Weed Image Classification using Wavelet Transform, Step-wise Linear Discriminant Analysis, and Support Vector Machines for an Automatic Spray Control System

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We tested and validated the accuracy of wavelet transform along with stepwise linear discriminant analysis (SWLDA) and support vector machines (SVMs) for crop/weed classification for real time selective herbicides systems. Unlike previous systems, the proposed algorithm involves a pre-processing step, which helps to eliminate lighting effects to ensure high accuracy in real-life scenarios. We tested a large group of wavelets (46) and decomposed them up to four levels to classify weed images into weeds with broad leaves versus weeds with narrow leaves classes. SWLDA was then employed to reduce the feature space by extracting only the most meaningful features. Finally, the features provided by SWLDA were fed to the SVMs for classification. The proposed method was tested on a database of 1200 samples, which is a much larger database size than that studied previously (200-400 samples). Using confusion matrices, the crop/weed classification results obtained using different wavelets at different decomposition levels were compared, and this approach was also compared with existing techniques that use statistical and structural approaches. The overall classification accuracy obtained using the symlet wavelet family was 98.1%. These results represent an improvement of 14% in performance compared with existing techniques.

Keywords: weed classification, global histogram equalization, wavelet transform, SWLDA, machine vision

1. INTRODUCTION

Precision agriculture presents an opportunity for increased productivity and decreased production costs with the best use of resources and minimal environmental damage [1]. In precision agriculture, imaging devices offer constructive information about in-field heterogeneities [2]. Weed image classification is still one of the most complex and significant concerns in precision agriculture [3]. Weeds come in numerous shapes and sizes and grow randomly, resulting in numerous texture characteristics.

For accurate classification, an automated weed discrimination system is reliant on good quality features with high discriminatory power. Therefore, a large number of researchers have proposed feature extraction methods, such as gray level co-occurrence (GLCM) [4 – 6], fast Fourier transform (FFT) [4 – 6], scale invariant feature transform
(SIFT) [7], a filtering technique similar to edge detection [8], Gabor wavelet and gradient field distribution [9], and the double Hough transform (DHT) [10]. However, each of these techniques has limitations that are described below.

The GLCM method does not consider edge information, even though this is a significant source of good features. Furthermore, GLCM has good two-pixel relationship performance but poor structural texture performance [11]. Similarly, FFT is also computationally expensive and requires a sample time of more than 1 second for true measurement [12]. Likewise, SIFT can only extract good features from gray level images; it cannot be applied to color images because it does not have the ability to obtain color information, therefore information in color space is ignored, which can result in misclassification [13]. The author of [8] proposed another feature extraction technique for weed classification systems that measures the continuity between neighborhood pixels by checking them at different angles to extract features. However, it is very hard for this technique to obtain an accurate feature vector if the leaves within the processing image are far away from one other. Moreover, this technique takes a long time to classify weed images. Furthermore, although this technique is similar to the edge detection technique, the edges are not continuous and sometimes stem edges are included because of noise, which makes it harder for this technique to extract informative features for classification.

In the presence of noise, it is difficult to extract the best features for classification. Therefore, two techniques, namely forward and inverse techniques, have been employed to illuminate the noise. However, this is one of the limitations of the Gabor wavelet proposed for weed classification systems [9]. Moreover, a huge amount of space is required for Gabor wavelet processing, and the resulting representation is therefore dense. Similarly, Double Hough transform (DHT) is used to detect lines of objects within objects. However, during line detection, there can be misperception of short lines and accidental alignment of pixels, which may prevent extraction of the best features. Moreover, this technique is also computationally expensive and misclassification may occur due to the sudden appearance of an object.

Many classification techniques have been investigated and proposed in recent years. Most of them are based on heuristics, such as histogram analysis [14], population variance [15], two-dimensional weed coverage rate (2D-WCR) [16], and histogram-based classification [17]. They lack accuracy because they just sum up the pixels of the whole image and keep that value as a threshold for weed image classification in the recognition phase. This may cause misclassification of real-time weed images, because there are no criteria for selecting a threshold value. Automated classification methods have also been employed, including support vector machines (SVMs) [18], the active shape model (ASM) [19], and neural networks (NNs) [20]. ASM technique is an offline process that does not work in real time. Neural networks have good classification accuracy (about 85–90%). However, a huge amount of high quality data is required to train the networks and NNs are computationally expensive.

