سیستم های اطلاعاتی هوشمند
نشریه علمی دانشگاه آزاد اسلامی
مجلد۱، شماره ۴
صفحات۴۱-۴۹
مقاله پژوهشی

A New Method for Transforming Classifying Plant Diseases Using Wavelet

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A B S T R A C T

Rapid detection of plant diseases has always been an important challenge for the agricultural industry. One of the approaches that has been welcomed in this field is the use of image processing methods. The advantage of these methods is that they are automatic, fast, low cost, non-destructive and accurate. In this study, by processing the leaves of plants and agricultural products, while distinguishing healthy plants from unhealthy ones, their type of disease is automatically detected. To do this, deep learning methods based on several different architectures of Convolutional neural networks have been used. The proposed method in this research can be generalized to different plants and products as well as to several plants simultaneously. Designed networks are represented and evaluated using two different subsets of database dataset images. In this research, the proposed method algorithm was expressed. In general, a classification model was created from the patient's leaf by means of a wavelet transform to diagnose the type of plant and the disease of that leaf. In this dissertation, using transfer learning (transfer of learning in neural networks means a slight change of a deeply trained network to solve problem A so that without the need for re-training the whole network can be used to solve a completely different problem B) We compared the performance of ResNet50, GoogleNet, AlexNet networks and a deep network with a simple design and selected the best performance model among them for our work. Deep learning is a fast and evolving knowledge that has many implications for agricultural imaging. Machine learning algorithms, such as SVM backup vector devices, are often used for detection and classification. But they are often limited to the assumptions made when defining features.

Key words: Wavelet, Algorithm, AlexNet, GoogleNet, ResNet50, Deep Learning

1. Introduction

Rapid detection of plant diseases has always been an important challenge for the agricultural industry. One of the approaches that has been welcomed in this field is the use of image processing methods. The advantage of these methods is that they are automatic, fast, low cost, non-destructive and accurate. In this study, by processing the leaves of plants and agricultural products, while distinguishing healthy plants from unhealthy ones, their type of disease is automatically detected. To do this, deep learning methods based on several different architectures of Convolutional neural networks have been used. In expressing the importance of this work, we all know that agriculture is of great importance for the survival of countries. In recent years, we have seen different types of viruses and bacteria on plants and humans. From a country like Iran where agriculture is the main occupation in some areas. We want to use my knowledge and expertise in a useful and useful way to solve the problems that we constantly face in agriculture.

The proposed method in this research can be generalized to different plants and products as well as to several plants simultaneously. Designed networks are trained and evaluated using two different subsets of database dataset images. In this chapter, the proposed method algorithm will be stated. In general, a classification model is created from a diseased leaf with the help of a wavelet transform to diagnose the type of plant and the disease of that leaf. In simple words, if we present the following image as any input without any further information. The model should identify it as "a grape leaf with black rot disease":

Figure 1: Sick leaf sample

Early detection of plant disease before crop destruction will be a major advantage to prevent complete crop degradation as well as to achieve high yield of the crop, so using our image classification methods and the latest methods to advance our deep learning We can easily diagnose the correct plant disease and act with the appropriate pesticide to overcome the plant disease.

Agricultural experts can directly identify plants, but we cannot fully respond to specialists for all crops around the world, so monitoring all crops by experts is not an easy task. Another advantage is that these images can be collected as a data set for future research to discover any new diseases. Therefore, the introduction of artificial intelligence in identifying plant diseases has a high advantage and is necessary. The proposed method in this dissertation will finally be tested on a database and the results will be reviewed in the next chapter.

2- The proposed method

As mentioned in the introduction, this section will present a method based on wavelet transform for accurate and reliable diagnosis of leaf disease. We want to implement the classification for the whole data set, because all the reference articles mentioned in the previous chapter only cover a specific type of plant to classify their diseases. On the contrary, we want to classify the type of plant and its disease using my model, that is, I want to create a complete classification of 38 classes in our model.

