Machine Learning for Soil Detection

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Applying Polynomial Learning for Soil Detection Based on Gabor Wavelet and Teager Kaiser Energy Operator

Kamel H. Rahouma[1(✉)] and Rabab Hamed M. Aly[2]

[1] Electrical Engineering Department, Faculty of Engineering, Minia University, Minia, Egypt
kamel_rahouma@yahoo.com
[2] The Higher Institute for Management Technology and Information, Minia, Egypt

Abstract. Soil detection is playing an important role in the environmental research. It helps the farmers to determine what kind of plants they can have. Also, it may help to mix plants in certain areas or farm new types. The main target of this paper is to classify the different types of soil. On the other hand, there are many researches which focus on the classification and detection process based on different applications of image processing and computer vision. The paper has two main goals. The first goal is to improve the extraction of soil features based on Gabor wavelet transform but followed by the Teager-Kaiser Operator. The second goal is to classify the types of soil based on group method data handling (polynomial neural networks). We applied these methods using different data sets of soil. Compared with previous work and research, we achieved accuracy limits of (98%–100%) while the previous algorithms were accurate to the limits of (95.1%–98.8%). Behind this improvement in accuracy, there are the methods we used here including the Teager Kaiser operator with Gabor wavelet and polynomial neural networks which have been proved to be more accurate than the methods used before.

Keywords: Soil detection · Gabor wavelet · Polynomial neural network (PNN) · Teager-Kaiser

1 Introduction

Nowadays, machine learning and computer vision play an important role in environment image analysis, especially in the detection of features processing (Bhattacharya and Solomatine 2006). Furthermore, the effective role of computer vision and image processing is to classify the type of different soils. The researchers try to make the classification very easier using the modern research technologies. Researchers try to improve the methods of extraction or classification. On the other hand, some researches have introduced some other methods for the features detection of soils or diseases of leaves of trees. In the following, we will show some of the recent researches and how the authors try to improve methods to classify and detect the medical images and environments images such as soils (Bhattacharya and Solomatine 2006; Lu et al. 2018; Odgers and McBratney 2018; Pham et al. 2017).

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On the other hand, in medical applications, some researchers focused on prediction methods for image analysis (Tekin and Akbas 2017). (Tekin and Akbas 2017) described how to use the Adaptive Neuro Fuzzy Inference System (ANFIS) to predict soil features and comparing to another type of soil. They tried groutability of granular soils with a piece of cement. It is one of the papers which helped us in the work of this paper. We will introduce some of another previous researches in the next section. The remainder of this paper is organized as follows: Section 2 concerns with a background and a literature review of previous work of prediction techniques. Section 3 illustrates the main methodology and it gives the main algorithm used in this paper. Section 4 discusses the results of the applied technique and compares it with the previous works. Section 5 presents a brief conclusion of our work and suggests some future work that can be accomplished.

2 A Literature Review

There are a lot of techniques that achieved accurate results in detection and classification. In the following, we will introduce the important cases of the previous researches about detection methods. Actually, the hybrid technique plays an important role in detection processing. (Sweilam et al. 2010) used a hybrid method based on some of information and support vector machine (SVM) to classify the types of tumors. The accuracy of this method is 90.3% for some specified types of cancer. On another hand, (Cheng and Han 2016) introduced a survey about object detections for optical remote and how to apply machine learning for this detection. Further, (Ford and Land 2014) applied a new model based on latent support vector machine as a model for cancer prognosis. The operations of this model are based on microarray operations and some of the gene expression and they improved the algorithm and technique of this model. The results showed that the increase of quality of curve receiver operating characteristic (ROC) when replacing least regression to SVM. Some authors invested new approaches of cancer features in soil detection and classification. (Khare et al. 2017) applied ANFIS (Neuro fuzzy) as a classification method. They used fuzzy system to detect the severity of the lung nodules depending on IF-Then rules method. They also applied 150 images in computer aided diagnosis (CAD) system. They achieved (sensitivity of 97.27%, specificity of 95% with accuracy of 96.66%). (Potter and Weigand 2018) introduced a study about the image analysis of soil crusts to get the properties of surface heating. Actually, the study approved moderate skewness toward negative tails and the other results can help to improve future mapping for any place having biocrust surfaces such as in the Mojave Desert.

