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Non-Magnetic Materials Assignment based on Artificial Neural Network

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Abstract – In this paper, signal recognition system is proposed for classification of soil types and buried object by using feature extraction and artificial neural networks. Using GprMax simulation program, 300 GPR A scan signals were obtained for different ground planes and materials with 206 Hz sampling frequency. Since the materials of buried objects are non-magnetic, these signals contain electric fields in the z direction (E_z) and magnetic fields in the x and y directions (H_x, H_Y). Features are extracted from them in time and frequency domain such as mean, standard deviation, skewness, kurtosis etc. Therefore, signal features are obtained for inputs of artificial neural networks. Feed forward backpropagation neural network is chosen as an artificial neural network model. The outputs of neural network are types of soil and materials. Also, classification accuracy is examined with changes in learning rates, iteration numbers, momentum constant and number of neurons in hidden layer. The obtained results show high accuracy rate for soil and material recognition.

Keywords –Ground Penetrating Radar, Signal Processing, Feature Extraction, Classification, Artificial Neural Network

I. INTRODUCTION

Ground Penetrating Radar (GPR) is a tool used for underground mapping using high frequency electromagnetic (EM) waves. GPR used to be detected such as buried objects, metal and non-metal mines, wire and pipes etc. [1]. GPR is used effectively in many fields such as engineering, geophysics and medicine. For example; infrastructural evaluation of bridges, roads and railways, detection of buried objects, glacier depth determination, groundwater mapping, mine and explosive ammunition recognition, and detection of breast cancer tumors. Modeling how EM waves propagate in naturally occurring or man-made heterogeneous environments is a difficult problem [2]. It is not always possible to use GPR to generate the data needed for the algorithms to be used for the detection of buried objects. Due to the difficulty of obtaining data with GPR and the component cost, a modeling software is needed for this need. GprMax is an open-source software that meets this need and imitates EM wave propagation by simulating the numerical modeling of GPR [2].

Wall-behind target detection and positioning systems are used in military defence and search-and-rescue operations. It is a radar that works on the S-band, to detect moving or stationary targets behind the wall. A 20 cm thick concrete wall can detect objects behind the wall at a distance of 20 m. Radar, which has an aperture of about 2.25 m, can be used by being mounted on a vehicle. It is used to provide tactical advantage in city type battlefields. It can be used for search and rescue work under earthquake disaster. Both the position of person behind walls and number and location of the walls in between are vital in such an application. In the same way, it will be very important to obtain information such as interior human, wall locations in case of fire [3].

The land mine crisis is a problem that covers every nation in the world. In the last 10 to 15 years, considerable precautionary measures about mine problem has resulted in a significant increase to develop safe and low cost techniques in the detection and cleaning of mines. However, effective and sensitive detection of mines remains a clear problem due to various types of mines and complex research scenarios. Recent research techniques include; metal detectors, acoustic technology, electro-optical detection, forward-looking infrared (FLIR) chemical detection, quadrupole resonance detection, ground-penetrating radar (GPR). Among these techniques, ground penetrating radar (GPR) has several significant advantages over other techniques and more feasible surveillance tool for landmine detection [4].

The study was evaluated in four parts. In Section I, the Introduction section, the aim of the research and the purpose of the research is stated. In Section II, materials and methods are explained. In Section III, which consists of results, obtained results with proposed method were evaluated. In the conclusion and discussion, it is envisaged that proposed algorithm for GPR A scan signals can be applied to real-time systems and that supervised algorithms can be used to detect buried objects.

II. MATERIALS AND METHOD

A. Ground Penetrating Radar

GPR is in principle composed of a receiver and a transmitter antenna, a center unit and computer divisions. An electromagnetic pulse is generated by the central unit or, more generally, an electromagnetic signal is emitted by the transmitter antenna into the ground. Although generated signals are dispersible in all directions, most of them propagate underground as a cone under transmitter antenna.

Electromagnetic waves sent to underground continue to progress deeper as they return, reflecting some of the objects or surfaces that have different dielectric properties.

The reflected signals are collected and recorded by the receiver antenna. It is called "radar gram" [5]. In Fig. 1, basic working principle of GPR is shown schematically.