The flowchart of this method, which has three phases of preprocessing, deep neural network presentation (CNN) and testing, is shown in the following figure:

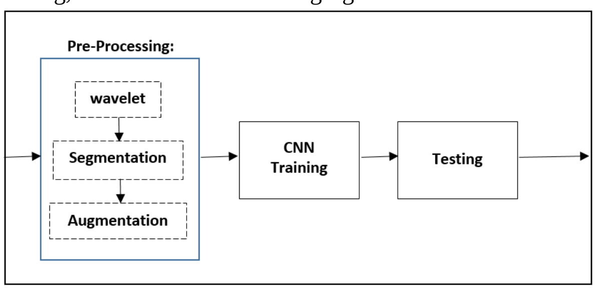


Figure 2: Flowchart of the method presented in the field of wavelet transform for the diagnosis of plant leaf disease

In the following, we will explain the different parts of this flowchart.

2-1- Pre-processing section

In general, preprocessing is all the steps that prepare the image to reach the neural network. Our preprocessors include wavelet transform operations, then bad image segmentation, and finally image enhancement in the database, which will be performed from top to bottom in the previous figure flowchart in the Pre-Processing section. Now we will explain each part of it.

- Wavelet conversion:

Wavelet Transform is one of the most important mathematical transformations used in various fields of science. The main idea of wavelet transform is to overcome the weaknesses and limitations of Fourier transform. Unlike Fourier transform, this conversion can also be used for non-static signals and dynamic systems. Wavelet conversion was proposed as an alternative to short-time Fourier transform and its purpose is to overcome the problems related to resolution in short-time Fourier conversion. In Wavelet analysis, similar to the time-short Fourier transform, the signal is multiplied by a function (Wavelet), which in fact acts as the same window function. Also, similar to the previous one, the Wavelet conversion is done separately on different time pieces of the signal. But in nature there are two major differences with short-time Fourier transforms: in the Wavelet conversion, the Fourier transform is not taken from the windowed signal, and therefore the individual peaks corresponding to a sine, or in other words negative frequencies, are not calculated.

Second, in Wavelet conversion, the width of the window changes in parallel with the change of frequency components, which is certainly the most important feature of Wavelet conversion. Accordingly, continuous Wavelet conversion is defined as follows:

$$CWT_x^{\psi}(\tau,s)=\Psi_x^{\psi}(\tau,s)=\frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} x(t)\ \psi^{*}(\frac{t-\tau}{s})\ dt$$

Where s, t are the transfer and scale parameters, respectively. The concept of transfer is exactly the same as the concept of time transfer in short-time Fourier transform, which determines the amount of window displacement and clearly contains the conversion time information. But unlike short-time Wavelet conversion, we do not have a frequency parameter in direct Wavelet conversion. Instead, we have the scale parameter, which is inversely related to frequency. in other words . s = 1 / f in the previous relation is a window function called the mother Wavelet. The word Wavelet means small wave, for which in some translations the term wavelet is given. The reason for using the word small is the limitation and shortness of the window function.

The reason for using the word wave is also due to the oscillating nature of this function. The word mother is also used to mean that all transcribed and scaled versions are all derived from a primary function called the mother Wavelet. Scientifically speaking, the mother Wavelet is a pattern function for the production of other windows. As mentioned earlier, there is a scale parameter in converting Wavelets to frequencies. As the meaning of this parameter implies, there is a kind of concept of scale within it. Just like the concept of scale in the map, in the Wavelet conversion, large scales correspond to a general view and are independent of details to the signal (corresponding to low frequencies), and small scales correspond to a detailed view of the signal, and therefore in Correspondence will be with high frequencies.

Scaling, as a mathematical operator, contracts or expands the signal. Thus, at the high scales where the signal expands, we will have the details, and at the low scales where the signal contracts, we will have the generalities. Note that the scale variable appears in the denominator in the definition of Wavelet conversion. Given the role of computers in today's computing, in addition to proposing processing ideas, they should also be somehow computed by the computer. The conversions described so far, from February to the Wavelet conversion, are all continuous and have no practical application in digital image processing. Therefore, it is necessary to use a discrete version of them. Like discrete Fourier transforms, the simplest way to discrete a Wavelet transform is to sample the frequency time plate at different points. Similarly, uniform sampling will be the easiest way to do this. However, in the case of Wavelet conversion, the sampling rate can be reduced by changing the scale. Thus, at higher scales (lower frequencies), the sampling rate can be reduced according to the Nyquist rate. Therefore, assuming that the sampling rate at S1 scale is N1, sampling at s2> s1 scale will be at N2 <N1. The exact relationship between these two rates can be expressed as follows:

$$N_2 = \frac{s_1}{s_2} N_1 = \frac{f_2}{f_1} N_1$$

Therefore, sampling rates can be reduced at low frequencies to save significant computational time. Also, if signal reconstruction from conversion is not considered, the Nyquist rate may not necessarily be observed. In order to discrete the Wavelet transform, first the scale parameter is discretized according to a logarithmic grading, then the time variable is discretized according to the scale parameter so that a separate sampling rate is used for each scale. Sampling is said to be based on a Dyadic gradient of the Wavelet mother discretization of the relationship. It is as follows:

$$\Psi_x^{\psi_{j,k}} = \int x(t) \psi_{j,k}^*(t)\, dt$$

Using the above view, the discrete version of the Wavelet converter is expressed as follows:

$$y_{high}[k] = \sum_n x[n].g[2k-n]$$
$$y_{low}[k] = \sum_n x[n].h[2k-n]$$

Similarly, to reconstruct the signal from a discrete version, we can write:

$$x(t) = c_\psi \sum_j \sum_k \Psi_x^{\psi_{j,k}} \psi_{j,k}(t)$$

Although the discrete version of the Wavelet converter we introduced in the previous section can be calculated by computer systems, it is not really a discrete converter. In fact, the discrete version of the Wavelet Converter is a series of Wavelet sampled from the continuous Wavelet Converter. Therefore, the information contained in it is too much and extra, which leads to an unreasonable increase in the computational load. Therefore, discrete Wavelet conversion is used, which is much simpler and more efficient in terms of implementation. The principles of discrete Wavelet conversion go back to a method called underlay coding, which was first laid the foundation stone in 1976.

The main idea of this method is similar to continuous Wavelet conversion, in which a time-scale description of the discrete signal using digital filters is presented. Keep in mind that Wavelet conversion is the result of correlation between the frequency (scale) content of the signal and the Wavelet function at different scales. To calculate the continuous Wavelet conversion, the desired window shrinks / expands and shifts, and in each situation, a time integral is taken from its product in the signal. In the discrete mode, filters with different cut-off frequencies are used to analyze the signal at different scales. By passing the signal through high-pass and low-pass filters, its different frequencies are analyzed. In the discrete mode, the signal resolution is controlled by the functions of the filters and the scale is changed by Downsampling or Upsampling.

The processing process begins with a discrete Wavelet conversion; Initially, the signal passes through a low-pass digital half-band filter with an impact response of h [n], and therefore the output of the filter is equal to the input convolution and the response of the filter. As a result of this filtering operation, all frequency components that are more than half of the largest frequency in the signal are removed. Since the maximum frequency of the filter output signal is equal to π / 2 radians, half of the samples can be removed. Therefore, by deleting one of the samples, the signal length will be halved without losing information. A similar process is performed using a half-band digital high-pass filter with a g [n] impact response. As a result, at the output of the first stage of the Wavelet conversion operation, two copies, one high-pass and one low-pass, are obtained with a reduced (halved) length of the initial signal as follows:

$$\psi_{j,k}(t) = s_0^{-j/2} \psi(s_0^{-j} t - k\tau_0)$$

By doing this, the temporal resolution is halved and the frequency resolution is doubled. This process can be applied again to the low-pass version, and in each step, by reducing the time resolution by half of the previous step, the frequency resolution is doubled. This idea is known as the filter bank method for calculating discrete Wavelet conversion.

It can be proved that the output coefficients of the low-pass filter follow the original shape of the signal, hence these coefficients are called approximation. Also, the output coefficients of the high-pass filter contain high-frequency details of the signal, hence these coefficients are called details. As the number of conversion steps increases, the amount of detail also decreases. It should be noted that the number of steps required for discrete Wavelet conversion depends on the frequency characteristics of the analyzed signal. Finally, the discrete Wavelet conversion of the signal by placing the filter outputs next to each other is obtained from the first stage of filtering. Thus, the number of Wavelet conversion coefficients will be equal to the number of input discrete signal samples:

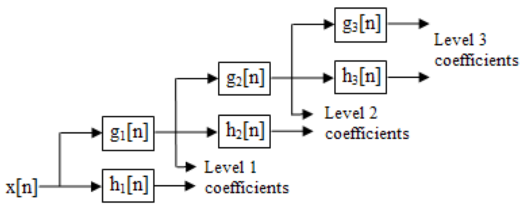


Figure 3: Wavelet conversion extraction method

In every two-dimensional signal commonly referred to as an image, there is a matrix of elements arranged in different rows and columns. With a little care it can be seen that each column or each row of an image can be thought of as a one-dimensional signal whose amplitude values indicate the brightness of the dots (pixels) in that particular column or row. With this idea, Wavelet conversion can be applied to each row or column of the image separately. In fact, this is how the 2D Wavelet conversion is implemented. In other words, in order to apply a two-dimensional Wavelet to an image, a one-dimensional Wavelet is first converted to rows, and then the columns are downsampled at a rate of 2 so that only the samples in the even places remain.

