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Retraction

Retracted: Improved Support Vector Machine and Image Processing Enabled Methodology for Detection and Classification of Grape Leaf Disease

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] A. S. Ansari, M. Jawarneh, M. Ritonga et al., "Improved Support Vector Machine and Image Processing Enabled Methodology for Detection and Classification of Grape Leaf Disease," *Journal of Food Quality*, vol. 2022, Article ID 9502475, 6 pages, 2022.

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Research Article

Improved Support Vector Machine and Image Processing Enabled Methodology for Detection and Classification of Grape Leaf Disease

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In recent years, agricultural image processing research has been a key emphasis. Image processing techniques are used by computers to analyze images. New advancements in image capture and data processing have simplified the resolution of a wide range of agricultural concerns. Crop disease classification and identification are crucial for the agricultural industry's technical and commercial well-being. In agriculture, image processing begins with a digital color picture of a diseased leaf. Plant health and disease detection must be monitored on a regular basis in property agriculture. Plant diseases have had a tremendous impact on civilization and the Earth as a whole. Extensions of detection strategies and classification methods try to identify and categorize each ailment that affects the plant rather than focusing on a single disease among several illnesses and symptoms. This article describes a new support vector machine and image processing-enabled approach for detecting and classifying grape leaf disease. The given architecture includes steps for image capture, denoising, enhancement, segmentation, feature extraction, classification, and detection. Image denoising is conducted using the mean function, image enhancement is performed using the CLAHE method, pictures are segmented using the fuzzy C Means algorithm, features are retrieved using PCA, and images are eventually classed using the PSO SVM, BPNN, and random forest algorithms. The accuracy of PSO SVM is higher in performing classification and detection of grape leaf diseases.

1. Introduction

In recent years, there has been a significant increase in the amount of focus placed on agricultural image processing [1, 2]. The use of image processing has been shown to be beneficial in a wide variety of sectors, including agriculture. In agriculture, pictures are captured by cameras, aircraft, or satellites and then processed to expose information. This may be done in a variety of ways. Computers using various image processing techniques examine these pictures for analysis. The capacity to handle a wider variety of agricultural challenges has been increased as a result of the processing of images and data. A variety of agricultural processes, including the removal of diseased leaves, stems, and fruits, the measurement of the area affected by the illness, and the formulation of a diagnosis based on the color, shape, and size of an image.

Image processing refers to the practice of applying various techniques to an image in order to improve it or extract relevant information from it [3, 4]. Image processing is a practice that has become more popular in recent years. When a single picture is used as an input, it is possible for more than one image to be created from that same picture. One of the technological disciplines that is now undergoing the most rapid change is image processing. Before a picture is used in another context, it may be improved and altered by the application of a number of distinct image processing techniques. Some of these techniques include enhancement, segmentation, feature extraction, classification, and others. As part of the process of improving an image, several aspects of the picture may have their brightness, color temperature, noise reduction, and sharpness adjusted. A huge image may be segmented into several smaller images using a specific method called picture segmentation. This is a common approach that is used to recognize digital photographs. Approaches such as thresholding, color-based, transform, and texture-based methods are only a few examples of the many options available for image segmentation. "Feature extraction" is a kind of "dimensionality reduction" that involves selecting just those aspects of an image that are both the most important and the most appealing among all of its constituents. It is appropriate for rapidly matching huge pictures while simultaneously cutting down on the number of feature representations. Image categorization refers to the practice of assigning each photograph to one of a number of distinct categories based on the criteria that have been established in advance.

It is critical for the agricultural industry's technical and commercial well-being that crop diseases be properly classified and identified. Picture processing in agriculture begins with a digital color image of a sick leaf. Property agriculture relies on regular monitoring of plant health and the identification of disease. Plant diseases [5] have had a significant influence on civilization and the planet at large. Extensions of detection tactics and classification methods aim to identify and classify any illness that affects the plant rather than focusing on one particular disease among a wide range of diseases and symptoms. Plant pathologists will use photos of plants to identify agricultural illnesses. For agricultural purposes, such as the identification of leaf and fruit diseases, computer systems have been created. If the backdrop is cluttered with distracting objects, then it might be difficult to isolate the area of focus where the symptoms are most prominent. A lack of control over the capture settings may result in pictures that are harder to anticipate and hence more difficult to identify diseases [6, 7].

