Fırat Üniversitesi Deneysel ve Hesaplamalı Mühendislik Dergisi

FUJECE

Geniş Frekans Bantlı Anten Sistemleriyle Gömülü Nesnelerin Türünün Tespitinde Yapay Zeka Tabanlı Hibrit Bir Yaklaşım

Ebru EFEOĞLU[1*]

[1,*] Yazılım Mühendisliği, Mühendislik Fakültesi, Kütahya Dumlupınar Üniversitesi, Kütahya, Türkiye.
[1]ebru.efeoglu@dpu.edu.tr

Geliş Tarihi: 01.05.2024
Kabul Tarihi: 18.07.2024

Düzeltme Tarihi: 26.06.2024

doi: 10.62520/fujece.1476716
Araştırma Makalesi

Alıntı: E. Efeoğlu, "Geniş frekans bantlı anten sistemleriyle gömülü nesnelerin türünün tespitinde yapay zeka tabanlı hibrit bir yaklaşım", Fırat Üni. Deny. ve Hes. Müh. Derg., vol. 3, no 3, pp. 362-376, Ekim 2024.

Öz

Kazı öncesinde gömülü nesnenin cinsinin bilinmesi gereksiz kazı yapılmasını önler. Üstelik zamandan ve paradan tasarruf sağlar. Bu çalışmada gömülü nesnelerin tespiti için bir deney seti hazırlandı. Deney seti, geniş frekans bandında elektromanyetik dalgalar gönderip alan bir anten, yansımaları kaydeden ve işleyen bir yazılımdan ve kum havuzundan oluşturuldu. Çalışmada bu kum havuzuna farklı derinlik, boyut ve şekillerde metalik ve metalik olmayan nesneler gömülerek bir profil boyunca ölçümler alındı. Yapılan ölçümlerden 2 boyutlu görüntüler oluşturuldu ve bu görüntülere görüntü işleme teknikleri uygulandı. İşlenmiş görüntülerden nesnenin türünü tespit etmek için sınıflandırma algoritmaları kullanıldı. Algoritmaların başarısını artırmak için, nitelik seçme teknikleri olarak korelasyona dayalı öznitelik seçimi (CFS) ve Temel Bileşen Analizi (PCA) kullanılmıştır. CFS ile öznitelik seçiminde arama yöntemleri olarak metasezgisel optimizasyon algoritmalarından genetik algoritma (GA), Parçacık Sürü Optimizasyonu (PSO), Harmony arama (HA) ve Evrimsel arama (EA) tercih edildi. Algoritmaların performansı 10 kat çapraz doğrulama yöntemi kullanılarak analiz edildi. Sonuç olarak PCA algoritmasının öznitelik seçiminde kullanımının metasezgisel algoritmalara göre sınıflandırma başarısını daha fazla arttırdığı anlaşıldı. Kullanılan sınıflandırma algoritmaları arasında en başarılı olanı Rastgele ağaç algoritması oldu. PCA sonrasında bu algoritmanın doğruluk değeri %95,8'e ulaşıldı. Bu nedenle ölçüm sistemine gömülü yazılımda PCA ve Rastgele ağaç algoritmalarının kullanıldığı hibrit bir yaklaşım önerilmektedir.

Anahtar kelimeler: Yapay Zeka, Gömülü nesne, Metasezgisel optimizasyon algoritmaları, PCA, Görüntü işleme.

*Yazışılan yazar

Firat University Journal of Experimental and Computational Engineering

An Artificial Intelligence-Based Hybrid Approach to Detect the Type of Buried Objects with Broad Frequency Band Antenna Systems

Ebru Efeoğlu [1*]

[1,*] Software Engineering, Faculty of Engineering, Kütahya Dumlupınar University, Kütahya, Türkiye.
[1]ebru.efeoglu@dpu.edu.tr

Received: 01.05.2024
Accepted: 18.07.2024

Revision: 26.06.2024

doi: 10.62520/fujece.1476716
Research Article

Citation: E. Efeoğlu "An artificial intelligence-based hybrid approach to detect the type of buried objects with broad frequency band antenna systems", Firat Univ. Jour.of Exper. and Comp. Eng., vol. 3, no 3, pp. 362-376, October 2024.

Abstract

Knowing the type of buried object before excavation prevents unnecessary excavation. Moreover, it saves time and money. In this study, an experiment set was prepared for the detection of buried objects. The experimental set was composed of an antenna that sends and receives electromagnetic waves in a wide frequency band, software that records and processes reflections, and a sandbox. In the study, metallic and non-metallic objects with different depths, sizes and shapes were buried in this sand pool and measurements were taken along a profile. 2D images were created from the measurements and image processing techniques were applied to these images. Classification algorithms were used to detect the type of bruied object from processed images. To increase the success of the algorithms, correlation-based attribute selection (CFS) and Principal Component Analysis (PCA) were used as attribute selection techniques. Genetic algorithm (GA), Particle Swarm Optimization (PSO), Harmony search (HA), and Evolutionary search (EA), which are among the metaheuristic optimization algorithms, were preferred as search methods in attribute selection with CFS. The performance of the algorithms was analyzed using the 10-fold cross-validation method. As a result, it was understood that the use of the PCA algorithm in attribute selection increases the classification success more than metaheuristic algorithms. The most successful among the classification algorithms used is the Random tree algorithm. After PCA, the accuracy value of this algorithm was 95.8 Therefore, a hybrid approach is proposed in which PCA and Random tree algorithms are used in the software embedded in the measurement system.