Recently, some authors presented a survey about the most recent image segmentation processing especially for medical images (Dallali et al. 2011). They improved the classification techniques to increase the classification rate accuracy by 99.9%. (Dallali et al. 2011) introduced a new classification algorithm based on fuzzy clustering method and improved the performance by neural networks to classify heart rate (HR) and RR intervals of the ECG signal and they called this method fuzzy clustering method neural network (FCMNN). (Nabizadeh and Kubat 2015) applied Gabor wavelet to extract features of MRI images. They also compared results with statistical features methods. The comparing technique for the features extraction method was based on some classifiers. Authors have evaluated the methods and Gabor wavelet achieved 95.3% based on some of the classification techniques.

Some authors introduced new classification methods for environment images. (Wang et al. 2017) applied deep learning for hyper spectral remote sensing images. They applied classification methods to achieve multi features learning and the accuracy is 99.7%. Furthermore, (Perez et al. 2017) introduced deep learning classification for soil related to illegal tunnel activities. They proposed a new method in handling imbalance learning. The result showed that the method improved the performance significant of soil detection. (Boudraa and Salzenstein 2018) proposed review about Teager Kaiser Operator (TKO) for image enhancement and improved the enhanced technique by following it by an energy operator of TKO. In the next section, based on the previous researches, we will introduce the Gabor wavelet transform followed by TKO in feature extraction of soil image datasets (Bhattacharya and Solomatine 2006) and after that we will classify the result based on polynomial neural network (PNN).

3 Methodologies and Algorithms

The system of this paper consists of two main parts:-

(a) First part is for enhancement and features extraction based on Gabor wavelet and Teager Kaiser.
(b) Second part is for classification based on the polynomial neural network (PNN). We, also, will compare the system methods with the other previous work of the soil classification and detection.

3.1 Enhancement Using Gabor Wavelet Followed by Teager-Kaiser Operators

In this paper, we used soil datasets taken from a set of online recorded images from different places and also based on the database images which have used by (Bhattacharya and Solomatine 2006). In this part, the practical work consists of two main steps:-

(1) The enhancement process of the soil datasets (see Fig. 1).
   (a) Find limits to contrast stretch an image (to increase the contrast of image).
   (b) Convert image to gray level.

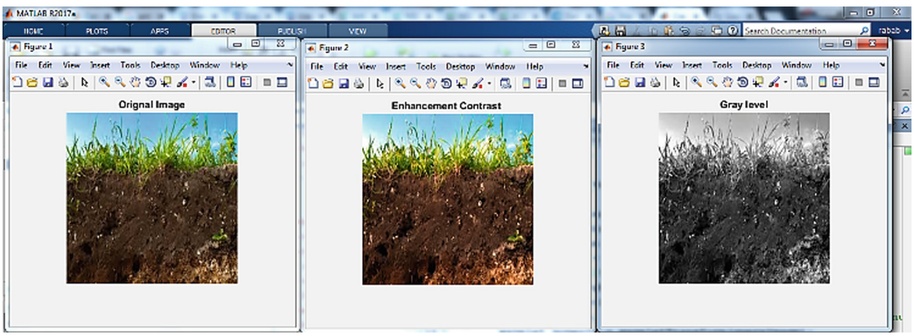

Fig. 1. Enhancement Process strategy

(2) Gabor wavelet features extraction followed by Teager Kaiser Operator:

Gabor wavelet is considered one of the most practical methods to extract the optimal features from images after the enhancement process. (Bhattacharya and Solomatine 2006) extracted features based on boundary energy. Furthermore, (Boudraa and Salzenstein 2018) approved that 2D Teager Kaiser Operator reflects better local activity than the amplitude of classical detection operators. The quadratic filter also is used to enhance the high frequency and combined with image gray values to estimate the edge strength value and all of that is used in the enhancement process.

The main function of this method is to generate energy pixels based on 2D Teager Kaiser Operator (TKO). The Teager Kaiser Energy operator is defined by the energy of the signal x(t) as follows (Boudraa and Salzenstein 2018; Rahouma et al. 2017):

$$\Psi_c[x(t)] = [x(\dot{t})]^2 - x(t)x(\ddot{t}) \tag{1}$$

Where x (t) is the signal, $x(\dot{t})$ is the first derivative and $x(\ddot{t})$ is the second derivative.