Most of the developed techniques have been validated using small datasets; in previous studies, about 200–400 broad and narrow weed images were used. Moreover, all these images were captured under the same conditions and therefore had little diversity. During the experiments, the assumption was made that light and wind effects were constant. Application of the same techniques to a bigger dataset (i.e., 1200 images) without any prior assumptions resulted in a low classification accuracy.
In our previous work in this area, we developed a system based on wavelet transform as a feature extraction technique and Euclidean distance as a classifier for weed image classification. The accuracy of our system was high at 97% [21]. However, we evaluated only 350 images in a laboratory environment, where all the images were taken under the same light conditions (bright light). Our system exhibited very low accuracy when tested on 1200 samples (i.e., 500 weeds with narrow leaves, 500 weed with broad leaves, and 200 unknown weed classes) from a real environment captured under different lighting conditions.

![Sample images for training (top-row) and testing (bottom-row) for the three categories: (a) broad weed, (b) narrow weed, and (c) unknown.](image)

We attributed the decrease in accuracy of our previous system to the absence of an efficient pre-processing step before feature extraction to eliminate the light and color differences. Some sample images used for training and testing for these three categories are shown in Fig. 1 to highlight these differences and thus the necessity of a pre-processing step to eliminate such differences. Moreover, in our previous work, the 100 highest wavelet coefficients were selected manually to form the final feature vector. This type of manual selection does not always guarantee the most meaningful features, especially in real-life scenarios where images are taken under different lighting conditions.

Our objective in this research was to develop an accurate and efficient weed classification system that can distinguish broad and narrow leafed weed with high accuracy even when tested with a large dataset (i.e., 1200 samples) without making any prior assumptions about environmental factors. Our proposed technique employs a pre-processing step that utilizes global histogram equalization to normalize the histograms of all the images to illuminate the lighting effect. After pre-processing, wavelet transform is performed. Wavelet transforms convert images into frequency and time domains allowing both of these features to be distinguished. In this work, we evaluated and compared six different wavelet families: the symlet wavelet family consisting of 10
sub-wavelets, the Daubechies wavelet family consisting of 10 sub-wavelets, the biorhogonal wavelet family consisting of 10 sub-wavelets, the reverse biorhogonal wavelet family consisting of 10 sub-wavelets, the Coiflet wavelet family consisted of 5 sub-wavelets, and the discrete Meyer wavelet (dmey) wavelet family. Moreover, we employed stepwise linear discriminant analysis (SWLDA) to extract only meaningful features from the images. Our reasons for employing this technique are stated later in the paper. Then, for classification, SVMs were used. The proposed method was tested on a database of 1200 samples. The overall accuracy of our proposed method using the abovementioned wavelet families was 98.1%.

Above, we discussed some related work in this field. The rest of the paper is organized as follows. Section 2 provides an overview of the proposed weed image classification system. Section 3 discusses experimental results, provides a comparison of different wavelet families, and also presents a comparison of the recognition accuracy of this work with those of some of the existing feature selection methods. Finally, the paper is concluded with some future directions in Section 4.

2. MATERIAL AND METHODS

2.1 Preprocessing

Most images have extra parameters such as lighting effects, as well as background information and unnecessary details that may cause misclassification. Therefore, it is important to remove unnecessary parameters for fast and easy processing and to improve the quality of the images. We exploited the usage of global histogram equalization (GHE) in the pre-processing stage to improve the quality of the images by lengthening the intensity of the dynamic range using the histogram of the whole image. It obtains the scale factor from the normalized cumulative distribution of the brightness distribution of the original image and multiplies this scale factor by the original image to redistribute the intensity. Basically, GHE discovers the consecutive sum of the histogram and then normalizes and further multiplies it by the maximum gray level value. These values are then mapped on the previous original values using one-to-one correspondence [22]. Images processed using this algorithm had a resolution of 240 x 320 pixels.

