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Passive Mine Detection and Classification Method Based on Hybrid Model

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ABSTRACT At present, active detectors are commonly used for detection of land mines. Land mines can be detected with high precision through active detectors. However, the operating principle of active detectors can also lead to vital dangers. When detecting mines in the field, electrical signals sent to the environment from active detectors sometimes trigger the mine blasting mechanism and cause mine explosion. Another way to detect land mines without triggering the blasting mechanisms is to use passive detectors. The biggest handicap of passive detectors is that they cannot detect mines as much as active detectors. This causes that passive detectors are as dangerous as at least active detectors. In this case, passive detectors can cause dangerous results like active detectors. In this paper, we have developed solutions that eliminate the handicaps of passive mine detectors. For this purpose, a new approach, which is established on artificial intelligence based on the magnetic anomaly, measurement height, and soil type, is suggested. The experimental setup is designed to verify and test the proposed approach. In this respect, the actual data measured under different conditions were recorded and processed with modern and effective artificial intelligence techniques; and alternative models were developed. With the proposed approach, the mines are detected with a success rate of 98.2%. This success rate in detection is promising for the passive mine detectors. A significant contribution of the developed model in terms of literature is the successful classification as well as the detection of mines. In experimental studies conducted with real data, five different types of mines are classified as 85.8% success rate. The proposed model has been a pioneering study on mine classification in the literature. Moreover, the realization of this paper with a passive mine detector proves the success of the proposed approach.

INDEX TERMS Mine detection and diagnosis, meta-heuristic classification, artificial neural network.

I. INTRODUCTION

Detection of mines buried in the ground is very important in terms of safety of life and property. Many different methods have been used in this regard; however, it has not yet been possible to achieve 100% success. Mine detection process consists of sensor design, data analysis and decision algorithm phases. When the previous publications are examined, the following studies came to the forefront.

Detection of explosive vapors from buried land mines by chemical sensors has been demonstrated [1]. Magnetic field changes of landmines could be measured with magnetic induction sensors [2]. Detection of mines by Ground Penetrating Radar (GPR) is a very common method [3]. Feature reduction methods have been used to classify multidimensional data from sensors [4]. The great difference between the elastic properties of the mine and the surrounding soil has been revealed using high frequency seismic waves for the detection of buried mines [5]. The Elliptic Systems Method has been developed to produce images of buried mines and this method is adapted to the problem of landmine imaging using the Helmholtz Equation [6]. One of the methods used in the literature for mine detection is the neutron retroreflective method. In this method, an increase in the number of reflected thermal neutrons on the ground where the mine is buried is detected [7]. Especially, for the detection of plastic land mines, a method combining electromagnetic induction and neutron back propagation (scatter) is designed [8]. Another approach has shown that landmines cause anomalies in the thermal image of the soil. Thus, thermal anomalies in measured infrared images are used for mine detection [9]. To increase the mine detection rate, the super resolution technique MUSIC algorithm and

SAR (Synthetic Aperture Radar) were applied together for signal processing and image reconstruction of the GPR signal [10]. Various algorithms are presented in a hierarchical manner to distinguish between Anti-Tank (AT) and Anti-Personnel (AP) land mines using the data gathered from Wide Area Electromagnetic Induction (WEMI) and GPR sensors. The KNN method based on angle model uses two parameter models. Linear Estimation Processing and Spectral Properties are calculated for GPR data when the parameters match the In-phase and Quadrature data [11]. Vehicles equipped with sensors and cameras [12] and robot designs [13], [14] are frequently used methods in mine search operations.

In mine detection, it is also important how the data obtained are analyzed as well as vehicle design, sensor technology and sensing methods. Very different methods have been used in the analysis of data obtained during mine detection and in the decision-making stages. Generalized Likelihood Ratio (GLRT) [15], Minimum Classification Error (MCE) to improve the performance of the Discrete Hidden Markov Model (DHMM)-based mine scanning system [16] and Wavelet Transform [18] and two-dimensional and three-dimensional NUFFT (Nonuniform Fast Fourier Transform) algorithms have also been used for land mine detection using GPR [19].

In another study, a discovery process based on Principal Component Analysis (PCA) and Support Vector Machine (SVM) techniques was proposed to detect land mines in real SAR images [20]. It is also seen that UWB-GPR data processing is used to identify anti-personnel landmines [21]. In another study, an SVM with a hypersphere classification boundary called HyperSphere-SVM (HS-SVM) using an HMM (Hidden Markov Model) kernel on a feature vector subtracted by a post-filter-based method was proposed for mine scanning [22]. Context-Dependent Multi-Sensor Fusion for mine detection is seen as another method [23].

Many different designs and methods have been developed for mine detection such as using Finite Difference Time-Domain (FDTD) and Artificial Neural Networks (ANNs) [24], FLGPVAR (Forward-Looking Ground Penetrating Virtual Aperture Radar) images [25], the contextual extraction approach for Fuzzy Integral Adaptive Local Fusion (CELF-FI) [26], 3D image analysis method [27], Electromagnetic band-gap (EBG) antenna design for GPR with Metal Detector [28], TLM method [29], Adaptive Neuro Fuzzy Inference System [30], comparison of Attribute Extraction Methods by Using Penetrating Radar [31], holographic radar [32], Thermal Display Time Series [33], RBF Kernel-based SVM classification [34] and mine detection by GPR mounted on drone [35]. The method of determining mines with the detection of anomalies in the earth's magnetic field has also entered the literature [36]. In the related studies, the anomaly in the Earth's magnetic field was measured using a fluxgate sensor (type FLC100).

When the studies in the literature are examined, it is seen that active detector design using a number of different methods is preferred [4], [5], [7], [15], [16], [31], [32], [35]. Despite all the studies done on mine detection today, people still lose their lives because of land mines. This is due to the handicap of existing mine detectors. Active detector design has not been adopted due to the hazards it creates. Magnetic anomaly method is considered to be very suitable for passive detector design [45]. The passive mine detector prevents the mines from being triggered unintentionally. However, there are also some restrictions on passive mine detectors. For example, the performance of passive detectors under actual conditions and on real dataset has not been adequately tested. When studies that only consider magnetic anomalies are examined, it is understood that passive detector studies have been tested on a limited set of very small numbers of data and problem space. The experimental results of related studies should be examined in this regard. Thus, the passive detection approaches [45] used in the literature in the experimental study section was also used in this article. We tested existing passive mine detection approaches on experimental data obtained in our own study. We have experimentally proved that up to 84% of mine detection successes are obtained only when the magnetic anomaly is taken into consideration. Similarly, when mine classification performance was measured, it was observed that this rate decreased to 57.7%. This fact reveals the handicaps of the existing approaches when the real world application is done. Briefly, in the passive mine detectors, it has not been realized that mines cannot be detected only by the magnetic anomaly. In other words, the performance of passive mine detectors working on the basis of the Earth's magnetic field does not meet the standards set by the United Nations in this regard. For this reason, the presence of other parameters that could be effective in determining mines has been researched. As a result of these investigations, it was evaluated that soil type and height parameters other than magnetic anomalies may be effective in mine detection.

In this study, a new approach to passive mine detector design is proposed. A way of expressing the mine type by a function of a three-dimensional problem such as magnetic anomaly value, measuring height and soil type has been suggested. Recently, stable and effective classification techniques have been used in the literature to model the problem depending on the new approach. Thanks to the artificial intelligence-based system developed on the basis of the proposed approach, analytical relations in the multi-dimensional mine problem are effectively modeled and problem-specific patterns can be successfully explored. The developed approach has been verified and tested on data obtained from a real experimental setup. The results obtained meet the 98.2% detection rate determined by the United Nations for landmines. Successful results obtained on real-world data are promising in terms of the spread of passive mine detection systems. The developed approach also improves the performance of passive mine detectors in classifying mines. This rate has reached up to 85.8% from 57.7%. All these comparisons are given in the experimental section.

In the second section of the paper, magnetic anomaly is discussed. In the third section, the method proposed in the article is applied in detail. In this section, detailed information is provided from the definition of the problem to the preparation of the datasets and modeling of the problem. In the fourth section, the data obtained from the experimental setup are modeled with modern and effective artificial intelligence techniques. In the experimental study section, several models are proposed and their performances are compared. Thanks to the proposed approach and developed models, it is shown in the experimental study that land mines can be detected effectively and their types can be identified.

II. METHOD OF THE STUDY

The magnetic anomaly method works according to the principle of measuring the anomalies resulting from the object in the magnetic field that disturbs the structure of it, the magnetic field, and the data obtained at this point are used to determine the conditions such as motion and position [37], [38]. The determination of parameters such as position, depth or direction of motion using magnetic anomaly has been carried out since 1970 [39]–[44].

In this study, a technique has been used to determine the extent of land mines by measuring the anomaly of the Earth's natural magnetic field. The main principle in this method is to determine the existence of anomaly in the environment where research is conducted. The different magnetic properties of different types of materials are the reason for the anomalies. In this case, if this method is used for mine detection, it is also possible to detect a metallic, semi-metallic, plastic explosive device. However, the main problem here is that objects such as rocks, metal wastes and even tree roots can be excluded from the definition of mine/explosives [45]. This problem is solved by an algorithm developed for the analysis of the data obtained in anomaly measurement. In this study, Fluxgate sensor was used to measure the magnetic anomaly. These sensors can measure DC or low frequency AC magnetic fields and have a measurement range of 10^{-10}-10^{-4} Tesla.

It is possible to classify detectors used in mine detection in two categories: passive and active ones. In the active methods, signals are sent to the objects and mine detection is done depending on the state of the signal reflected from the objects as shown in Figure 1. The biggest handicap of such methods is that the transmitted signal explodes the mine by activating the trigger mechanism of it. During the mine clearance, there have been incidents that caused a large number of deaths resulting from this. There is not any triggering handicap in passive methods. Passive methods, however, cannot detect remotely and effectively as well as active methods. In this paper, a passive mine detection and classification method based on the magnetic anomaly, the height of the detector and the soil type has been developed to remove the danger created by the active methods. One goal of the developed method is to classify mines beyond mine detection. For this purpose, the mine detection problem has been redefined as "mine detection and diagnosis problem".

