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Plant leaf disease detection using local binary pattern and deep convolutional neural networks

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ABSTRACT
Plants are susceptible to pathogen infections during their growing period leading to reduced crop quality and yield. Traditional disease detection methods such as expert diagnosis and pathogen analysis rely on experienced professionals and could be time-consuming and prone to errors. Deep convolutional neural networks (CNNs) have exhibited their potential to detect plant diseases on the basis of visual patterns of leaves. Most of the existing CNN based methods do not take advantage of additional information. Most of the disease significantly affects the texture of the plant leaves. Therefore, texture features can provide complementary information to get better results. In this paper, local binary pat tern (LBP) technique is used to extract texture information that is stacked with original image. A CNN model is proposed that takes embedded texture and spectral information to detect crop diseases using leaf images. The experiments are carried out on Apple, Corn, and Potato crops from Plant Village dataset. The proposed method achieved the overall accuracy up to 98.73% (κ = 98.04). It is found that LBP makes significant difference in disease classification accuracy and helps the proposed method exhibit better performance than some existing well known CNN models.

Introduction
World population relies on agriculture for food security and various other needs. Agriculture isthe backbone of the economy of many countries. A large population of the world depends on agriculture sector for employment. Crops are susceptible to a wide variety of diseases caused by viruses, bacteria, fungi, and some environmental factors (Khamparia *et al*., 2020). Plant diseases have devastating effects on crops. Loss of crop yield can lead to food shortages and loss of employment that adversely affect the economy. Early detection and accurate diagnosis of plant diseases are crucial for effective disease management. Traditionally, plant disease management relies on human expert knowledge that could be subjective and biased sometimes. Recent advances in computer vision and image processing have enabled the development of automated systems for plant disease detection (Vishnoi *et al.,* 2021). The images of different parts of plants are captured and processed using machine learning techniques that capture information on colour, shape, and texture, etc. to detect and diagnose plant diseases. These methods consist of two major components: feature extraction techniques and a classifier. Feature extraction is a process of transforming raw data into a set of representative features that are used as input to the classifier (Kumar, 2020). Based on the extracted features, the classifier identifies the diseases. These techniques can be used to develop automatic methods for plant disease identification. However, training the machine learning models could be computationally expensive depending on the size of the training set. Advent of graphical processing unit(GPU) based processors has paved the way for the development of advanced machine learning models. Over the years, various feature extraction and classification techniques have been used to develop plant disease detection systems. Feature extraction is a process of transforming raw data into a set of representative features such as edges, texture (Kumar and Dikshit, 2014, 2015a, 2015b) shape, and size, etc. that more useful in classification. The similarities in disease symptoms or infected areas adversely affect the performance of the classifier to identify/classify the in-

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fected leaves. Therefore, feature extraction is crucial for disease detection. (Esmaeel *et al.,* 2018) determined texture information using Gray level co-occurrence matrix (GLCM) to detect diseases in Bean plants using leaf images. Local binary pattern (LBP) is another well known technique for texture analysis. (Mathew *et al.,* 2021) introduced a method for classifying three fungal diseases in banana using local texture features extracted with ELBP resulting in high accuracy. (Dhar *et al.,* 2022) presented a method to classify leaf diseases using Gist and LBP features, which are extracted separately and then combined. (Pattnaik and Parvathi, 2021) compared histogram of oriented gradient (HOG) and LBP where HOG outperforming LBP with an accuracy of 97%. (Chaudhari *et al.,* 2022) compared LBP and (GLCM) features with color features for recognizing banana plant leaf diseases. LBP features were found to be more accurate than GLCM features when used with SVM, while KNN gave better results with GLCM. (Basavaiah *et al.*, 2020) fused multiple features including color histograms, Hu Moments, GLCM, and LBP for classifying leaf diseases using tree based classifiers with 94% accuracy. (Kusumo *et al.,* 2018) investigated different types of features including color, scale-invariant feature transform (SIFT), speed up robust features (SURF), oriented FAST and rotated BRIEF (ORB), and HOG. Results suggest that color is the most informative feature with RGB providing the highest accuracy. (Devi and egam, 2019) analyzed the leaf disease of rice plants using a wavelet transform, SIFT, and GLCM techniques. Classification labels the plant image indicating whether it is healthy or diseased. In recent years, the image based plant disease detection has moved to deep learning era (Zhang *et al.,* 2018). Convolutional neural network (CNN) is a modern deep learning method having a layered architecture that can learn hierarchical features from the images to perform various computer vision tasks. Different layers of a CNN perform the tasks of feature extraction and classification (Xu *et al.,* 2017) making them highly effective in accurately classifying plant diseases. (Zhao *et al.,* 2021) developed a CNN model that achieves an average identification accuracy of 96.81% for diseases in tomato and 99.24% accuracy for diseases in grape crop. (Bensaadi and Louchene, 2023) developed a low-complexity CNN architecture for automatic plant disease classification that achieves 97.04% accuracy using over 57,000 tomato leaf images from nine classes. (Kawasaki *et al.,* 2015) developed a CNN based disease detection system that demonstrated the accuracy of 94.9%. (Thakur *et al.,* 2023) introduced a lightweight Convolutional Neural Network called VGG-ICNN for identifying crop diseases using plant-leaf images. The model achieved a high accuracy of 99.16%. (Agarwal *et al.,* 2020) proposed a simplified CNN model with 8 hidden layers outperforming several other CNN models with 98.4% accuracy. (Zhang *et al.,* 2019) proposed a faster R-CNN approach to detect rice diseases with high accuracy. Another R-CNN based method was developed by (Carion *et al.,* 2020) for plant diseases detection. (Chen and Wu, 2023) used faster R-CNN to mark grape leaf lesions and ResNet or disease identification. It also used DCGAN to generate synthetic grape lesion images, which were combined with real images to train ResNet. (Gajjar *et al.,* 2022) developed a deep CNN model for crop disease identification and deployed the model on an embedded platform. They reported a classification accuracy of 96.88%. (Vishnoi *et al.*, 2023) proposed a comparatively smaller CNN model for apple disease identification. It takes the advantage of augmentation to increase the training set size. The model performed well with the overall accuracy of 98%. (Stephen *et al.,* 2023) extracted useful features with a 3D2D CNN, which are used in an optimized deep generative adversarial network (GAN) to classify rice diseases. The authors achieved good classification accuracy of 98.7% by integrating different deep learning techniques. Most of the existing deep CNN methods do not use external source of information besides the input image and rely on their own feature extraction capabilities. However, there are some issues with CNNs such as limited generalization, sensitive to noise, and insensitivity to texture as they are designed to learn features from the spatial layout of pixels instead of texture patterns. that need special consideration. These issues can be mitigated by providing some additional informationas input. Additional input to CNNs about shape, size, or texture can provide following advantages.

Improved Generalization: By combining the learned features from CNNs and texture information, the model can learn more robust and discriminative features that can generalize better to new data (Li *et al.,* 2015).

Improved Robustness to Noise: Texture information can enhance the robustness of the model to image noise, which can improve the model's accuracy in noisy environments (Kylberg and Sintorn, 2013).

