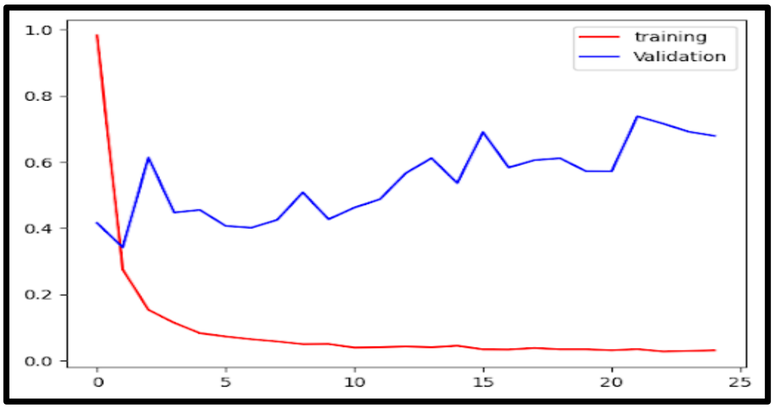

Fig 7: Loss curve

The following Table 4 produced the data for accuracy curve and loss curve for the CNN model.

Table 4: Data for Accuracy and Loss Curves for CNN

	1st epoch	25th epoch
training accuracy	71.27%	99.30%
loss	0.9822	0.0305
validation accuracy	86.94%	91.80%
val_loss	0.4155	0.6787

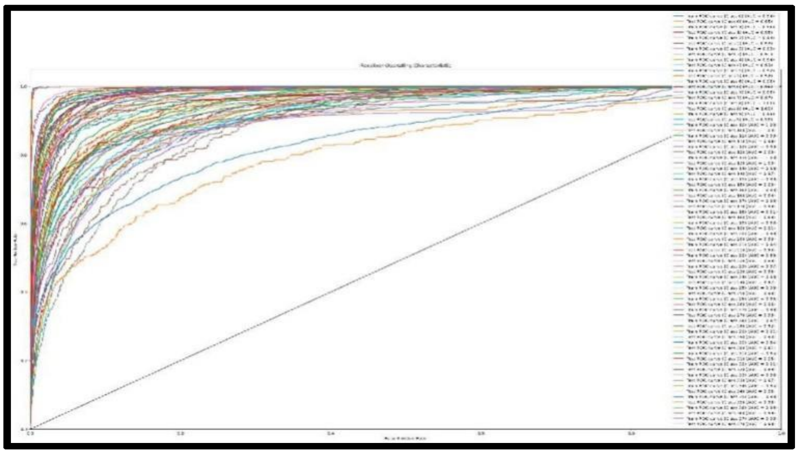

Fig 8: ROC curve

In Figure 8, the ROC curve represents the performance evaluation of a classification model for 37 different classes. It provides a graphical representation of thetrade-off between true positive rate and false positive rate across multiple classes.

CONCLUSION

By developing two ML and DL models we have learnt that DL model is efficient in classifying images ratherthan using ML models. We were able to predict most of the images in DL models using Convolution Neural Network (CNN). The classification of plant diseases using image- based methods is expected to make significant strides in the future. Several important fields are projected to experience major advancements thanks to continuous research and technological development. The development of deep learning models, particularly CNN architectures, for the categorization of plant diseases is one such topic. The development of more complex network architectures that canextract even more nuanced characteristics from plant photos in the future may be the focus to improve the accuracy and resilience of the system. Additionally, improvements in dataaccess and collecting will be very important. Machine learning models will have access to more comprehensive data when larger, more varied, and well-annotated datasets are accumulated, improving generalization and performance. theincorporation of multi-modal data, such as spectral or hyperspectral data with image-based information.

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