2.2 Feature Extraction

At this stage, the RGB images were subjected to a decomposition process using different types of wavelet families. The reason for keeping the images in RGB form was to utilize information in the color space to improve the efficiency of the proposed algorithm.

Basically, RGB image decomposition by wavelet transform (i.e., wavelet families) involves decomposition of the signal. If we have a 2D RGB image, namely image $I$, then the decomposition of the wavelet transform up to one level can be expressed as follows:

$$ I = A_i + D_i $$

(1)
where the decomposed image is indicated by \( I \) and \( A_j \) and \( D_j \) represent the approximation and detail coefficients, respectively. If the image is decomposed up to multilevels, then Equation 2 can then be rewritten as

\[
I = A_j + D_j + D_{j-1} + D_{j-2} + \ldots + D_2 + D_1
\]  

(2)

where \( j \) represents the level of decomposition. Mostly, the detail coefficients consist of noise, so for feature extraction, only approximation coefficients are used. Each image was decomposed up to four levels, i.e., \( j = 4 \), because after this value, there is loss of information such that informative coefficients cannot be detected properly, which may result in misclassification. As a result, a one-dimensional matrix is obtained by summing all the approximation coefficients at each level as follows:

\[
Mat = A_4 + A_3 + A_2 + A_1
\]  

(3)

where \( A \) indicates the approximation coefficients at each level of decomposition and \( Mat \) represents the one-dimensional matrix obtained from summation of all the approximation coefficients.

After decomposition, the one-dimensional matrix is subjected to wavelet transform to generate the feature vector. The general form of the wavelet transform can be written as

\[
W(s_j, p_j) = \frac{1}{\sqrt{s_j}} \int_{-\infty}^{\infty} y(t) \psi_{f,e}^* \left( \frac{t - p_j}{s_j} \right) dt
\]  

(4)

where \( s_j \) indicates the scale of the wavelet transform that is used to obtain a better frequency approximation between the lower and upper frequency boundaries, \( p_j \) represents the position of the wavelet transform from the start and the end time of the window in the image sampling period, \( t \) indicates time, and by \( \psi_{f,e} \) is the wavelet function used for frequency approximation [23]. \( W(s_j, p_j) \) indicates the wavelet coefficients with the required scale and position parameters. This wavelet coefficient is converted into the mode of frequency (i.e., \( f_m \)) to generate the feature vector from the one-dimensional matrix (\( M \)) produced in Eq. (4) and is given as

\[
f_{v_i} = f_{avg}(\psi_{f,e}) - a(\psi_{f,e}) \cdot \Delta
\]  

(5)

where \( f_{avg}(\psi_{f,e}) \) is the average frequency of the wavelet function, \( a(\psi_{f,e}) \) represents the approximation coefficients at all levels of decomposition, \( \Delta \) indicates the image decomposition period, and \( f_v \) indicates the resultant feature vector for an image.

2.3 Need for discriminant feature extraction

The 3D feature plots for the broad and narrow weed classes after wavelet transform using a symlet wavelet are shown in Fig. 2. Because features for the two distinct classes are highly fused, misclassification could occur.
The use of inappropriate coefficients results in high within-class differences and low between-class differences. Therefore, a method is required to address the aforementioned problem and to reduce the dimension space and increase the between-class difference to increase class separability.

The dimensions of a feature space can be reduced by extracting discriminating features that are reliant on exploiting the total distribution of the data, while lessening the differences within classes. This idea is employed by various machine-learning methodologies, mainly Principal Component Analysis (PCA) [24], Kernel Principal Component Analysis (KPCA) [25], Linear Discriminant Analysis (LDA) [26], and Stepwise Linear Discriminant Analysis (SWLDA) [27].

PCA is one of the most commonly used methods for reducing the dimensionality of the feature space. However, PCA optimizes global criteria and does not guarantee what happens to the individual data points. Moreover, PCA selects the global features and cannot capture the simplest invariance of the image.

To solve the limitations of PCA, recently, KPCA has been proposed that has the capability to extract more meaningful features than the PCA. Mostly, real time systems like automatic spray control systems need online data processing. However, KPCA process has to restart whenever new data is added, due to which the whole process of KPCA becomes an offline process, making it inapplicable for such real time systems. Also, KPCA requires large amount of memory for its processing [28].