Improved Texture Sensitivity: Texture patterns that are not easily detected by CNNs, which can improve the model's performance on texture-based classification tasks (Zhou *et al.,* 2008). In this work, a deep CNN model is developed that takes leaf image and its texture information as input to detect plant disease. The effectiveness of the system is examined on different cropsincluding apple, corn, and potato.

Materials and method

A new CNN plant disease detection method is proposed that makes use of a widely acceptable texture analysis technique known as LBP to extract texture information on plant leaf images. It uses leaf image and its texture information as input to CNN to identify the disease. The complete flow of the process is shown in Fig. 1. The raw leaf image is segmented with the help of Grabcut method to separte foreground and background. LBP technique works better on binary images, therefore, Otsu thresholding is applied to binarize the image. The segmented image and texture information obtained from LBP are combined to from the joint input dataset, which is divided into training and test sets. The CNN model is trained to classify the input leaf image into one of the healthy or disease class to detect the disease.

Dataset

Leaf images for various crop disease datasets are obtained from the Plant Village repository containing over 54,000 images across 38 crop categories. Three crops including apple (*Malus domestica*), corn (*Zea mays*), and potato (*Solanum tuberosum*) are considered for this work. The leaf images for the chosen crops are divided in a total of 11 different classes. Some sample images are shown in Fig. 2. The training and test sets are formed with a ratio of 75:25 ratio for each class. Table 1 presents the distribution of images among different classes in the dataset. A brief description of different classes is

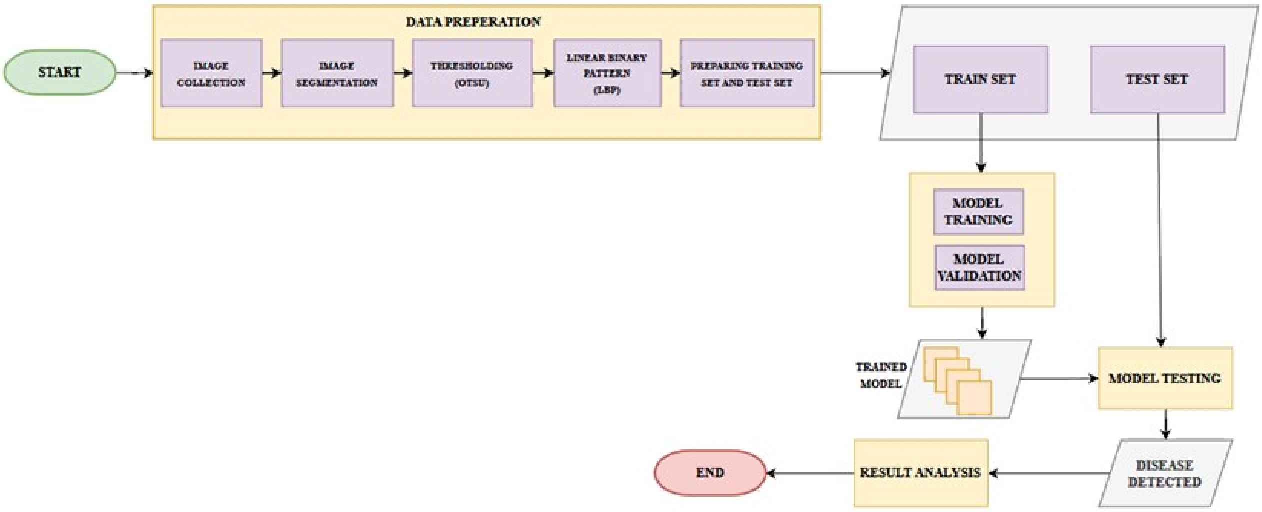

Fig 1 : Work flow for plant disease detection and identification

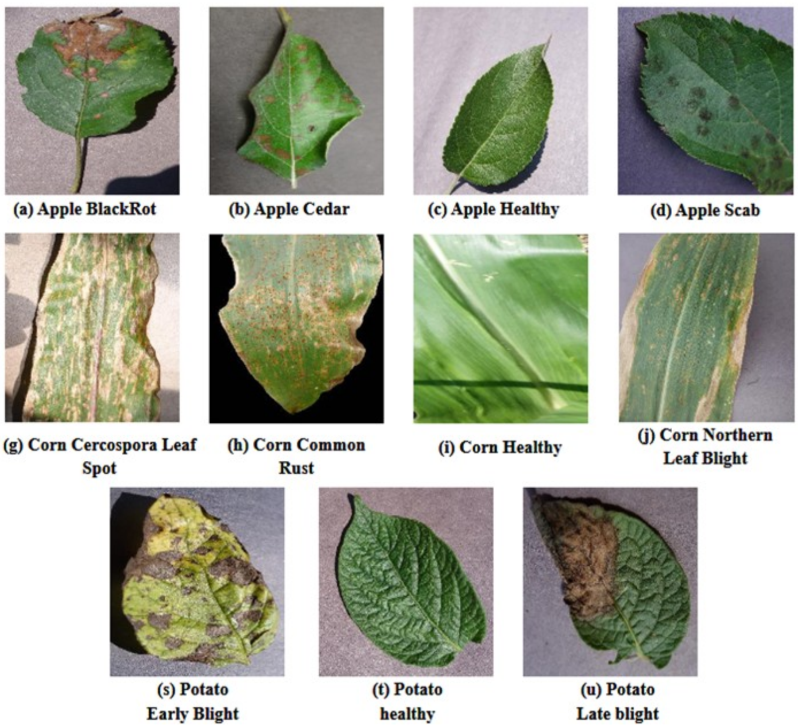

Fig. 2 Samples from dataset for different crops

Table 1 Dataset for image classification of apple corn and potato leaf disease

Disease Class	Total images	Training set (75%)	Test set (25%)
Apple.Scab	504	378	126
Apple.BlackRot	497	373	124
Apple.CedarRust	220	165	55
Apple.Healthy	1316	987	329
Corn.Gray leaf spot	411	308	103
Corn.Common rust	954	716	239
Corn.healthy	930	698	233
Corn.Northern Leaf Blight	788	591	197
Potato.Early blight	800	600	150
Potato.healthy	122	92	31
Potato.Late blight	800	600	150

given as follows.

Black rot, caused by Diplodia seriata, presents as frog-eye spots with purplish or reddish edges and a brown center on leaves, which can lead to defoliation and tree weakening in severe cases (Crespo *et al.,* 2018). Scab, an intense fungal disease, causes olive-green or brown leaf spots and impacts apples, potatoes, and other crops, spreading quickly in dry soils through Streptomyces scabies (Bowen *et al.,* 2011). Cedar rust, resulting from Gymnosporangium juniperi-virginianae, produces bright orange spots on apple and juniper species, with severe symptoms potentially damaging apple crops (Crowell, 1934). Gray leaf spot, caused by Cercospora zeae-maydis, affects corn by creating brown-gray lesions that spread seasonally (Ward *et al.,* 1999). Common rust, an airborne disease supported by cool, humid conditions, manifests as brown pustules that blacken with age, although its impact on yield is minimal (Raid and Comstock, 2000). Leaf blight, from Helminthosporium turcicum, appears as reddish-purple spots on corn leaves, with significant damage in susceptible hybrids (Perkins *et al.,* 1987). Early blight, driven by Alternaria solani, shows as concentric-ringed spots on tomato and potato leaves, potentially causing leaf yellowing and wilting (Van der Waals *et al.,* 2001). Lastly, late blight, caused by Phytophthora infestans, induces dark lesions resembling frost damage on tomato and potato plants, with rot extending deeply into tubers (Mizubuti and Fry, 2006).