Keywords: Artificial Intelligence, Buried object, Metaheuristic optimization algorithms, PCA, Image processing

*Corresponding author

Plagiarism Checks: Yes – Turnitin
Complaints: fujece@firat.edu.tr

1. Introduction

There are many Geophysical prospecting methods. Seismic [1], Electrical Resistivity Tomography [2] etc. for detection of buried objects underground. However, the GroundPenetrating Radar (GPR) method is often used in near-surface applications. Buried objects can be metallic or non-metallic. Detection of buried non-metallic objects is more difficult than detection of metallic objects. Although metallic objects are detected using Electromagnetic Induction (EMI) sensors, Magnetic induction spectroscopy [3], non-metallic objects cannot be detected by EMI sensors [4]. For this reason, the GPR method is preferred especially for the detection of non-metallic objects [5]. This method is very popular in military and engineering fields due to its fast data collection [5,6]. It was often used to detect mines and buried explosives [7,8], objects buried at different depths [9], archaeological remains [10,11], underground pipeline [12].

GPR systems are divided into pulse-modulated systems and non-pulse-modulated systems. Pulseless modulation systems operate in the time domain and use a pulse signal [13]. Pulse modulation systems emit a Gaussian electromagnetic wave signal. This system uses a signal over a wide frequency band. Detecting buried objects from such systems requires expertise and time [12]. Therefore, approaches that automatically detect objects have been researched and proposed. Wavelet transform [14], Hough transform [15] and radon transform [13], image processing techniques [16], Ellipse inversion model [17] are some of these approaches. In recent years, studies on automatic detection of buried objects with machine learning techniques have been examined [18]. Automatic detection of consecutive lines from sonar images was done using machine learning methods [19]. Machine learning methods were used to detect underwater mines with synthetic aperture sonar images [20], to detect voids in underground pipelines, and to analyze GPR radargrams [21]. In addition, an automatic flaw detection system for sewer pipes has been developed from CCTV images [22]. It is difficult and costly to produce real data in studies for the detection of buried objects. For this reason, many researchers preferred to use synthetic data in their studies [23]. For example, synthetic images were created for the detection of buried pipes and hyperbolas in these images were detected by machine learning techniques [24]. Synthetic data were used for automatic recognition of tunnel lining elements from GPR images [25].

Synthetic data were not used in this study. An experimental setup was created. Metallic and non-metallic objects (Brick, tile, marble ceramic) of different shapes were buried in the sandbox at different depths. Measurements were taken. Then, classification algorithms were used with the data obtained from the measurement system. To date, many studies have been carried out for the detection of metallic and non-metallic buried objects. The buried objects were detected, but the buried objects were not classified as metallic or non-metallic. In this study, a measurement system and software based on artificial intelligence techniques are proposed to classify buried objects as metallic and non-metallic objects. The difference of the proposed system from other systems is that it determines the type of buried object regardless of its shape.

2. Experimental Setup and Data Collecting

The experimental setup consists of an antenna used as both a transmitter and a receiver, a laptop, a Vector Network Analyzer (VNA) and a sand box (Figure. 2). A signal is sent from the VNA to the sand box with a set step frequency and frequency band range (Figure. 1)**.**

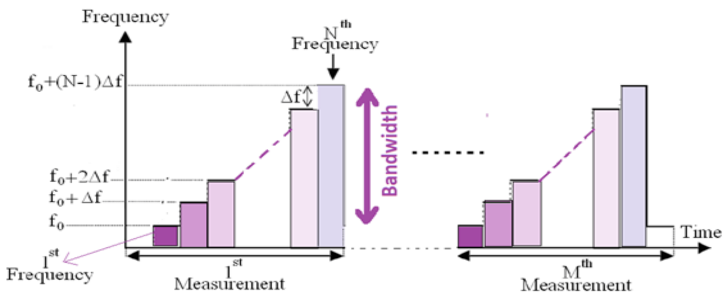


Figure 1. Implementation of measurement

The transmitted signal is a sequence of rising step frequencies. It starts from the starting frequency and the frequency is increased step by step. The frequency of the nth sample in the sequence can be calculated by Equation (1) when the starting frequency F_0 is taken as the constant rise frequency Δf.

$$Fn = F0 + \Delta f \qquad n = 0, \ldots . M - 1 \tag{1}$$

The maximum penetration depth (dmax) of the signal is calculated using equation (2).

$$d_{max} = \frac{c}{2\Delta f} \tag{2}$$

where c is the speed of light.