Another popular feature selection technique is LDA that attains maximal class separability by exploiting the ratio of the between-class change to the within-class difference in any particular data set. LDA was exploited for speech data classification by [29].
LDA produces an optimal linear discriminant function by plotting the input data into a discrimination space in which class labels are decided.

However, LDA suffers from two main problems. First, it requires mixture models that have an accurate number of components. Second, LDA is a linear classifier and may therefore not be useful for complex datasets. Furthermore, assumptions such as the same within-class covariance matrix are not valid for all classes. Furthermore, it is necessary to increase the robustness of LDA conversion, which requires a large amount of data. However, there may not be sufficient data to distinguish between classes [30]. Therefore, we argue that LDA is not appropriate for improving the accuracy of classification for real-time automatic spray control systems. To address the aforementioned limitations, we decided to use stepwise linear discriminant analysis (SWLDA) in our proposed methodology.

2.4 Step-wise Linear Discriminant Analysis (SWLDA)

Fisher’s linear discriminant (FLD) is a well-known linear classification method that has been employed to find the optimal separation between two classes [26]. For two classes that have a Gaussian distribution with an identical covariance, FLD is more robust than other linear classifiers with regard to finding the optimal separation. FLD and other regression methods, such as the least-squares regression method, are comparable with each other and project feature masses in binary jobs as follows:

\[
L = (M^t M)^{-1} M^t y
\]

where \(M\) indicates the pragmatic feature vectors matrix and \(L\) is the label of the class. FLD has the capability to provide best classification solution for linear data; however, FLD does not provide a better solution when the data is non-linear.

Therefore, we propose the use of a new non-linear classification technique, stepwise linear discriminant analysis (SWLDA), which has been verified to be able to discriminate P300 Speller responses [27]. Basically, SWLDA is an extended version of FLD that performs two operations in parallel: reduces the feature space by extracting informative features, and removes irrelevant features.

As mentioned before, SWLDA extracts and selects best features by employing two algorithms, namely forward and backward algorithms that work in parallel. The most substantial interpreter value is obtained with a model that has a “p-value < 0.13” because there is no initial model at the start. When the new values are entered by the forward technique, the backward algorithm is used to remove irrelevant values i.e. those that have a “p-value > 0.2”. This entry and removal procedure continues until the predefined criteria are satisfied, and at the end, the resultant function is constrained to the extreme number of 120 features.

In contrast, regression methods select the best variable, such as \(X\), and then move on to form more \(X’s\) in meaningful situations. In this method, the new entry and the selection of the best values are based on F-test values that are used to determine which value should be entered first or second. Then, the two values, namely the partial F-value and the selected value, are compared. This whole process is done using the forward technique. In the next process, the deletion process is initiated using a backwards regression technique (known as backward deletion) in which the testing values for all interpreter
variables that had previously been present in the backlog are calculated. If the testing value with the lowest value, \( V_L \), is compared with the pre-selected value, \( P_S \), then
- The calculation of F-test will start again if \( V_L < P_S \).
- Otherwise, accept the regression equation if \( V_L > P_S \).

For more details on SWLDA, please refer to the study of [27]. The 3D feature plots of the narrow and broad weed classes obtained after applying SWLDA are shown in Fig. 3; the separation in feature space has improved noticeably.

![3D feature plots](image)

Fig. 3. 3D feature plots for broad and narrow weed classes, after applying SWLDA on the same feature space as shown in Fig. 2; however, now showing an almost complete separation between the two classes.