This paper proposes an improved approach for detecting and classifying grape leaf diseases that is enabled by support vector machines and image processing. The phases of acquiring an image, removing noise from an image, improving an image, segmenting an image, extracting features, classifying the data, and finding the data are included in the proposed framework. After performing image denoising using the mean function, performing image enhancement with the CLAHE method, segmenting pictures with the fuzzy C Means algorithm, extracting features with PCA, and ultimately classifying images with the PSO SVM, BPNN, and random forest algorithm.

1.1. Literature Survey. Research by Sanyal [9] focused on rice leaf analysis to identify both mineral deficits and illnesses. The lesions on the plant leaves caused by mineral shortages, such as brown spots and blast disease, are different in shape and size. They utilized 400 rice leaf photos to extract texture and color features, and then input the results into an ANN with a single hidden layer called a Multilayer Perceptron (MLP). Researchers have also worked on the identification of rice leaf disease. Segmentation was performed using entropy-based thresholding after the RGB pictures were transformed to HSI color space. An edge detection technique was used to analyze the segmented pictures before they were converted to grey scale. Self-organizing maps were used to categorize illnesses based on the photos.

In order to identify illnesses in grape leaves, Meunkaewjinda et al. [10] created an intelligent system. First, an MLP-ANN was used to distinguish between the leaves and the backdrop of the image. A Support Vector Machine (SVM) was used to identify sick and healthy leaf sections, and the result was input into a multiclass SVM to categorize illnesses. It was found that barley leaves were deficient in nitrogen, as measured by Pagola et al. [11]. In the end, they chose to use RGB alterations followed by PCA and softmax regression to see how it affected the final result. The accuracy of the results was checked against that of a chlorophyll meter. According to Carmargo and Smith [12], a classification algorithm for picture patterns was devised to help diagnose plant illnesses, and cotton was used to evaluate the method's accuracy. Camargo and Smith's segmentation approach was used. In order to handle many classes in SVM, the segmented output was fed to an SVM with an on-one approach. Using texture characteristics in their strategy proved to be successful.

Cucumber plant leaf disease detection was addressed by Jian and Wei [13] using an SVM-based technique. Using a basic thresholding method, features were retrieved from the data. An SVM was trained using these characteristics. Radial basis function kernel, polynomial kernel, and sigmoid kernel function were used to compare the models' performance. The SVM using a radial basis function kernel was the most effective. There is a deficit of nutrients in palm plants that may be detected by the use of a spectrometer. The first step in their process is the segmentation of photos based on similarities in color. Color and texture characteristics were then extracted from these segmented pictures using an algorithm. Fuzzy classifiers were used to sort the data based on these attributes. In any case, there was no explanation in the study as to how this was done.

Tomatoes with nutritional inadequacies were identified using a classifier developed. The L ∗ a ∗ b ∗ and RGB color spaces were first transformed into each other in order to extract color and texture attributes from the data as well. In order to extract color and texture from the leaves, Fourier transforms, wavelet packets, and percent intensity histograms were used. For classification, the output was input into a fuzzy K-nearest neighbor model, and 82.5 percent accuracy was attained. To classify plant diseases, Wang et al [14] employed neural networks. They used wheat and grapevines as test examples. Color, shape, and texture characteristics were retrieved after segmentation with K-means. MLP, Radial Basis Function, Generalized Regression, and Probabilistic ANNs were all used to process the data. Their greatest accuracy was reached using the Radial Basis Function (RBF).

Mwebaze and Owomugisha [15] created a method that uses leaf pictures to identify disease occurrence and severity in plants. They included five disorders and five phases of disease development in their research. Color and ORB feature transformations were used to extract features, which were then input into an SVM classifier. In addition, a mobile application was created and hosted on a distant server.