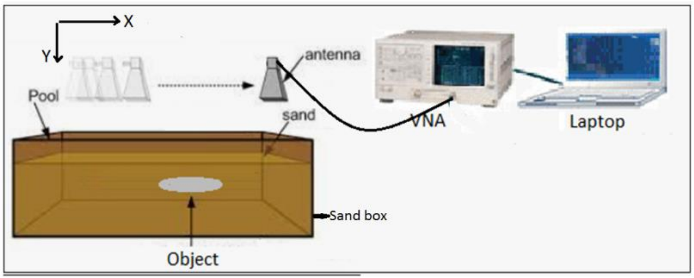


Figure 2. Experimental setup

For measurements metallic and non-metallic objects of different depths and shapes were buried in the sand box. Measurements were taken by slowly moving the antenna along the x axis from the surface of the sand box as shown in Figure. 2.The profile length is 60 cm, the number of measuring points is 61, the frequency band range is 1Ghz 6Ghz, the number of frequency steps is 64.

3. Imaging and Image Processing

1-D depth profiles were created by applying the inverse Fourier transform to the data collected at each measurement point. Then, these 1-dimensional depth profiles were aligned side by side to obtain 2-D images. Color layout filter applied to 2D images.

3.1. Color layout filter

Color is the most basic quality of the image. Colors can be used to describe and represent an image. The Color Layout Descriptor (CLD) is designed to capture the saptial distribution of dominant colors in an image. for cld computation, color are expressed in the YCbCr color space. CLD is very compact descriptor, therefore it fits perfectly for fast browsing and search applications. It is also resolution invariant.
CLD can be computed by following these steps.

1-Image Partitioning: The image is divided into 8*8(64) block. This makes CLD Scale invariant.

2- Representative Colour Detection: There is a representative color for each block. The average color of the block is used to select the representative color. Also the image is reduced to 64x64 so each block shrinks to 8x8.

3-color space change: The image having average color blocks is in RGB space. Now this RGB is changed toYCbCr color space.

4- DCT transformation: Each color channel (Y,Cb,Cr) is transformed into DCT coeffients by performing 8x8 discrete Cosine Transform (DCT) of each 8x8 block.Therefore, each block carries 64 DCT coefficients.

5- Quantization: Zigzag scanning is used. A few low frequency coefficients are selected and quantized to form the descriptor. For Y-DCT only 6 coeffients are selected while from both Cb and Cr only three coefficients are selected and quantized.

6- Forming CLD attribute vector: For avarage image and its DCT it can be seen that expect DC coefficient, rest of coefficients are zero as one 8x8 block is a constant function. Therefore instead of taking 6,3 and 3 coefficients from DCT-Y, DCT-Cb and DCT-Cr respectively, it is sufficient to take only single DC coefficient from each block. The coefficients are arranged as given in Equation 1.

$$CLD = [Y_{dct1}, Y_{dct2}, \dots \dots . Y_{dtc64}, Cb_{dct1}, Cb_{dct2} \dots .., Cb_{dct64}, Cr_{dct1}, Cr_{dct2}, \dots \dots \dots, Cr_{dct64} \quad (1)$$

4. Attribute Selection

Using all attributes in classifications may not yield good results in some cases. In particular, the use of all attributes in noisy data and images negatively affects the success. Therefore, it is necessary to remove some unnecessary attributes. By using accurate data and relevant attributes, classification success is increased and the size of the data set is reduced. As the size of the dataset decreases, the computation speed increases and the memory requirement decreases. Attribute selection is very important to increase classification success and computational speed. There are algorithms used in the selection of attributes. In this study Correlation-based attribute selection (CFS) and PCA method will be used. The generalized version of attribute selection is given in Figure 3.

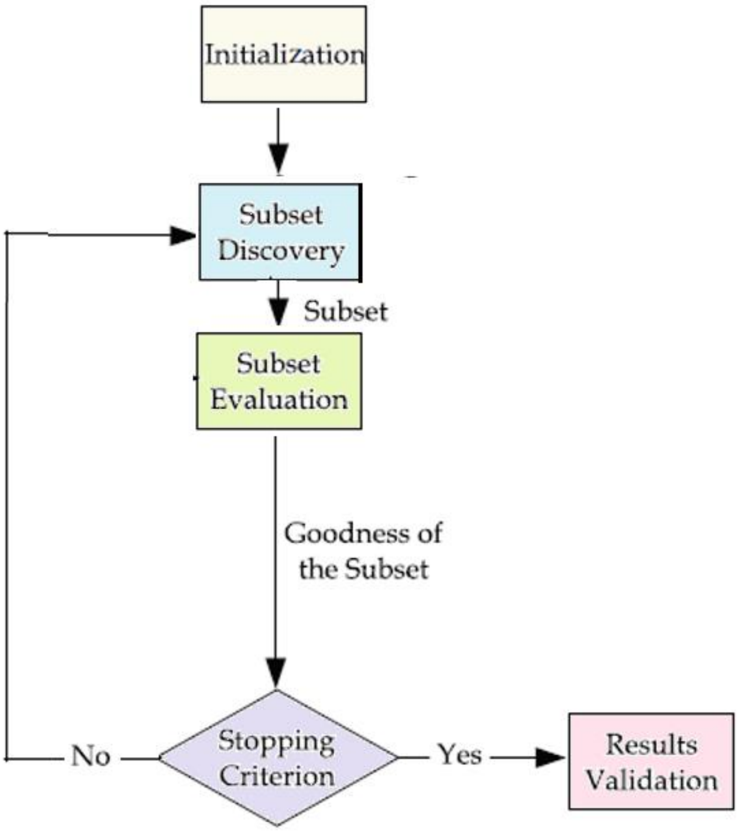


Figure 3. Generalized version of attribute selection flowchart [26].