### 2.5 Classification using support vector machines (SVMs)

After obtaining the feature vector, we used a classifier to label each category of weed images. The complexity paradigm of classifiers varies from a simple threshold to more advanced algorithms; for example, SVMs and artificial neural networks (ANNs). These classification algorithms should be able to learn and recognize each category of weed images (such as weeds with broad or narrow leaves) from the specified patterns of the input features. A classifier that correctly classifies two or more classes would be considered a significant and adaptive classifier. In other words, features must be interpreted correctly by a classifier even if those features are different from the ones that it has encountered before; we therefore decided to use SVMs for classification.
SVMs are well-known statistical techniques that are used in machine vision, computer vision, and pattern recognition [32]. Basically, these techniques have been exploited for the purposes of linear and binary classifications tasks in the abovementioned areas. SVMs are reliant on the optimal separating decision hyper-plane between two or more classes with the maximum boundary among the patterns of each class. SVMs employ an additional function, named the so-called function that projects data from the original feature space to an alternative higher dimensional space so that linear classification in the new space is equivalent to non-linear classification in the original space.

SVMs are able to classify two or more different types of classes via hyper-planes. We used an optimization method to find the optimal separating hyper-plane between classes. The general form of a SVM is

$$\left \langle N, \Phi(x) \right \rangle + t = 0$$

(8)

where $N$ represents the normal vector to the hyper-plane that separates the two classes, $\Phi$ is the inherent function of the input data, $x$ indicates the data point, and $t$ represents the
training data. This corresponds to the resultant function as follows:

\[ R(x) = \text{sign}\left( N, \Phi(x) + t \right) \]  

(9)

where \( R(x) \) is the resultant function that shows the training patterns; this is the so-called support vector that holds all the information about the classification problem. According to theory of SVM, multiclass classification can be attained in SVM by assuming one-against-rest or several two-class problems in order to make a binary decision. One-against-rest method has been adopted in this work, in which a binary classifier has been trained for each weed class (broad and narrow) in order to differentiate one weed class from others. As proposed by [33], a grid-search on the hyper-parameters in a cross-validation method has been carried out for choosing the parameters, and the setting of parameters that produced highest cross-validation accuracy was selected. The overall process that we followed in the proposed weed classification system is shown in Fig. 4.

3. RESULTS AND DISCUSSION

This study conducted a detailed testing of the idea of employing six wavelet families combined with SWLDA and SVMs to create a real-time weed discrimination system. The proposed system has been tested and validated on real time weed images. During experiments, the size of each input image was 60x60, where the images were first converted to a zero-mean vector of size 1x3600 for feature extraction. A total of 1200 images were employed for the experimentation; among them 500 images were taken from broad category, 500 images were used from narrow category, and 200 images were employed from unknown category respectively.

We employed the `bsvmtrain-T` library to train the SVMs in Matlab. For training, 600 samples (250 images of weeds with broad leaves, 250 images of weeds with narrow leaves, and 100 unknown weeds) were used. A cross-validation approach was used to select the best parameters and those parameters that had the best cross-validation accuracy were selected. The remaining 600 samples (250 images of weeds with broad leaves, 250 images of weeds with narrow leaves, and 100 unknown weeds) were used for testing.

Firstly, the classification accuracy of our system for three weed classes (broad, narrow, and unknown) using the six wavelet families was evaluated without using the SWLDA. The results for this experiment are shown in the confusion matrix presented in Table 1.

<table>
<thead>
<tr>
<th>Wavelet Family</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symlet (sym)</td>
<td>Broad</td>
</tr>
<tr>
<td></td>
<td>Broad</td>
</tr>
<tr>
<td></td>
<td>Narrow</td>
</tr>
<tr>
<td></td>
<td>Unknown</td>
</tr>
<tr>
<td>Daubechies</td>
<td>Broad</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Among the methods that are presented in Table 1, the symlet wavelet family achieved the highest accuracy. This is because symlet wavelet extracts the most prominent information from the images. Furthermore, symlet wavelet is a compactly supported wavelet on any kind of images with the least asymmetry and highest number of vanishing moments for a given support width. The symlet wavelet has the capability to support the characteristics of orthogonal, biorthogonal, and reverse biorthogonal of gray scale images. On the other hand, it can also be noted from Table 1 that our approach, when used without SWLDA, is not highly accurate due to the occurrence of inappropriate features that produce low between-class differences, as shown in Fig. 2.

Secondly, the same experiment was repeated but this time using the SWLDA as the feature selection technique before feeding the features to the classifier. The classification accuracy of the system for the six-wavelet families for this experiment is presented as a confusion matrix in Table 2.