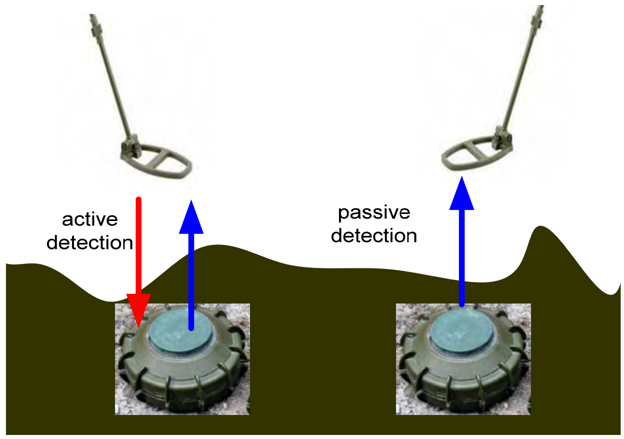

FIGURE 1. Mine detection methods.

Beyond the detection of mine, a new approach has been developed primarily to identify the type of mine. In the developed approach, the class of objects buried underground is defined according to the state of three independent characteristics/variables (input parameters). These are the type of soil to which the mine is buried, the height of the mine detector from the ground <H> and the size of the magnetic anomaly <V>. The fluxgate sensor is used to measure the magnetic anomaly. With the developed method, it is first determined whether objects buried in the earth are mines or not. The type of mine is determined when mine presence is detected. For this purpose, the magnetic anomaly created by the objects buried in the soil is measured and the mines are identified and classified according to the soil type and distance of the sensor to the soil. Modern and effective machine learning techniques are used to classify mine types according to their state as three independent variables Mtype = f (V, H, S). In order to develop the model, it is necessary to define the problem in detail (to analyze dependent and independent variables).

A. DEFINITION OF THE PROBLEM

The parameters of the problem and the data types of these parameters, their values and limits are given in Table 1. FLC100 type sensors are used to measure the magnetic anomaly due to the fact that output voltage is stable but not suitable for the passive detector design.

B. OBTAINING THE DATA AND ANALYZING THE PROBLEM

Depending on the information given in Table 1, the data samples of the problem are represented with a 4-dimensional vector as <V, H, S, M>. The dataset is prepared to model the problem. The data samples represent the problem space in a homogeneous manner. For this, the data samples were collected for all types of mines. An experimental set (test simulator) was prepared to obtain a sample subset of the problem space. Training, validation and test sets were established with the sample data obtained from the test simulator. The photograph of the experimental setup is given in Figure 2 [46].

TABLE 1. Parameters of the problem.

	The Parameters					
	Inputs “independent variables”				Output “dependent variable”	
	Voltage (V)	*High (H)*	*Soil Type (S)*		*Mine Type (M)*	
Definition	Output voltage value of FLC sensor due to magnetic distortion.	The height of the sensor from the ground.	6 different soil types depending on the moisture condition.		Mine types commonly encountered on land. 5 different mine classes.	
Boundary Values / Class	[0V, 10.6V]	[0 cm, 20cm]	1	Dry and Sandy	1	Null
			2	Dry and Humus	2	Anti-Tank
			3	Dry and Limy	3	Anti-personnel
			4	Humid and Sandy	4	Booby Trapped Anti-personnel
			5	Humid and Humus	5	M14 Anti-personnel
			6	Humid and Limy		

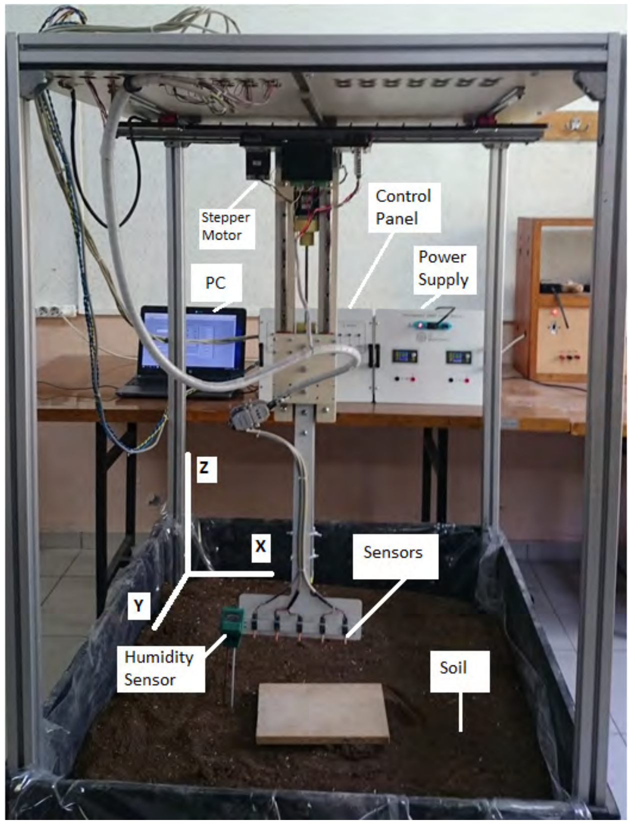

FIGURE 2. Test simulator.

In the test simulator, symmetrical power supply meets the voltage and current required by the entire system. In the experiments, the system is set to ± 15 V voltage value. The stepper motor control panel enables movement control on X, Y, Z axes. It allows information to be recorded and processed on the display screen via the NI DAQ 6800. A stepper motor driver card is used to carry out computer-controlled movement of stepper motors moving in Cartesian coordinates. The imaging unit defines the data exchange characteristics with the sensors; and stores the data. All parameters related to the operation of the system are controlled here. The soil pool is the place where the explosives are buried and consists of an area of 110*80*30 cm filled with different soil types.

The detector carrying the FLC sensors in the test simulator can move in three axes. In this case, the height of the detector can be adjusted from the ground. It is thus possible to examine the magnitude of the magnetic anomaly created by buried objects in the earth, depending on the height. Before developing the proposed artificial intelligence-based classifier model, the relation between anomaly voltage (V), soil type (S), height (H) and mine type (M) was investigated.

Information on these investigations is given in Figures 3-5. First, the existence of magnetic anomalies created by a mine buried in the soil, namely the relationship between V and M is observed. In this experimental study, the soil type is dry and humus. The FLC sensor is moved 15 cm above the ground surface. During this movement, the position of the sensor changes and the output voltage value is continuously recorded. As the sensor passes over the mine, there is an increase in the output voltage depending on the magnetic anomaly created by the mine. Mine creates a high magnetic permeability for the magnetic flux in this direction. With this effect, it is possible to detect the position where the mine is located. There is also an increase in the amplitude of the magnetic anomalies as the density of the metal particles used to increase the mine effect increases. The experimental work was carried out for five different situations, one with no mines in the ground and four with different types of mines. The graphs of the obtained data are given in Figure 3.

Figure 3 gives the magnetic anomaly for five different cases. When the graph in Fig. 3 (a) is investigated, it is seen that the magnetic field generated by the earth has oscillated at a low band interval. Therefore, the magnetic field of the earth can be observed steadily with the FLC sensor. When the graphics given in Figure 3 (b, c, d, e) are examined, it is seen that each mine type creates a magnetic anomaly in its own characteristic. In Figure 3 (f), it is seen that all cases are collected in a graph and these cases can be distinguished from each other. The voltage values in the graphs indicate that magnetic anomalies at different levels are caused by the types of mines. This information leads to the idea that the mines can be detected depending on the output voltage value of the FLC sensor. However, this information is partially correct. Today, passive mine detectors designed with FLC sensor are

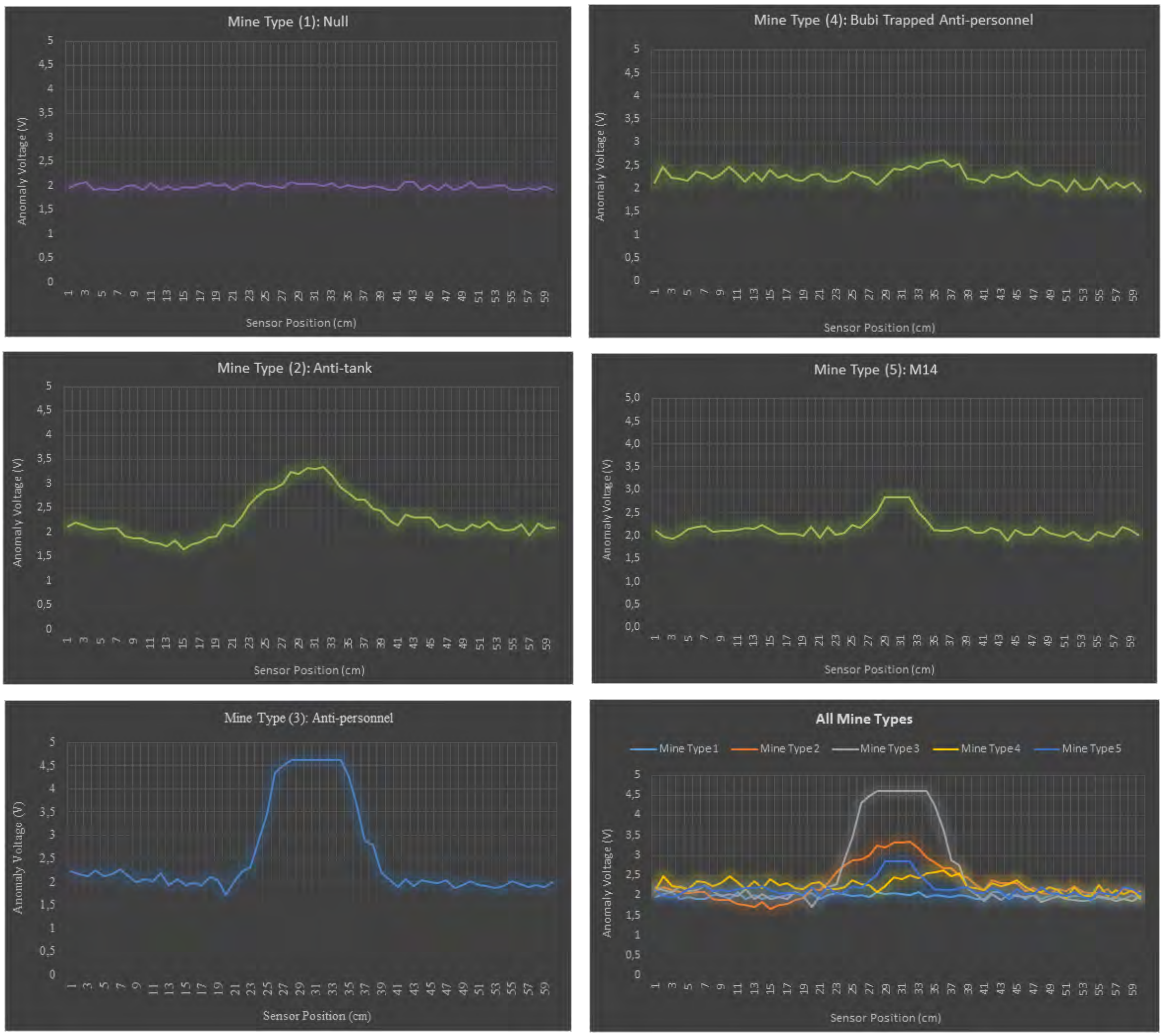

FIGURE 3. **Magnetic anomaly created by buried mines.**

not at the desired level to detect mines. The most important reason for this is that the value of the magnetic anomaly changes as it moves away from the ground (soil surface). In other words, the measurement results vary depending on the distance between the point at which the mine is buried and the point at which the magnetic anomaly is measured. This suggests that considering the magnetic anomaly alone is an inadequate approach for mine detection. It is clear that the change of the measurement height with the movement of the mine detector also changes the magnetic anomaly values. We have also seen that the soil type is also effective on the magnetic anomaly created by the mines. The relation between soil type and measurement height with magnetic anomaly is given in Figures 4 and 5.

