International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 4, August 2024, pp. 3971~3985
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i4.pp3971-3985

Deep autoencoder based image enhancement approach with hybrid feature extraction for plant disease detection using supervised classification

Suma Huddar[1], Kopparagaon Prabhushetty[2], Jagadish Jakati[3], Raviraj Havaldar[4], Nandakishore Sirdeshpande[5]

[1]Department of Electronics and Communication Engineering, S. G. Balekundri Institute of Technology, Belagavi, Affiliated to Visvesvaraya Technological University, Belagavi, India
[2]Department of Electronics and Communication Engineering, Veerappa Nisty Engineering College, Hasnapur, Affiliated to Visvesvaraya Technological University, Belagavi, India
[3]School of Computer Science Engineering and Applications, D. Y. Patil International University Akurdi, Pune, India
[4]Department of Biomedical Engineering, KLE DR. M S Sheshgiri College of Engineering and Technology, Belagavi, Affiliated to Visvesvaraya Technological University, Belagavi, India
[5]Department of Computer Engineering, Atharva College of Engineering Malad, West Mumbai, India

Article Info

Article history:

Received Nov 10, 2023
Revised Mar 23, 2024
Accepted Apr 2, 2024

Keywords:

Autoencoder
Combined feature extraction
Feature fusion
Plant disease
Support vector machine classification

ABSTRACT

Plant leaf diseases pose significant threats to global agriculture, leading to reduced crop yields and economic losses. Rapid and accurate disease detection is essential for timely interventions and sustainable farming practices. This study presents an innovative approach for plant leaf disease detection by integrating wavelet analysis, color, and texture features, coupled with autoencoder denoising and support vector machine (SVM) classification. Wavelet analysis is employed to extract multi-resolution features, capturing intricate details at different scales. Furthermore, color and texture characteristics are extracted to encompass a broad spectrum of visual information crucial for distinguishing diseases. The Autoencoder model helps to enhance the feature representation that mitigates the impact of noise and irrelevant data. The SVM classifier is utilized to learn complex patterns and accurately classify different disease classes. The combined model of wavelet, color, and texture attributes, in combination with autoencoder denoising and SVM classification, markedly enhances the precision and efficiency of disease detection in contrast to conventional methods. The system's performance is evaluated using a PlantVillage dataset, showcasing its adaptability to different plant species and disease types. The overall performance is obtained as 98.60%, 97.25%, 96.89%, and 97.20% in terms of accuracy, precision, recall, and F-Score, respectively.

Corresponding Author:

Suma Huddar
Department of Electronics and Communication Engineering, S. G. Balekundri Institute of Technology Belagavi. Affiliated to Visvesvaraya Technological University
Belagavi, India
Email: sumavehaan18@gmail.com

1. INTRODUCTION

Agriculture holds a significant position in shaping India's economy, contributing to its overall development with a gross domestic product of 3.732 trillion [1]. India boasts approximately 75% of its workforce engaged in agriculture and agriculture accounted for 23% of Gross domestic product (GDP) [2]. Unlike the advancements observed in the electronic and automotive industries, agricultural progress in India remains distinctive. In the fiscal year 2020-2021, agriculture accounted for 18.3 of India's GDP [3]. However, the growth of crops is hindered by plant diseases, leading to substantial economic losses.

Plant diseases are inevitable, stemming from environmental factors, necessitating the implementation of a preventive system in agriculture [4]. Various plant parts, including fruits, leaves, and stems, are susceptible to common ailments such as bacterial, fungal, and viral infections [5]. Figure 1 depicts the classification of various plant diseases. Pathogens like Canker, Anthracnose, Alternaria, and Bacterial Spot, along with other harmful germs, can severely hamper plant growth. Leaf fungus diseases, specifically, are triggered by environmental elements. Identifying leaf diseases involves observing visible signs on plant leaves, but the complexity of these diseases is rapidly increasing [6]. The intricacy and density of crops often lead to psychopathological issues among farmers. Even experts in agriculture and plant pathology frequently struggle to pinpoint the origins of diseases, resulting in limited and sometimes pessimistic solutions and conclusions [7]. Therefore, plant disease detection plays a crucial role in improving the productivity by 60% [8].

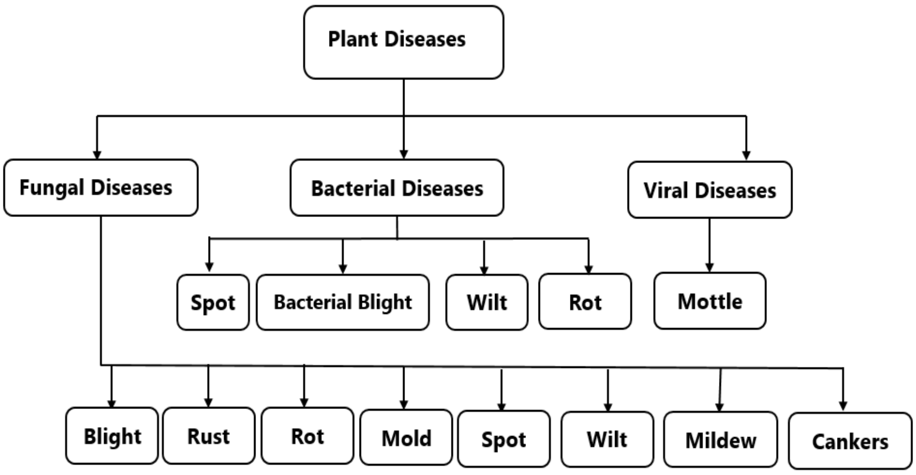

Figure 1. General classification of plant disease

Plants face continuous and escalating threats from pests and diseases. Currently, global food crops experience losses ranging from 20% to 40% due to these issues [9], with plant diseases alone causing damage amounting to 14.1%, translating to annual agricultural trade losses of $220 billion [10]. Fungi are the causative agents in roughly 83% of documented plant infectious diseases, viruses and phytoplasmas collectively contribute to 9%, while bacteria are responsible for over 7% [11]. To effectively combat these diseases, it is crucial to promptly diagnose and identify the species composition of the pathogens. Delay in diagnosis and the failure to implement control measures can result in significant crop losses and a drastic reduction in product quality.

The traditional approaches include symptom-based identification where farmers and agricultural experts visually inspect plants for characteristic symptoms such as leaf discoloration, wilting, or unusual growth patterns. This method is subjective and relies heavily on the experience of the observer [12], in Traditional pathology, pathogens are isolated from plant samples and cultivated in a controlled environment for subsequent analysis. In sensor-based technologies, sensors measure alterations in soil properties and analyze the spectral reflectance of leaves, which can provide indications of the presence of specific diseases. [13]. However, the performance of these methods relies on the individual’s expertise, and the precision of sensing devices. Hence, the research community has directed its efforts toward the advancement of automated systems that offer superior precision and detection accuracy.

Contemporary technological progress has integrated computer vision-based solutions to automate the process of identifying plant diseases. Computer vision technology equips machines with the ability to interpret and understand visual information from the world, making it a powerful tool in agriculture. Regarding the detection of plant diseases, computer vision systems can assess images of plant leaves, fruits, or stems, capturing subtle disease indicators that may escape human observation. By employing sophisticated algorithms, these systems can distinguish between healthy and diseased plants with remarkable precision. But in the field of automated plant disease diagnosis, machine learning methods are essential. Because these algorithms are built to learn from large datasets, they can identify patterns associated with various diseases [14]. As the system is exposed to more data, its ability to identify diseases becomes notably more accurate and efficient. These models are adept at processing intricate datasets, pinpointing disease-related features, and thereby ensuring consistent and reliable results.