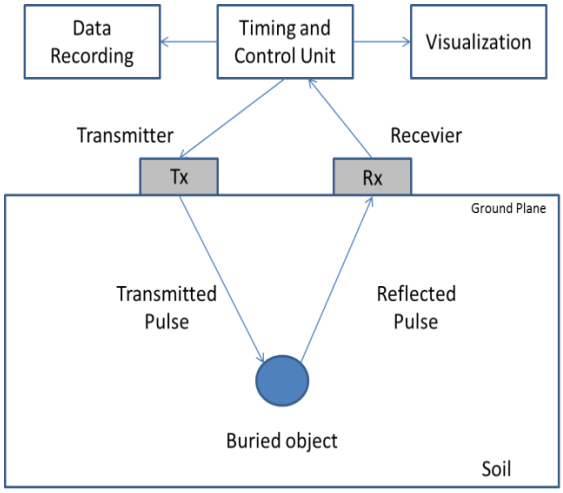


Fig. 1 GPR System

Generally, receiver and transmitter antennas are contained within a rigid box that is resistant to collision and move together. Thanks to GPR equipment with an integrated structure, radar grams obtained can be displayed during real-time operation and recorded on the hard disk of the laptop computer. Signals that are sent out from the transmitter and sent to the ground and reflected from the circles are recorded as a function of time. Depth determinations can also be made on this count. In the ground radar method, environment is examined by using high frequency electromagnetic fields which are sent to surface to be studied and changing over time.

Electrical properties of soil are important parameters in GPR design. The electrical property of the soil depends on the structural parameters of the soil such as dielectric constant, permeability and electrical conductivity. When relative dielectric and magnetic constants determine effective wavelength, electrical conductivity of soil determines loss of propagation.

The radar equation given in Eq.1-2 specifies range at which a target with a radar cross section can be detected [6].

$$P_r = \frac{P_t G_t}{(4\pi R^2)^2} \frac{A_e RCS}{L} \quad (1)$$

$$L(dB) = L_a(dB) + L_{r_1}(dB) + L_{s_1}(dB) + L_{s_2}(dB) + L_{r_2}(dB) \quad (2)$$

Transmitter antenna gain (G_t) depends on antenna type, geometry and wave frequency. Effective cross section of the receiver antenna is expressed by the antenna gain as follows.

$$A_e = \frac{G_r \lambda^2}{4\pi} \quad (3)$$

GPR data can be processed and displayed in three different ways such as A, B and C-scan. Coordinate system used for the display of GPR data is shown in Fig. 2.

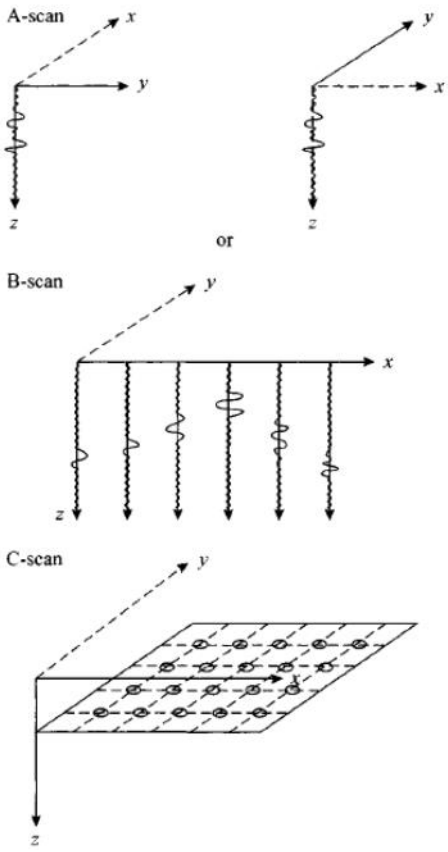


Fig. 2 Coordinate system of GPR data

B. Discrete Fourier Transform

Fourier transformation is a continuous transformation. However, in practical applications, discrete data points are being studied. That is, a signal is represented by its values taken at certain points of that signal. The definition of discrete Fourier transform is given by Eq. 4 where f is a sequence between 0 and N, f_n is the value of $t=t_n$ and k is an integer [7]:

$$f_k = \sum_{n=0}^{N-1} f_n e^{-2\pi i n k/N} \quad (4)$$

The inverse of discrete Fourier transform is similar to the inverse of Fourier transform and is given in Eq. 5:

$$f_n = \frac{1}{N} \sum_{n=0}^{N-1} f_k e^{-2\pi i n k/N} \quad (5)$$

The simplest indicator of whether a transformation is suitable for working with discrete signals which are discrete data points. They are generated by samples how accurately original signal can be represented in combination process [8].