It was Gupta's idea to utilize image processing and a classifier to identify illnesses [16]. Histogram equalization was used to enhance contrast before K-means clustering was used to partition the data. An SVM-Cuckoo Search classifier with a 95% accuracy rate was used to analyze this data.

1.2. Methodology. This section describes a new support vector machine and image processing-enabled approach (Figure 1) for detecting and classifying grape leaf disease. The given architecture includes steps for image capture, denoising, enhancement, segmentation, feature extraction, classification, and detection. Image denoising is conducted using the mean function, image enhancement is performed using the CLAHE method, pictures are segmented using the fuzzy C Means algorithm, features are retrieved using PCA, and images are eventually classed using the PSO SVM, BPNN, and random forest algorithms. Figure 2 shows the image processing-enabled methodology for detection and classification of grape leaf disease.

One of the most widely used and effective strategies for removing unwanted noise from photos is known as adaptive median filtering (AMF). The AMF technique is used in order to determine which pixels in an image are influenced by impulse noise in order to take appropriate corrective action. The appearance of impulsive noise in an image is caused when a significant percentage of the pixels in that image are misaligned with one another. In order to mask the noise-free pixels in the surrounding pixels, the median value of the noise-free pixels in the neighboring pixels is used [17].

In order to identify a picture, the background extraction process has to be able to adapt to the specific qualities of each individual photograph. Histograms of pixel values and the values of the regions around them may be produced with the help of CLAHE. CLAHE will confine the maximum contrast adjustment to the local histogram height and, as a result, the maximum contrast enhancement factor by specifying a maximum, also referred to as a "clip level." The end product has a cleaner look as a consequence of this. CLAHE [18] improves the clarity of mammograms, making it easier to see minute details. In spite of the fact that this method makes it possible to differentiate between the signal and the noise, the pictures that are produced have a discernible graininess.

A preprocessed image's pixel values are separated into various classes using the intensity value of the pixel as a foundation for clustering. As a consequence, pixels within the same class are comparable, whereas pixels within different classes are not. Prior to this period, various clustering algorithms had been established. A potential classification of clustering methods is based on whether subsets are fuzzy or crisp, since clusters may be formally defined as subsets of a larger data set. As a matter of thumb, fuzzy clustering algorithms perform better than other known clustering approaches. There is an extra characteristic of FCM, which separates the image into n different clusters, with each one having some degree of overlap with the other clusters. In image processing, fuzzy c-means is a significant approach for finding the clusters of objects in a picture. In order to boost the accuracy of clustering under noise, mathematicians introduced a spatial element to the FCM algorithm [19].

The Haar wavelet transformation [20] is the most basic wavelet transform. In mathematics, the Haar transform joins Haar wavelets. All wavelet transformations use the Haar transform as a sampling procedure. For example, a signal may be reduced by 50% using the Haar transform. In contrast to the second example, the first example is a running average.

Binary linear classification may be accomplished in a brisk and straightforward manner by using PSO SVM. Using this strategy, it is possible to determine one or more of the target groups. Dots are used to denote individual pieces of information, and each dot represents a single bit of data (or point). It expands as a consequence of the many different cultures that are represented in it. The additional instances are used to determine where the target class allocation should be placed. Nonlinear classification is an option to consider in situations when the datasets used as input are not labeled. In this case, there are no objective classes that need to be assigned to the instances, so an unsupervised learning approach is used. When constructing clusters based on functions, it is possible to add extra instances. A recommendation system that is based on support vector machines has been shown. In the case of unlabeled data, nonlinear support vector machine algorithms are used the majority of the time [21].

The back propagation technique created by Haykin and Anderson is one of the most frequently used learning algorithms. When it comes to simple pattern recognition and mapping jobs, BPN is an excellent choice. Rather than a network, back propagation is a learning process. Using algorithm examples, the network will be trained to generate the proper output for every input pattern. The weights of the network are altered as a result. A training pair consists of an input and a target [22].

(a) (b) (c)

Figure 1: Images of grape leaf disease [8].