The accuracy of these systems relies on quality of images. In real-time scenarios, noise can be introduced to plant leaf images during image capturing through various natural and environmental factors such as low-lighting conditions, sensor limitation, atmospheric condition, camera shake, and environmental interference due to which different types of noises are added to the original image such as Gaussian, salt-pepper, speckle, and Motion blur. therefore, reduction of these noise plays a crucial role as pre-processing phase for disease detection of plant leaf. In this work, we provide a machine learning classification model to detect the plant illness and concentrate on developing a novel deep learning autoencoder based strategy for filtering plant leaf images. The following are this work's primary contributions: i) to improve image quality, we present a deep autoencoder based method for image denoising; ii) we provide a combined feature extraction model for the process of feature extraction, in which wavelet, shape, and texture features are taken out and combined to create the final feature vector; and iii) lastly, the model is trained using a support vector machine (SVM) classifier, and its classification performance is assessed.

Rest of the article is organized as follows: section 2 deals with analyzing the traditional methods of plant leaf disease detection and presents a brief literature review about these methods, The proposed solution is presented in section 3, section 4 assesses the suggested approach's performance and contrasts the results with those of other approaches and the final thoughts and the work's future scope are presented in section 5.

2. LITURATURE SURVEY

As discussed before, the plant disease detection plays significant role in improving the food quality and economy of the country. As a result, a number of techniques have been put forth to introduce the automated method to complete this task. The proposed work mainly focused on image denoising and applying machine learning classification to obtain the final classification result. Therefore, this section describes the existing approaches related to these domains.

Jian *et al.* [15] introduced an improved adaptive Gaussian filtering approach for plant disease detection. Using this technique, the variance ratio between the two-dimensional Gauss filtering function and the neighborhood surrounding the central pixel in the image matrix area is calculated. Gauss's standard deviation was calculated, and the Gaussian convolution kernel was dynamically generated as a result. Consequently, the speckle image was smoothly and successfully denoised by the algorithm. Similarly, Malathi *et al.* [16] focused on noise reduction from paddy images. Therefore, a data repository was created from different paddy areas and three distinct noises were added namely salt and pepper, speckle noise and Poisson noise. Later, median and wiener filtering scheme were applied to remove the noise. Raigonda and Terdal [17] presented a combined approach for plant leaf image filtering, feature extraction and classification. Gaussian and median filtering are part of the filtering phase, along with contrast enhancement. The following stage uses feature extraction, extracting color, shape, and texture features. The final feature vector is then processed using k-means clustering to produce the final classification outcome. Similar to this Trivedi *et al.* [18] presented a three-stage approach for plant disease detection. In the initial stage, pre-processing is applied, incorporating a novel rank order fuzzy (ROF) filter designed to effectively diminish background noise in plant images. After that, cutting-edge methods based on the min-max hue histogram are used to detect disease spots. To ensure precise segmentation using k-means clustering, this initial identification of the disease spot is essential.

Conversely, though plant disease classification is also widely studied by several researchers. Shrivastava and Pradhan [19] presented rice disease detection and classification based on color feature extraction. According to this approach total 14 different color space models were analyzed and extracted total 174 features and there were seven distinct classifiers used where SVM has reported the highest accuracy. Similarly, Hussein and Abbas [20] also used the SVM classifier model. Hossain *et al.* [21] used texture feature analysis and employed k-nearest neighbor (K-NN) classification model for identifying plant leaf diseases. Sood *et al.* [22] generated a combined model where k-means clustering is applied to identify the affected region. Later, it performs gray level co-occurrence (GLCM) feature extraction and employs SVM classification. Sahu and Pandey [23] introduced hybrid random forest multiclass SVM, a novel method for detecting plant diseases. This model also applies partial fuzzy C means for image pre-processing and segmentation. Aruraj *et al.* [24] offered a technique based on texture feature extraction to identify the disease in the leaves of banana plants. This method is divided into two stages: the first stage uses a local binary pattern to extract texture features, and the second stage uses SVM and KNN classifiers to get the final classification. Currently, deep learning-based systems also have gained huge attention in various computer vision-based applications. Ashok *et al.* [25] adopted deep learning and presented a novel architecture for tomato leaf disease detection where discrete wavelet transform (DWT) and GLCM feature extraction methods are employed followed by segmentation. Finally, convolution neural network (CNN) classifier is used to perform the classification. Similarly, Gayathri *et al.* [26] applied deep learning based system to detect the tea leaf diseases where it has reported the highest classification accuracy as 90.23%. Zaghbani *et al.* [27] used autoencoder model for computer vision application and developed facial feature extraction method further, a semi-supervised classifier is designed to learn these autoencoder features and performs the face classification. In Al-Sbou and Abd Rahim [28] used autoencoder for recommender system and presented semi-supervised mechanism to improve the accuracy of recommendation system.

3. PROPOSED MODEL

The machine learning approach for plant disease detection is presented in this section. The noise factor, which can significantly affect the classification accuracy, has not been taken into consideration by the traditional methods. Therefore, we incorporate a novel approach for image denoising. The main steps of this process are as follows: i) pre-processing: in this phase, we present a novel autoencoder based approach to perform image denoising; ii) feature extraction: in this section we present a hybrid feature extraction model where features like color, texture, and wavelet have been extracted from images of plant leaves; and iii) classification: in this stage, use the extracted color, texture, and wavelet features to train the SVM classifier. The suggested approach's general architecture is shown in the Figure 2.