Grab-Cut Segmentation

A leaf image may contain several other details or sometimes others objects apart from leaf itself. Segmentation can help to remove unwanted background from an image and identify specific region of interest (ROI). Therefore, in the proposed method, the raw image is segmented to separate plant leaf and background. GrabCut (Qi *et al.,* 2022) is a well known segmentation technique that uses Gaussian mixture model to estimate the color distribution of the ROI and background. It creates a Markov random field over pixel labels with an energy function that favors connected regions with identical labels. The mathematical formulation of GrabCut can be expressed as an energy minimization problem, where the objective is to find a segmentation of the image that minimizes the energy function (Xiong *et al.,* 2020). The energy function for GrabCut is defined as follows:

$$E(S) = E_{data}(S) + E_{smooth}(S) \quad (1)$$

where S is the segmentation mask, ^{E}data is the data term that measures the difference between the color of the pixels and the color of the foreground and background models, and ^{E}smooth is the smoothness term that encourages spatial coherence of the segmentation. The data term can be expressed as:

$$E_{data}(S) = \sum_{i \in S_f} D(i) + \sum_{i \in S_b} D(i) \quad (2)$$

where i is the pixel location, S_f and S_b are the foreground and background regions defined by the user, and D(i) is the color vector of pixel i. The term $\Sigma_{i \in Sf}$ D(i) measures the similarity of the foreground model to the color of pixel i, while the term $\Sigma_{i \in S_b}$ D(i) measures the similarity of the background model to the color of pixel i. The smoothness term can be expressed as:

$$E_{smooth}(S) = \lambda \sum_{i,j \in N} w(i,j)(1 - S(i)S(j)) \quad (3)$$

where λ is a parameter that controls the tradeoff between data and smoothness terms, N is the set of neighboring pixel pairs, w(i, j) is a spatial weight that measures the proximity of pixels i and j, and S(i) and S(j) are the segmentation values of pixels i and j. The term (1 − S(i)S(j)) encourages the segmentation to be spatially smooth i.e. neighboring pixels with similar colors are assigned the same segmentation value. The GrabCut algorithm solves this energy minimization problem using the graph cut technique, which involves constructing a graph of the image and partitioning it into foreground and background regions. The algorithm iteratively updates the foreground and background models and the segmentation mask until convergence.

Otsu Thresholding

Thresholding is a common image processing technique that can produce a binary image by turning the pixels with intensities above or below a threshold as white and other pixels as black (Kohler, 1981). Otsu's thresholding method works by analyzing the histogram of pixel intensities in an image and identifying the threshold value that maximizes the between-class variance as shown in Fig. 3. The between -class variance is a measure of the separation between the two classes of pixels (foreground and background) and is calculated as the sum of the weighted variances of the two classes. The thresold value is determined as follows.

$$th^* = argmax_{th=0}^{L_i-1}\omega_0(th)\omega_1(th)[\mu_0(th)-\mu_1(th)]^2 \quad (4)$$

where th* is the estimated threshold, L_i is the maximum intensity value of the image, w_0(th) and w_1(th) are the probabilities of a pixel being in the background and foreground, respectively, based on the intensity value of the pixel, and μ_0(th) and μ_1(th) are the mean intensity values of the background and foreground, respectively, calculated using the pixels that fall below and above the threshold th. Once the optimal threshold is determined, the image regions are separated by classifying pixels with intensities above the threshold as foreground and those below the threshold as background. This process helps to separate ROI from the background, enhance edges, and remove noise from an image.

Local Binary Pattern

Local binary patterns (LBP) (Nikam and Agarwal, 2008) is a popular feature extraction technique used in various applications such as face recognition, object detection, and texture classification. LBP is a texture descriptor that can effectively represent local spatial patterns in an image. LBP operator works by comparing the intensity value of each pixel with its neighboring pixels as shown in Fig. 3. The resulting binary code is then used to describe the texture pattern of the image. This process involves converting an image into grayscale and selecting a neighborhood around each pixel. The neighborhood for a pixel at location (x, y) is determined as follows (Priya *et al.,* 2018).

$$\left(cp_x - R\sin\left(\frac{2\pi p}{P}\right), cp_y + R\cos\left(\frac{2\pi p}{P}\right)\right) \quad (5)$$

Where cp_x and cp_y are the x and y coordinates of the center point of a circle, R is the radius of the circle, p is the index of a point on the circle (ranging from 0 to P − 1), and P is the total number of points on the circle. This expression gives the coordinates of the pth point on the circle centered at (cp_x, cp_y) with radius R. The x coordinate of the point is given by cp_x − R sin 2πp/P, while the y coordinate is given by cp_y + R cos 2πp/P. If a pixel is darker than the central pixel, it is marked as black. If it is lighter, it is marked as white. This decision is based on a threshold value set by the central pixel. After marking the surrounding pixels, the algorithm uses the resulting pattern of black and white dots to create a code that describes the texture of the picture in that area. This code is called LBP and is used as a characteristic to identify the local texture of the image.

$$LBP_{P,R} = \sum_{p=0}^{P-1} 2^p . s(i_p - i_c) \quad (6)$$

where $LBP_{P,R}$ is LBP feature value for a pixel, P is the number of sampling points on a circle of radius R centered on the pixel, i_c is the intensity value of the center pixel, i_p is the intensity value of the p-th sampling point, s(x) is the step function defined as:

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (7)$$

The LBP operator calculates a binary pattern by comparing the intensity values of the sampling points with the center pixel. If the intensity of a sampling point is greater than or equal to that of the center pixel, the corresponding bit in the binary pattern is set to 1, otherwise it is set to 0. The binary pattern is then converted to a decimal value to obtain the final LBP feature value for the pixel. The LBP operator can be applied at different scales and with different neighborhood sizes, making it a versatile technique for feature extraction. One of the unique features of LBP is its computational efficiency. LBP can be computed very quickly and requires minimal memory, making it suitable for real-time applications. Additionally, LBP is robust to imagenoise and illumination variations, which are common challenges in computer vision tasks. Another unique aspect of LBP is its ability to encode both spatial and textural information. This makes LBP particularly useful for tasks that require both global and local feature representation, such as object detection and recognition (Priya *et al.,* 2018). The outputs of segmentation, thresholding, and LBP are shown Fig. 3

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are popular deep learning models that are commonly used for image classification, object detection, and other computer vision tasks. CNNs are designed to mimic the way that the human visual cortex processes visual information, making them highly effective for image analysis. The key feature of CNNs is the use of convolutional layers, which apply a set of filters to the input image to extract features that are relevant to the task at hand. The filters parameters are learned during the training process and their values are adjusted to maximize the accuracy of the network. The output of the convolutional layers is then passed through a series of fully connected layers, which are similar to the layers in a traditional neural network. The output of a CNN can be given as follows:

$$Y = f(W_n * f(W_{n-1} * f(W_{n-2} * \dots * f(W_2 * f(W_1 * X + b_1) + b_2) + \dots + b_n) \quad (8)$$