Actually, we applied Teager Kaiser Energy operator in the discrete as follows Eq. (2):

$$\Psi_d[x(t)] = x_n^2 - x_{n+1}x_{n-1} \tag{2}$$

On the other hand, the Gabor wavelet equations which we applied in our system are based on the Gabor transform employed in one dimension as a Gaussian window shape as shown in Eq. (3) but in the two dimension case, it provides the spectral energy density concentrated around a given position and frequency in a certain direction (Boudraa and Salzenstein 2018).

$$g_{\alpha\mathcal{E}}(x) = \sqrt{\frac{\alpha}{\pi e^{-\alpha x^2}}} e^{-i\mathcal{E}x} \tag{3}$$

Where $\mathcal{E}$, $x \in R$, $\alpha \in R^+$ and $\alpha = (2\sigma^2)^{-1}$, σ^2 is the variance and $\mathcal{E}$ is the frequency.

Then, the mother wavelet of the Gabor wavelet as follows:

$$g_{\alpha,\mathcal{E},a,b}(x) = |a|^{-0.5} g_{\alpha,\mathcal{E}}\left(\frac{x-b}{a}\right) \tag{4}$$

Where $a \in R^+$ (scale), and $b \in R$ (shift).

Note that, the Gabor wavelet doesn't form orthonormal bases. Actually, the Gabor wavelet can detect edge corner and blob of an image (Boudraa and Salzenstein 2018). We applied blob detection and used the main function of energy operator of Teager Kaiser in the calculation of Gabor energy. Gabor wavelet followed by Teager Kaiser achieved a set of features from soils datasets images which helped us to classify the types of soil. Actually, we extracted 98 as a general but the optimal calculated features from 98 features are Correlation, Energy and Kurtosis based on Eqs. (5–7) (Potter and Weigand 2018). We will discuss the details in Sect. 4.

$$Energy = \sum_{i=1}^{m} \sum_{j=1}^{n} (GLCM(i,j))^2 \tag{5}$$

$$Correlation = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{\{ij\}GLCM(i,j) - \{\mu_x \mu_y\}}{\sigma_x \sigma_y} \tag{6}$$

Where i, j index instant $\mu_x \mu_y$ and $\sigma_x \sigma_y$ are the mean and standard deviations of probability matrix Gray level coherence Matrix (GLCM) along row wise x and column wise y.

$$\text{Kurtosis} = \frac{1}{\sigma^4} \sum_{i=0}^{m-1} (i - \mu)^4 x(i) - 3 \tag{7}$$

In the following section, we introduce the classification method to classify the types of the soils based on the previous features.

3.2 Polynomial Neural Network Classification Method (PNN)

There are many types of ANN based on a mathematical classification equation such as PNN (Polynomial neural network) which will discussed in this section. On the other hand, ANN is used in classification in data mining and also to predict future data. GMDH is a multilayer network which used quadratic neurons offering an effective solution to modeling non-linear systems. The PNN is one of the most popular types of neural networks based on polynomial equation. It is used for classification and regression. It is more practical and accurate in prediction of behavior of the system model (Rahouma et al. 2017). A class of polynomials (linear, modified quadratic, cubic, etc.) is utilized. We can obtain the best description of the class by choosing the most significant input variables and polynomial according to the number of nodes and layers. Ivakhnenko used a polynomial (Ivakhnenko Polynomial) with the grouping method of data handling (GMDH) to obtain a more complex PNN. Layers connections were simplified and an automatic algorithms was developed to design and adjust the structure of PNN neuron (see Fig. 2).

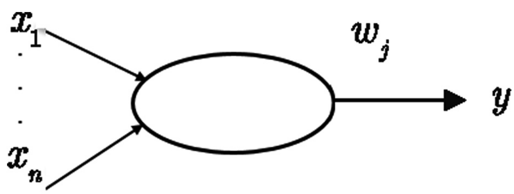

Fig. 2. The neuron inputs and output

To obtain the nonlinear characteristic relationship between the inputs and outputs of the PNN a structure of a multilayer network of second order polynomials is used. Each quadratic neuron has two inputs (x_1, x_2) and the output is calculated as described in Eq. (8) where "Fig. 3" shows the structure of PNN.

$$g = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1 x_2 + w_4 x_1^2 + w_5 x_2^2 \tag{8}$$