It is important that sample data points collected from an analog signal should not be lost during the creation of a function from these points by bringing them together again and again. According to this theory, sampling frequency of sample data points collected from the signal must be 2 times or the highest frequency in the signal to be sampled [9]. Thus, collected data represents only specific signal in a specific way. If examined signal contains frequencies higher than half of sampling frequency, also called Nyquist frequency, a phenomenon called as aliasing occurs [10]. When this signal

is reconstructed from the sample points, it is observed as the inverse of the part up to Nyquist frequency.

The following expression applies for an (t) function that is continuously defined in a certain frequency range, such as T, with the Fourier transform x.

$$x(t) = \sum_{-\infty}^{\infty} x(\frac{n\pi}{T}) \frac{\sin(Tt-n\pi)}{Tt-n\pi} \quad (6)$$

C. Artificial Neural Network

Artificial neural networks are formed by combination of multiple neurons.. For this reason, it is necessary to understand properties of a neuron for entire network. There are five main items such as inputs, weights, activation function, summation function and outputs. The network formed by neurons consist of three layers: input, hidden and output layer [11].

Artificial neural networks have a learning structure through the input of the training set. Artificial neural networks have the ability to learn from sample data or to learn in their own experience. Data inputs can be made to neurons in the artificial neural network [12].

The weight of input data in artificial neural networks is called coefficient that determines influence factor on neuron. The weights provide communication information between neurons [13].

In an artificial neural network, a neuron can exchange data with more than one neuron. The summation function is used to calculate data input of network obtained in this data traffic. It is expressed as general summation of data by weights which are usually given. There are many addition functions such as maximum, minimum, majority and cumulative. In the maximum addition function, the system inputs are multiplied by their respective weights and the largest of the results is considered as neuron input [14]. In the minimum addition function, the smallest value between results obtained by multiplying the inputs by weights is assigned as input of system. In majority addition function, signs of the values obtained as a result of multiplication of inputs and weights. In the classifications made according to the labels, input assignment is performed according to majority. The new input values are calculated by adding the previous values to the input values multiplied by the weights in the sum total [15].

Once neuron inputs are identified using summation function, neural network must process this raw information and generate a response. Activation functions are used to calculate magnitudes of this reaction, which neurons generate. One of activation functions is linear function to convey output to input data without any action. In the step function, if the input value is greater than the threshold value, the output value is 1, and if it is smaller, the output value is 0. If information to be learned in sinus function that indicates a sinus curve distribution, input values will be sinusoidal. Threshold values are used to set sigmoid function input values between 0 and 1. In the hyperbolic tangent function, the input values must pass through the hyperbolic tangent function.

The value obtained after evaluation by the acquisition and activation functions of the data at neuron input is regarded as neuron output. Neurons may have multiple inputs and outputs.

D. GPR A Scan Data Generation

In general, an A-scan with 256 or 512 samples will suffice to obtain sufficient resolution and bandwidth. As a result of at least 12-bit or 16-bit digitization of this data, it will take up to 1 Kbytes of memory for each A-scan data. By using data compression techniques, the amount of memory required can be reduced. In the created system, classification process was performed by using A-scan signals obtained from different depth of materials in different soil scenarios.

Before generating GPR A scan signals, necessary scenarios must be created. Two cylindrical objects made of different materials in different depths were used to create these scenarios. Fig. 3 shows the scenario used to obtain GPR A scan signals. Three types of soil and five different material types for buried objects were used in the scenarios. Wet, moist and dry soil was chosen as soil type. Buried object materials are alumina, nylon, pec, silicon and wood.