In this case, one-dimensional Wavelet conversion is applied to the columns again, and finally the rows are downsample at a rate of 2. Thus, 4 subbands. Different are obtained as Wavelet conversion coefficients of the image. Similar to the one-dimensional mode, the first subband of the Wavelet conversion coefficients is related to the approximation coefficients, which is similar in size and appearance to the original image. Apart from the approximation subband, we will have 3 detail subbands, one of which is related to the horizontal details in the image, one of which is related to the vertical details in the image and the last one is related to the other details in the image, which sometimes It is also called Qatari detail.

Figure 5 shows a two-dimensional two-dimensional Wavelet conversion of a sample image. As can be seen, the original shape is preserved in the approximate subband (which is at the top left). Also, in the horizontal detail submenu (top, right), the sections with horizontal behavior in the image are displayed. Similarly, in the vertical details submenu (bottom left) the vertically behaved sections are displayed in the image. In this dissertation, it is sufficient to use only the approximation subband for segmentation in the next step. Therefore, other bands have not been used.

The last subdivision is for details, which is located at the bottom right. Also, Figure 6 and 4 below the two-dimensional Wavelet conversion band of a sample image in MATLAB software with the help of the haar wavelet function with a Wavelet conversion level.

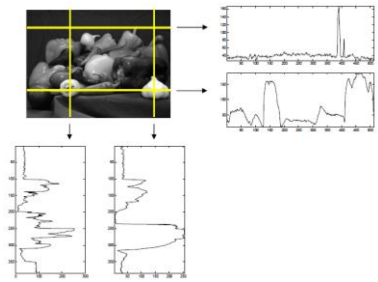


Figure 4: One-dimensional signals obtained from multiple rows and columns of a two-dimensional signal sample (image)

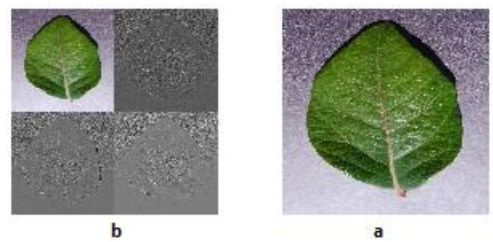


Figure 5: (a) An image sample containing a variety of details, (b) An image- Wavelet conversion step, and 4 created subbands.

- Segmentation:

Because the data set we are dealing with is from leaf images, there is a possibility of losing accuracy due to the background color of the leaf. So to overcome this, I want to segment all the images before feeding them on CNN to provide and extract the best features. Therefore, the extracted part at this stage will have no background other than the leaf, and so in the future we will see that using an image with any complex background to be tested, the model will be classified because of the data segmentation I use the image background to separate the main data.

- Data boost

Because we are trying to present the model for more periods, then the model slowly begins to over-fit, and only learns to recognize specific images in the presented set, instead of being able to Generalize another set. One way to solve this problem is to create more data by increasing the data (strengthening the data set). The following is an image of an unhealthy data sheet:

Figure 6: Unhealthy leaves before strengthening

The following is an image of a leaf with various augmentation techniques including horizontal scrolling, zooming and rotation:

Figure 7: Leaf images rotate left, rotate right, and move right, respectively

Also, in the next step of amplification, by increasing the RGB data to gray scale in the preprocessing step, we increase the number of data, because it is much easier to recognize the outline of the leaf in the image on the gray scale than RGB.

2-2- Deep network training

In this dissertation we intend to use transitional learning (transfer of learning in neural networks means a slight change of a deeply trained network to solve problem A so that without the need for re-training the whole network can be used to solve the problem completely Use different B) to compare the performance of ResNet50, GoogleNet, AlexNet networks and a deep network with a simple design, and choose the best performance model from them for our work. Deep learning is a fast and evolving knowledge that has many implications for agricultural imaging. Machine learning algorithms, such as SVM backup vector devices, are often used for detection and classification. But they are often limited to the assumptions made when defining features.