The magnetic anomaly values generated by the mines are shown in Fig. 4 depending on the soil type (the actual data obtained from the experimental setup are given in Figure 2). The horizontal axis indicates the soil type.

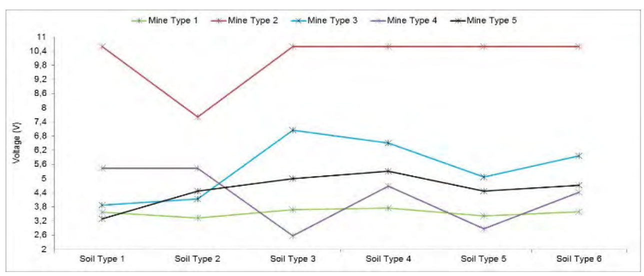

FIGURE 4. **Investigation of the effect of soil type (S) on magnetic anomaly.**

The data in Figure 4 belong to a total of 30 data samples obtained from measurements made with the constant height for six different soil types and five different mine types. Under these conditions, the number of anomalies generated by different soil types is measured separately for each mine type. Thus, the relation between soil type and magnetic

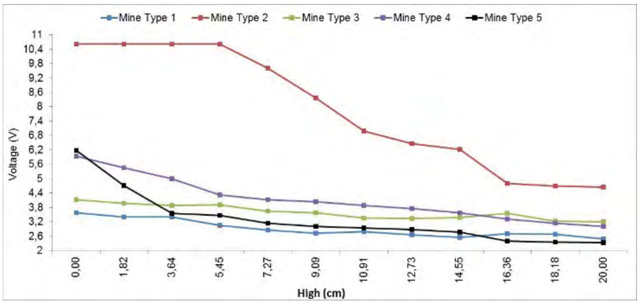

FIGURE 5. **The effect of height (H) on magnetic anomalies.**

anomaly has been investigated for five different mine types. The red line in Figure 4 belongs to the anti-tank mine. Magnetic anomaly values were recorded by changing the soil where the mine was buried. For example, the red line shows the voltage values obtained by placing the anti-tank mine in six different soil types. There is no direct or explicit relation between soil type and magnetic anomaly for anti-tank mines. This may be due to the fact that the anti-tank mines show magnetic anomalies that can be measured to a maximum extent because anti-tank mines show a much larger magnetic anomaly than other types of mines. This anomaly keeps the output voltage of the sensor at the maximum value even if the soil type is changed. For different types of mines, different anomaly values were measured in different soil types. In order to investigate the effect of soil type on mine classification problem, it was decided to create two different models. One of these models included the soil type, while the other did not take into account the soil type. Another information obtained from Fig.4 is that the size of the anomaly varies depending on the type of mine. This can be clearly seen from the graphs obtained for mine types given in five different colors.

After the soil type, the effect of the height (H) on the magnetic anomaly was investigated. In other words, the FLC sensor's ability to measure the magnetic anomaly from different heights was examined. In addition, the relation between the magnetic anomalies of the mine type was investigated. The soil type was kept constant for this; and the magnetic anomaly value obtained from the sensor depending on the different altitude values was measured and recorded for each type of mine. In Figure 5, the horizontal axis shows height, while the vertical axis shows the output voltage of the sensor.

For the different altitude values given in Figure 5, the voltage value at the sensor output is understandable and shows a clear change. Therefore, it is seen that the FLC sensor produces different signals (voltage amplitudes) for the selected height range. To assess the mine type, it is necessary to follow the lines in the different colors given in Figure 5. The red line belongs to the anti-tank mine. Since the anti-tank mine generates a large magnetic anomaly, the sensor output produces an output signal with a maximum amplitude between 0 cm and 4 cm. Moreover, it is very clear that all the colors, i.e. the magnetic anomaly effects of each mine type, are different. For different types of mines at the same height, the amplitude value of the signal generated by the FLC sensor is different. This also applies to different heights. The summary of this subsection and the explanations necessary for motivation in the next section are given below.

- When the problem is analyzed, it is seen that magnetic anomalies change depending on the type of mine, the measurement height and the type of soil. Therefore, considering only the magnetic anomaly for the design of a passive mine detector may be an incomplete or even a faulty approach. Until now, the failure of passive mine detectors may not be an effective analysis of the problem.
- Magnetic anomaly value, soil type and height of measurement should be considered as independent variables in the design of a passive mine detector. Models of combinations of these three independent variables were developed in the experimental study section. The performances of the developed models have been measured and compared with each other. Depending on the information obtained, the most suitable model for the design of the passive mine detector has been developed and proposed.

C. PREPARING THE DATASET

Figure 6 gives the magnetic anomaly value (V) of the data samples obtained from the experimental setup and the type of mine (M) for different soil types and different height values. The vertical axis represents the value of V and the horizontal axis represents the data sample number. Seventy-one of 352 data samples belong to non-mine cases. The class of these data samples is labeled as "Type 1". Similarly, mine samples are classified with labels "Type 2", "Type 3", "Type 4" and "Type 5". The red lines in Figure 6 give the average of the magnetic anomaly values created by the data samples of each class. For example, the data samples between 71-143rd on the horizontal axis and shown with Type-2 belong to the "anti-tank" mine class. The average voltage value of data samples of class "Type 2" is about 0.7 V. Data samples include noisy data. Data cleaning is an effective step on the success of data mining. Therefore, to successfully model the mine problem, the noisy data must be removed from the database. In the dataset cleaning process, a total

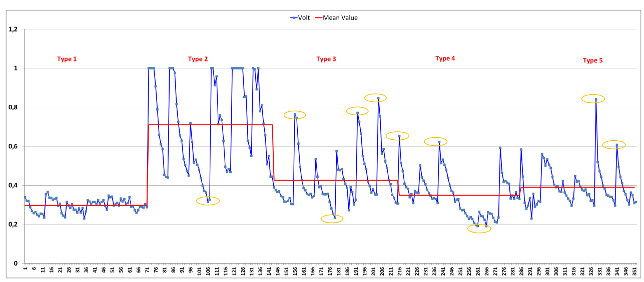

FIGURE 6. **Mine types and voltage values of the data samples obtained from the test simulator.**

of 14 noisy data samples were deleted. In the modeling of the problem, 338 data samples were used.

D. MODELLING OF THE PROBLEM

The general principle of the mine detection and diagnosis (classification) process is given in Figure 7. According to this function, the target parameter (dependent variable) in the system is the type of mine. The mine type appears to be discrete (labeled) when considering the data type. For this reason, this is a classification problem. Commonly used algorithms in classification problems are Naive Bayes, Support Vector Machine (SVM), decision trees, k-Nearest Neighbor (k-nn) and ANN [11], [20], [22], [30], [34].

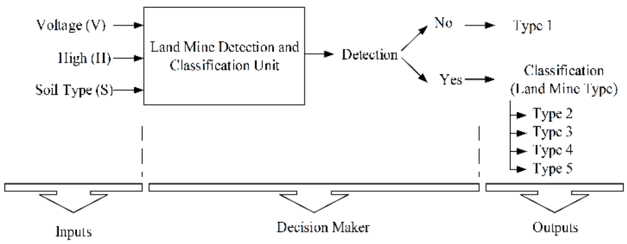

FIGURE 7. Mine detection and diagnosis process in the developed system.

The data types of the independent variables must be considered in order to determine the classification algorithms which can be applied to the problem among alternative artificial intelligence techniques. When the independent variables of the system are examined, the "voltage" and "high" parameters are continuous values while the soil type is discrete value. In order to apply classification algorithms that work with numerical data, it is necessary to convert the soil type to a discrete numeric value. Figure 7 presents the most modern and effective classification techniques which can be applied to the problem.

Among the artificial intelligence techniques presented in Figure 8, the meta-heuristic k-NN with fuzzy metric is an effective hybrid classification technique recently developed [47]. ANNs and meta-heuristic classifiers, which are the most effective and modern classification techniques for modeling the problem, are used.

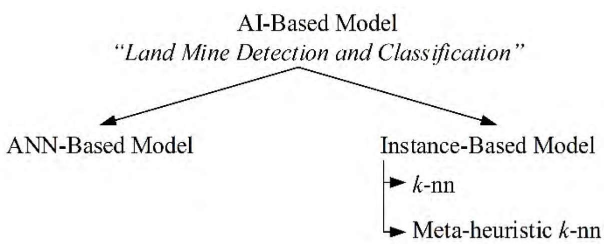

FIGURE 8. AI-based effective classification techniques.

1) DEVELOPMENT OF ANN-BASED MODEL

Multilayer, feed forward and back propagation network structure is adopted as ANN model. The structure of the model, which is designed as a 3-input and 5-output network, is given in Fig 9.

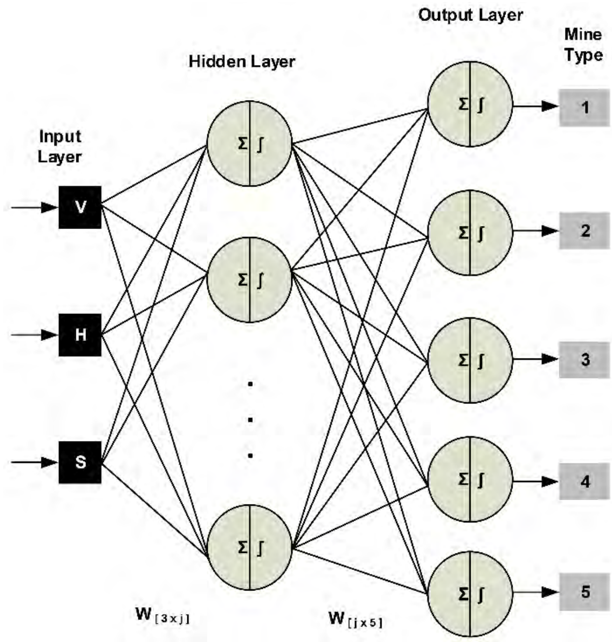

FIGURE 9. ANN model designed for mine classification problem.