Where $w_i; i = 0, \ldots, 5$ are weights of the quadratic neuron to be learnt. The main equations for PNN structure which is the basic of GMDH-PNN are:

$$(X_i, y_i) = x_{1i}, x_{2i}, \ldots\ldots.., x_{Ni}, y_i \tag{9}$$

Where $\mathbf{X_i}, \mathbf{y_i}$ **are data variables and** $\mathbf{i = 1; 2; 3; \ldots.; n}$
The input and output relationship of PNN- structure of "Fig. 3" is:

$$Y = F(x_1, x_2, \ldots\ldots\ldots\ldots\ldots\ldots.x_N) \tag{10}$$

The estimated output is:

$$\begin{aligned} \grave{y} &= \grave{f}(x_1, x_2, \ldots\ldots\ldots x_N) \\ &= c_0 + \sum\nolimits_i c_i x_i + \sum\nolimits_i \sum\nolimits_j c_{ij} x_i x_j + \sum\nolimits_i \sum\nolimits_j \sum\nolimits_k c_i c_j c_k x_i x_j x_k + \ldots \end{aligned} \tag{11}$$

The PNN is the best and fastest solution in classification data techniques of data.

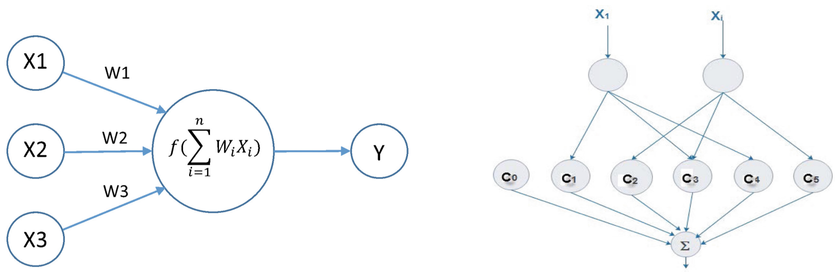

Fig. 3. The polynomial network structure

The main steps to apply the GMDH-PNN algorithm for classification based on polynomial Eq. (8) are:

(a) Determine the system input variables according to Eq. (9).
(b) Formulate the training and testing data according to Eqs. (10, 11).
(c) Select the structure of the PNN.

(d) Estimate the coefficients of the polynomial of nodes to estimate the error between y_i, $y_i^{'}$ then:

$$E = \frac{1}{n_{tr}} \sum_{i}^{n_{tr}} \left(y_i - y_i^{'} \right)^2 \quad (12)$$

Where n_{tr} is the number of training data subsets, i is the node number, k is the data number, n is the number of the selected input variables, m is the maximum order and n_0 is the number of estimated coefficients(Rahouma et al. 2017). By using the training data, the output is given by a linear equation as:

$$Y = X_i C_i \quad (13)$$

$$C_i = (X_i^T X_i)^{-1} X_i^T Y \quad (14)$$

Where $Y = [y_1, y_2, y_3, \ldots\ldots, y_{ntr}]^T, \quad X_i = [X_{1i}, X_{2i}, X_{3i}, \ldots, X_{ntri}]^T,$
$X_{ki}^T = \left[X_{ki1}, X_{ki2}, X_{kin}, \ldots\ldots, X_{ki1}^m, X_{ki2}^m, \ldots, X_{kin}^m\right]^T$ *and*
$C_i = [C_{0i}, C_{1i}, \ldots\ldots, C_{n'i}]^T$, and after that, check the stopping criterion.

(e) Determine the new input variables for the next layer.

Note That: The database which have applied in this paper for classification process based on the online datasets which applied in (Bhattacharya and Solomatine 2006). Furthermore, the Fig. 4 shows the general flow chart of the system.

The general algorithm of the detection and the classification PNN for soil datasets

Start

1) Enter number of images n, Maximum Number of Neurons (Nu) =50 and the Maximum of Layer (NL) =10, Alpha (AL)=0.6,The train ratio (TR)=0.7.

2) Enter n datasets of soil images.

3) Loop i =1: n

a) Enhance the soil image using Low pass filter

b) Apply the gray level of the image.

4) Extract the image features (nf =98 features) based on Gabor wavelet and TKO energy operator.

5) Calculate Correlation, Energy, and Kurtosis from discussed equations (5-7).

Start a loop

Use 80% of the datasets for training using PNN structure to obtain the system coefficient.

Use the trained system to estimate the classification the rest of 20% of datasets.