4.1. Correlation-based attribute selection (CFS)

This method selects attributes that are low correlated to other attributes and highly correlated to class [27]. A function and different search algorithms are used to calculate the information values of the attribute subsets of the dataset. Metaheuristic optimization algorithms are preferred as search algorithms. In this study, PSO, GA, HA, EA algorithms were used in metaheuristic optimization algorithms.

4.1.1. Particle Swarm Optimization (PSO)

This algorithm was inspired by the foraging behavior of flocks and was developed by Dr. Kennedy and Dr. Eberhart. This method is a population-based metaheuristic optimization method [28]. In this method, each individual is defined as a particle. Particles in random coordinates update their position and velocity information to reach the best solution value. The experience of the particles from their neighbors is taken into account in the update.

4.1.2. Genetic Search Algorithm (GA)

This algorithm was proposed by Charles Darwin [29]. It was put forward, inspired by the theory of evolution [30]. The theory of evolution is based on the rule of survival of the fittest. The algorithm searches in accordance with this rule and tries to find a solution. Chromosomes are the variables of the problem to be solved. On these chromosomes, a random solution is first created and then the best solution is reached by making changes in the chromosomes.

4.1.3 Harmony Search Algorithm (HA)

It was suggested by Geem et al. [31]. This algorithm was inspired by the notes in the music. Notes combine to form harmony. Each harmony represents a workaround. It is aimed to reach the best melody in terms of harmonic with the notes in the music [32].

4.1.4 Evolutionary Search Algorithm (EA)

It is used to find the best solution to a problem in the search space. This algorithm uses mutation and elitist selection as search operators. Chromosomes are represented by strategy parameters and pairs of individuals. The strategy parameter is the parameter that mutates the individual it belongs to. It evolves to have optimal value in each generation.

4.2 Principal Component Analysis (PCA)

The first studies on PCA were started in 1901 by Karl Pearson Pearson [33]. PCA preserves the existing changes in the data set containing interrelated variables. It is a transformation that includes a large number of interrelated variables and reduces the size of the data set to less size by preserving the existing changes in the data as much as possible. PCA is a very effective statistical method in revealing the necessary information in the data. With this method, a new set of dimensions is found to better represent the diversity of the data. The first dimension shows the most variety. 2. The dimension is chosen to be perpendicular to the first dimension and to show as much variation as possible.

5. Clasification Algorithms

Decision trees are used in classification and regression. In decision trees, the model can be compared to an inverted tree. This model consists of root node, branches and leaves. Nodes have variables, branches have values of variables, leaves have results. The first node in the decision tree is called the root node. The root node can be split. Branching starts from the root node and new nodes are obtained. Decisions are made by following successive nodes until they reach the leaf from the root node. Two popular methods are used to select the best attribute for nodes in a Decision tree. These are the information gain and the Gini index. Knowledge Gain calculates the extent to which a attribute provides information about a class. The nodes are split using the value of the information gain. During the division, the node with high information gain is divided first. The Gini Index is a measure of purity in constructing the Decision tree. Node with low Gini index is preferred for attribute selection. Pruning is removing unnecessary nodes from the tree. It is applied to obtain an optimal decision tree. In the study, AD tree [34], BF tree [35], Randon forest [36], Random tree, Decision Stump [37], Simple Cart [38] and

Optimized forest algorithms [39]. were used. The characteristic attributes of the algorithms are given in Figure.4.