This reduces their sensitivity. In the meantime, deep learning can be an ideal solution. Because these algorithms are able to learn features from raw image data. But a challenge in implementing these algorithms is the lack of labeled image data. Although this is a limitation for all deep learning programs, most medical image data are not published due to concerns about the confidentiality of patient information, and there is good information and labels in agriculture. In this section, we need to introduce a number of famous convolutional neural networks (CNN). These networks are known for the fact that many people today use them in their articles or projects, and also when they were introduced, they were able to win the ImageNet award, which is one of the most prestigious awards in this field. This competition has been held every year since 2010. Its purpose is to identify and categorize images on a large scale.

Participating networks must distinguish between images with 1000 different classes. The measure of network accuracy is the error of the top 5 classes. As the network sees the picture, it introduces 5 classes. If the desired class was among them, the network answer is accepted. The most common of these are the ones we used in our classification discussion:

1- AlexNet

The first major convolutional neural network to be named is the AlexNet network, introduced by Alex Krizhevsky in 2012, some fourteen years after LeNet. This network has 8 layers (five convolutional layers and three layers (fully connected), which makes it in the category of shallow networks.

2- GoogLeNet

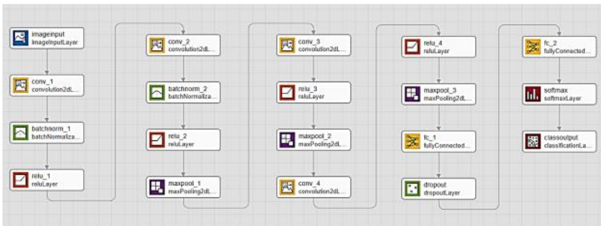
The network was introduced by Google in 2014. Its name is a tribute to Yann Lecun, the creator of LeNet, the first convolutional network. The network is based on the idea of deepening convolutional networks, which, according to the creator, is taken from the dialogue in Inception. That is why it is also known by this name. In this network, with the approach of turning network hyper parameters into a learnable parameter, a module called Inception module was designed. In this module, 3 convolutional filters with different sizes and a pulling filter are applied on the previous layer. And puts the results together as a single tensor. In this case, the network can decide in the next layer which filter it wants to use and to what extent. The size of convolutional filters as shown in the picture is 1 * 1, 3 * 3 and 5 * 5 and the polishing filter with 3 * 3 size is applied on it. In this network, by placing two layers of polishing at the beginning of the work, the learnable parameters of the problem are greatly reduced. In the following, 9 layers of Inception module are used.

3- ResNet

This network was provided by Microsoft, which stands for Residual Network. In this network, communication outside the convolutional structure is provided next to it between the layers to transfer the inputs of the previous layer to the next layer without intermediaries, and in the back propagation stage, the error of each layer is transferred to the previous layer to You can deepen the network and deliver it faster. These connections are called skip connections and the resulting structure is called Residual block.

4- SimpleCNN

This network is provided by us, which is the simplest form of a deep network for multi-class classification. This network with inputs of 258 x 258 pixels has 19 layers as follows: 3 convolutional layers with a normalization layer and Relu will be connected to the Pulling layer, and finally the FC layer will be applied to classify 38 different classes. Convolutional windows have 5 * 5 and 3 * 3 filter dimensions with 1 step and layering.



1	''	Image Input	258x258x3 images with 'zerocenter' normalization
2	''	Convolution	70 5x5 convolutions with stride [2 2] and padding [2 2 2
3	''	Batch Normalization	Batch normalization
4	''	ReLU	ReLU
5	''	Convolution	30 5x5 convolutions with stride [2 2] and padding [2 2 2
6	''	Batch Normalization	Batch normalization
7	''	ReLU	ReLU
8	''	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
9	''	Convolution	50 3x3 convolutions with stride [1 1] and padding [1 1 1
10	''	ReLU	ReLU
11	''	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
12	''	Convolution	40 3x3 convolutions with stride [1 1] and padding [1 1 1
13	''	ReLU	ReLU
14	''	Max Pooling	2x2 max pooling with stride [1 1] and padding [0 0 0 0]
15	''	Fully Connected	25 fully connected layer
16	''	Dropout	25% dropout
17	''	Fully Connected	38 fully connected layer
18	''	Softmax	softmax
19	''	Classification Output	crossentropyex