End Loop

4) Compute the error of the accuracy of features as follows:

Err = (actual value-Estimated value)/actual value*100%

5) Calculate the accuracy = 100 – Err.

6) Print the results.

End

Table 1. The percentages values of GW- MSVM classification (Energy Feature)

Datasets	The percentages values of Classification (GW-MSVM) result %																			
Clay	95.1	95.1	95.1	95.1	95.1	95.1	96	96	96	96	96	96.6	96.7	96.7	97	97	97.1	97.1	97.1	98
Clayey_Peat	95.1	95.1	95.1	95.1	96.7	96.7	96	96.77	96.7	96.7	96	96.6	96.77	96.77	98	98	98	98	98	98
Clayey Sand	96	96.6	96.7	96.7	96.7	96.7	96.7	96.7	96.7	98	98.1	98.1	98.1	98	98	98	98	98.7	98.7	98.7
Peat	96.7	96.7	96.7	96.7	96.7	96.7	96.7	96.7	96.7	96.7	96.7	98.3	98.3	98.3	98.3	98.8	98.8	98.8	98.8	98.8
Sandy Clay	96	96.8	96.8	96.77	96.77	96.77	96.77	96.77	96.77	98.2	98.2	98.2	98.2	98.37	98.37	98.37	98.4	98.4	98.4	98.4
Silty Sand	96.77	96.77	96.77	96.77	96.77	96.77	96.77	98	98	98.3	98.3	98.2	98.2	98.2	98.2	98.3	98.3	98.3	98.3	98.3

4 Results and Discussions

In this paper, we applied our system based on image processing toolbox of MATLAB2017a. Actually, the paper operated two cases, the first case uses the Gabor Wavelet for features extraction and multi support vector machine (MSVM) for classification. The second case uses the Gabor Wavelet followed by Teager Kaiser Energy Operator for features extraction and the PNN for classification. Actually, the accuracy of

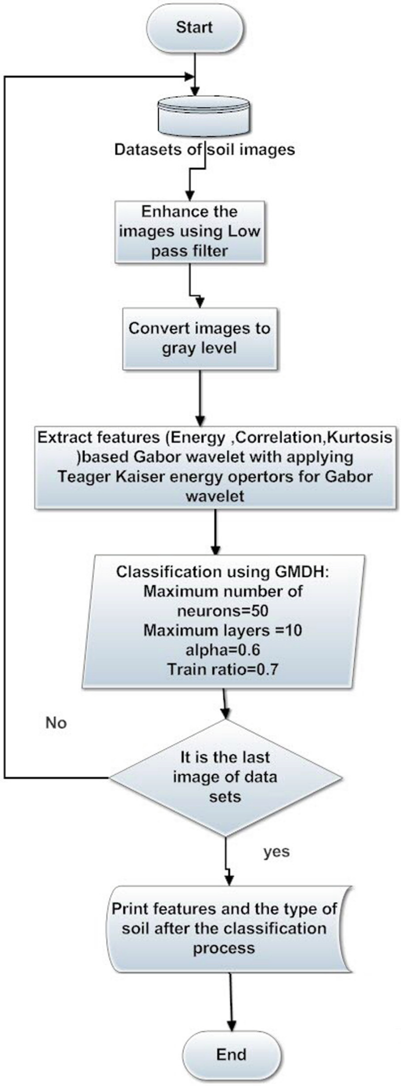

Fig. 4. The general Flow chart of the system

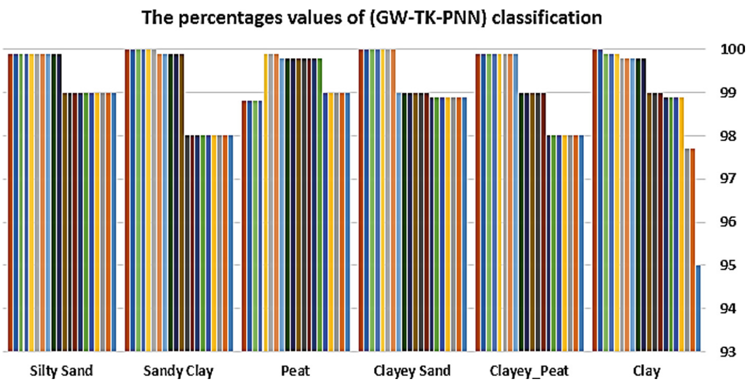

Fig. 5. The result of GW-Multi-SVM of the previous research(Energy)