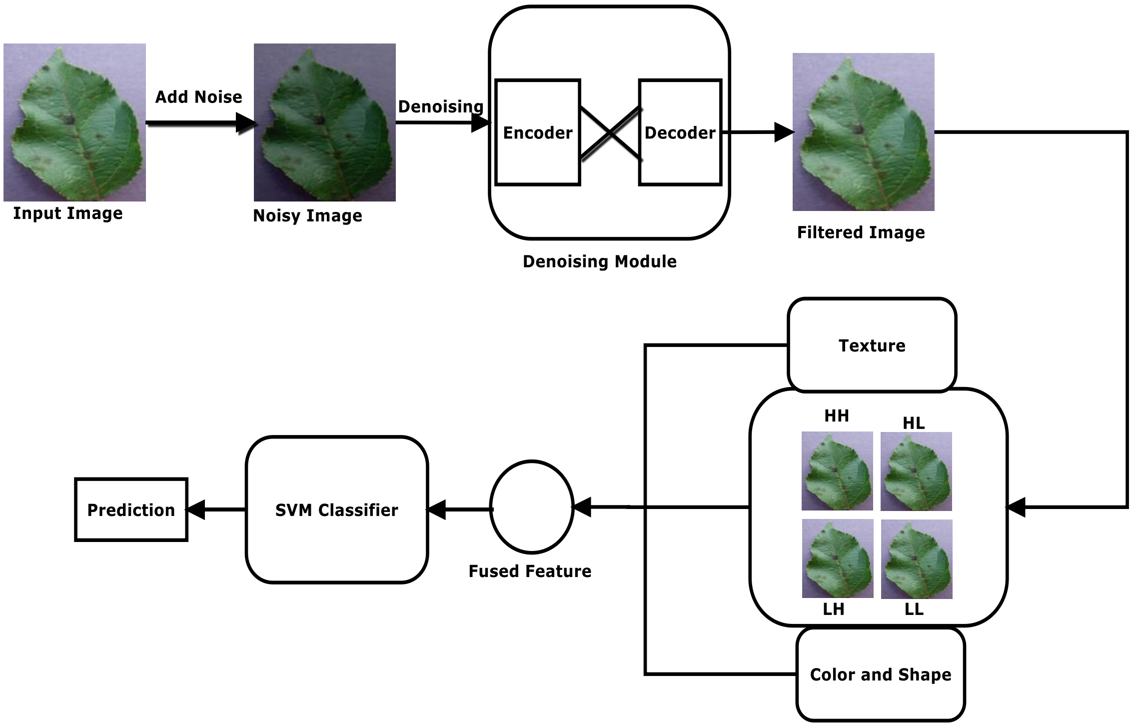

Figure 2. Overall architecture of proposed model

3.1. Autoencoder for image denoising

A type of a neural network variant is the autoencoder, which is used to compress or encode an unlabeled input into a dimensional space. This space may or may not have the same order as the input but typically reduces the input to a lower dimensional space, often referred to as the latent space. Subsequently, this encoding is utilized to reconstruct the original image. In the course of this procedure, the model learns how various input images correspond to specific points within the latent space through training. The autoencoder is specifically trained to ignore any noise or inconsistencies in the input during this training, which improves its ability to accurately represent important features. The basic architecture of the autoencoder with the encoder and decoder modules is shown in Figure 3.

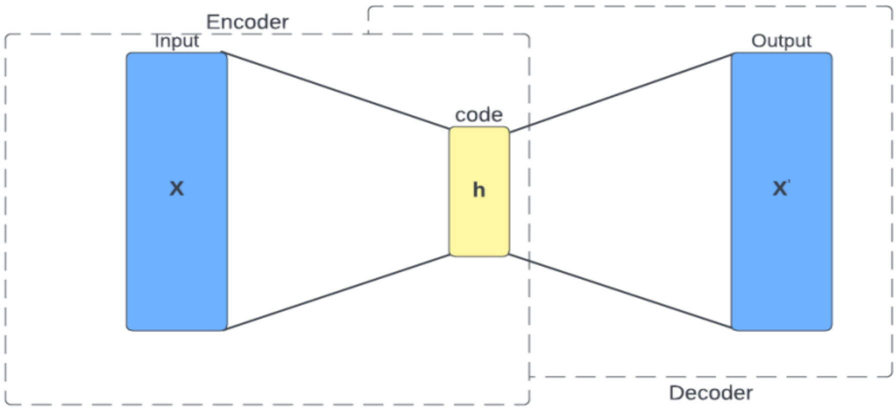

Figure 3. Encoder and decoder module placement

Let us consider that the encoder module is defined as ϕ and decoder module is expressed as ψ. For any given input X, encoder decoder functions can be expressed as (1):

$$\psi: X \rightarrow F$$
$$\psi: F \rightarrow X$$
$$\phi, \psi = \arg min_{\phi,\psi} \|X - (\phi \circ \psi)X\|^2 \quad (1)$$

The encoder takes input $x \in \mathbb{R}^2 = X$ and produces mapping to hidden layer $h \in \mathbb{R}^p = F$ which is expressed as (2):

$$h = \sigma(Wx + b) \quad (2)$$

where h represents the coded latent expression of given input, σ is the activation function, W represents weight matrix and b denotes the bias vector. Finally, the decoder module performs the decoding to reconstruct the x as x' which is expressed as (3):

$$x' = \sigma'(W'h + b') \quad (3)$$

W' stands for the weight and b' for the bias of the decoder module, and σ' is the rectified linear unit (ReLU) activation function. The estimated loss that happened during the training process is:

$$L(x, x') = \|x - x'\|^2 = \left\|x - \sigma'(W'\left(\sigma(Wx + b)\right) + b'\right\|^2 \quad (4)$$

We take the advantage of its reconstruction process and utilize the autoencoder and denoising module which is known as denoising autoencoder. It is similar to the standard autoencoder except that it consists of a module to incorporate noise in the original image. The introduced noise is random in nature. Let us consider that the T is the function to generate the random noise and an input x is given to it which produces its noisy version denoted as $T(x)$. This generated noisy sample is then fed to the neural network as (5):

$$T : X \rightarrow T(X) \quad (5)$$

In this work, we introduce a convolutional autoencoder based mechanism to obtain the denoised image.

The convolutional autoencoder is based on the concept of traditional autoencoder except it replaces Dense layers with convolution layers. According to this process, a 28×28×1-dimensional input undergoes two rounds of 2D convolutional processing with 32 filters, using a 3×3 weight matrix and ReLU activation function. This process encodes the input into a latent space with dimensions 7×7×32. Subsequently, these latent coordinates serve as inputs for Conv2D Transpose layers, employing 32 filters and a 3×3 weight matrix with ReLU activation, to upscale the image back to its original dimensions. Figure 4 depicts the detailed architecture of autoencoder module. Additionally, Figure 5 provides additional architecture-related details, such as kernel size, stride, and padding details for every layer.

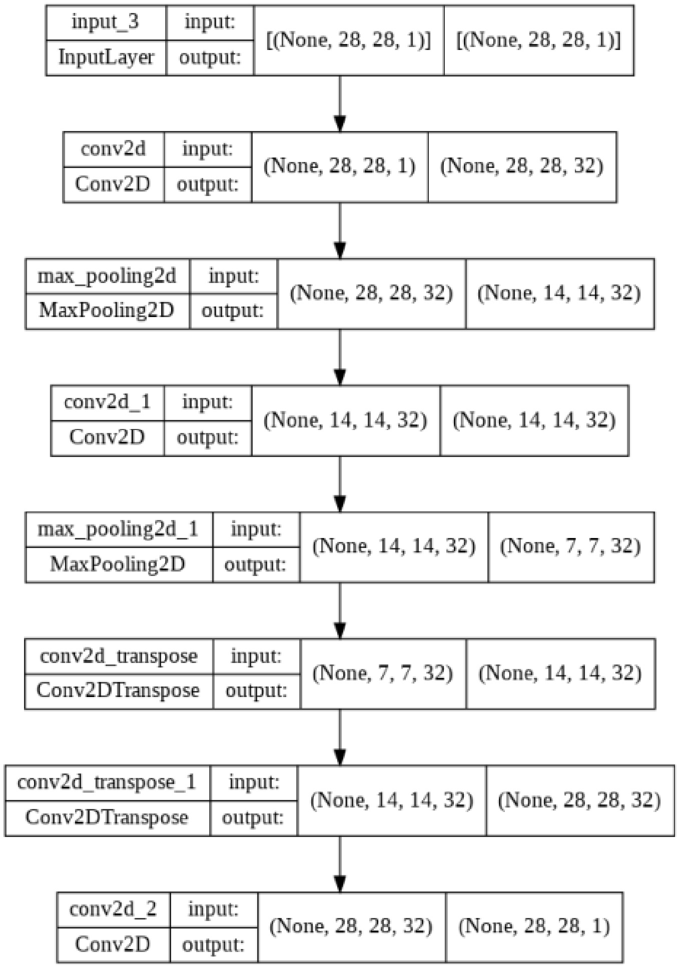

Figure 4. architecture of denoising autoencoder

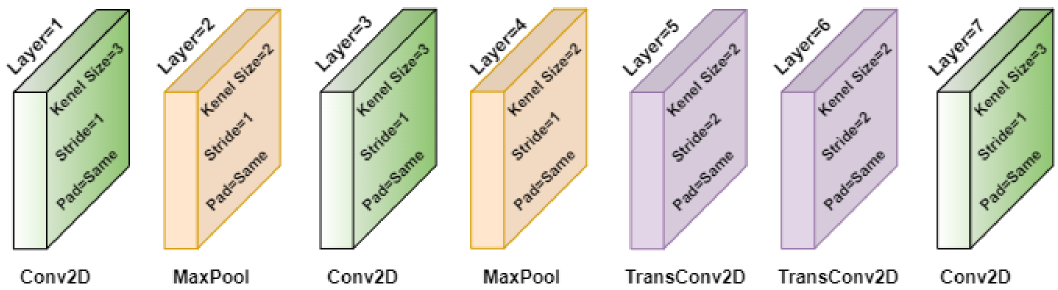

Figure 5. Layer details of convolutional autoencoder

3.2. Feature extraction

The suggested method for feature extraction is presented in this subsection. Three distinct feature types-color, texture, and wavelet features-have been taken into consideration. Explanation of each feature that is used in study is described in subsequent paragraphs.