Where, X is the input image, Y is the output class probabilities, f is the activation function, Wn is the weight matrix for the nth layer, bn is the bias vector for the nth layer. A new CNN model is developed in this work that takes a four band image as input. The segmented image is stacked with LBP generated texture image making it a 4-band input X. The first layer of the CNN is a convolutional layer, which applies a set of filters to the input image to extract features. The result of this computation is a new feature map, which highlights the regions of the input image that are relevant to the task at hand (Zhang *et al.,* 2018). After the convolutional layer, the output is passed through a nonlinear activation function ReLU to introduce nonlinearity into the network. This is followed by a max pooling layer, which reduces the spatial dimensions of the feature map, while preserving the most important information. The process of convolution, activation, and pooling is repeated multiple times in the network, with each successive layer learning increasingly complex features. There are total 12 layers of different types in the network as shown in Fig. 4.The final layer of the

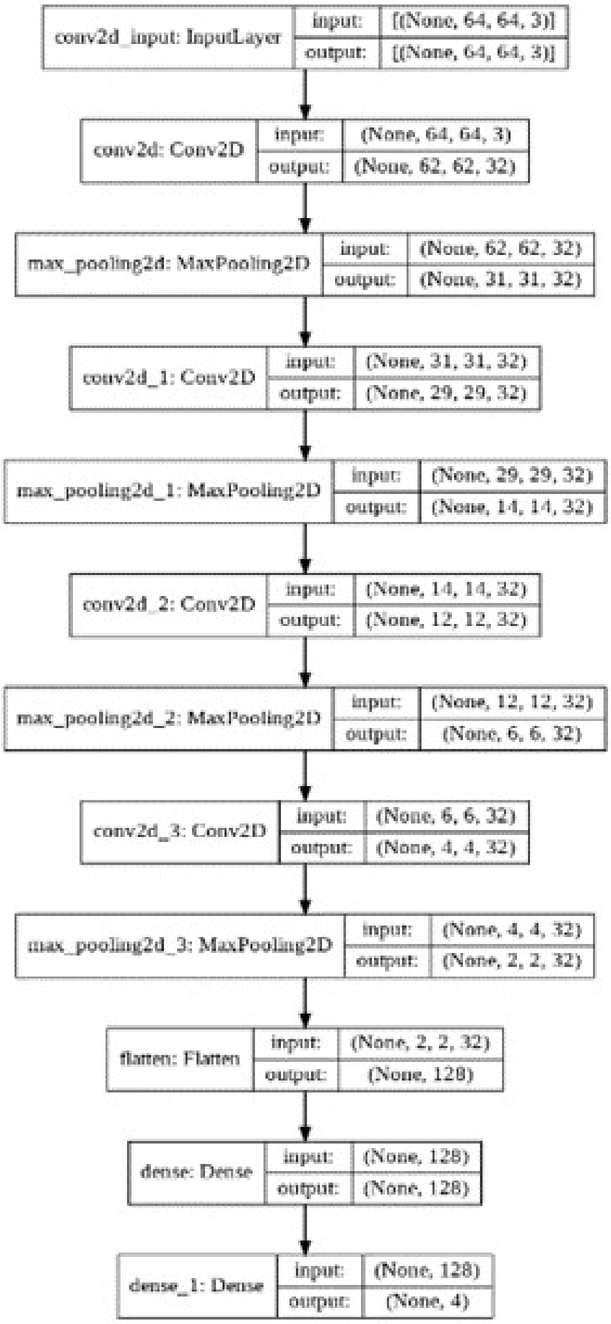

Fig. 4 Architecture of CNN model for classification

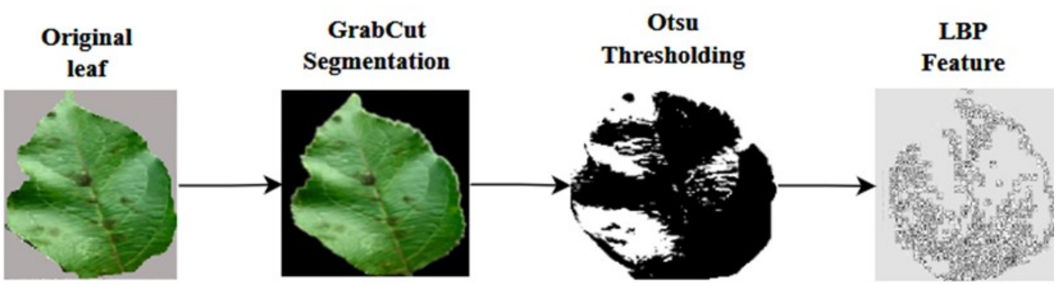

Fig. 3 LBP feature extraction

network is a fully connected layer, which maps the output of the previous layer to the output class probabilities. The weights and biases in this layer are learned during training, and the network is optimized to minimize the loss function, which measures the difference between the predicted and actual output.

Results and Discussion

The experiments are performed on a Linux machine equipped with 2 Xeon processors, 8GB GPU and 128 GB RAM. The implementation is done in Python using the libraries such Keras and TensorFlow, etc. The CNN model is trained using stochastic gradient descent method up to 300 epochs. The learning rate is set to 0.01. The batch size is taken as 32. The results are compared to four well-known pre-trained CNN models InceptionResnetV2 (InRsV2), InceptionV3 (IncpV3), VGG16 and VGG19. The accuracy is determined in terms of na¨ıve-accuracy and Kappa coefficient (κ). The parameter naive-accuracy measures the overal accuracy, while κ measures the agreement between the predicted and actual classes, taking into account the possibility of correct predictions occurring by chance. In addition, the impact of several other parameters is also analyzed. All the experiments are carried out for three crops namely Apple, Corn, and Potato from a publiclly available dataset known as PlantVillage.

Accuracy analysis

The naive-accuracy for disease classification in Apple, Corn and Potato crops is reported in Table 2 along with accuracy variance. The proposed method observed a good overall accuracy as 98.73%, 95.84%, and 96.9% for Apple, Corn and Potato crops respectively. The accuracy is also determined for individual diseases of different crops. All the health classes except Corn.Common rust and Corn.Healthy are classified with good accuracy of more than 96%. These two classes are classified with little inferior accuracy leading to overall accuracy under 96% for Corn crop. The learning errors are also reported in the table. The proposed method observed smaller variance in accuracy not more than 4.15%. For Apple and Potato crops it is as small as 1.26% and 2.09% respectively. The performance of the developed method is also compared with some existing pre-trained CNN based methods.