<table>
<thead>
<tr>
<th>Wavelet Family</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symlet (sym)</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>98</td>
</tr>
<tr>
<td>Narrow</td>
<td>1</td>
</tr>
<tr>
<td>Unknown</td>
<td>0</td>
</tr>
<tr>
<td>Daubechies (db)</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>96</td>
</tr>
<tr>
<td>Narrow</td>
<td>95</td>
</tr>
<tr>
<td>Unknown</td>
<td>1</td>
</tr>
<tr>
<td>Biorthogonal</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>86</td>
</tr>
<tr>
<td>Narrow</td>
<td>85</td>
</tr>
<tr>
<td>Unknown</td>
<td>89</td>
</tr>
<tr>
<td>Reverse Biorthogonal (rbior)</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>85</td>
</tr>
<tr>
<td>Narrow</td>
<td>85</td>
</tr>
<tr>
<td>Unknown</td>
<td>87</td>
</tr>
<tr>
<td>Coiflet (coif)</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>85</td>
</tr>
<tr>
<td>Narrow</td>
<td>85</td>
</tr>
<tr>
<td>Unknown</td>
<td>87</td>
</tr>
<tr>
<td>Discrete Meyer (dmey)</td>
<td></td>
</tr>
<tr>
<td>Broad</td>
<td>80</td>
</tr>
<tr>
<td>Narrow</td>
<td>79</td>
</tr>
<tr>
<td>Unknown</td>
<td>84</td>
</tr>
</tbody>
</table>

Table 2. Comparison of overall weed classification accuracy for six wavelet families at the fourth level of decomposition using SWLDA.
It is obvious from Table 3 that the use of SWLDA as a feature selection technique after the proposed feature extraction technique (symlet wavelet transform) has significantly increased the recognition rate. The overall average classification accuracies for all classes and the elapsed time for the six wavelet families with and without SWLDA are summarized in Table 3.

<table>
<thead>
<tr>
<th>Wavelet Families</th>
<th>Accuracy of Classification (%) without SWLDA</th>
<th>Accuracy of Classification (%) with SWLDA</th>
<th>Elapsed Time (m sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symlet</td>
<td>92.66</td>
<td>98.1</td>
<td>40.53</td>
</tr>
<tr>
<td>Daubechies</td>
<td>87.66</td>
<td>95</td>
<td>55.29</td>
</tr>
<tr>
<td>Biorthogonal</td>
<td>87.66</td>
<td>95.66</td>
<td>61.12</td>
</tr>
<tr>
<td>Reverse Biorthogonal</td>
<td>86.66</td>
<td>95.33</td>
<td>65.31</td>
</tr>
<tr>
<td>Coiflet</td>
<td>85.66</td>
<td>94.66</td>
<td>69.70</td>
</tr>
<tr>
<td>Discrete Meyer</td>
<td>81</td>
<td>93.33</td>
<td>79.7</td>
</tr>
</tbody>
</table>

It is obvious from Table 3 that the combination of the two techniques (symlet wavelet transform and SWLDA) achieved the highest accuracy.

It is also to be noted from Table 3 that the Daubechies, biorthogonal, reverse biorthogonal, and Coiflet wavelet families provided almost the same accuracy and took almost the same amount of time as one another, i.e., 95.5% and 62 msec, respectively. In terms of accuracy, the discrete Meyer was the worst wavelet family (93.3%) whereas the symlet wave family was the most accurate and efficient among all wavelet families, i.e., 98.1% in 40.53 msec. This is due to the characteristics of the symlet wavelet, i.e., it is an efficiently maintained wavelet with minimum irregularity and the highest number of vanishing moments for a given support width. The symlet wavelet family supports all the characteristics of orthogonal, biorthogonal, and reverse biorthogonal wavelet families. Therefore, it provided better classification results than the other wavelet families. Finally,
the average accuracies for six different wavelet families at four different levels of decomposition are shown in Fig. 5. It can be seen that the symlet wavelet family provided the highest accuracy of classification at each level.

![Comparison of classification accuracy of six different wavelet families at four different levels of decomposition.](image)

Fig. 5. Comparison of classification accuracy of six different wavelet families at four different levels of decomposition.