3.2.1. Color features

We have taken into account the red green blue (RGB) color space and computed statistical features like mean, standard deviation, skewness, and kurtosis in order to extract the color features. Therefore, we extract four unique features for each plane R, G, and B, which can be expressed as (6):

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}$$

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}$$

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}$$

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij} \quad (6)$$

In this case, μ, σ, θ, and γ stand for the respective values of mean, standard deviation, skewness, and kurtosis.

3.2.2. Texture feature

In order for humans to perceive images, textures are essential. The spatial distribution of gray values in an image is the main focus of statistical techniques for texture analysis. They achieve this by looking at the local properties of every pixel in the picture and using these properties to derive a set of statistical parameters. This method is widely applied in a wide range of image analysis and comprehension applications. The process is divided into two main steps: first, calculating the GLCM, and then using the GLCM to derive texture features. The number of gray levels, *Ng*, is represented by the square matrix that makes up the GLCM. Although there are many GLCM features available, we have only used the most important ones, including the inverse difference method, variance, angular moment, contrast, and correlation. These are computed in the following way mentioned in Table 1.

Table 1. Texture feature computation

Attribute name	Computation formula
Angular moment	$\sum_i \sum_j p(i,j)^2$
Contrast	$\sum_{n=0}^{N_g-1} n^2 \left\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\right\}, \lvert i-j\rvert = n$
Correlation	$\frac{\sum_i \sum_j (ij)p(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$
Variance	$\sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse difference method	$\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$

3.2.3 Wavelet features

Wavelet analysis serves as a valuable mathematical technique utilized for discerning image properties, demonstrating efficacy in numerous image analysis tasks. Through wavelet decomposition, distinct aspects of the main signal, such as high or low frequency segments, can be extracted. This transformation proves invaluable in signal and image analysis across various scales and resolutions, enhancing classification accuracy significantly. Figure 3 illustrates a schematic representation of 2D DWT. In the context of images, DWT is applied individually to different sizes, allowing for nuanced analysis and interpretation. Figure 6 depicts the image and its corresponding

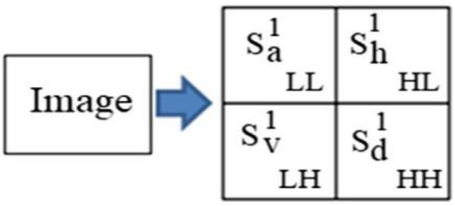

Figure 6. Wavelet feature extraction a schematic diagram of 2D DWT

Let us consider that a 2D image is denoted as $f(x, y)$ and it is characterized as connection between input image and family of wavelet function $\phi_{s,t}(x, y)$, then the wavelet function can be expressed as (7):

$$W_{f(s,t;x,y)} = \int\int f(x,y)\phi_s,t(x,y)\, dxdy \quad (7)$$

The wavelets $\phi_{s,t}(x, y)$ are produced with the help of mother wavelet function which is expressed as (8):

$$\phi_{s,t}(x, y) = \frac{1}{s}\phi\left(\frac{(x-t_x)}{s}, \frac{(y-t_y)}{s}\right) \tag{8}$$

where s represents the scale parameter, t_x represents the translation parameter in x-axis and t_y represents the translation parameter in y axis. In this work, we have adopted the Daubechies wavelet transform because of its significant nature of pattern extraction. It can also extract basic structural information from an image and is computationally efficient. This wavelet decomposition produces four different subgroups corresponding to frequency bands as low-low, high –low, high-high and low-low which are expressed as (9):

$$S^1 = S_a^1 + S_v^1 + S_h^1 + S_d^1 \tag{9}$$

According to this, the input image S^1 is decomposed as S_a^1 in its initial stage and produces LL decomposition which is also known as approximation coefficient. Similarly, vertical (S_v^1), horizontal (S_h^1) and diagonal components (S_d^1) are obtained with the help of DWT. Finally, 24 distinct statistical qualities are collected from each image at the DWT block's output. These attributes include the lowest, maximum, mean, standard deviation, variance, and third moment of each of the aforementioned sub bands.

These obtained features are fused together and used in training the SVM classifier as supervised training and classification approach. A supervised machine learning technique used for regression and classification problems is called SVM. When it comes to classification, SVM looks for the best hyperplane to divide a dataset into several classes.

Consider a training dataset $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, where x_i denotes the input features and $y_i$represents the corresponding class labels $y_i \in \{-1,1\}$ for binary classification). The primary goal of SVM is to determine a hyperplane characterized by $w.x + b = 0$, where:

a) Decision function: the decision function for SVM is $f(x) = w.x + b$, where w signifies the weight vector perpendicular to the hyperplane, and b represents the bias term.
b) Optimization objective: the distance between the hyperplane and the closest data points from both classes is called the margin, and SVM optimizes this distance. The challenge of optimization can be expressed as:

   – $minimize\, \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\zeta_i$
   – $s.t.\, y_i(w.x_i + b) \geq 1 - \zeta_i$

   For $i = 1,2, \ldots, n$ and ζ is the slack variable allowing for some misclassification, and C is a regularization parameter balancing margin maximization and misclassification minimization.
c) SVM achieves nonlinear classification by utilizing kernel functions $K(x_i,\, x_j)$ implicitly mapping input features into higher-dimensional spaces.
d) Prediction: in order to classify the new data, point X_{new} it evaluates $f(x_{new})$ and if $f(x_{new}) > 0$ then it assigns predicted class 1, or if $f(x_{new}) < 0$ then it assigns predicted class as -1.

4. RESULTS AND DISCUSSION

This section explains the dataset used in this study in detail. Various plant disease image samples were processed for the testing purpose. The suggested approach's output, the performance evaluation parameter, and a comparison with cutting-edge algorithms is performed to demonstrate the suggested approach's robustness.

4.1. Dataset details

We have used PlantVillage data to assess the suggested approach's performance, and we have put the suggested feature extraction, denoising, and classification techniques into practice. In this research, the PlantVillage dataset was utilized, encompassing 38 distinct classes and a total of 54,305 images representing 14 different plant species. Among these, 12 classes depict healthy plants, while 26 classes represent diseased plants, as documented by Hughes and Salathe in 2015 [29]. The dataset comprises colored images of diverse sizes. Additionally, there is an extra class denoting 1143 background images, bringing the overall number of images in the dataset to 55,448. Figure 7 displays eight randomly selected pairs of plant-disease combinations from the dataset. This Figures 7 shows 6 different images from different classes where the corresponding class is mention on image as numerical value where class 0, 1, 2, 3, 4, and 5 represents the bacterial spot, early blight, healthy, septoria leaf spot, leaf mold, and yellow leaf curl virus, respectively.