Similar observations can be made from Table 3 also, where accuracy is reported in terms of κ. For different crops, overall κ varies 0.9465 − 0.9804 and variance lies between 0.0068 − 0.0122 with lowest accuracy for Corn. In recent times, a number of CNN based methods have been developed for plant disease detection. Many of these methods use pre-trained CNN models. For a specific problem, a pre-trained CNN model is fine tuned that also involve minor modifications in the original architecture. The accuracy of the proposed method is compared with some of the pre-trained CNN-based methods including InceptionResNetV2, InceptionNetV3, VGG16, and VGG19. The proposed method outperformed pre-trained CNN-based methods as observed from Table 2 and Table 3. Sometimes accuracy parameters may be misleading, therefore, the performance is also evaluated in terms precision, recall, and F1-score, which are more sensitive parameters. The detailed classification report is given in Table 4. All parameters indicate that LBP and CNN based method can reliably identify crop diseases. The training accuracy is plotted against validation accuracy for all the crops in Fig. 5 to check the fitness of the CNN model used in the proposed method. It is observed from the graphs that both accuracy curves close to each other indicating that CNN model is well fit to identify the crop diseases. Similar opinion can be derived from the curves of training and vali-

Table 2 Naive-accuracy (%) for with learning error

Class	InRsV2	IncpV3	VGG16	VGG19	Proposed Model
Apple.Scab	88.32 ± 2.74	82.55 ± 3.10	97.48 ± 1.44	88.57 ± 2.69	98.38 ± 1.13
Apple.Black.Rot	98.33 ± 1.17	99.21 ± 0.78	100.00 ± 0.00	100.00 ± 0.00	99.61 ± 1.35
Apple.Cedar.Rust	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00	100.00 ± 0.00
Apple.Healthy	96.40 ± 1.02	98.17 ± 0.74	98.19 ± 0.73	99.07 ± 0.53	99.39 ± 0.43
OA	95.27 ± 4.73	94.87 ± 5.12	98.28 ± 1.71	97.00 ± 3.00	98.73 ± 1.26
Corn.Gray.leaf.spot	100.00 ± 0	99.55 ± 0.44	99.14 ± 0.60	97.07 ± 1.09	97.82 ± 0.96
Corn.Common.rust	93.33 ± 1.85	91.35 ± 3.18	96.10 ± 2.21	95.14 ± 1.82	98.87 ± 0.62
Corn.healthy	74.80 ± 3.85	76.92 ± 3.89	96.94 ± 2.91	91.53 ± 2.35	92.81 ± 3.07
Corn.Northern.Leaf.Blight	99.14 ± 0.60	100.00 ± 0	99.58 ± 0.41	99.63 ± 0.36	100.00 ± 0
OA	94.02 ± 5.97	94.15 ± 5.84	95.06 ± 4.93	93.63 ± 6.36	95.84 ± 4.15
Potato.Early.blight	95.23 ± 1.47	90.86 ± 1.94	95.65 ± 1.41	100.00 ± 0	97.99 ± 0.99
Potato.healthy	96.15 ± 3.77	100.00 ± 0	100.00 ± 0	75.07 ± 0	96.66 ± 3.27
Potato.Late.blight	98.45 ± 0.86	94.24 ± 1.68	94.43 ± 1.67	94.41 ± 1.64	98.01 ± 0.98
OA	96.74 ± 3.25	92.79 ± 7.20	95.34 ± 4.65	94.65 ± 5.34	96.90 ± 2.09

Table 3 Classification accuracy with learning error in terms of κ

Class	InRsV2	IncpV3	VGG16	VGG19	Proposed Model
Apple.Scab	0.8642 ± 0.0333	0.7881 ± 0.0370	0.9688 ± 0.0177	0.8574 ± 0.0326	0.9798 ± 0.0140
Apple.Black.rot	0.9693 ± 0.0145	0.9000 ± 0.0099	0.9814 ± 0.0130	1.0000 ± 0	0.9704 ± 0.0167
Apple.Cedar.rust	1.0000 ± 0	0.9334 ± 0.0168	1.0000 ± 0	1.0000 ± 0	1.0000 ± 0
Apple.Healthy	0.9253 ± 0.0206	0.9625 ± 0.0150	0.9629 ± 0.0149	0.9807 ± 0.0118	0.9878 ± 0.0088
OA	0.9926 ± 0.0131	0.9210 ± 0.0132	0.9735 ± 0.0079	0.9537 ± 0.0141	0.9804 ± 0.0068
Corn.Gray.leaf.spot	1.0000 ± 0	0.9937 ± 0.0026	0.9877 ± 0.0085	0.9580 ± 0.0154	0.9688 ± 0.0136
Corn.Common.rust	0.9104 ± 0.0245	0.8777 ± 0.0217	0.8204 ± 0.0226	0.7881 ± 0.0181	0.8935 ± 0.0489
Corn.Healthy	0.7091 ± 0.0424	0.7335 ± 0.0424	0.9144 ± 0.0333	0.8922 ± 0.0311	0.8755 ± 0.0349
Corn.Leaf.Blight	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0	1.000 ± 0
OA	0.9186 ± 0.0115	0.9202 ± 0.0114	0.9320 ± 0.0116	0.9123 ± 0.0119	0.9465 ± 0.0098
Potato.Early.blight	0.9190 ± 0.0265	0.8292 ± 0.0339	0.8917 ± 0.0257	1.0000 ± 0	0.9624 ± 0.0138
Potato.Healthy	0.9586 ± 0.0140	0.9422 ± 0.0162	0.9883 ± 0.0129	0.9977 ± 0.0036	0.9976 ± 0.0044
Potato.Late.blight	0.9710 ± 0.0164	0.8923 ± 0.0303	0.8883 ± 0.0229	0.9395 ± 0.0294	0.9627 ± 0.0154
OA	0.9417 ± 0.0152	0.8607 ± 0.0222	0.9036 ± 0.0192	0.9175 ± 0.0177	0.9627 ± 0.0122

Table 4 Classification report of the proposed method

Class	Precision	Recall	F1-Score
Apple.Scab	0.99	0.92	0.97
Apple.BlackRot	0.99	0.97	1.00
Apple.CedarRust	0.99	0.97	0.98
Apple.Healthy	0.96	0.98	0.97
Macro avg (Apple)	0.98	0.96	0.98
Weighted avg (Apple)	0.98	0.99	0.99
Corn.Gray leaf spot	0.92	0.73	0.81
Corn.Common rust	0.98	0.97	0.97
Corn.healthy	0.88	0.96	0.92
Corn.Northern Leaf Blight	0.96	0.97	0.96
Macro avg (Corn)	0.96	0.96	0.96
Weighted avg (Corn)	0.96	0.98	0.98
Potato.Early blight	0.97	0.89	0.93
Potato.healthy	0.98	0.94	0.96
Potato.Late blight	0.84	0.88	0.86
Macro avg (Potato)	0.96	0.90	0.96
Weighted avg (Potato)	0.97	0.97	0.97