Lastly, the employed feature selection method (SWLDA) has also been compared with the discussed unsupervised feature selection techniques, i.e., PCA, KPCA, and LDA. For this comparison, we employed the same feature extraction technique (symlet wavelet transform) while changing the feature selection technique, accordingly. The comparison results are shown in Fig. 6.

![Experimental results with respect to different feature selection techniques.](image)

Fig. 6. Experimental results with respect to different feature selection techniques.

As expected, the use of SWLDA as the feature selection technique resulted in better separation in feature space between narrow and broad weed classes. These findings in-
dicate that wavelet transform and SWLDA have great potential for feature vector representation of weed images. We exploited CCTV camera for collecting the data; however, further research is needed to use the video for collecting data in real field.

3.1 Comparison with Existing Algorithms

Numerous methods for real-time automatic spray control systems have been proposed; however, most of these lack accuracy and are computationally expensive. The author of [13] proposed a real-time system, but this system only had an accuracy of about 81%. This low accuracy is because classification was based only on one highest intensity value taken from the histogram. The author of [7] also presented a method for a real-time automatic spray system, and reported a classification accuracy of 85%. This method lacks accuracy because at the feature extraction stage, a continuity measure is employed; therefore only edges of the image are utilized as inputs for a classifier, and if leaves overlap with each other, then this algorithm cannot detect the edges because it considers overlapping regions as one leaf, resulting in misclassification.

Our proposed algorithm appears to be the most accurate compared with the existing algorithms we evaluated. The results obtained by comparing our algorithm and the existing algorithms using a database of broad and narrow weed leaves are shown in Fig. 7 and 8, respectively. The overall average accuracy of the five existing algorithms was calculated as follows:

\[
\text{Average Accuracy} = \frac{82.3 + 83.1 + 91.7 + 81.5 + 85.6}{5} = \frac{420.5}{5} = 84.84
\]

In contrast, the accuracy of our proposed algorithm is 98.1%, representing an improvement in accuracy of about 14% (see Fig. 7 and 8).

We implemented our system in Matlab using a dual-core Pentium processor 2.5 GHz with a RAM capacity of 3 GB. The total number of sub-wavelets that were used in this paper was 46 (sub-wavelets).

![Fig. 7. The comparison results between the developed algorithm and the existing algorithms using](image)
the database of broad weed leaves. It is to be noted that the proposed algorithm improved the classification accuracy by about 6-14% in broad weed leaf category.

![Comparison results between the developed algorithm and the existing algorithms using the database of narrow weed leaves.](image)

Fig. 8. The comparison results between the developed algorithm and the existing algorithms using the database of narrow weed leaves. It is to be noted that the proposed algorithm improved the classification accuracy by about 5-14% in narrow weed leaf category.

4. CONCLUSION

Weeds destroy crops by competing for water, light, nutrients, and space. To reduce the quantity of weeds in a field and to improve the effectiveness of machinery, a real-time weed classification system is important.

Numerous real-time weed classification systems have been developed, but are not very accurate or efficient. Moreover, environmental factors such as lighting effects may reduce the accuracy of classification. Therefore, we developed an accurate and efficient method for real-time weed classification that employs global histogram equalization to diminish lighting effects and multilevel wavelet decomposition to extract the prominent features from images. To increase accuracy and efficiency, we developed new pre-processing and post-processing methods. We investigated six different types of wavelet families: symlet, Daubechies, biorthogonal, reverse biorthogonal, Coiflet, and discrete Meyer. We used support vector machines (SVMs) for classification. To improve the performance of the SVMs, we applied stepwise linear discriminant analysis (SWLDA) to the images before feeding the raw features into the SVMs, which made classification more efficient. Our proposed approach using the symlet wavelet family yielded a classification accuracy of 98.1% when tested on a database of 1200 samples. We also compared our approach with existing algorithms, and confirmed that the proposed algorithm is more accurate than existing algorithms.

REFERENCES


16. A. M. Naeem, I. Ahmad and M. Islam, “Weed Classification using Two Dimensional Weed Coverage Rate (2D-WCR) for Real-Time Selective Herbicide Appli-


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