2) DEVELOPMENT OF INSTANCE-BASED MODELS

a: k-NN MODEL

k-NN is a sample-based classification technique. Parameters that are effective on classification success are k-neighbor number, distance metric and voting method. Apart from the parameters of k-NN, the sample dataset of probing also has a decisive influence on the classification performance. For this reason, different k-values and models for distance metrics have been developed and tested in experimental studies. It is also very important to sample the problem space of the dataset in a homogeneous way. Please refer to [47]–[49] for detailed information on the implementation steps of the k-NN algorithm.

b: META-HEURISTIC k-NN

The meta-heuristic classification model consists of two basic elements. These are the weighting and classification modules [47]–[49]. The task of the weighting module is to explore the effect of the independent variables of problem $<V, H, S>$ on the dependent variable $<M>$. For this purpose, the effect of the three input parameters on the target parameter is represented with coefficients taking continuous value in [0, 1] range $<W_V, W_H, W_S>$ by using a meta-heuristic search method. Optimization of these coefficients is performed by finding the values that maximize the classification performance. The task of the classification unit is to estimate the class to which M belongs, depending on the values of the input parameters $<V, H, S>$. The design of this unit (meta-heuristic weighting unit) has been done with genetic algorithm. The classification unit is designed with the k-NN algorithm. Parameter optimization and classification process are given in Figure 10.

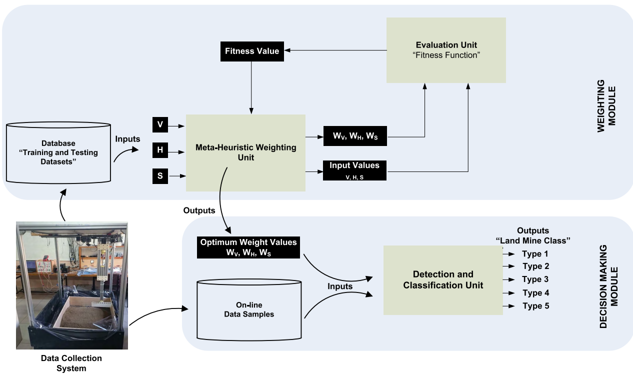

FIGURE 10. Parameter optimization and classification process.

Meta-heuristic algorithms search multiple solution candidates to find the optimum solution of a problem. Thus, in this optimization problem, the cost function is k-Nearest Neighbor classifier (fk-NN). The fk-NN function determines the class of the dependence of independent variables of the problem <V, H, S>. When the measurement result obtained from the experimental setup is represented by an observation q, the class of this observation q is obtained as given in Equation 1.

$$q_M = f_{k-nn}(W_V * V, W_H * H, W_S * S) \tag{1}$$

The weight coefficients $<W_V, W_H, W_S>$ given in Equation 1 are optimum values that maximize the performance of the classifier f_{k-nn}. The optimal values of these coefficients are found by the genetic algorithm at the end of the heuristic search process given in Algorithm 1.

When the problem parameters are taken into consideration, a solution candidate (p) in the genetic algorithm is represented by three genes and one fitness value ('u') as follows (Equation 2).

$$P \equiv [WV, WH, WS], [u] \tag{2}$$

The fitness value of a solution candidate depends on its classification performance. A dataset consisting of "test observations" is used to measure the classification performance. The k-Nearest Neighbor algorithm given in Equation 1 is used to estimate the classes of test observations. Accordingly, if it is assumed that there are k-observations in a test data set, the fitness value of any solution candidate is calculated as given in Equation 3.

$$u = \frac{number\ of\ correctly\ estimated\ observations\ of\ the\ class}{k} \times 100 \tag{3}$$

Algorithm 1 The Pseudo-Code of the Optimization Process

Setting parameters and operators, defining cost function
Determining the number (n) of solution candidates in the population (P)
Start
  Create Population (P community with n solution candidates)
  loop** i=1:n **(genetic life cycle)
    Calculate the fitness value ($\forall_{i=1}^{n}\forall_{i=1}^{n}\forall_{i=1}^{n}\forall_{i=1}^{n}$ P[i] candidate)
    if (*ending*)
      P *save the best individual in the population* $<W_V, W_H, W_S>$ *and*
      exit
    else
      Choice parent
      Cross over
      Mutation
      Update
    end loop

Depending on the information given above, a population of n solution candidates can be represented as given in Equation 4.

$$P_{[i]} \equiv \begin{bmatrix} W_{V(1,1)} & W_{H(1,2)} & W_{S(1,3)} \\ \vdots & \ddots & \vdots \\ W_{V(i,1)} & W_{H(i,2)} & W_{S(i,3)} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_i \end{bmatrix} \tag{4}$$

Optimum weights are obtained by passing the P population through the genetic life cycle as in Algorithm 1. At the end of this process, the best individual from the set of P solution candidates is registered and used in the k-NN classification process. References [47]–[49] can be reviewed to obtain more detailed information on k-NN and meta-heuristic k-NN with fuzzy metric algorithms.

III. EXPERIMENTAL STUDY: LANDMINE DETECTION AND CLASSIFICATION PERFORMANCES

In experimental studies, training and test sets were prepared by random sampling from 338 data samples. Approximately 3 out of 2 data samples were randomly separated for testing, while the remaining was separated for training. Accordingly, the distributions of land mine samples according to their classes in training and test datasets are given in Figure 11.

Accordingly, two decision models were developed with each of the three different techniques to determine the most appropriate detection and diagnosis model. The detection model decides whether or not there is mine depending on the values of the <V, H, S> data from the sensors. In this case, Type 1 represents non-mine condition and Type (2-5) represents mine condition. That is, according to the distribution in Fig. 11, 21% of the data samples in the training and test sets of the detection model belong to non-mine situations whereas 79% belong to mined situations. In the following section, performances of six different models, ANN, k-NN and

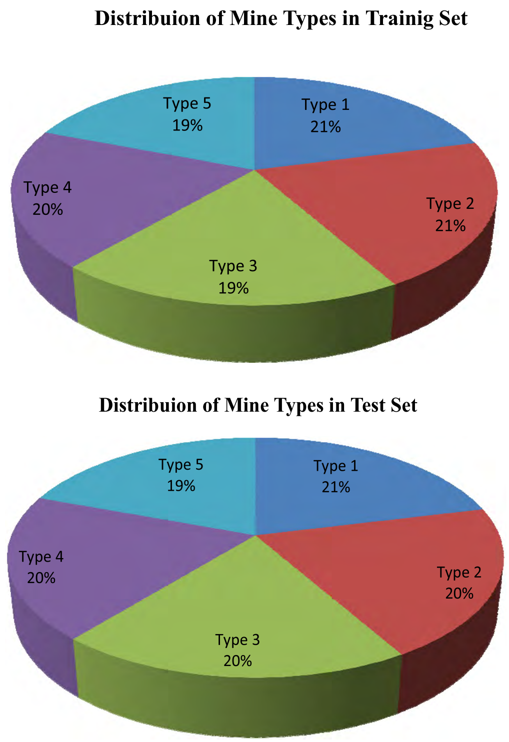

FIGURE 11. Distribution of randomly selected training and test samples according to their classes for experimental studies.

meta-heuristic k-NN based detection and diagnosis models are given, respectively.

In the following sub-section, the results of the two main studies are shared. In the first study, alternative models are being created for the problem of mine detection and classification. Among the created models, the most successful ones are identified. For this, firstly, a model consisting of combinations of probing independent variables (V, H and S) was developed. These models are solved by ANN-based classification technique. In the analysis process, design variables defined for mine detection and diagnosis (classification) are modeled by ANNs and their performance is measured. By considering the performances of the models, optimum design variables are determined for the determination and classification of the mines. After determining the most suitable design variables for the problem, the second study was started. In the second study (the optimum design variables are set in the previous phase), alternative models are created with modern and hybrid artificial intelligence techniques. The aim of this study is to explore a more effective detection and diagnostic model of the developed approach. For this purpose, successful meta-heuristic classification techniques and fuzzy distance-based meta-heuristic classification technique, a modern method, have been applied. In the next subsections, the optimum design variables are determined, and then the most suitable artificial intelligence model is investigated.

A. MODELING OF PROBLEM WITH ANN

In this section, the most suitable design variables are investigated for modeling the problem. In this process, ANN-based models are created in accordance with the different combinations of design parameters, the V, H, and S. The performances of the created models are being tested. For this purpose, four different ANN models are created for mine detection. These are; $M_{sense\_1} = f_{ANN\_detect}(V, H, S)$, the detection model in which the V, H and S are taken into consideration, the $M_{sense\_2} = f_{ANN\_detect}(V, H)$ model, in which the S is neglected, the $M_{sense\_3} = f_{ANN\_detect}(V, S)$ model, in which the H is neglected, and the $M_{sense\_4} = f_{ANN\_detect}(V)$ model, in which the S and H are neglected. The second study has been conducted to determine the type or class of mine. Four different ANN-based classification models have been developed for this purpose. These are; $M_{class\_1} = f_{ANN\_classify}(V, H, S)$, the classification model in which the V, H and S are taken into consideration, the $M_{class\_2} = f_{ANN\_classify}(V, H)$ model, in which the S is neglected, the $M_{class\_3} = f_{ANN\_classify}(V, S)$ model, in which the H is neglected and the $M_{class\_4} = f_{ANN\_classify}(V)$ model, in which the S and H are neglected.

1) DETECTION PERFORMANCE OF ANN-BASED MODELS

In this sub-section, four different ANN models are created, each consisting of combinations of design variables. Each of the created models is measured for the performance of detecting mines. The first model is represented by $M_{sense\_1} = f_{ANN\_detect}(V, H, S)$, the second model is represented by $M_{sense\_2} = f_{ANN\_detect}(V, H)$, the third model is represented by $M_{sense\_3} = f_{ANN\_detect}(V, S)$ and the fourth model is represented by $M_{sense\_4} = f_{ANN\_detect}(V)$. Fourth of these models $M_{sense\_4} = f_{ANN\_detect}(V)$ is based on the approach used in the design of the passive mine detector in the literature [45]. The performances obtained in these four models are compared with each other to investigate the most appropriate approach (design variant combination or input parameters of problem) to detect and classify mines with a passive mine detector.