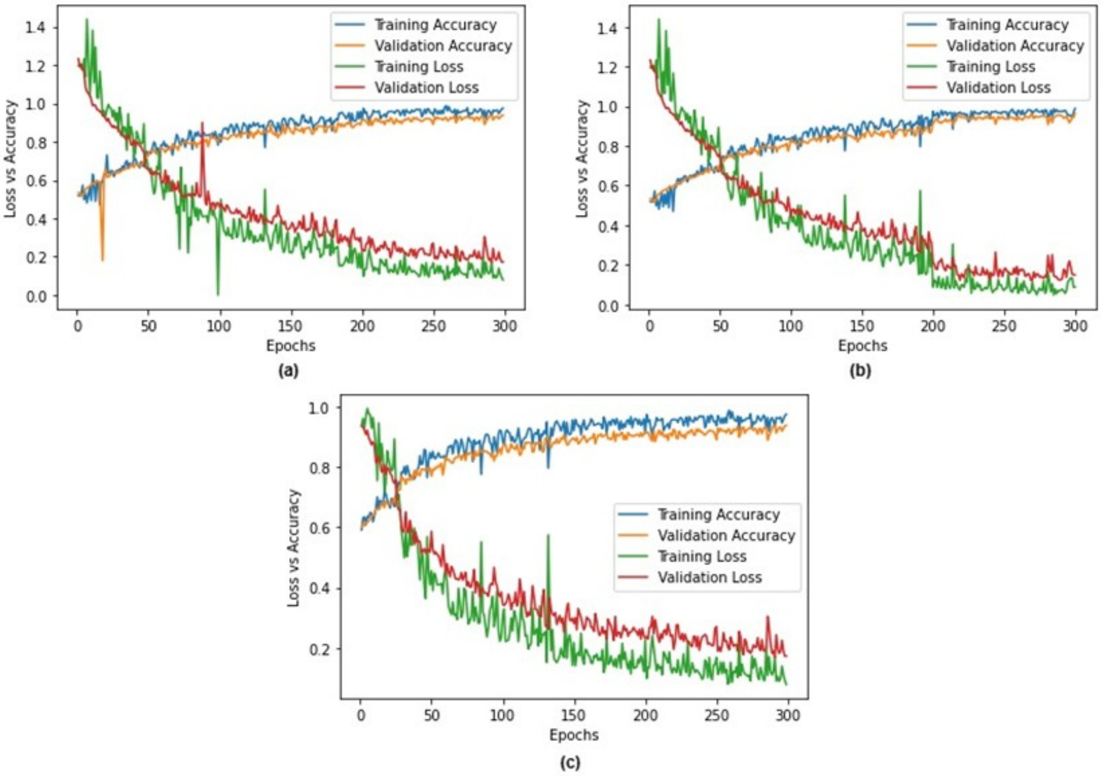

Fig. 5 Training accuracy vs. validation accuracy and training loss vs. validation loss: (a) Apple (b) Corn (c) Potato

dation losses. The impact of LBP on overall accuracy of the method is analyzed by comparing the results of CNN with and without LBP in Table 5. It is observed that LBP helps to significantly boost the performance of the CNN model. The accuracy for Apple is improved from 96.76% to 98.73%. It is increased from 94.10% to 95.84% for Corn and 91.79% to 96.90% for Potato. The κ values also show an improvement between 2% to 7% for different crops.

Table 6 presents a comparison of the accuracy of the proposed method with several existing methods that use texture information. All these methods utilize texture information as input for their learning models. Different techniques are employed to extract texture features in these methods. It is observed from the table that the proposed method outperforms several other approaches.

Table 6: Comparison of the proposed method with some existing methods for plant disease detection based on texture features

Reference	Crop	Features	Technique for Texture Feature Extraction	Class	Accuracy
(Patil *et al.,* 2017)	Soybean	Color, shape, and texture	LBP and Gabor filter	Mosaic Virus, Septoria Brown Spot and Pod Mottle	96%
(Patil *et al.,* 2024)	Maize	Color and texture	YCbCr color histogram and Local Gradient Binary Pattern histogram	Leaf Blight, Leaf Rust	98.33%
(Pinto *et al.,* 2016)	Sunflower	Texture	GLMC		89%
(Hlaing *et al.,* 2018)	Tomato	Color and texture	SIFT	Bacterial Spot, Leaf Mold, Mosaic Virus, Late Blight, Two Spotted Spider Mite, Target Spot, Healthy	85%
(Pantazi *et al.,* 2019)	Vine leaves	Color and texture	LBP	Downy mildew, Powdery mildew, and Black rot	95%
Proposed Method	Apple, Corn, Potato, Tomato	Color and texture	RGB, LBP	Scab, Black Rot, Cedar Rust, Healthy, etc.	98.73%

Impact of learning rate

In this experiment, one of the important hyperparameters learning rate is varied and its impact on classification accuracy is analyzed. The κ values in percentage are plotted against learning rate in Fig. 6. The learning rate varies from 0.0001 to 0.1. It is observed from the graphs that disease identification or classification accuracy is inferior when learning rate is too small or too large. The best accuracy is obtained for a learning rate of 0.01. Both training and validation accuracies have shown the same trend for all the crops. Therefore, the recommended learning rate for the proposed method is 0.01.

Impact of batch size

The batch size is another hyper-parameter that is analyzed here. The disease classification accuracy is obtained for different batch sizes. The batchsize is taken as 16, 32, 64, and 128. The κ values in percentage obtained at different batch sizes are plotted in Fig. 7. It can be observed from the figure that disease classification accuracy is good at moderate batch size. The best κ values are obtained when batch size is 32 for all the three crops. Both at smaller and larger batch sizes the accuracy is inferior. The similar observations can be made for both training and validation accuraies from the figure.