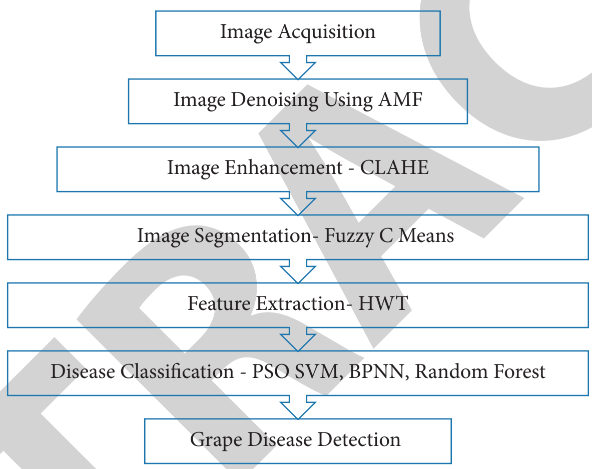

Figure 2: Image processing-enabled methodology for detection and classification of grape leaf disease.

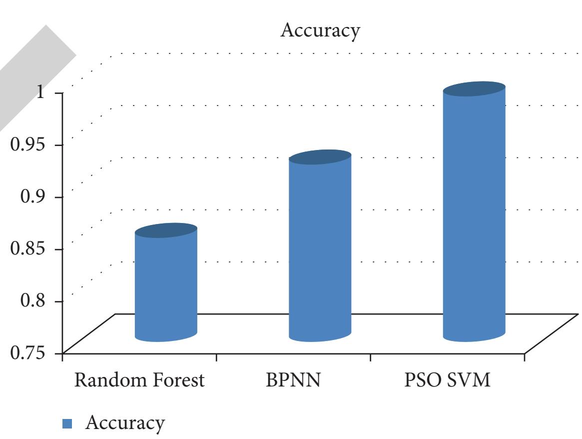

Figure 3: Accuracy of classifiers for grape leaf disease classification.

Random Forest is one of the decision-tree-based classifiers that is used the most. A bootstrap sample of the data is used, in addition to a random sampling of features, to generate each tree in the model. Bagging and random selection are two methods that may be used to generate trees. The relationship between any two trees in a forest may have a significant impact on the accuracy of the class predictions made by the trees as the forest matures. These

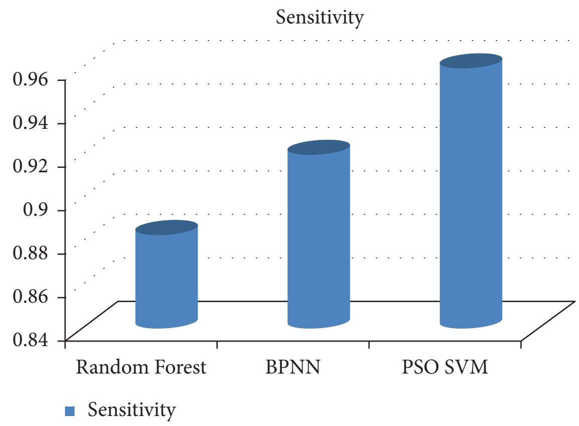

FIGURE 4: Sensitivity of classifiers for grape leaf disease classification.

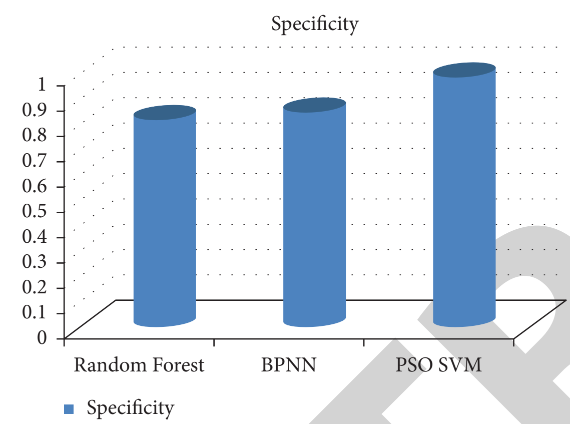

FIGURE 5: Specificity of classifiers for grape leaf disease classification.