Figure 12 shows the performance curves of the Msense_1, Msense_2, Msense_3 and Msense_4 models. In the chart on the top left (a), mine detection is performed according to the input parameters of problem (design variables) V, H and S. In this model, the learning process continued effectively for about 80 epochs. The cross-entropy value is also reduced to a value close to 10^{-2}. In the chart on the top right (b), the soil type was not taken into consideration when mine was detected. In this case, the learning process lasted about 50 epochs. The cross-entropy value is reduced to 10^{-1}. It was tried to determine the existence of mines according to (Figure 12 c) V and S design variables as given in the lower left and (Figure 12 d) only according to the V parameter as given in the lower right. In both (c and d), the learning process was interrupted at low epoch values and was not able to learn. The information obtained from these four graphs indicates

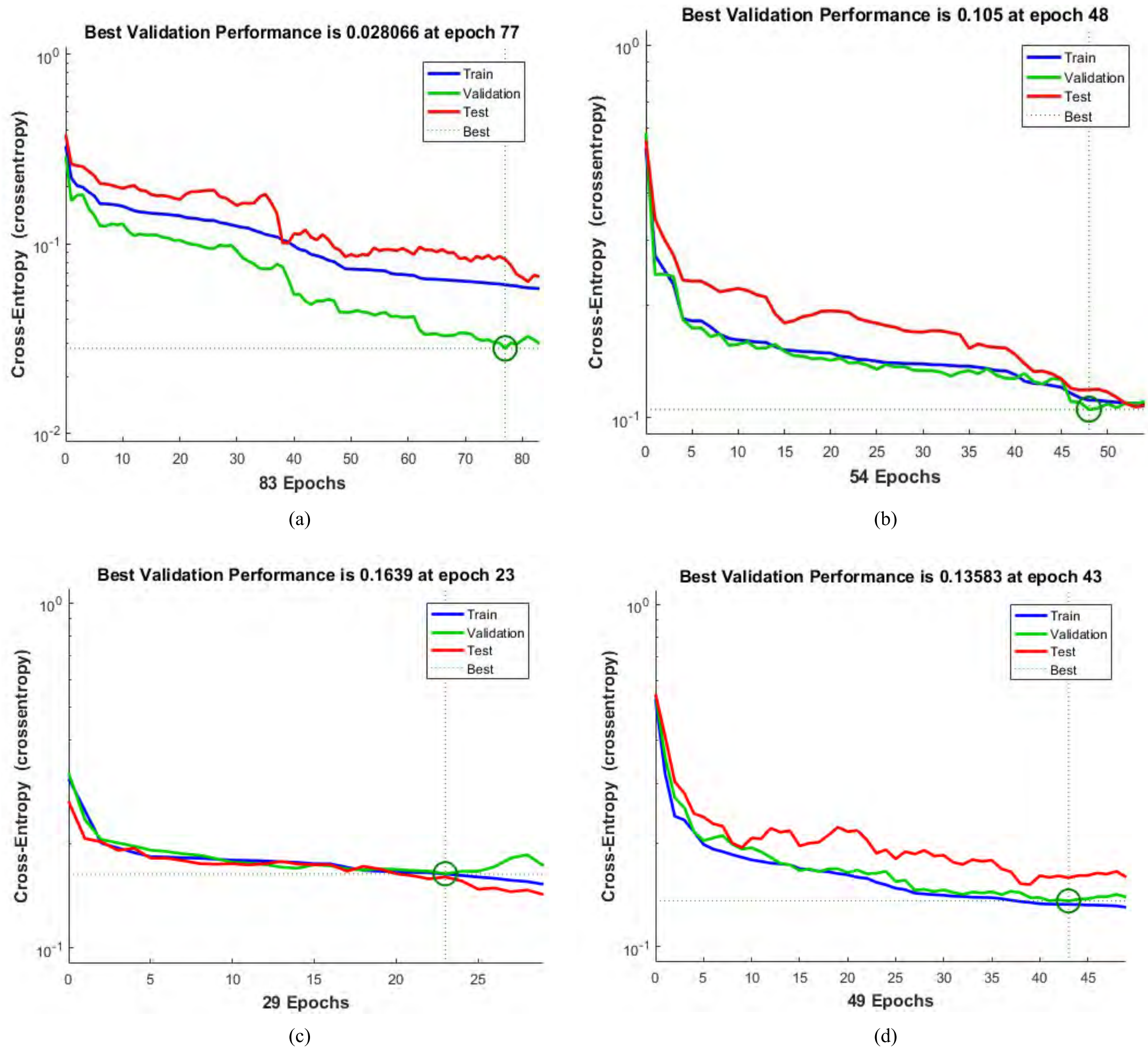

FIGURE 12. Training performances of ANN-based mine detection models. (a) $M_{sense\_1} = f_{ANN\_detect}(V, H, S)$ (proposed). (b) $M_{sense\_2} = f_{ANN\_detect}(V, H)$. (c) $M_{sense\_3} = f_{ANN\_detect}(V, S)$. (d) $M_{sense\_4} = f_{ANN\_detect}(V)$.

that V, H and S are more effective than the other combinations of input parameters in mine detection.

The Receiver Operating Characteristic (ROC curve) and confusion matrix will be examined to determine this effect of this effect. Figure 13 shows the ROC curves obtained for the formation of the Msense_1, Msense_2, Msense_3, and Msense_4 models. The area of the curve below the ROC curve shows the discrimination accuracy of the respective models. It is desirable that the ROC curve of the model developed in classification problems has the closest value to 1. According to the ROC curves shown in Figure 13, the accuracy of the Msense_1 model is higher. This information also supports that the soil type and height of measurement should be taken into consideration in mine detection.

The information that most clearly and quantitatively reveals the mine detection performances of the Msense_1, Msense_2, Msense_3 and Msense_4 models is the confusion matrices given in Figure 14. According to these comparison matrices, there is a difference 5.4% in the mine detection between the Msense_1 and Msense_2 models. The mine detection problem for Msense_1 is 10.4% and 11.6% higher than for the Msense_3 and Msense_4 models. This proves that independent variables should be selected as V, H, S in the mine detection problem. When the experimental study results of Msense_1 are examined, it is seen that the mine detection is successful with 95.6% accuracy.

2) CLASSIFICATION PERFORMANCE OF ANN-BASED MODELS

The mine detection performance of models developed in the previous section based on four different approaches was

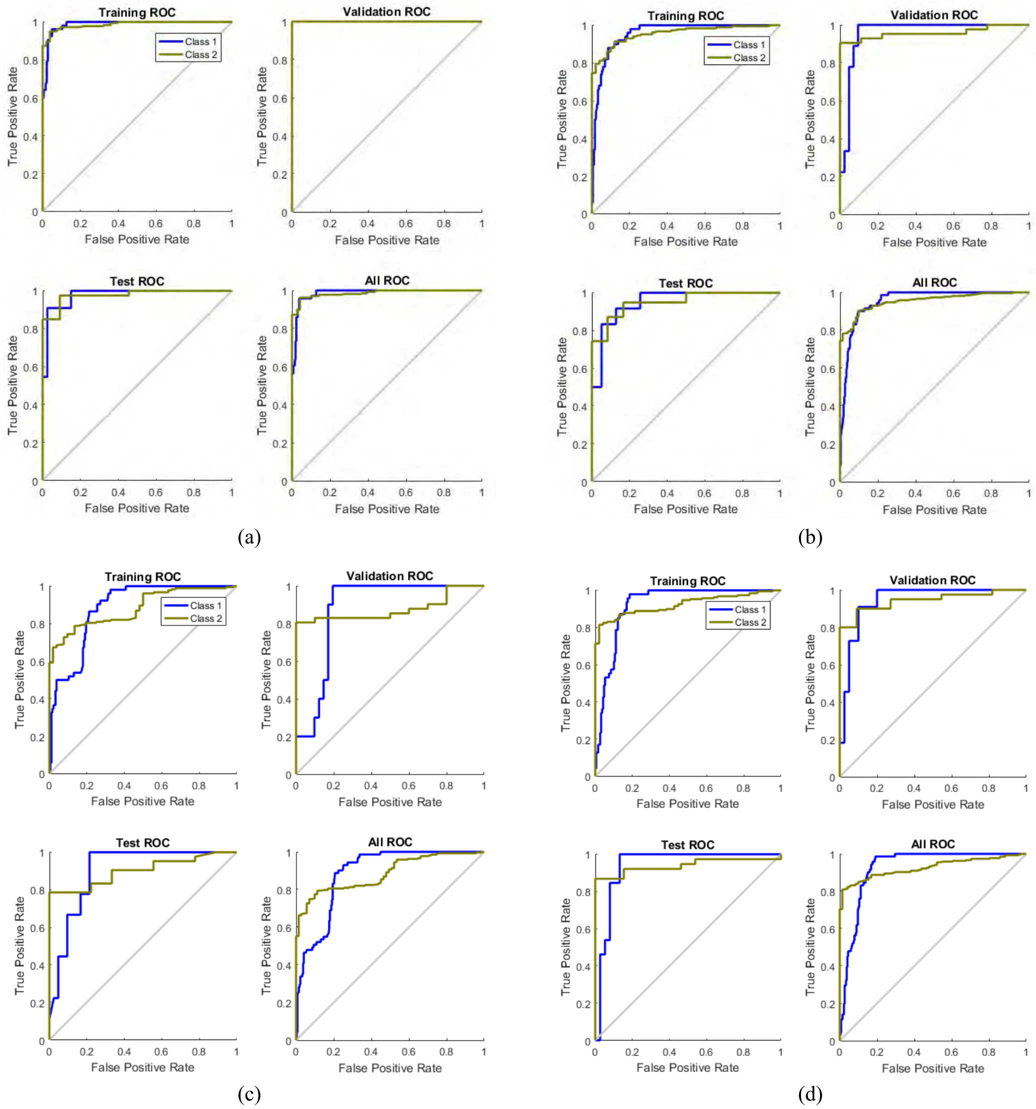

FIGURE 13. **ROC curves ANN-based mine detection models. (a) $M_{sense\_1} = f_{ANN\_detect}(V, H, S)$ (Proposed). (b) $M_{sense\_2} = f_{ANN\_detect}(V, H)$. (c) $M_{sense\_3} = f_{ANN\_detect}(V, S)$. (d) $M_{sense\_4} = f_{ANN\_detect}(V)$.**

tested experimentally. Mine diagnostic (classification) models are created based on the same approaches in this section. The objective of experimental work is to determine the most successful approach to the classification of mines. For this purpose, $M_{class\_1} = f_{ANN\_classify}(V, H, S) M_{class\_2} = f_{ANN\_classify}(V, H)$, $M_{class\_3} = f_{ANN\_classify}(V, S)$ and $M_{class\_4} = f_{ANN\_classify}(V)$ models are created and tested. The performances of four models are given comparatively. Figure 15 shows the performance curves of the models.