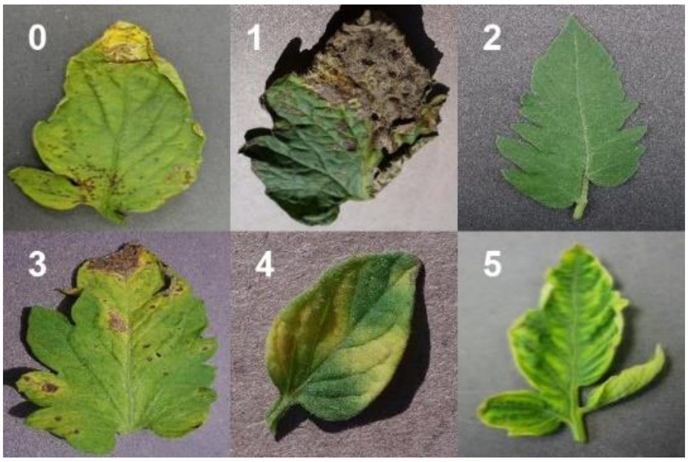

Figure 7. Sample leaf images

4.2. Performance evaluation parameters

In this work, we have performed image denoising and classification therefore we evaluate performance of both tasks separately. In order to evaluate the denoising performance we focus on the quality of reconstructed image which is measured in terms of peak signal to noise ratio (PSNR) and mean square error (MSE) whereas the classification performance is measured whether the deployed classification mechanism is able to predict the correct class of query image. The PSNR and MSE is used to analyze the image quality analysis where higher PSNR, lower MSE and high structured similarity indexing method (SSIM) represents better performance.

4.2.1. Performance measurement for denoising method

This section describes the different parameters to measure the performance of proposed denoting method. We used PSNR and MSE parameters to measure the overall denoising performance which can be computed as (10) to (12):

$$PSNR = 10\ \log_{10}\left(\frac{255^2}{MSE}\right) \tag{10}$$

$$MSE = \frac{\sum_i \sum_j \left(Y(i,j) - \hat{Y}(i,j)\right)^2}{M \times N} \tag{11}$$

$$SSIM = f\Big(l(x(m,n), c\big(x(m,n)\big), s\big(x(m,n)\big)\Big) \tag{12}$$

where M and N denotes the size of image, Y is the original image and $\hat{Y}$ is the reconstructed image.

$$AD = \big(x(m,n) - \hat{x}(m,n)\big) \tag{13}$$

$$NAE = \sum_{m=1}^{M} \sum_{n=1}^{N} \|x(m-n) - \hat{x}(m,n)\|^2 \tag{14}$$

4.2.2. Classification performance

This section presents the performance evaluation parameters to evaluate the classification performance. The efficiency of proposed solution is assessed by four parameters, i.e., accuracy, sensitivity, specificity, and F-measure by using confusion matrix. Table 2 shows the confusion matrix and based on this; other parameters are computed as mentioned in (15) to (18).

Table 2. Representation of confusion matrix

	Positive	Negative	Total
Positive	T_p	F_p	$T_p + F_p$
Negative	F_N	T_N	$F_N + T_N$
Total	$T_P + F_N$	$T_P + T_N$	

The detection accuracy is computed based on the values obtained as mentioned in confusion matrix such as true positive, false positive, false negative, and true positive. The accuracy can be computed as (15):

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \tag{15}$$

Similarly, we compute the sensitivity performance with the help of confusion matrix. The sensitivity can be expressed as (16):

$$Sensitivity = \frac{T_P}{T_P+F_N} \tag{16}$$

The specificity can be computed as (17):

$$Specificity = \frac{T_N}{T_N+F_P} \tag{17}$$

and, F-measure is can be computed as (18):

$$F - measure = \frac{2\times T_P}{2\times T_P+F_N+F_P} \tag{18}$$

4.3. Comparative analysis

This section provides a comparative analysis of the suggested approach. Here, the results of the denoising performance are presented in the first subsection and the classification performance is in the next subsection. The denoising performance is measured for 5 dB signal to noise ratio (PSNR) noise and is compared with the state-of-art methods.

4.3.1. Outcome of proposed denoising model

The performance of proposed model is measured in terms of PSNR, MSE, SSIM, SNR, average difference (AD), and normalized absolute error (NAE). The obtained performance is compared with state-of-art methods such as bilateral filter, contrast limited adaptive histogram equalization (CLAHE), Gaussian, Weiner and median filter. Table 3 shows the obtained performance for image denoising task for different types of noise with different level of noise.

Table 3. Comparative performance for 5 dB SNR

	Gaussian Noise					
	PSNR	MSE	SSIM	SNR	AD	NAE
Bilateral	24.12	50.55	0.89	26.30	0.23	0.31
CLAHE	26.30	46.23	0.85	22.10	0.18	0.25
Gaussian	27.55	44.58	0.86	25.5	0.15	0.18
Weiner	25.55	40.23	0.88	32.10	0.10	0.12
Median	26.32	35.50	0.91	33.5	0.08	0.10
Proposed	32.35	31.50	0.95	34.2	0.02	0.08

4.3.2. Outcome of proposed denoising model

This section presents the outcome of the proposed classification approach and provides a comparative analysis with existing classification approach such as neural network, random forest, decision tree, and naïve Bayes classification. Table 4 shows the obtained performance by employing different classifiers. The proposed approach has reported the accuracy, precision, recall, and F1-Score as 98.60%, 97.25%, 96.89%, and 97.20%, respectively.

Table 4. Comparative classification performance

Classifier	Accuracy	Precision	Recall	F-Score
Neural network	95.60	94.5	93.60	92.10
Random forest	94.60	92.8	95.51	94.40
Decision tree	95.20	93.20	94.20	94.85
Naïve Bayes	95.80	94.1	94.85	95.50
SVM on raw data	96.25	94.80	95.88	95.90
SVM with proposed approach	98.60	97.25	96.89	97.20

The comparative analysis shows that the classification accuracy of SVM is improved by incorporating the proposed denoising and feature extraction. The denoising model helps to enhance the image quality whereas the hybrid feature extraction method helps to obtain the robust features which provide rich information to the training module which produces a robust trained model. Similarly, we extended this experiment and measured the performance for each category of image. Figure 8 shows the obtained performance in terms of accuracy, sensitivity, specificity, and precision for apple, blueberry, cherry, and corn leaf diseases. Figure 9 shows the obtained performance in terms of accuracy, sensitivity, specificity, and precision for bell pepper, peach, orange, and grape leaf diseases.