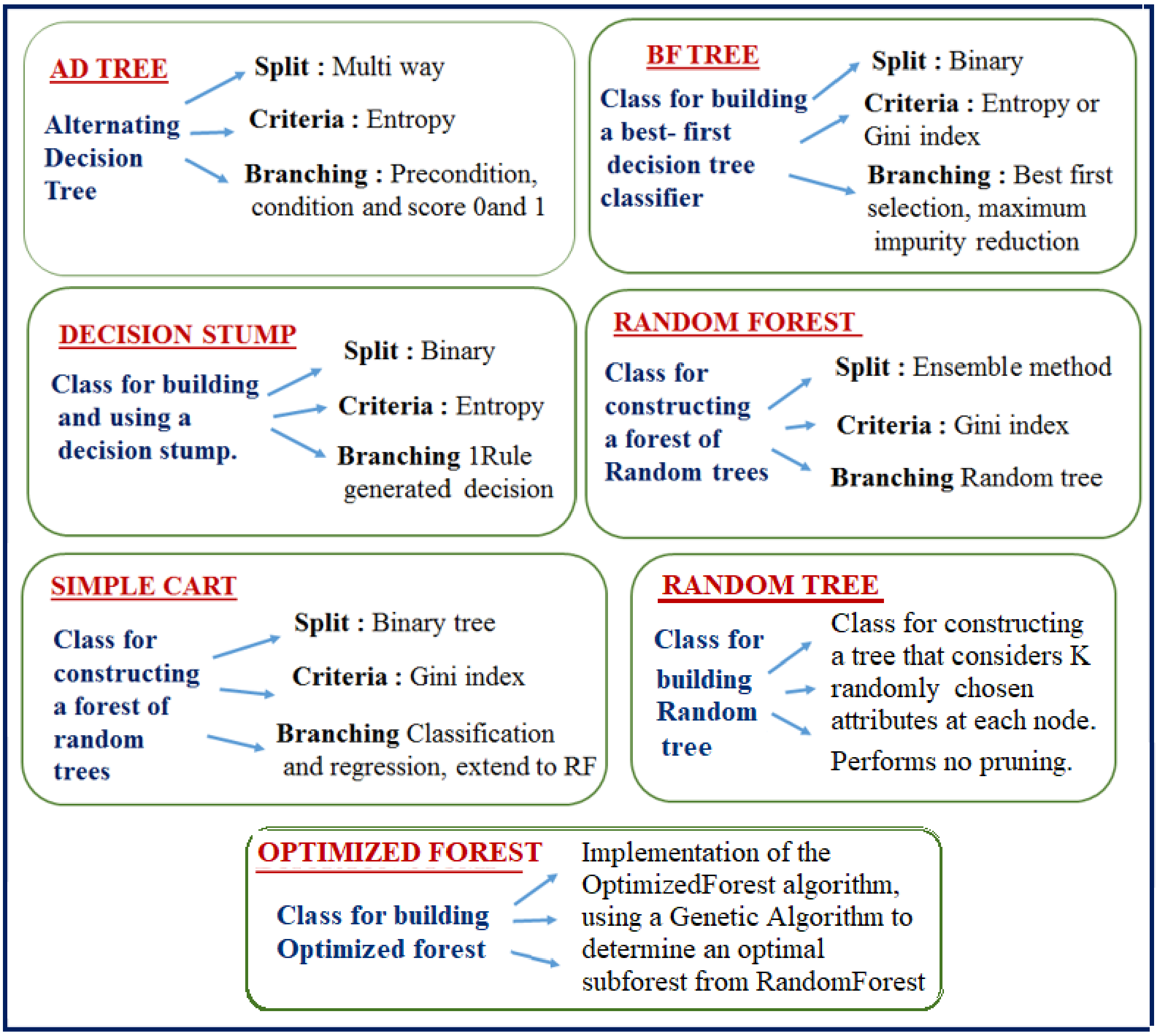


Figure 4. Decision Tree Algorithm Characteristics

6. Performance Metrics

Some metrics are used to compare the classification performance of algorithms. Thanks to these metrics, it is decided which algorithm is more successful. The formulas of the metrics are given in Figure 5. In the formula, TP and TN represent the number of samples that the algorithms predicted correctly, and FP and FN represent the number of samples that the algorithms predicted incorrectly.

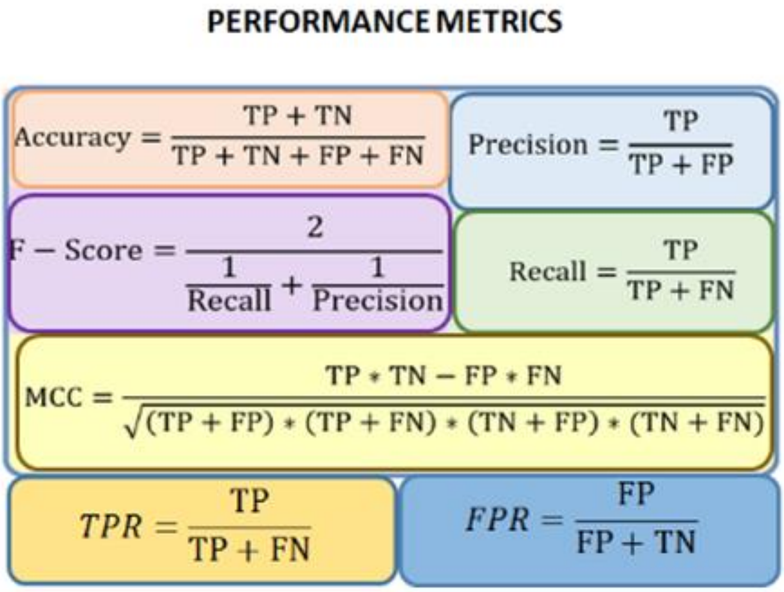


Figure 5. Performance metrics

MCC value is generally preferred to evaluate the classification performance when unbalanced datasets are used. The F-measure value is used when precision and Recall are incompatible. Apart from the metrics indicated in Figure (1), there are other metrics that can be used in performance analysis. These are Area Under the ROC Curve (AUC), Precision Recall curve, Kappa and RMS. The ROC curve is plotted with TPR against the FPR where TPR is on the y-axis. The area under the ROC curve is the AUC value. PR curves are created by plotting precision (x-axis) versus recall (y-axis). Kappa refers to the agreement between the actual classes and the predicted classes. Performance metrics take a minimum of 0 and a maximum of 1.The root mean square (RMS) error value is used when the performance of the two algorithms is almost the same [40]. Indicates the error rate in classification. Unlike other metrics, a low rms value is required for successful classification.