In Figure 15-a, the mine class is realized according to the input parameters V, H and S. In this model, the learning process continued effectively for about 85 epochs. The cross-entropy value is also reduced to a value close to 10^{-1}. In Figure 15-b, the soil type was not considered in the classification of mines. In this case, the learning process lasted about 60 epochs. The cross-entropy value is not sufficiently lower than the first model. When the graphs c and d in Figure 15 are examined, it is seen that the learning process is terminated in a short time. Both approaches (M_{class_3} and M_{class_4}) are found to have very low epoch values and a low classification performance. These results indicate that the most suitable independent variables (design parameters) for the mine classification problem are the V, H, S combination (i.e. the proposed approach).

The Receiver Operating Characteristic (ROC curve) and confusion matrix will be examined to determine the effect. In Figure 16, the ROC curves obtained for the formation of M_{class_1}, M_{class_2}, M_{class_3} and M_{class_4} models are given. According to the ROC curves shown in Figure 16, the accuracy of the M_{class_1} model is higher. This information also supports that the design parameters, the V, H and S should be taken into account in mine classification as in the mine detection process.

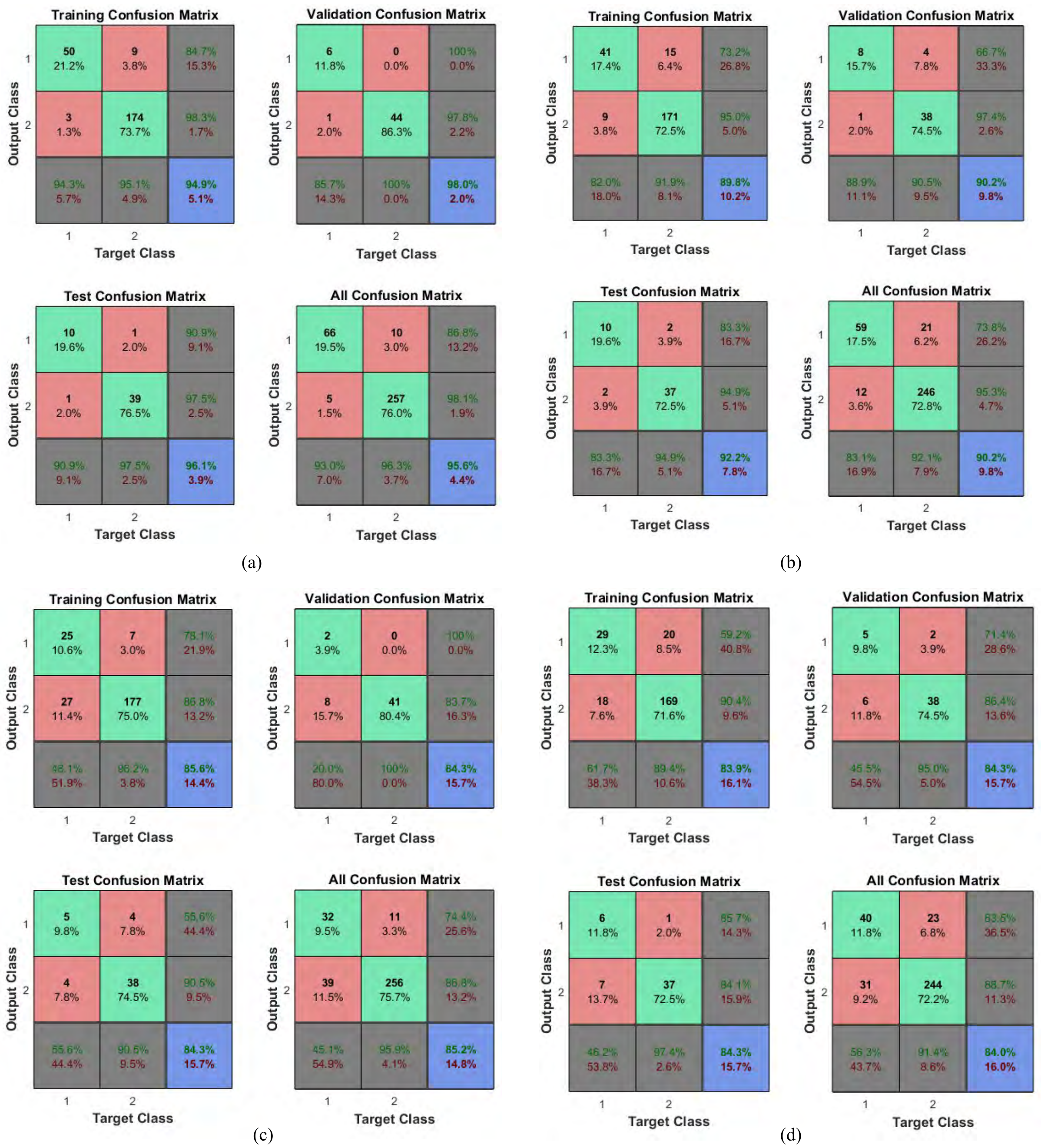

FIGURE 14. Confusion matrixes of ANN-based mine detection models. (a) $M_{sense\_1} = f_{ANN\_detect}(V, H, S)$ (Proposed). (b) $M_{sense\_2} = f_{ANN\_detect}(V, H)$. (c) $M_{sense\_3} = f_{ANN\_detect}(V, S)$. (d) $M_{sense\_4} = f_{ANN\_detect}(V)$.

The information that most clearly reveals the mine classification performances of the M_{class_1}, M_{class_2}, M_{class_3} and M_{class_4} models is the confusion matrices given in Figure 17. According to these comparison matrices, there is a difference of about 15%-20% in the mine detection between the M_{class_1} and the other models. When the experimental study results of M_{class_1} are examined, it is seen that the mines are classified with an accuracy 71.3%. It is not possible to ignore this great difference in mine classification performances of the four models. For this reason, in order to develop a strong mine classifier, the combination of VHS parameters must be considered. In this section, it has been proven experimentally that the most appropriate approach for the design of the passive mine detector consists of the V, H and S parameters.

B. PERFORMANCE OF INSTANCE-BASED TECHNIQUES

In the previous subsection, a new approach has been proposed to consider the V, H, and S parameters for passive mine detec-

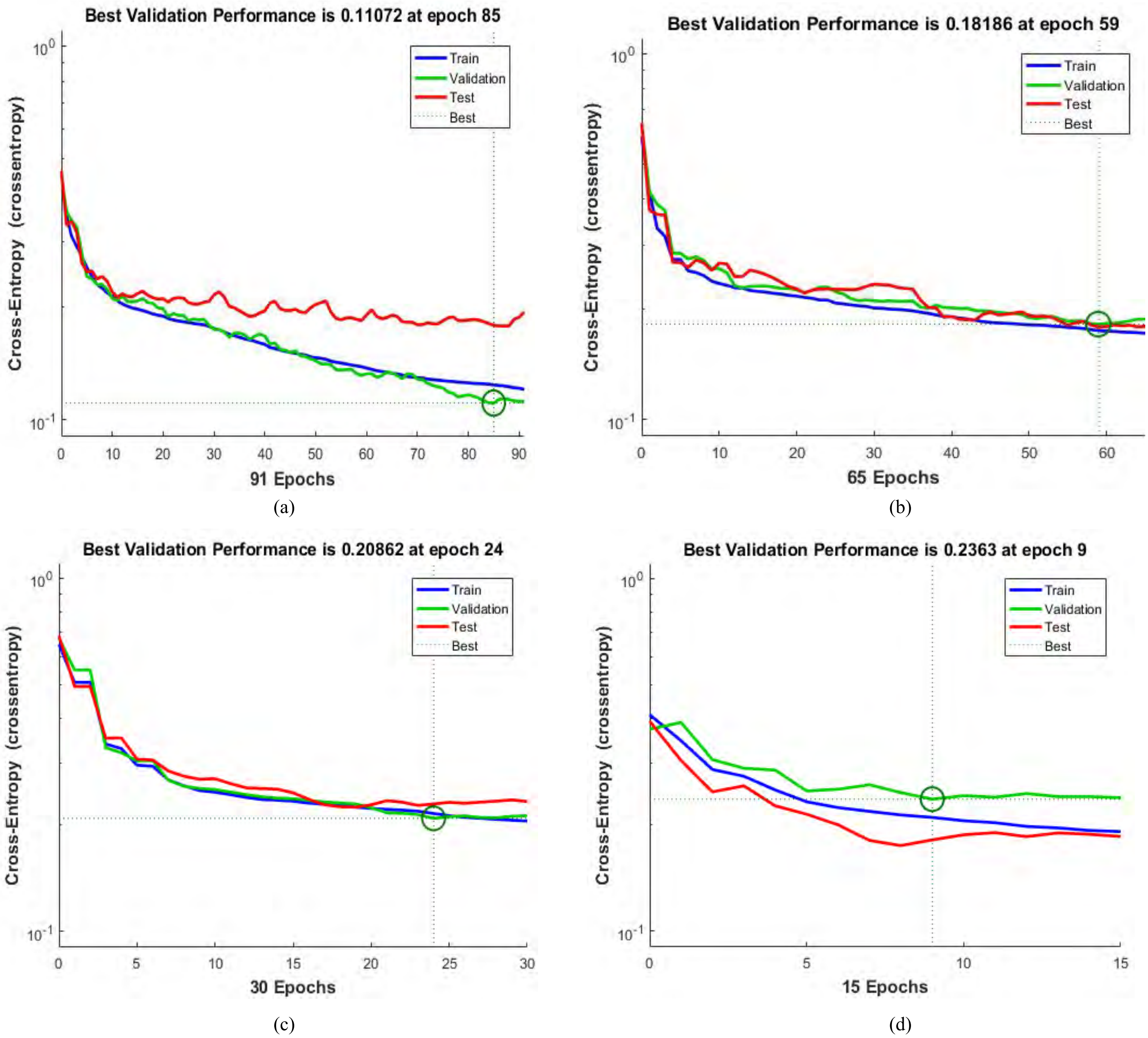

FIGURE 15. Training performances of ANN-based mine classification models. (a) $M_{class\_1} = f_{ANN\_classify}(V, H, S)$ (proposed). (b) $M_{class\_2} = f_{ANN\_classify}(V, H)$. (c) $M_{class\_3} = f_{ANN\_classify}(V, S)$. (d) $M_{class\_4} = f_{ANN\_detect}(V)$.

tor design. In this subsection, the problem is modeled using alternative techniques to the ANNs, considering the proposed approach. At the beginning of alternative techniques are sample-based, modern and hybrid classification algorithms. To learn more about the modern meta-heuristic classification techniques, the one developed by Kahraman [47] can be examined. The parameters of the algorithms applied in the experimental study are given in Table 2. In the tests for the k-neighborhood number of the user-defined parameters of the k-NN algorithm, the best performance was found in 2, 3, 4 and 5 neighboring numbers. Euclidean (EU), Manhattan (MA), Minkowski (MI), and Fuzzy Distance relations were used to measure the distance. Both weighted voting and majority voting have been tried in class determination and successful results have been obtained in both.