Figure 8: Deep neural network images designed under the name SimpleCNN

The input size requested by the AlexNet network is 227 x 227 pixels, so when using this transition learning model, I have to convert the images to the specified size, while GoogLeNet accepts the size of 224 x 224 pixels. ResNet with 224 x 224 pixels is the same as GoogLeNet. In most cases, we will use ReLu as the activation filter between the different activation filters. But since the model has to classify 38 different classes, the last step, the FC network, has to be modified to fit our 38-class classification. In the process of presenting neural networks, it is always customary to use 70% of the database data (as stated in Table 1) for network training, which we also used at this stage and presented our 4 deep neural networks.

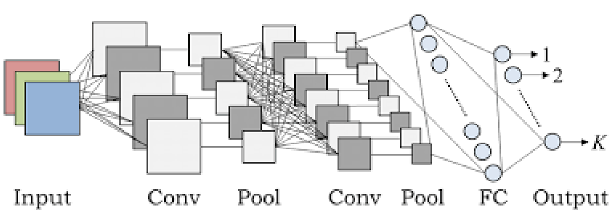


Figure 9: CNN reference chart

3- Results and analysis

As mentioned in the previous section, the pre-training data has been added to the data set for the model and the preliminary results have been reported in the following sections.

3-1- Data preprocessing

Because the desired results were not obtained with raw and amplified data, some more techniques such as preprocessing were used to better enhance the image so that the grid could easily select the best performance features from the leaf screen for detection.

- Convert to gray scale and edge detection

Visually, the diagnosis of leaf type depends more on the shape of the leaf because it will be different between different types of leaf trees. In deep neural network processing, all training data are scaled to gray before testing, and the test image for prediction is scaled to gray before being fed to the network.

The results with this preprocessing step will be discussed later in the preliminary results. As we can see in the image below, in the detected edge image, the characteristics of the leaf disease spots are not preserved and only the edges are present in the image. Since no significant information is stored about dark spots, this type of preprocessing reduces network performance. Our main goal is to increase the images at this stage so that the edges from the background to the ground are easily recognizable and the leaf spots and wrinkles are better recognized. To achieve this, the leaf is split from the background using the threshold segmentation method.

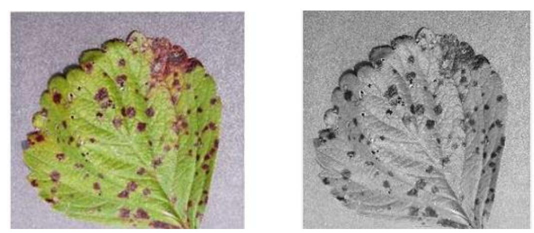


Figure 10: Raw image (color) and gray scale image

Figure 11: Edge detection

Image Thresholding is a way to convert a color image to a binary image based on the specific pixel intensity threshold. This is very useful in extracting dominant background and background objects. It can also be used to create a design like images. Here we have used the multi-level threshold using the Otsu method for RGB images.
At this stage we select the threshold level values for the RGB images and test between the different threshold levels to see what is the best way to get the best background image of the

leaf and also increase the leaf disease spots to better identify the features. Finds.

Figure 12: Raw image

Figure 13: Two-level threshold Figure 12 Single-level threshold

From the images above, it can be seen that thresholding has greatly increased the image quality. Compared to two threshold levels with a one-level threshold, the background of the image is almost suppressed and those pixels turn white.

When compared to the raw image, which is even the background of some high-intensity pixels, when training with raw data, there is a risk of network detection and training of some features. Therefore, by using these threshold images, we can overcome the risk of unwanted features and teach the model only on the segmented image of only the leaf. Also in the images above, the difference between the spots and the green part of the leaf in this image is better because the color distribution is suppressed and low-intensity pixels are covered by the threshold, and pixels with a higher intensity above the threshold will be highlighted. Therefore, these segmented images should improve the performance of network training, and we will see them in the test results in the following sections.