In the study, data collected in the frequency domain were transferred to the time domain using IFFT. Zero padding has been applied to increase resolution in the IFTT application. 1D depth profiles were created for each measurement point. Then, 1D depth profiles were lined up side by side to obtain 2D color images. Color layout Filter has been applied to these images. Data was classified without and with attribute selection. To analyze the classification performances of the algorithms, various performance metrics were calculated and the results were interpreted. PCA and CFS methods were preferred in feature selection.The flow chart of the study is shown in Figure 6. When evaluating the performance of algorithms, the data set is generally divided into two: test data set and training data set. The algorithm is tested with a specific test data. In this study, the cross-validation method was used to test the entire data set. Another reason for using the cross-validation method is to test the success of the algorithms in classifying data that is not in the database.

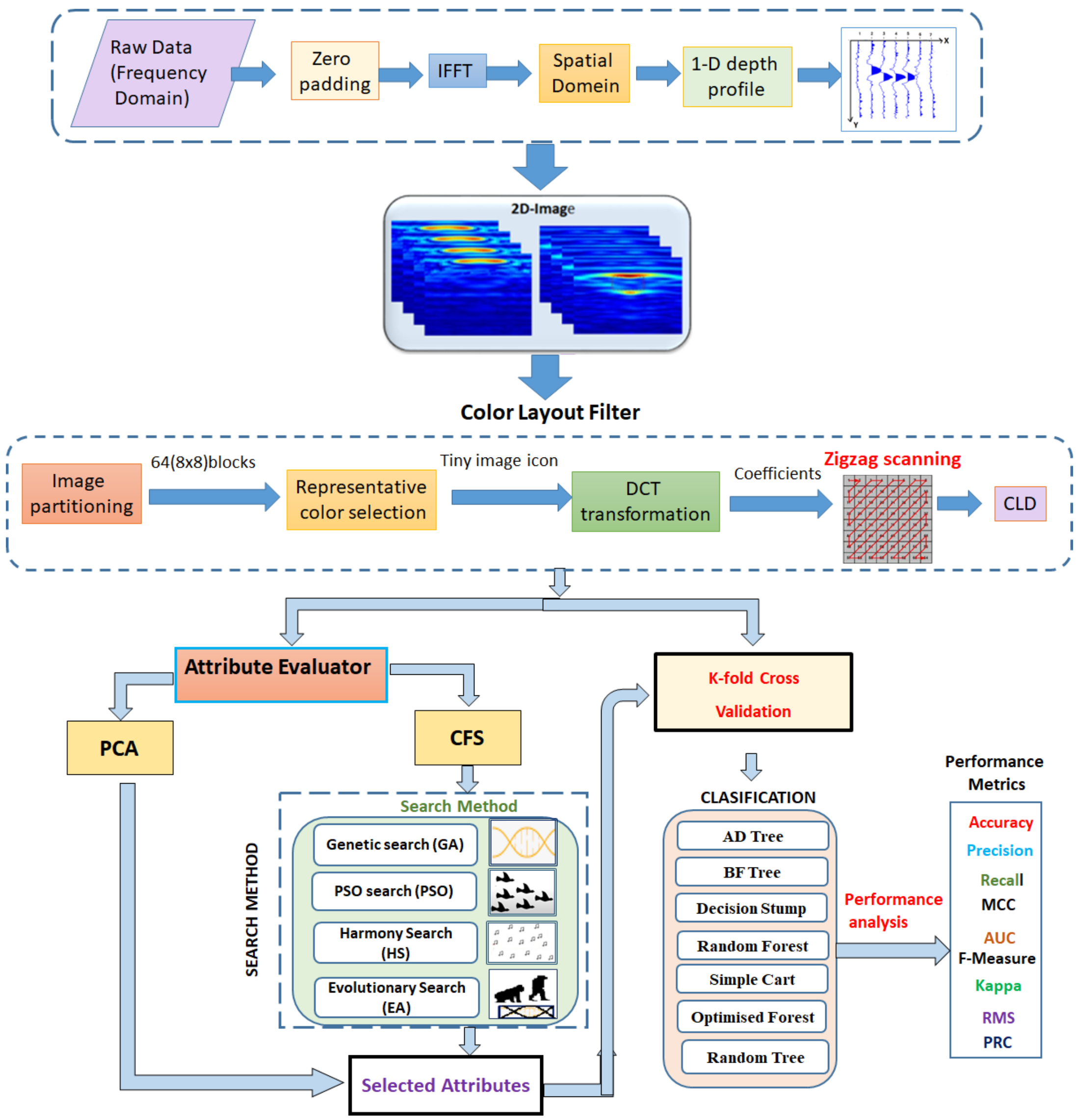
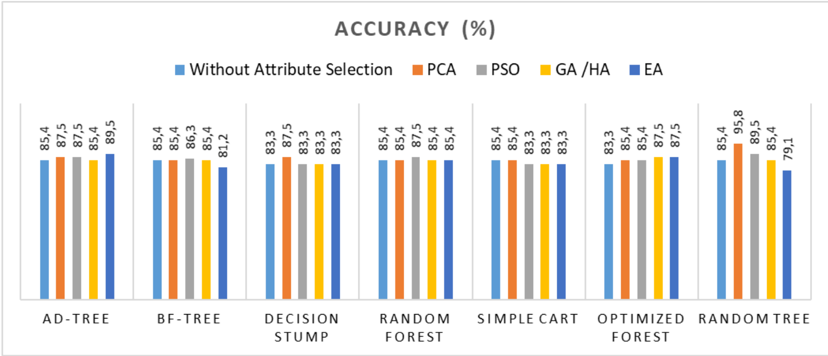