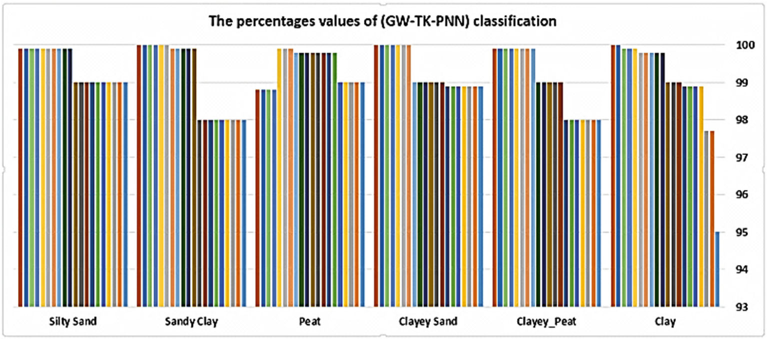

Fig. 6. The result of applying-Gabor wavelet–TK-PNN(Energy)

second case consists of the three optimal features (Correlation, Energy, and Kurtosis) is from 95 to 98%. The three optimal features came from 98 features which are extracted from soil images based GW-TK operators as discussed in pervious section. In Figs. 5 and 6 show the accuracy of the energy feature for all datasets and also Tables 1 and 2.

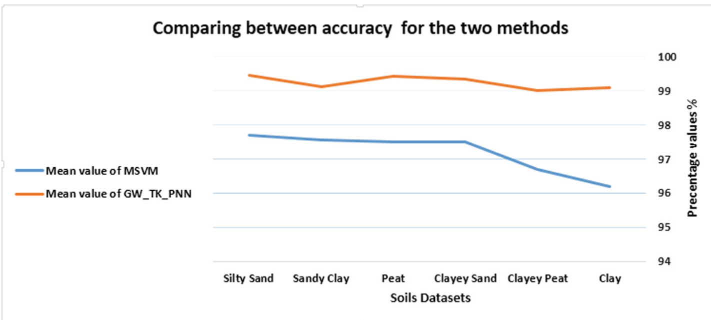

Fig. 7. The comparing between our method with pervious work

Table 2. The percentages values of GW-TK-PNN classification (Energy Feature)

Datasets	The percentages values of Classification (GW-TK-PNN) result %																			
Clay	95	97.7	97.7	98.9	98.9	98.9	98.9	99	99	99	99.8	99.8	99.8	99.8	99.8	99.9	99.9	99.9	100	100
Clayey_Peat	98	98	98	98	98	98	98	99	99	99	99	99	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9
Clayey Sand	98.9	98.9	98.9	98.9	98.9	98.9	98.9	99	99	99	99	99	99	100	100	100	100	100	100	100
Peat	99	99	99	99	99	99.8	99.8	99.8	99.8	99.8	99.8	99.8	99.8	99.9	99.9	99.9	98.8	98.8	98.8	98.8
Sandy Clay	98	98	98	98	98	98	98	98	98	99.9	99.9	99.9	99.9	99.9	100	100	100	100	100	100
Silty Sand	99	99	99	99	99	99	99	99	99	99	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9	99.9

The datasets of this work consist of 6 types of soils and each type has 20 different images. Actually, the CPU time approved the operations of GW-Tk-PNN in 13 s for each image in datasets so, applying Gabor wavelet followed by Teager- Kaiser Energy operator improved the accuracy of the extraction which is found to be 98.8% or higher. We compared between our results and the results from previous work (Bhattacharya and Solomatine 2006) and show that in Fig. 7. Actually, the most of pervious work based on SVM or MSVM so, we tried to improve the accuracy as discussed before. The applied techniques of this paper can be utilized in the detection and diagnosis of plants' problems, defects, and diseases. A future work may be done to study images of the plants leaves, roots, and stalks and then extract their features and classify their problems, defects and diseases.

5 Conclusions

This paper aimed to extract features based on Gabor wavelet followed by Teager Kaiser Energy operator and to apply the polynomial learning technique to classify the different types of the soil datasets images. We obtained our results and compared them with the results of previous research. The previous algorithms achieved accuracy limits of (95.1% - 98.8%) while our results achieved accuracy limits of (98% - 100%). However, the applied techniques can be utilized in the analysis, feature extraction, and classification of the plants' problems, defects, and diseases.

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