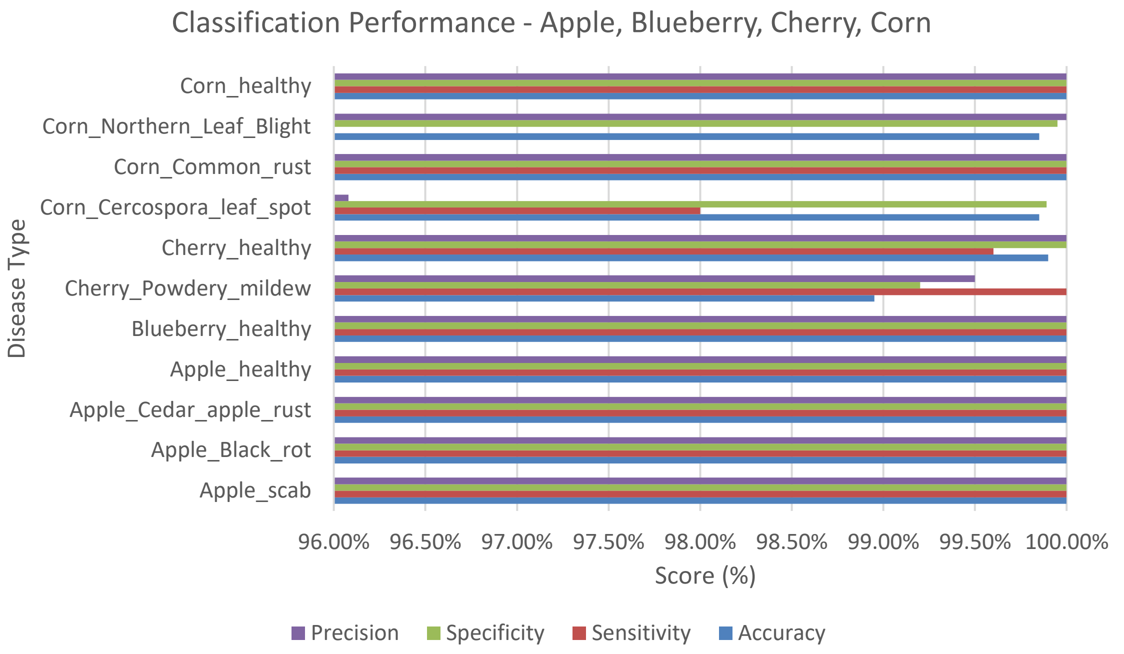

Figure 8. Classification performance for apple, blueberry, cherry, and corn

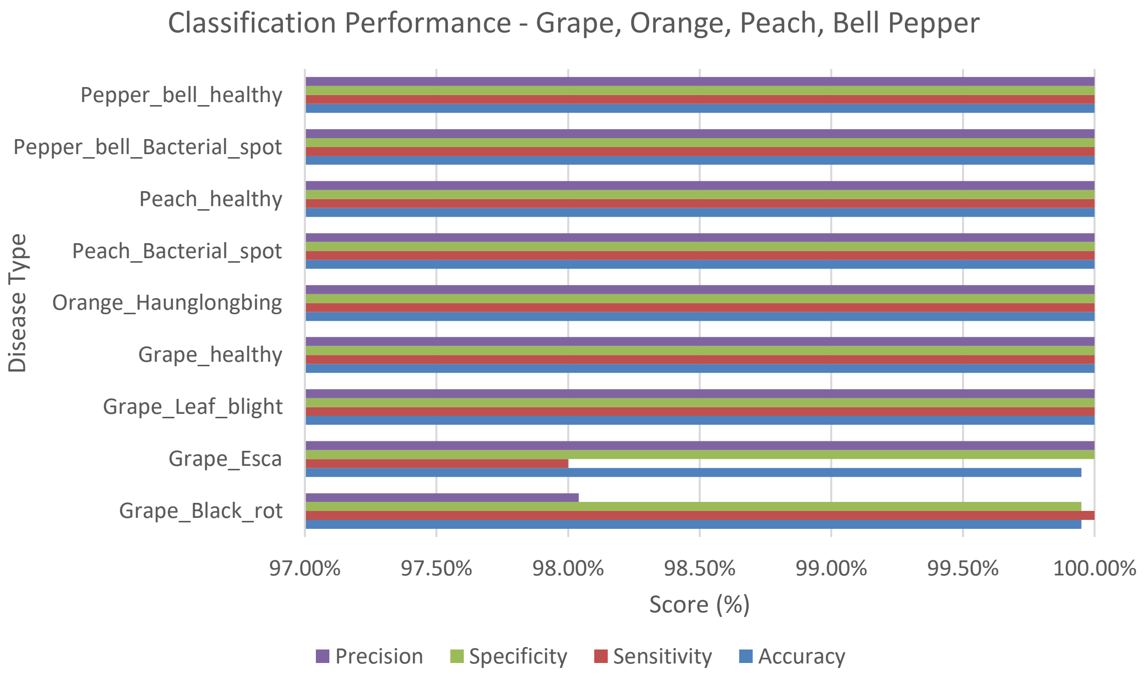

Figure 9. Classification performance for bell pepper, peach, orange, and grape leaves

Figure 10 shows the obtained performance in terms of accuracy, sensitivity, specificity, and precision for strawberry, squash, soyabean and potato leaves diseases. Figure 11 shows the obtained performance in terms of accuracy, sensitivity, specificity, and precision for tomato leaves diseases. In this experiment, we have measured the performance for each category of leaf. The experimental analysis shows that proposed approach achieves a significant performance for each category. The overall experimental analysis shows that the proposed approach obtains improved performance when compared with state-of-art classification schemes.

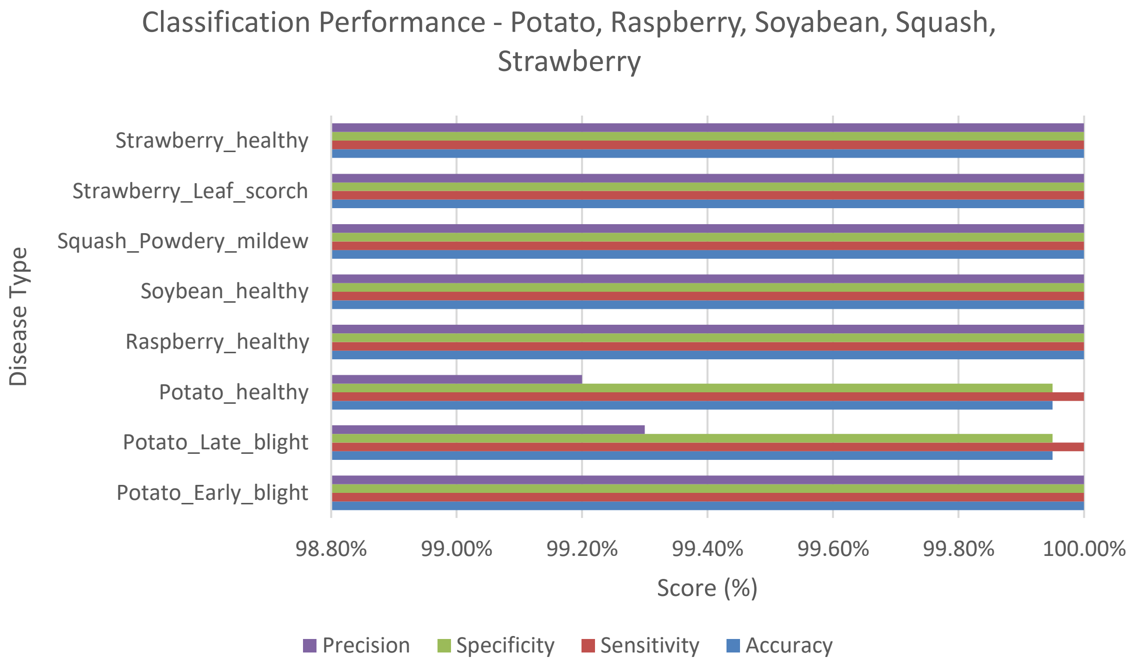

Figure 10. Classification performance for strawberry, squash, soyabean, and potato leaves