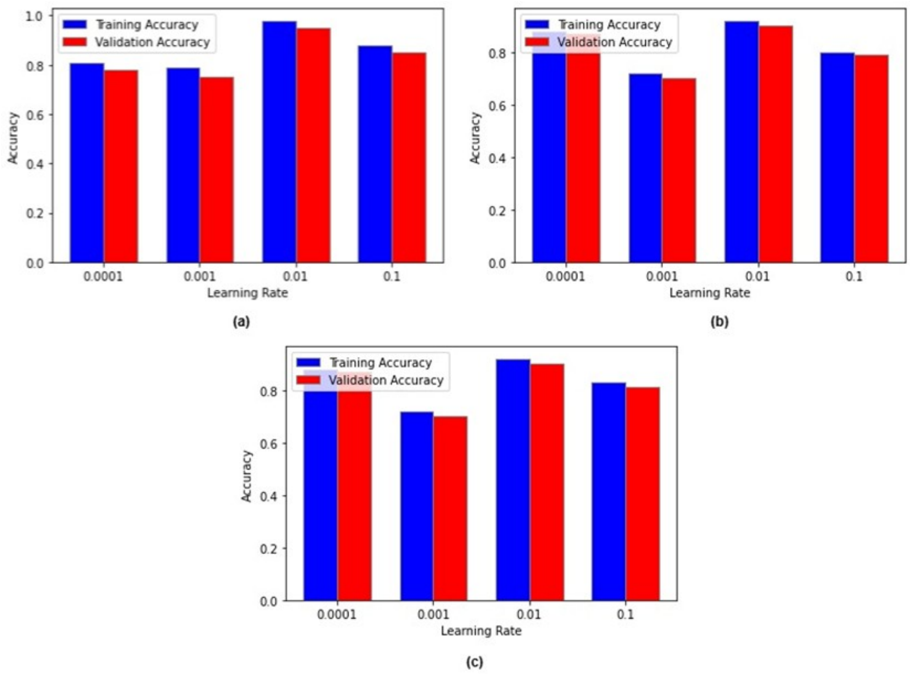

Fig. 6 Accuracy at different learning rates: (a) Apple (b) Corn (c) Potato

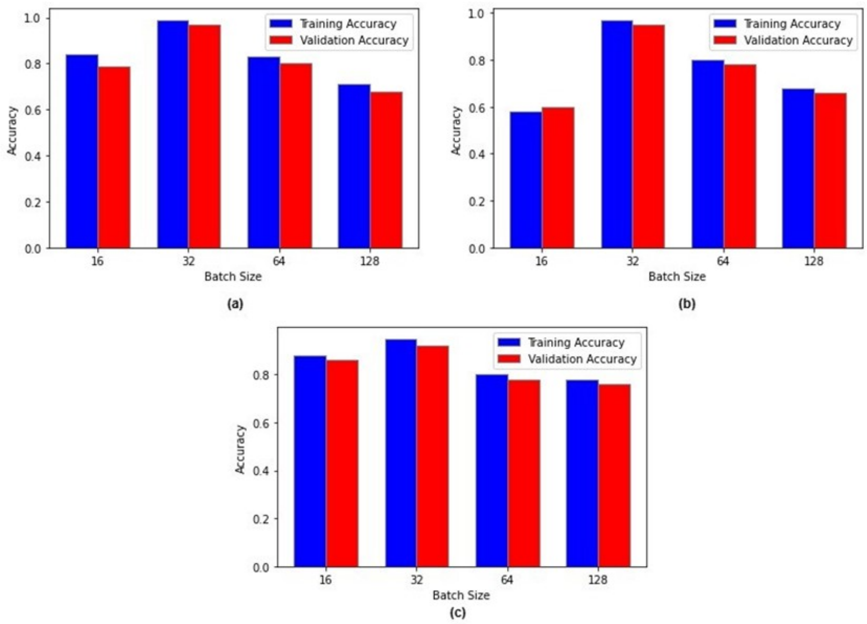

Fig. 7 Accuracy at different batch sizes: (a) Apple (b) Corn (c) Potato

Conclusion

In this work, CNN models have been developed for plant leaf disease identification using leaf images. The developed model consists of four convolutions four max-pooling
layers, and a fully connected layer. The texture of a leaf is highly affected by the adverse impact of a disease. Therefore, texture information can complement the capability of a CNN model. Furthermore, a plant disease detection framework was proposed that uses LBP for textuire feature extraction. The texture features are stacked with original image that produces a four-band image for input to CNN model. In addition, GrabCut segmentation and Otsu's thresholding thechniques are also used to remove background details in the image. These techniques collectively enhance the model's ability to discern disease-related patterns within the image.
The experiments were carried out on Apple, Corn, Potato, and Tomato crops from the PlantVillage dataset. The model was trained for 300 epochs. The results demonstrated the good performance of the framework. It was observed that the texture information complemented the CNN model very well to produce better results. The overall accuracy of 95.84 -98.73% was observed for different crops. The inclusion of texture information resulted in the improvement of accuracy up to 5.11%. The performance of the proposed method was compared with some pre-trained CNN-based methods and some existing texture-based disease detection methods. The proposed method performed better than several methods.

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Conflict of interest

The authors declare that they have no conflicts of interest.

References

Agarwal, M., Gupta, S. K., & Biswas, K. (2020). Development of efficient CNN model for tomato crop disease identification. *Sustainable Computing: Informatics and Systems, 28*, 100407. https://doi.org/10.1016/j.suscom.2020.100407.

Basavaiah, J., & Arlene Anthony, A. (2020). Tomato leaf disease classification using multiple feature extraction techniques. *Wireless Personal Communications*, *115*(1), 633-651.

Bensaadi, S., & Louchene, A. (2023). Low-cost convolutional neural network for tomato plant diseases classification. *International Journal of Artificial Intelligence, 12* (1), 162. https://doi.org/10.11591/ijai.v12.i1.pp162-170

Bowen, J. K., Mesarich, C. H., Bus, V. G., Beresford, R. M., Plummer, K. M., & Templeton, M. D. (2011). Venturia inaequalis: The causal agent of apple scab. *Molecular Plant Pathology, 12*(2), 105–122. https://doi.org/10.1111/j.1364-3703.2010.00656.x

Carion, N., Massa, F., Synnaeve, G., Usunier, N., Kirillov, A., & Zagoruyko, S. (2020). End-to-end object detection with transformers. *European Conference on Computer Vision* (pp. 213–229). https://doi.org/10.1007/978-3-030-58452-8_13

Chaudhari, V., Dawoodi, H. H., & Patil, M. P. (2022). Banana leaf disease recognition based on local binary pattern. *Smart Trends in Computing and Communications: Proceedings of SmartCom 2021* (pp. 653–661). https://doi.org/10.1007/978-981-16-4016-2_62

Chen, Y., & Wu, Q. (2023). Grape leaf disease identification with sparse data via generative adversarial networks and convolutional neural networks. *Precision Agriculture, 24* (1), 235–253. https://doi.org/10.1007/s11119-022-09941-z

Crespo, M., Moral, J., Michailides, T., & Trouillas, F. (2018). First report of black rot on apple fruit caused by Diplodia seriata in California. *Plant Disease, 102* (4), 824. https://doi.org/10.1094/PDIS-07-17-1023-PDN

Crowell, I. H. (1934). The hosts, life history and control of the cedar-apple rust fungus Gymnosporangium juniperi-virginianae Schw. *Journal of the Arnold Arboretum, 15* (3), 163–232.

Dhar, P., Rahman, M. S., & Abedin, Z. (2022). Classification of leaf disease using global and local features. *International Journal of Information Technology and Computer Science (IJITCS), 14* (1), 43–57. https://doi.org/10.5815/ijitcs.2022.01.05

Esmaeel, A. A., Gajjar, R., Gajjar, N., Thakor, V. J., & Patel, N. P. (2018). A novel approach to classify and detect bean diseases based on image processing. *IEEE Symposium on Computer Applications & Industrial Electronics* (pp. 297–302). https://doi.org/10.1109/ISCAIE.2018.8405488

Gayathri Devi, T., & Neelamegam, P. (2019). Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu. *Cluster Computing, 22* (6), 13415–13428. https://doi.org/10.1007/s10586-018-1949-x

Hlaing, C. S. and Zaw, S. M. M. (2018). Tomato plant diseases classification using statistical texture feature and color feature. In 2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS), pages 439–444. IEEE. DOI: 10.1109/ICIS.2018.8466483

Kawasaki, Y., Uga, H., Kagiwada, S., & Iyatomi, H. (2015). Basic study of automated diagnosis of viral plant diseases using convolutional neural networks. *Advances in Visual Computing: 11th International Symposium, ISVC 2015, Las Vegas, NV, USA, December 14-16, 2015, Proceedings, Part II* (pp. 638–645). https://doi.org/10.1007/978-3-319-27863-6_59

Khamparia, A., Saini, G., Gupta, D., Khanna, A., Tiwari, S., & de Albuquerque, V. H. C. (2020). Seasonal crops disease prediction and classification using deep convolutional encoder network. *Circuits, Systems, and Signal Processing, 39* (2), 818–836. https://doi.org/10.1007/s00034-019-01041-0

Kohler, R. (1981). A segmentation system based on thresholding. *Computer Graphics and Image Processing, 15* (4), 319–338. https://doi.org/10.1016/S0146-664X(81)80015-9

Kumar, B. (2020). Hyperspectral image classification using three-dimensional geometric moments. *IET Image Processing, 14* (10), 2175–2186. https://doi.org/10.1049/iet-ipr.2019.0603

Kumar, B., & Dikshit, O. (2014). Texture based hyperspectral image classification. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences ISPRS Archives, 40* (8), 793–798. https://doi.org/10.5194/isprsarchives-XL-8-793-2014