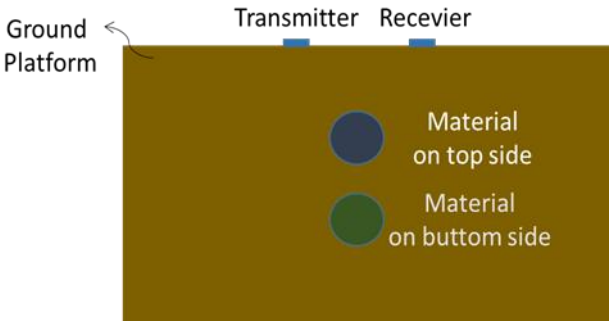


Fig. 3 GPR A scan signals scenario

GPR A scan signals consist of electric field and magnetic field components. These field signals have different components in the x, y and z directions. GPR A scan signals obtained using the GprMax program are shown in Fig.4.

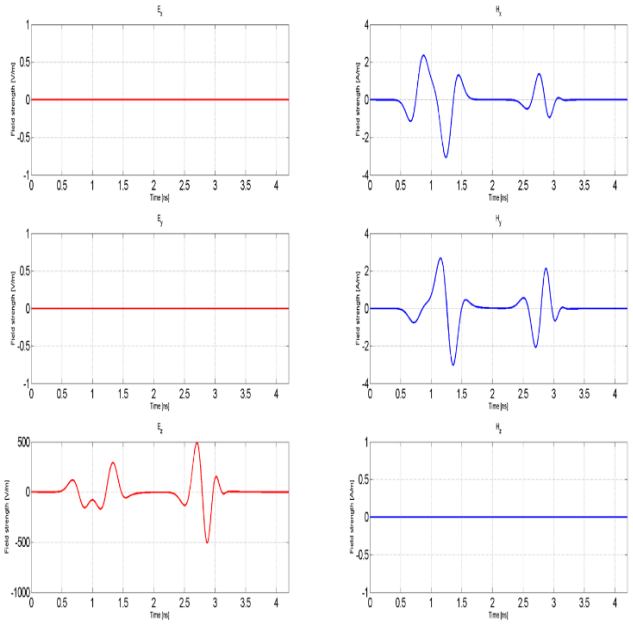


Fig. 4 Generated GPR A scan signals

GPR A scan signals are obtained by creating scenarios in the GprMax program. GprMax program obtains these scan signals by the Finite Difference Time Domain (FDTD)

method. When Fig. 4 is examined, the amplitudes in the z direction of the electric field components change. In the magnetic field components, the amplitudes in the x and y directions change. For this reason, it is planned to use E_z, H_x and H_y components of the generated signals. In this study, 105 A scan signals were obtained. These signals include 315 signals that need to be processed using the necessary electrical and magnetic field components.

E. Proposed Method

In this study, proposed method basically consists of two parts. Feature extraction process is first part of proposed method. Various features have been introduced to better represent 315 GPR A scan signals obtained from the GprMax program. In order to increase number of obtained features, Fourier transform is applied on signal in the time domain to convert frequency domain. In this way, features have been extracted in both time and frequency domain. Fig.5 shows features of both time and frequency domain.

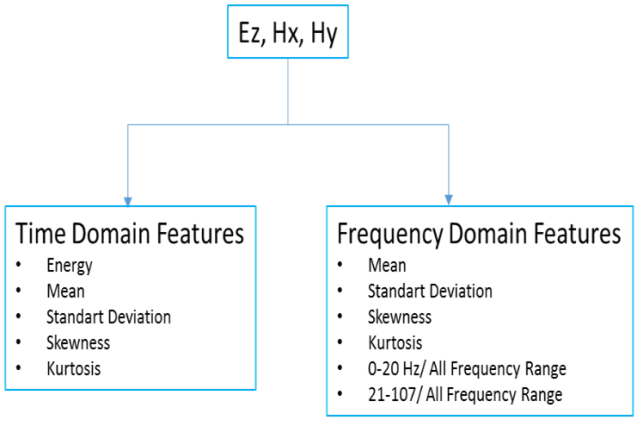


Fig. 5 Features Extraction Process in Time and Frequency Domain

In Fig. 5, 11 features were obtained in total in time and frequency domain. In order to process obtained signals, it is necessary to extract properties in time and frequency domain. For this reason, Fourier transform is used to convert the signals in the time domain to the frequency domain. At this point, the features of the signal in both time domain and frequency domain can be examined. At the same time, features such as energy, mean, standard deviation, skewness, kurtosis, 0-20 Hz / Full Frequency range and 21-107 / Full Frequency range have been extracted in time and frequency domain.