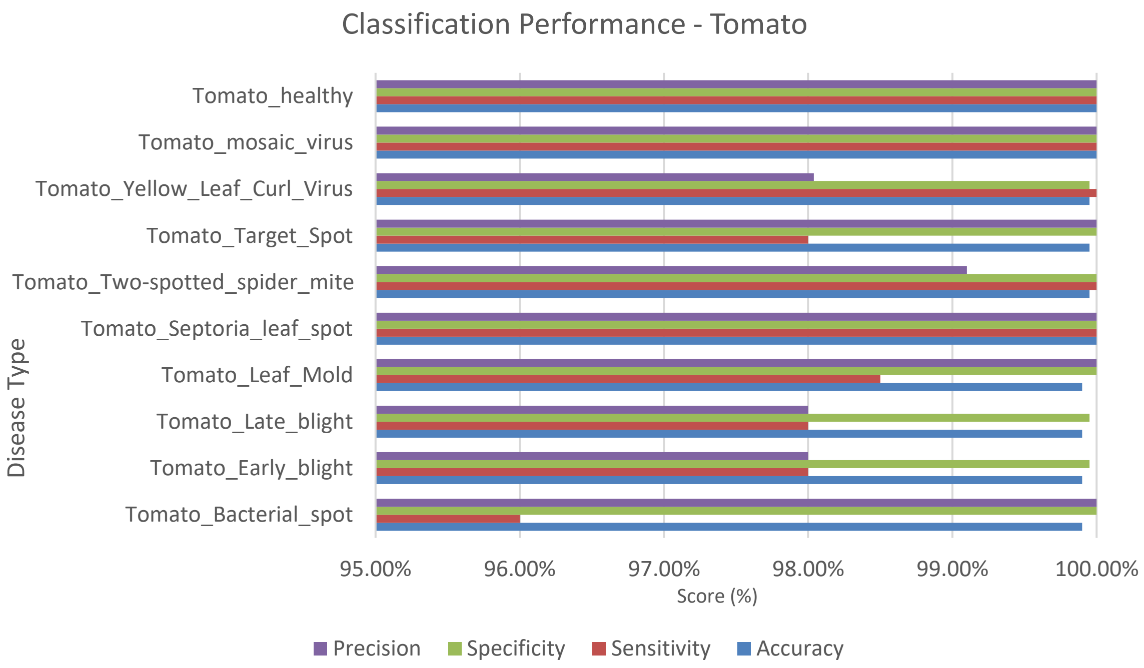

Figure 11. Classification performance for tomato leaves

5. CONCLUSION

This work has focused on development of automated computer vision and machine learning based approach for plant leaf disease detection and classification. The complete approach is a combination of image denoising, hybrid feature extraction and classification. The integration of wavelet, color, and texture features combined with autoencoder denoising and SVM classification represents a powerful and innovative approach to plant leaf disease detection. The utilization of wavelet analysis allows for multi-resolution feature extraction, enabling a comprehensive understanding of the intricate details within plant leaf images. Incorporating color and texture features further enriches the feature set, capturing a wide array of visual cues that are crucial for disease identification. Additionally, the application of autoencoder denoising techniques enhances the robustness of the feature representation, ensuring that the model focuses on relevant patterns and minimizes the impact of noise and irrelevant information. The SVM classifier, known for its effectiveness in handling high-dimensional data, proves to be an excellent choice for disease classification in this context. By utilizing the extracted features, SVM efficiently learns the underlying patterns and boundaries between different classes of plant diseases. This results in accurate and reliable disease detection, enabling timely interventions to mitigate the impact of diseases on crops. The performance of proposed approach is validated on PlantVillage dataset and the overall performance is obtained.

REFERENCES

[1] M. E. Pothen and M. L. Pai, "Detection of rice leaf diseases using image processing," *2020 fourth international conference on computing methodologies and communication (ICCMC)*, pp. 424–430, 2020.

[2] F. M. Kheirkhah and H. Asghari, "Plant leaf classification using GIST texture features," *IET computer vision*, vol. 13, no. 4, pp. 369–375, 2019.

[3] N. Nandhini and R. Bhavani, "Feature extraction for diseased leaf image classification using machine learning," *2020 International Conference on Computer Communication and Informatics (ICCCI)*, pp. 1–4, 2020.

[4] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning-a review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

[5] L. S. P. Annabel, T. Annapoorani, and P. Deepalakshmi, "Machine learning for plant leaf disease detection and classification–a review," in *2019 International Conference on Communication and Signal Processing (ICCSP)*, Apr. 2019, pp. 538–542, doi: 10.1109/ICCSP.2019.8698004.

[6] V. K. Vishnoi, K. Kumar, and B. Kumar, "Plant disease detection using computational intelligence and image processing," *Journal of Plant Diseases and Protection*, vol. 128, no. 1, pp. 19–53, Feb. 2021, doi: 10.1007/s41348-020-00368-0.

[7] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," *Computers and Electronics in Agriculture*, vol. 134, pp. 135–141, Mar. 2017, doi: 10.1016/j.compag.2017.01.014.

[8] C. Mattihalli, E. Gedefaye, F. Endalamaw, and A. Necho, "Plant leaf diseases detection and auto-medicine," *Internet of Things*, vol. 1–2, pp. 67–73, Sep. 2018, doi: 10.1016/j.iot.2018.08.007.

[9] S. Savary, L. Willocquet, S. J. Pethybridge, P. Esker, N. McRoberts, and A. Nelson, "The global burden of pathogens and pests on major food crops," *Nature Ecology & Evolution*, vol. 3, no. 3, pp. 430–439, Feb. 2019, doi: 10.1038/s41559-018-0793-y.

[10] A. A. Khakimov, A. U. Omonlikov, and S. B. U. Utaganov, "Current status and prospects of the use of biofungicides against plant diseases," *GSC Biological and Pharmaceutical Sciences*, vol. 13, no. 3, pp. 119–126, Dec. 2020, doi: 10.30574/gscbps.2020.13.3.0403.

[11] A. Khakimov, I. Salakhutdinov, A. Omolikov, and S. Utaganov, "Traditional and current-prospective methods of agricultural plant diseases detection: a review," *IOP Conference Series: Earth and Environmental Science*, vol. 951, no. 1, Jan. 2022, doi: 10.1088/1755-1315/951/1/012002.

[12] H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors," *Computers and Electronics in Agriculture*, vol. 138, pp. 92–104, Jun. 2017, doi: 10.1016/j.compag.2017.04.008.

[13] K. S. Patle, R. Saini, A. Kumar, S. G. Surya, V. S. Palaparthy, and K. N. Salama, "IoT enabled, leaf wetness sensor on the flexible substrates for in-situ plant disease management," *IEEE Sensors Journal*, vol. 21, no. 17, pp. 19481–19491, Sep. 2021, doi: 10.1109/JSEN.2021.3089722.

[14] P. Sajitha, A. D. Andrushia, N. Anand, and M. Z. Naser, "A review on machine learning and deep learning image-based plant disease classification for industrial farming systems," *Journal of Industrial Information Integration*, vol. 38, Mar. 2024, doi: 10.1016/j.jii.2024.100572.

[15] L. J. L. Jian, D. X. D. Xiao Qi, C. G. C. Guang, S. Y. S. Yang, and J. N. J. Nan, "Blade image denoising method based on improved Gauss filtering algorithm," *2019*.

[16] V. Malathi and M. P. Gopinath, "Noise deduction in novel paddy data repository using filtering techniques," *Scalable Computing: Practice and Experience*, vol. 21, no. 4, pp. 601–610, 2020.