It has been proved in the previous section that the most appropriate approach for the detection and classification of mines is model_1 (V, H, S). In the following subsections, experimental studies are carried out by using this model_1 (V, H, S) and alternative artificial intelligence techniques. These studies consist of two parts. The first study is for the detection of mines and the second is for the classification of mines.

1) DETECTION PERFORMANCE OF k-NN AND META-HEURISTIC k-NN TECHNIQUES

Thirty-two independent mine detection models have been developed using four different k-values, four different distance metrics and two different algorithms. The detection performance of the developed models was measured by

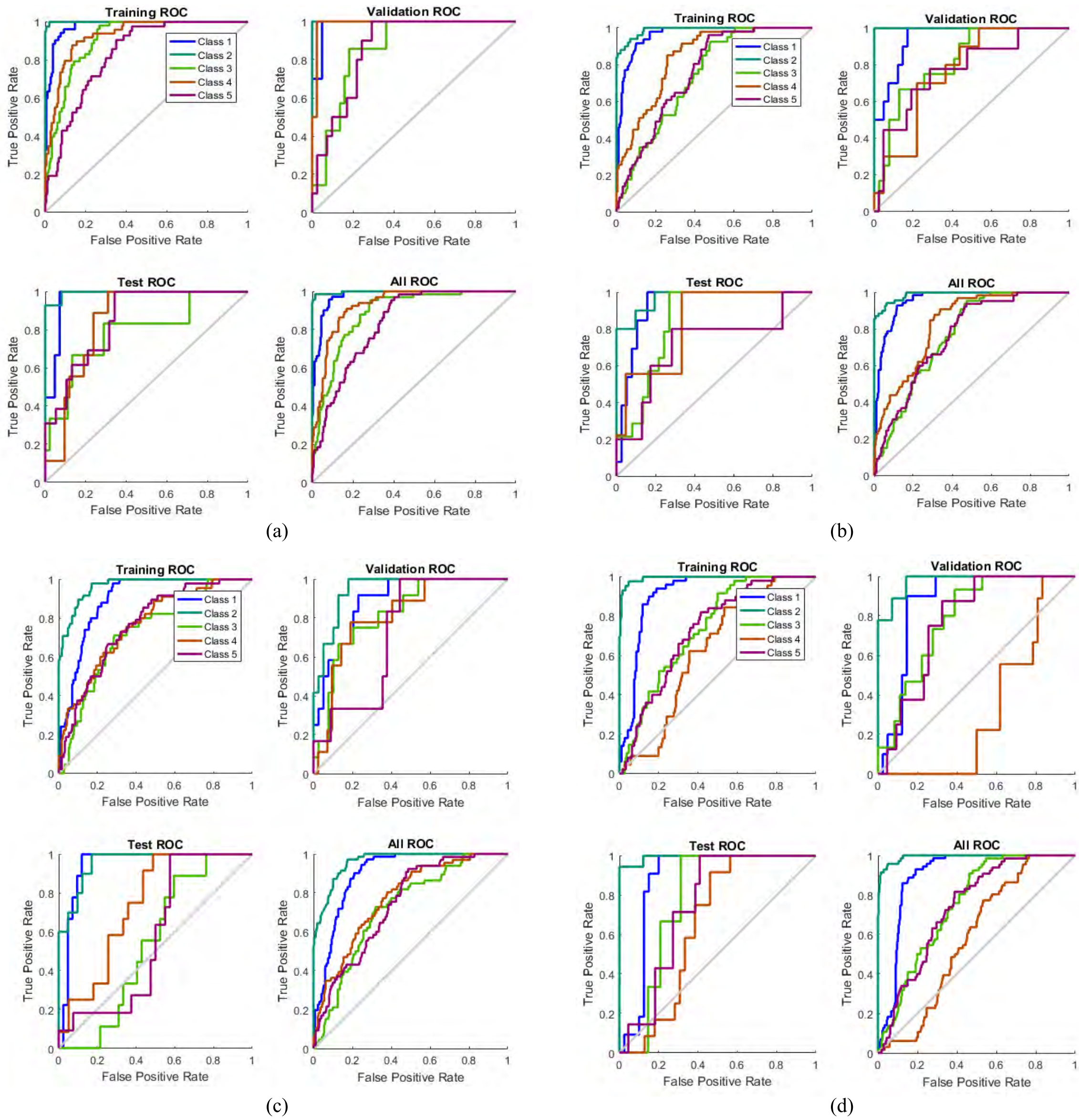

FIGURE 16. **ROC curves of ANN-based mine classification models. (a) $M_{class\_1} = f_{ANN\_classify}$(V, H, S) (proposed). (b) $M_{class\_2} = f_{ANN\_classify}$(V, H). (c) $M_{class\_3} = f_{ANN\_classify}$(V, S). (d) $M_{class\_4} = f_{ANN\_detect}$(V).**

experimental studies. The detection performances obtained from 32 independent models for the 113 data samples in the dataset are given in Table 3. The detection performance of meta-heuristic algorithm-based models is considerably higher than that of classical k-NN-based models. These differences between the performances of the two algorithms correspond to the results of other studies in the literature on problems in different domains [47].

The results given in Table 3 show that sample-based classification technique detects mines at a high rate of 95% in many cases. The detection performance of the meta-heuristic k-NN algorithm with fuzzy metric is 98.2%. If the k-value is 2, 3, 4 and the distance metric is fuzzy, then only 2 out of 113 data samples are evaluated incorrectly. This is a result of the success of the modeling approach (<M> <V, H, S>), which is especially recommended in this study. The meta-heuristic search unit has discovered the optimal values of the effects of the independent variables (V, H, S) on the dependent variable (M) as $<W_V = 0.757036, W_H = 0.657224, W_S = 0.603281>$.

2) CLASSIFICATION PERFORMANCE OF k-NN AND META-HEURISTIC k-NN TECHNIQUES

Classification performances of k-NN and meta-heuristic k-NN algorithms are given under this heading. Please refer to Reference 47 to learn about a wide range of these algorithms. As in the previous section, a total of 32 different models have been created for mine classification studies. As a result of the classifications performed using these models, the error percentages given in Table 4 are obtained.

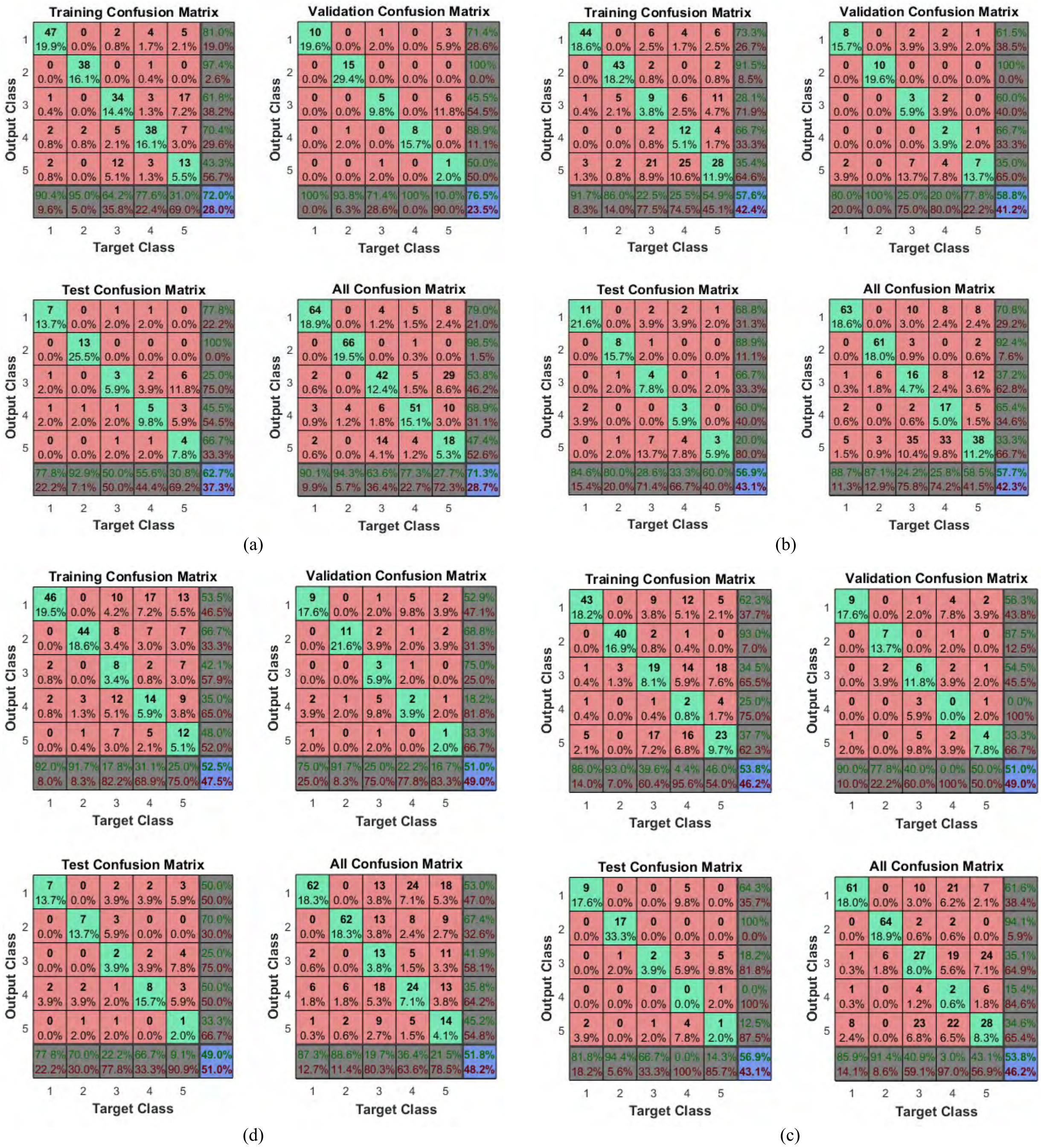

FIGURE 17. **Confusion matrixes of ANN-based mine classification models. (a) $M_{class\_1} = f_{ANN\_classify}(V, H, S)$ (proposed). (b) $M_{class\_2} = f_{ANN\_classify}(V, H)$. (c) $M_{class\_3} = f_{ANN\_classify}(V, S)$. (d) $M_{class\_4} = f_{ANN\_detect}(V)$.**

Classical sample-based classification models fail according to the classification performances given in Table 4. On the other hand, the performance of the model-based classical models at mine detection was acceptable (see Table 3). This situation indicates the difficulty of diagnosing mine types. The meta-heuristic k-NN-based models are twice more successful in detecting mines than the classical models.