Kumar, B., & Dikshit, O. (2015a). Integrating spectral and textural features for urban land cover classification with hyperspectral data. *Joint Urban Remote Sensing Event* (pp. 1-4). https://doi.org/10.1109/JURSE.2015.7120517

Kumar, B., & Dikshit, O. (2015b). Spectral–spatial classification of hyperspectral imagery based on moment invariants. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(6), 2457–2463. https://doi.org/10.1109/JSTARS.2015.2446611

Kusumo, B. S., Heryana, A., Mahendra, O., & Pardede, H. F. (2018). Machine learning-based for automatic detection of corn-plant diseases using image processing. *International Conference on Computer, Control, Informatics and Its Applications* (pp. 93–97). https://doi.org/10.1109/IC3INA.2018.8629507

Kylberg, G., & Sintorn, I.-M. (2013). Evaluation of noise robustness for local binary pattern descriptors in texture classification. *Journal on Image and Video Processing, 2013* (1), 1–20. https://doi.org/10.1186/1687-5281-2013-17

Li, W., Chen, C., Su, H., & Du, Q. (2015). Local binary patterns and extreme learning machine for hyperspectral imagery classification. *IEEE Transactions on Geoscience and Remote Sensing, 53(*7), 3681–3693. https://doi.org/10.1109/TGRS.2014.2381602

Mathew, D., Kumar, C. S., & Cherian, K. A. (2021). Foliar fungal disease classification in banana plants using elliptical local binary pattern on multiresolution dual tree complex wavelet transform domain. *Information Processing in Agriculture, 8* (4), 581–592. https://doi.org/10.1016/j.inpa.2020.11.002

Mizubuti, E. S., & Fry, W. E. (2006). *Potato late blight*. Springer.

Nikam, S. B., & Agarwal, S. (2008). Local binary pattern and wavelet-based spoof fingerprint detection. *International Journal of Biometrics, 1* (2), 141–159. https://doi.org/10.1504/IJBM.2008.020141

Pattnaik, G., & Parvathi, K. (2021). Automatic detection and classification of tomato pests using support vector machine based on hog and lbp feature extraction technique. *Progress in Advanced Computing and Intelligent Engineering: Proceedings of ICACIE 2019, Volume 2* (pp. 49–55). https://doi.org/10.1007/978-981-15-6353-9_5

Pantazi, X. E., Moshou, D., and Tamouridou, A. A. (2019). Automated leaf disease detection in different crop species through image features analysis and one class classifiers. Computers and electronics in agriculture, 156:96–104. https://doi.org/10.1016/j.compag.2018.11.005.

Patil, J. K. and Kumar, R. (2017). Analysis of content based image retrieval for plant leaf diseases using color, shape and texture features. Engineering in agriculture, environment and food, 10(2):69–78. https://doi.org/10.1016/j.eaef.2016.11.004.

Patil, J. K. and Mandlik, V. S. (2024). Plant leaf disease detection using integrated color and texture features. Nature Environment & Pollution Technology, 23(4). https://doi.org/10.46488/NEPT.2024.v23i04.016.

Pinto, L. S., Ray, A., Reddy, M. U., Perumal, P., and Aishwarya, P. (2016). Crop disease classification using texture analysis. In 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), pages 825–828. IEEE. DOI: 10.1109/RTEICT.2016.7807942.

Perkins, J., Pedersen, W., et al. (1987). Disease development and yield losses associated with northern leaf blight on corn. *Plant Disease, 71* (10), 940–943.

Priya, T. V., Sanchez, G. V., & Raajan, N. (2018). Facial recognition system using local binary patterns (lbp). *International Journal of Pure and Applied Mathematics, 119* (15), 1895–1899.

Qi, F., Wang, Y., & Tang, Z. (2022). Lightweight plant disease classification combining grabcut algorithm, new coordinate attention, and channel pruning. *Neural Processing Letters*, 1–15. https://doi.org/10.1007/s11063-022-10863-0

Raid, R. N., & Comstock, J. C. (2000). Common rust. *A Guide to Sugarcane Diseases* (pp. 85–89).

Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. *Information processing in Agriculture*, *4*(1), 41-49. https://doi.org/10.1016/j.inpa.2016.10.005

Stephen, A., Punitha, A., & Chandrasekar, A. (2023). Optimal deep generative adversarial network and convolutional neural network for rice leaf disease prediction. *The Visual Compute*. https://doi.org/10.1007/s00371-023-02823-z

Thakur, P. S., Sheorey, T., & Ojha, A. (2023). VGG-ICNN: A lightweight CNN model for crop disease identification. *Multimedia Tools and Applications, 82*(1), 497–520. https://doi.org/10.1007/s11042-022-13144-z

Treceñe, J. K. D. (2021, July). Brassicaceae leaf disease detection using image segmentation technique. In *IEEE EUROCON 2021-19th International Conference on Smart Technologies* (pp. 30-34). IEEE. doi: 10.1109/EUROCON52738.2021.9535574.

Van der Waals, J., Korsten, L., & Aveling, T. (2001). A review of early blight of potato. *African Plant Protection, 7* (2), 91–102.

Vishnoi, V. K., Kumar, K., & Kumar, B. (2020). Plant disease detection using computational intelligence and image processing. *Journal of Plant Diseases and Protection*, 1–35. https://doi.org/10.1007/s41348-020-00368-0

Vishnoi, V. K., Kumar, K., & Kumar, B. (2021). A comprehensive study of feature extraction techniques for plant leaf disease detection. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-021-11375-0

Vishnoi, V. K., Kumar, K., Kumar, B., Mohan, S., & Khan, A. A. (2023). Detection of apple plant diseases using leaf images through convolutional neural network. *IEEE Access, 11*, 6594–6609. https://doi.org/10.1109/ACCESS.2022.3232917

Ward, J. M., Stromberg, E. L., Nowell, D. C., & Nutter Jr, F. W. (1999). Gray leaf spot: A disease of global importance in maize production. *Plant Disease, 83* (10), 884–895. https://doi.org/10.1094/PDIS.1999.83.10.884

Xiong, Y., Liang, L., Wang, L., She, J., & Wu, M. (2020). Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset. *Computers and Electronics in Agriculture, 177*, 105712. https://doi.org/10.1016/j.compag.2020.105712

Xu, Y., Yu, G., Wang, Y., Wu, X., & Ma, Y. (2017). Car detection from low-altitude UAV imagery with the faster R-CNN. *Journal of Advanced Transportation, 2017*. https://doi.org/10.1155/2017/2823617

Zhang, S., Zhang, S., Zhang, C., Wang, X., & Shi, Y. (2019). Cucumber leaf disease identification with global pooling dilated convolutional neural network. *Computers and Electronics in Agriculture, 162*, 422–430. https://doi.org/10.1016/j.compag.2019.03.012

Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. *IEEE Access, 6*, 30370–30377. https://doi.org/10.1109/ACCESS.2018.2844405

Zhao, S., Peng, Y., Liu, J., & Wu, S. (2021). Tomato leaf disease diagnosis based on improved convolution neural network by attention module. *Agriculture, 11* (7), 651. https://doi.org/10.3390/agriculture11070651

Zhou, H., Wang, R., & Wang, C. (2008). A novel extended local -binary-pattern operator for texture analysis. *Information Sciences, 178* (22), 4314–4325. https://doi.org/10.1016/j.ins.2008.07.015