[17] M. R. Raigonda and S. P. Terdal, "A preprocessing and segmentation approach for accurate identification of diseases in potato plant," *Proceedings of the 2nd International Conference on Cognitive and Intelligent Computing. ICCIC 2022*, pp. 259–267, 2023, doi: 10.1007/978-981-99-2746-3_27.

[18] V. K. Trivedi, P. K. Shukla, and A. Pandey, "Automatic segmentation of plant leaves disease using min-max hue histogram and k-mean clustering," *Multimedia Tools and Applications*, vol. 81, no. 14, pp. 20201–20228, 2022.

[19] V. K. Shrivastava and M. K. Pradhan, "Rice plant disease classification using color features: a machine learning paradigm," *Journal of Plant Pathology*, vol. 103, no. 1, pp. 17–26, Feb. 2021, doi: 10.1007/s42161-020-00683-3.

[20] M. Hussein and A. H. Abbas, "Plant leaf disease detection using support vector machine," *Al-Mustansiriyah Journal of Science*, vol. 30, no. 1, pp. 105–110, Aug. 2019, doi: 10.23851/mjs.v30i1.487.

[21] E. Hossain, M. F. Hossain, and M. A. Rahaman, "A color and texture based approach for the detection and classification of plant leaf disease using KNN classifier," in *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Feb. 2019, pp. 1–6, doi: 10.1109/ECACE.2019.8679247.

[22] Anjna, M. Sood, and P. K. Singh, “Hybrid system for detection and classification of plant disease using qualitative texture features analysis,” *Procedia Computer Science*, vol. 167, pp. 1056–1065, 2020, doi: 10.1016/j.procs.2020.03.404.

[23] S. K. Sahu and M. Pandey, “An optimal hybrid multiclass SVM for plant leaf disease detection using spatial fuzzy c-means model,” *Expert Systems with Applications*, vol. 214, Mar. 2023, doi: 10.1016/j.eswa.2022.118989.

[24] A. Aruraj, A. Alex, M. S. P. Subathra, N. J. Sairamya, S. T. George, and S. E. V. Ewards, “Detection and classification of diseases of banana plant using local binary pattern and support vector machine,” in *2019 2nd International Conference on Signal Processing and Communication (ICSPC)*, Mar. 2019, pp. 231–235, doi: 10.1109/ICSPC46172.2019.8976582.

[25] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S. G. G. Sophia, and B. Pavithra, “Tomato leaf disease detection using deep learning techniques,” in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, Jun. 2020, pp. 979–983, doi: 10.1109/ICCES48766.2020.9137986.

[26] S. Gayathri, D. C. J. W. Wise, P. B. Shamini, and N. Muthukumaran, “Image analysis and detection of tea leaf disease using deep learning,” in *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Jul. 2020, pp. 398–403, doi: 10.1109/ICESC48915.2020.9155850.

[27] S. Zaghbani, N. Boujneh, and M. S. Bouhlel, “Semi-supervised auto-encoder for facial attributes recognition,” *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 18, no. 4, pp. 2169–2176, Aug. 2020, doi: 10.12928/telkomnika.v18i4.14836.

[28] A. M. Al-Sbou and N. H. Abd Rahim, “An improved hybrid semi-stacked autoencoder for item-features of recommendation system (iHSARS),” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 30, no. 1, pp. 481–490, Apr. 2023, doi: 10.11591/ijeecs.v30.i1.pp481-490.

[29] D. P. Hughes and M. Salathé, “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” *arXiv:1511.08060*, 2015, doi: 10.48550/arXiv.1511.08060.

BIOGRAPHIES OF AUTHORS

Suma Huddar received the B.Eng. degree in electronics and communication engineering from Gogte Institute of Technology which is Affiliated to Visvesvaraya Technological University, Belagavi, India, in 2011 and the M.Tech. degree in digital electronics and communication systems, in 2013 from Adichunchanagiri Institite of Technology Chickmagaluru, which is affiliated to Visvesvaraya Technological University, Belagavi, India. Currently, she is a research scholar at the Department of Electronics and Communication Engineering, Visvesvaraya Technological University. Her research interests include data science, deep learning algorithms, machine learning algorithms, time series forecasting, computer vision, and natural language processing. She can be contacted at email: sumavehaan18@gmail.com.

Kopparagaon Prabhushetty received his Ph.D. degree from Shivaji University, Maharashtra in 2014. He has a vast teaching experience of more than 35 years. He worked as a professor and head of the Department of ECE at S. G. Balekundri Institute of Technology, Belagavi. He is guiding 7 scholars towards their Ph.D. He is currently associated with S. G. Balekundri Institute of Technology, Belagavi, India as a research supervisor. His research interests include image processing, artificial intelligence, deep learning, machine learning, and computer vision. He can be contacted at email: kprabhushetty1@gmail.com.

Jagadish S. Jakati he received B.E. in electronics and communication engineering in 2010, M.Tech. in 2012 and Ph.D. in 2022 from VTU, Belagavi. Presently he is working as assistant professor at School of Computer Science Engineering and Application, D. Y. Patil International University Akurdi, Pune, Maharashtra, India. He Holds a Ph.D. degree in electrical engineering with specialization in speech processing. His research areas are image/signal processing, biometrics, medical image analysis and pattern recognition. Dr Jagadish has filed a number of patents and industrial designs on his innovative ideas and has been published with four Indian patents and more than 20 international journals. His research interests include image/signal processing, biometrics, medical image and analysis, and pattern recognition. He can be contacted at email: jagadishjs30@gmail.com and jagadish.jakati@dypiu.ac.in.

Raviraj H. Havaldar is a professor of biomedical engineering at KLE Technological University's Dr. MS Sheshgiri College of Engineering and Technology Belagavi campus, Belagavi, India. He obtained his undergraduate degree in Biomedical Engineering from Mangalore University and post-graduation from Manipal University, Manipal. Dr. Havaldar received his Ph.D. in biomedical engineering from the KLE University, Belagavi in 2014 under the supervision of professor S. C. Pilli and professor B. B. Putti, Dr. Havaldar has served as an associate editor for the Journal of Osteoarthritis, and as an editor for EnggMed News. Dr. Havaldar is a senior IEEE member and presently holds the responsibility as the Joint Secretary, IEEE EMBS Bangalore Chapter and also the member, Executive Committee Biomedical Engineering Society of India Manipal Chapter, Manipal. Dr. Havaldar has made over 40 scholarly contributions, including nearly 20 peer-reviewed research papers and 20 International Conference papers. He has three Indian patents granted to his credit. He currently serves as member board of studies at Visvesvaraya Technological University, member board of studies at KLE Technological University and member board of examinations at Visvesvaraya Technological University Belagavi in biomedical engineering. His research areas are biomedical image processing, biomedical signal processing and speech signal processing. He can be contacted at email: dr.rhhavaldar@gmail.com.

Nandakishor Sirdeshpande received his Ph.D. in computer science and engineering from Department KLS Gogte Institute of Technology, Belgaum, and Karnataka. He obtained his undergraduate degree in electronics and communication engineering from Bapuji Institute of Engineering and Technology, Davangere, Affiliated to the University of Mysore and post-graduation in communication systems from PDA College of Engineering, Gulbarga. Affiliated to the Visvesvaraya Technological University, Belgaum. He has a vast teaching experience of more than 35 years. Currently he is working as an associate professor at Atharva College of engineering Malad, West Mumbai. His research interests include wireless communication, networking, wireless sensor networks, and digital communication. He can be contacted at email: ns.sirdeshpande@gmail.com.