Best known is the mean of the values $x_1,\ldots,x_N$,

$$Mean = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{7}$$

Standard deviation is formulized as:

$$Standard\ Deviation = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(x_j - x)^2} \tag{8}$$

Skewness and kurtosis formulas are defined as:

$$Skewness = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - x}{\sigma}\right]^3 \tag{9}$$

$$Kurtosis = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - x}{\sigma}\right]^4 - 3 \tag{10}$$

Energy formula is represented in below.

$$Energy = \sum_{j=1}^{N}[x[n]]^2 \tag{11}$$

After feature extraction process, it is necessary to convert linguistic parameters to digital parameters at the neural network output. Digitization process has been done for classification of soil and material types. Digitization for soil type was done as 1, 2, 3. For buried object materials, numbers 1, 2, 3, 4 and 5 are assigned. Soil and material types are defined in different classes as indicated in the Table 1.

Table 1. Electrical properties of soil and buried objects in GPR scenarios

Types of Soil	Dielectiric Constant	Class
Wet Soil	20	1
Dry Soil	3	2
Moist Soil	8	3

Types of Materials	Dielectric Constant	Class
Alimunia	9.3	1
Naylon	5	2
Superconductive	1	3
Silicon	11	4
Wood	2.2	5

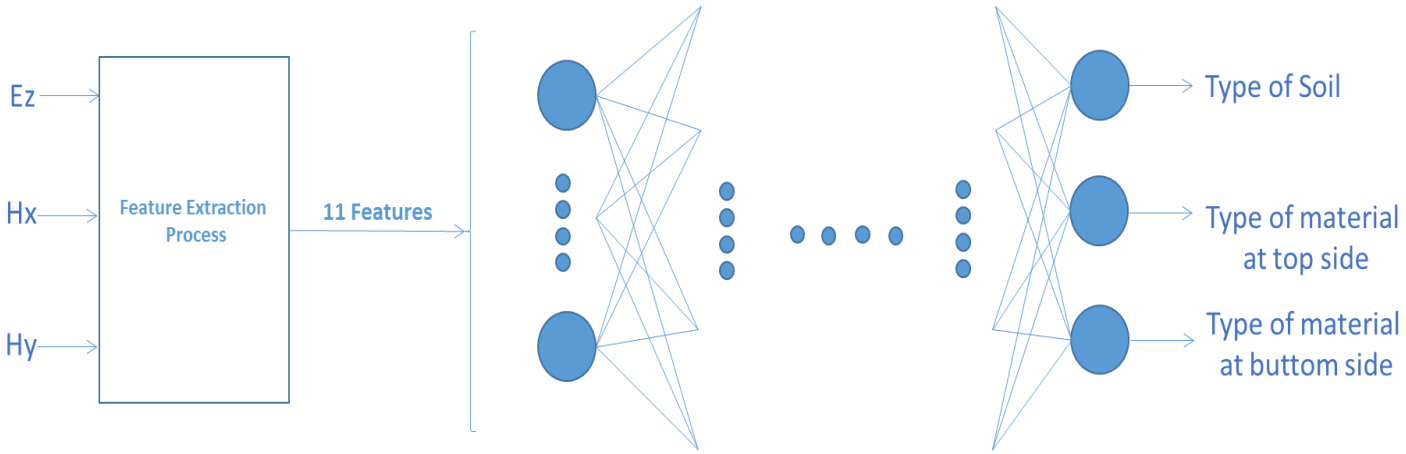


Fig. 6 Proposed Method

Material and soil estimation can be performed using a total of 11 features obtained from A scan signals. Artificial neural networks have been proposed for this prediction. Artificial neural networks have training and testing steps. After the current total data were randomly mixed, 70% of data were selected for training. With the remaining 30% of the data, the trained network classification performance will be tested. Artificial neural networks will have 11 inputs and 3 outputs. About 20 hidden layers are used in this network. The proposed method is shown in Fig 6.

III. RESULTS

In this study, the feature of GPR A scan signals was extracted and the buried object and soil surface prediction were performed. In addition, the effect of parameters of artificial neural networks on network performance is examined. Different learning coefficients, moment constants and iteration numbers have been tried to classify the extracted features. The effect of these parameters on the accuracy rate is given in tables and graphs.