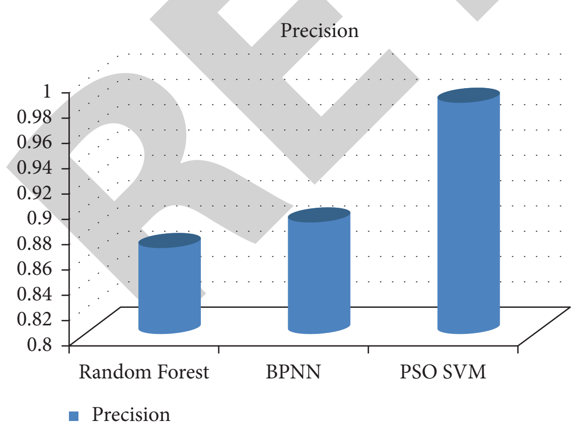

FIGURE 6: Precision of classifiers for grape leaf disease classification.

class predictions can have a broad range of error rates. By using this strategy, a natural ranking of the difficulties posed by regression and classification may be accomplished [23].

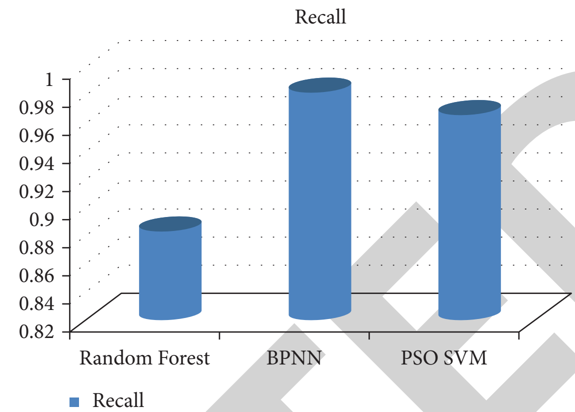

FIGURE 7: Recall of classifiers for grape leaf disease classification.

2. Results and Discussion

For experimental work, 400 images related to grape leaves were collected. 250 leaves have disease and the remaining 150 leaf images are normal. For the training of machine learning classifiers, 250 images are used. Image denoising is performed using mean function, image enhancement is performed using the CLAHE algorithm, images are segmented using the fuzzy C Means algorithm, features are extracted using PCA, finally images are classified using PSO SVM, BPNN, and random forest algorithm.

Performance is compared on the basis of the following parameters. Results are shown below in Figures 3–7.

$$\begin{aligned} \text{Accuracy} &= \frac{(TP+TN)}{(TP+TN+FP+FN)},\\ \text{Sensitivity} &= \frac{TP}{(TP+FN)},\\ \text{Specificity} &= \frac{TN}{(TN+FP)},\\ \text{Precision} &= \frac{TP}{(TP+FP)},\\ \text{Recall} &= \frac{TP}{(TP+FN)}, \end{aligned} \tag{1}$$

where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative.

3. Conclusion

Agricultural image processing research has received a great deal of attention in recent years. Computers utilize image processing techniques to analyze pictures that have been captured. In recent years, technological advances in picture capture and data processing have made it easier to resolve a wide range of agricultural challenges. The categorization and diagnosis of crop diseases are critical for the technical and commercial well-being of the agricultural business as a whole. A digital color photograph of a sick leaf is used to begin the image processing process in agriculture. In property agriculture, plant health and disease detection must be monitored on a regular basis to ensure that no problems arise. Plant diseases have had a significant influence on civilization as well as the environment as a whole throughout history. The classification approaches used as extensions of detection tactics attempt to identify and categorize each disease that affects the plant, rather than focusing on a particular disease among a variety of diseases and symptoms. According to this paper, a novel support vector machine and image processing-enabled technique for identifying and categorizing grape leaf disease has been developed. An image capture, denoising, and enhancement process are followed by segmentation, feature extraction, classification, and detection processes. The mean function is used to perform image denoising, the CLAHE method is used to perform image enhancement, pictures are segmented using the fuzzy C Means algorithm, features are retrieved using PCA, and images are finally classified using the PSO SVM, BPNN, and random forest algorithms, among others. When it comes to conducting classification and detection of grape leaf diseases, the accuracy of PSO SVM is greater.

Data Availability

The data shall be made available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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