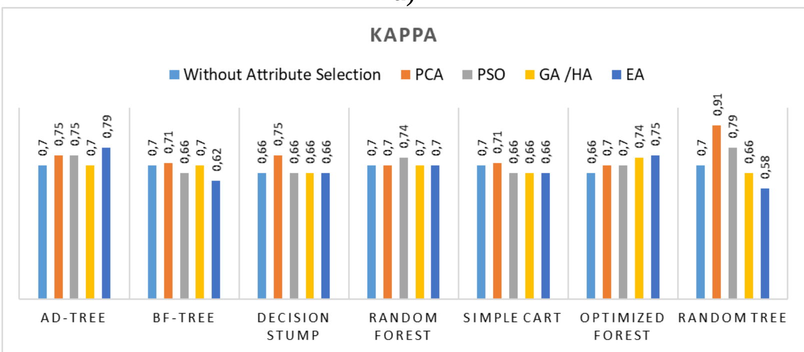
Figure 6. The flow chart of the study

7. Results

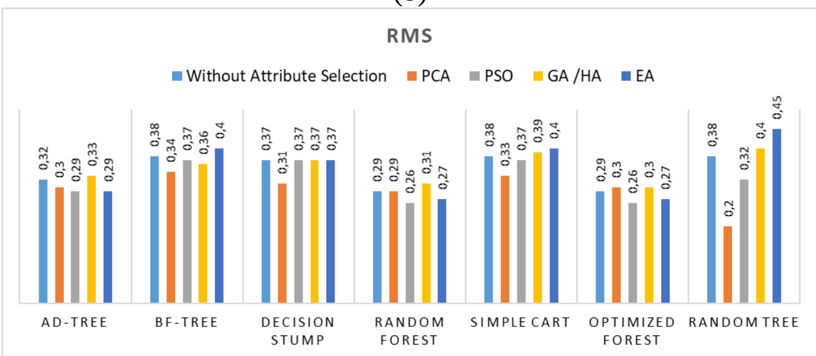
The most important metric used in performance analysis is accuracy. Without attribute selected the highest accuracy rate obtained in the classications was 85,4%. The use of the PCA algorithm increased the accuracy of all algorithms. The accuracy value of the random tree algorithm was 95.8%. As can be seen, the PCA algorithm was more effective than CFS in increasing the accuracy of the algorithms. It is unreliable to evaluate performance using just accuracy without using other performance metrics [41]. Therefore, other metric values were also calculated. Calculated metrics are given in Tables and Figures. The highest kappa and lowest rms values were obtained when the random tree and PCA method were used together.(Figure. 7b,7c).



a)



(b)



(c)

Figure 7. Performance metrics of algorithms a) Accuracy b) Kappa c) Rms

In order to understand which algorithm is more successful in detecting which type of object, the performance metrics of the two classes are calculated separately. The results are given in Table 1 and Table 2. The Recall value indicates how many of the objects that should be predicted as metallic are predicted as metallic, or how many of the objects that we should predict as non-metallic are predicted as non metallic. In archaeological studies, predict a non-metallic object as metallic will lead to incorrect excavation and damage to the buried object. When the algorithm correctly predicts all objects of the non-metallic class, the Recall value of the non-metallic class is 1. For example, when the Random forest algorithm is applied without attribute selection, the recall value of the metallic class is lower than the recall value of the non-metallic class. This result is an indication that the algorithm is more successful in detecting non-metallic objects. On the other hand, when the Decision strrump algorithm is applied without attribute selection, the recall of the non-metallic class is lower than the recall of the metallic class. This result is an indication that the algorithm is more successful in detecting metallic objects. When the metal object is searched, if the algorithm predicts the metal as non metal, there will be a loss because the metal object cannot be detected. For this reason, high precision value is an important criterion for us in model selection. According to the table, the highest Recall and Precision values were obtained with the hybridization of PCA and Random tree algorithm. Other performance metrics given in the table are also compatible with these values. The MCC metric is often used on unbalanced datasets. Since the data used in the study is not unbalanced, the MCC values of the two classes are approximately the same. It was understood from the tables that PCA increased all metrics more than CFS. In PCA and

Random tree hybridization, the calculated metric values of the non-metallic class are higher than the metrics of the metallic class. This result shows that the algorithm is more successful in detecting non-metallic objects.