The error rate is 14.2% when the mine classification performance is the highest according to the error rates obtained. On condition that this success is granted; the distance metric is ''fuzzy'' and the k-value is 4. In this case, the meta-heuristic search unit discovered the optimal values of the effects of the independent variables (V, H, S) on the dependent variable (M) as $<W_V = 0.997804, W_H = 0.703208, W_S = 0.792557>$. Of the 113 data samples, 16 were classified as erroneous, provided that an error rate of 14.2% was obtained. The confusion matrix for these 16 misclassifications is given in Figure 17.

TABLE 2. **The design parameters of meta-heuristic k-NN algorithm.**

Genetic Algorithm		
Individual Number in Population	*Generation Number*	*Parent Selection Method*
45	2000	*Roulette Wheel *Tournament
Crossover Method	*Mutation Coefficient*	*Mutation Method*
* Flip bit , * Boundary* Non-Uniform,* Uniform	interval [0.01;0.001]	*single point,*two points,*inversion
k-NN Classifier		
Number of Neighbor (k)	*Distance Metric*	*Voting Method*
2,3,4,5	EU, MA, MI, Fuzzy	Majority Vote Weighted Voting

TABLE 3. **The percentage of misdetections in instance-based algorithms.**

Algorithm	k-NN				meta-heuristic k-NN (proposed)			
k-value/ DM	EU	MA	MI	Fuzzy	EU	MA	MI	Fuzzy
2	20.4	20.4	20.4	6.2	7.1	5.3	8.0	1.8
3	13.3	16.8	13.3	9.7	5.3	5.3	8.0	1.8
4	15.9	15.9	16.8	9.7	7.1	6.2	6.2	1.8
5	21.2	19.5	22.1	15.0	4.4	4.4	5.3	2.7

TABLE 4. **The percentage of misclassifications in instance-based algorithms.**

Algorithm	k-NN				meta-heuristic k-NN (proposed)			
k-value/ DM	EU	MA	MI	Fuzzy	EU	MA	MI	Fuzzy
2	61.9	66.4	61.9	31.0	31.9	32.7	31.9	18.6
3	56.6	63.7	54.9	30.1	29.2	31.0	27.4	15.0
4	53.1	55.8	54.9	26.5	27.4	30.1	25.7	14.2
5	55.8	54.9	54.9	36.3	27.4	31.9	27.4	17.7

As shown in Figure 18, the difference between the types of mines could be diagnosed with a minimum performance of 77.3%, a maximum of 100% and an average of 85.8%. This result is the most successful of both ANN-based and sample-based models. When searching with the mine detector, many data are received and evaluated within a few seconds. The evaluation these data from the same point within the range of seconds significantly reduces the likelihood of an erroneous decision being made. In other words, the model developed according to the performance in Figure 18 can successfully diagnose the mine even under the worst conditions. In addition, if the detector is kept close

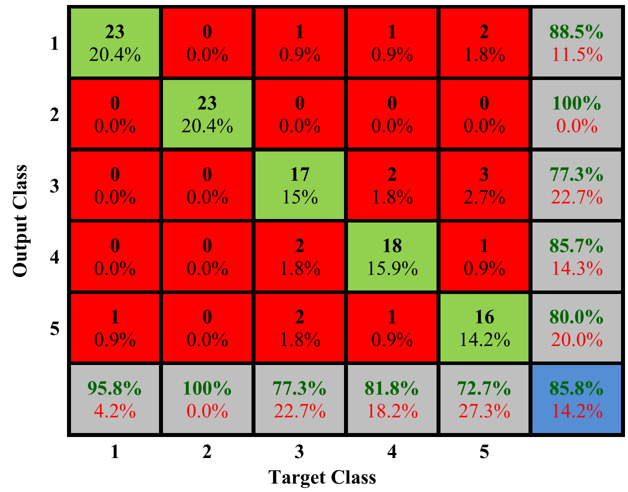

FIGURE 18. **Confusion Matrix of meta-heuristic k-NN with fuzzy (k) = 4.**

to the ground after mine detection, the classification performance is 100%. To understand this, please refer to Figure 7 again. Near-distant (up to 4cm above ground) magnetic anomaly values can be distinguished by mine types only.

IV. COMPARISONS AND DISCUSSION

It is possible to decide the most successful model after examining the detection and diagnostic performance obtained with both ANN and k-NN-based models. In the ANN-based detection model, the average success performance was 95.6% (error rate 4.4%). The mine detection percentages obtained from 32 different k-NN-based models are given in Figure 19. The detection performances of all alternative models are noteworthy. This is promising for passive detector design. The heuristic k-NN algorithm, designed with fuzzy metrics in all developed models, is the most successful. In this model, mine detection performance was 98.2%. This achievement is also a result of the mine modeling approach.

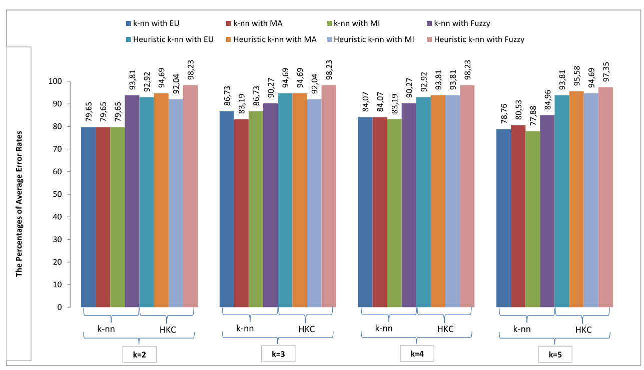

FIGURE 19. **The detection performance percentages obtained from k-NN-based detection models.**

In the ANN-based diagnostic model, the average success rate was 71.3%. Successful detection percentages obtained from 32 different models with k-NN base are given in Figure 20. Accordingly, the highest classification performance of the heuristic k-NN model with fuzzy metric

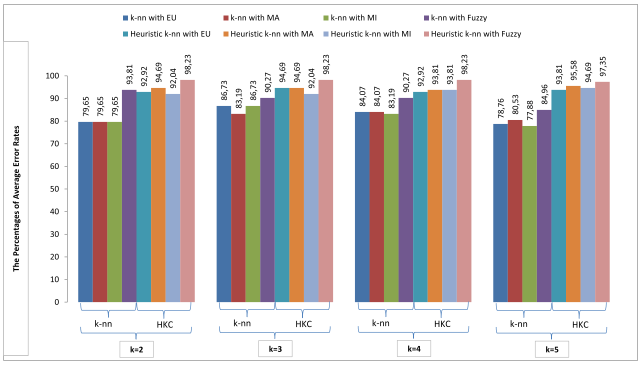

FIGURE 20. Classification performance percentages obtained from k-NN-based classification models.

is 85.8%. This is also the most successful of all developed models.

V. CONCLUSIONS

It is possible to explain the results obtained from this study carried out in order to solve the problem of detection and classification of landmines under four headings. These include the approach, method, technique, and experimental findings obtained to model the problem. The contribution and results of the study in terms of literature are given below:

i) It was known in the literature that magnetic anomalies were caused by mine presence. However, this study proves for the first time in experimental studies that the size of this anomaly exhibits a change that can be modeled depending on the height of measurement (distance of the detector/sensor from the soil surface) and soil type. Therefore, a model based on the parameters ''magnetic anomaly'', ''height'' and ''soil type'', which is a mine type dependent variable, is defined for the first time in the land mine problem. Based on this definition, the problem model was developed to define underground buried objects in a multi-dimensional problem space. It was thus possible to model the characteristics of objects more accurately. This information is vital in terms of real world practices. Because in a real application, the height of the mine detector from the ground is not constant and the soil type changes.

ii) In the literature, mine detection with active mine detectors was performed with a high detection performance, but with the risk of triggering the mine blasting system at any moment. The second advantage of the approach proposed (meta-heuristic k-NN with fuzzy metric) in this study is that the mine detection with a passive detector design is performed with 98.2% performance. This successful detection performance will give momentum and direction to future studies related to passive detectors.

iii) Most of the studies in the literature focused on mine detection. The classification of mines with a passive detector design has never been achieved before. The approach proposed in this study has created a function of the magnetic anomalies created by the mines buried in the soil depending on the mine type, height and soil type. Thanks to this model, mines are located in multidimensional space according to their types. In this way, a passive detector design has opened the way for the detection of mines. Experimental studies have shown that mine detection is successfully performed at approximately 85.8%. It is important that this ratio is obtained in a real-world application where the detector is moving and its height changes at any time.

iv) Another important contribution of this study to the literature is to convert the mine detection problem into a mine classification problem and model it effectively with artificial intelligence-based techniques. In the literature, ANNs have been the most frequently used technique for modeling classification problems with multidimensional and numerical valued input properties. ANN is preferred because it is easy to apply through ready toolboxes and creates successful models. In addition, recently developed hybrid classification algorithms have shown remarkable classification performance. However, applying new and powerful algorithms to a problem is not as easy as conventional artificial intelligence techniques. For this, expert support is needed in the field of artificial intelligence. In this paper, alternative and modern classification techniques have been successfully applied to model problem. The most successful of these techniques is the fuzzy logic-based meta-heuristic classification algorithm. This algorithm has proven to be very successful, especially in the mine diagnostic process.

As a result, it is expected that this paper will encourage accelerating passive mine detector-based studies attempting to identify mine types; and redefining the mine problem as a multi-dimensional problem.

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