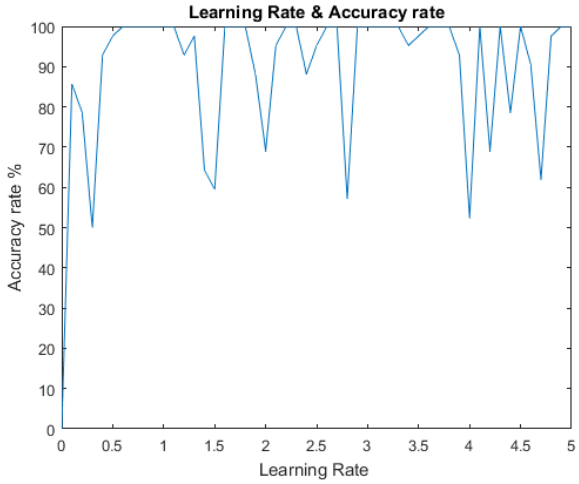


Fig. 7 Learning Rate & Accuracy Rate

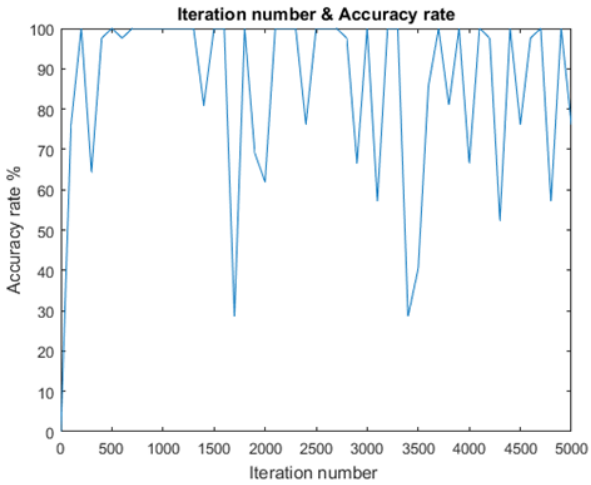


Fig. 8 Iteration number & Accuracy Rate

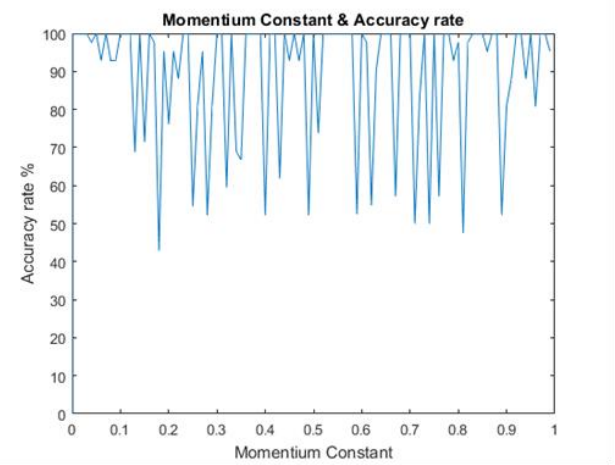


Fig. 8 Momentum Constant & Accuracy Rate

When graphs of different network parameters are examined, classification accuracy in test data varies between 100-28.57%. As can be seen from these graphs, the most suitable values for the learning rate for network training varied between 0.6-1.1. In the iteration numbers, it was understood that the most suitable values are between 700-1300. In Mometium constants, the highest accuracy ratios were obtained between 0.04-0.17.

IV. CONCLUSION AND DISCUSSION

Efficient GPR A scan signal classification method is presented. The proposed method is basically based on Fourier transform and artificial neural network. The general purpose is to determine type of soil and materials of buried objects. It is performed in 315 different GPR A scan signals. In the artificial neural network, learning rate values varying with 0.1 step between 1 and 4 and average accuracy rate are achieved by 90.57%. The highest accuracy is 100% while the lowest accuracy is 50%. At the same time, the number of iterations has been changed between 0-5000 and 100 iteration increases in each step. The highest accuracy was 100% while the lowest accuracy was 28.57%. Finally, momentum constants were changed from 0 to 0.99 in 0.01 steps. The average accuracy rate was 88.33%. The highest accuracy rate is 100% while the lowest accuracy rate is 42.85%. A real-time detection system can be built using the network structure with the highest degree of accuracy in operation.

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