3-2- Analysis of preliminary results

At the beginning of the study, we tried to use the HOG method to extract image properties and to use different classifiers to classify only 6 classes of the data set, ie we only wanted to identify a subset of this data set. Therefore, the same method was followed and the classification was implemented using these HOG features. But these classes did not result in high accuracy. The results showed that the classification of these leaves depends more on the shape of the leaf. But the HOG properties could not provide a specific meaning for the leaf shape because they only depend on the intensity of the color difference. As we can see in the following pictures, the highest features are just green pixels, dark spots and leaf plates.

Figure 14: Top 25 features - Top 50 features - Top 25 features

The results of the previous section were 72.8% for binary classification for 2 classes of leaf versus healthy disease and 34.2% for the classification of all diseases in 38 classes. Therefore, these features have the most information about whether the leaf is sick or not. So by using classification and using these features we can only determine if the leaf is sick or not. Binary classification, then, can be reasonably accurate, but for classification of 38 classes, it is not able to obtain acceptable accuracy for this set. Therefore, from these observations, it was concluded that this approach would not be suitable for this multi-class problem, and it is necessary to go to deep learning approaches for this problem in the same data set, the results of which are given below.

4- Compare the results

Table 1: Results of proposed method (a)

Network	**Train Val Test**	**Training Acc**	**Validation Accuracy**	**Test Accuracy**
Basic CNN	60:20:20	58.96%	58.67%	58.73%
Basic CNN	70:10:20	55.23%	54.93%	52.86%
Basic CNN	50:20:20	54.22%	52.16%	51.59%
AlexNet	70:15:15	80.92%	80.05%	78.92%
AlexNet	70:10:20	84.23%	83.23%	81.78%
AlexNet	60:20:20	82.03%	81.50%	80.97%
AlexNet	50:20:30	81.68%	81.03%	80.62%
ResNet	60:20:20	99.92%	99.11%	99.09%
ResNet	70:15:15	99.94%	99.48%	99.21%
ResNet	70:10:20	99.93%	99.23%	99.12%

Table 2: Results of proposed method (b)

Network	Training Acc	Validation Accuracy	Test Accuracy
Basic CNN (Mean)	56.14%	55.25%	54.39%
AlexNet (Mean)	82.22%	81.45%	80.57%
ResNet (Mean)	99.93%	99.27%	99.14%
Basic CNN (Std)	59:55:15	326.70%	380.90%
AlexNet (Std)	34:06:14	133.01%	120.40%
ResNet (Std)	0:14:24	18.88%	6.24%

5. Conclusion

In this dissertation, an effective and accurate method for automatic diagnosis was presented to diagnose the disease in plant leaves. This method was based on wavelet transform and in this analysis, by selecting the appropriate wavelet parameters, while improving the structures related to leaf veins, at the same time, structures related to spot-like areas were extracted in the inner parts of the leaf.

In fact, the size of the final coefficients indicates the amount of vein of each point and the absolute value of the imaginary part of the coefficients indicates the similarity of that point to the points related to the edges of the stairs. Using the same edge-similarity criterion, an adaptive thresholding method was proposed to automatically detect vessels and wall them. From all the observations of this dissertation, it can be concluded that for this particular data set, the classification of 38 separate classes with deep learning techniques was efficient, while by extracting the HOG features and classifying it, we gained much less accuracy. It can also be seen that there are only 5-6 classes that give the wrong answer to about 5% of the classification data with test images, which are used to obtain accuracy (accuracy is about 95%).

From the observations of visual images, it can be concluded that by updating the data set and extracting clearer images for the samples of that class, a better visualization can be achieved. We can also further improve the classification problem by adding additional plant classes. In many articles, the dataset is done by adding new images to the collection, and so we can expect that as the number of classes increases, the classification becomes more complex compared to our current 38 classes.

Also, according to the findings of this dissertation, we can increase the initial challenge of our design so that instead of just diagnosing the disease, we can add the diagnostic features of the patient part of the leaf images. To do this, the data must be blocked and labeled for training. The peculiarity of this method of machine learning is that along with the diagnosis of the disease, fertilizers can be suggested to the farmer for that disease, by feeding it, deep network, re-diagnose leaf disease and also correct the list of fertilizers and so on.

As part of this dissertation, various approaches to improve the accuracy of the network and its other parameters were reviewed and the importance of data and their main role in classification training was practically researched alongside this project. Various methods for extracting features from images, data preprocessing, data amplification to equalize the number of samples in all classes and its importance are also practically observed in this project.

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