Table 1. Performance metrics without attribute selection and after attribute selection for Non metallic class

Attribute Evaluator	Search Method	Clasification Algorithm	Precision	Recall	F-Score	MCC	AUC	PRC
Without attribute selection		AD Tree	0,88	0,84	0,86	0,70	0,93	0,95
		BF Tree	0,88	0,84	0,86	0,70	0,84	0,83
		Decision Stump	0,90	0,76	0,83	0,67	0,82	0,88
		Randon Forest	0,85	0,88	0,86	0,70	0,70	0,94
		Simple Cart	0,85	0,88	0,86	0,70	0,83	0,81
		Optimized Forest	0,84	0,84	0,84	0,66	0,94	0,95
		Random Tree	0,85	0,88	0,86	0,70	0,85	0,81
PCA		AD Tree	0,91	0,84	0,88	0,75	0,93	0,95
		BF Tree	0,95	0,76	0,85	0,72	0,84	0,91
		Decision Stump	1	0,76	0,87	0,77	0,83	0,90
		Randon Forest	0,85	0,88	0,86	0,70	0,95	0,96
		Simple Cart	0,95	0,76	0,85	0,72	0,84	0,90
		Optimized Forest	0,85	0,88	0,86	0,70	0,94	0,96
		Random Tree	**0,96**	**0,96**	**0,96**	**0,91**	**0,95**	**0,94**
CFS	PSO	AD Tree	0,91	0,84	0,88	0,75	0,94	0,96
		BF Tree	0,84	0,84	0,84	0,66	0,89	0,88
		Decision Stump	0,90	0,76	0,83	0,67	0,82	0,88
		Randon Forest	0,88	0,88	0,88	0,74	0,96	0,97
		Simple Cart	0,87	0,80	0,84	0,66	0,86	0,85
		Optimized Forest	0,88	0,84	0,86	0,70	0,96	0,97
		Random Tree	0,95	0,84	0,89	0,79	0,90	0,89
	GA /HA	AD Tree	0,88	0,84	0,86	0,70	0,95	0,96
		BF Tree	0,85	0,88	0,86	0,70	0,86	0,85
		Decision Stump	0,90	0,76	0,83	0,67	0,82	0,88
		Randon Forest	0,88	0,84	0,86	0,70	0,95	0,96
		Simple Cart	0,84	0,84	0,84	0,66	0,80	0,77
		Optimized Forest	0,88	0,88	0,88	0,74	0,95	0,96
		Random Tree	0,88	0,84	0,86	0,70	0,85	0,82
	EA	AD Tree	0,95	0,84	0,89	0,79	0,95	0,97
		BF Tree	0,87	0,76	0,81	0,63	0,85	0,87
		Decision Stump	0,90	0,76	0,83	0,67	0,82	0,88
		Randon Forest	0,88	0,84	0,86	0,70	0,96	0,96
		Simple Cart	0,87	0,80	0,84	0,66	0,78	0,79
		Optimized Forest	0,91	0,84	0,88	0,75	0,96	0,97
		Random Tree	0,83	0,76	0,80	0,58	0,79	0,76

Table 2. Performance metrics without attribute selection and after attribute selection for metallic class

Attribute Evaluator	Search Method	Clasification Algorithm	Precision	Recall	F-Score	MCC	AUC	PRC
Without attribute selection		AD Tree	0,82	0,86	0,84	0,70	0,93	0,90
		BF Tree	0,82	0,86	0,84	0,70	0,84	0,76
		Decision Stump	0,76	0,90	0,83	0,67	0,82	0,69
		Randon Forest	0,85	0,81	0,83	0,70	0,94	0,94
		Simple Cart	0,85	0,81	0,83	0,70	0,83	0,79
		Optimized Forest	0,81	0,81	0,81	0,66	0,94	0,94
		Random Tree	0,85	0,81	0,83	0,70	0,85	0,78
PCA		AD Tree	0,83	0,90	0,87	0,75	0,93	0,90
		BF Tree	0,77	0,95	0,85	0,72	0,84	0,72
		Decision Stump	0,78	1	0,88	0,77	0,83	0,71
		Randon Forest	0,85	0,81	0,83	0,70	0,95	0,94
		Simple Cart	0,77	0,95	0,85	0,72	0,84	0,72
		Optimized Forest	0,85	0,81	0,83	0,70	0,94	0,96
		Random Tree	**0,95**	**0,95**	**0,95**	**0,91**	**0,95**	**0,93**
CFS	PSO	AD Tree	0,83	0,90	0,87	0,75	0,94	0,89
		BF Tree	0,81	0,81	0,81	0,66	0,89	0,86
		Decision Stump	0,76	0,90	0,83	0,67	0,82	0,69
		Randon Forest	0,86	0,86	0,86	0,74	0,96	0,96
		Simple Cart	0,79	0,86	0,82	0,66	0,86	0,82
		Optimized Forest	0,82	0,86	0,84	0,70	0,96	0,96
		Random Tree	0,84	0,95	0,89	0,79	0,90	0,82
	GA /HA	AD Tree	0,82	0,86	0,84	0,70	0,95	0,95
		BF Tree	0,85	0,81	0,83	0,70	0,86	0,82
		Decision Stump	0,76	0,90	0,83	0,67	0,82	0,69
		Randon Forest	0,82	0,86	0,84	0,70	0,95	0,95
		Simple Cart	0,81	0,81	0,81	0,66	0,80	0,78
		Optimized Forest	0,86	0,86	0,86	0,74	0,95	0,95
		Random Tree	0,82	0,86	0,84	0,70	0,85	0,77
	EA	AD Tree	0,84	0,95	0,89	0,79	0,95	0,94
		BF Tree	0,76	0,86	0,80	0,63	0,85	0,76
		Decision Stump	0,76	0,90	0,83	0,67	0,82	0,69
		Randon Forest	0,82	0,86	0,84	0,70	0,96	0,95
		Simple Cart	0,79	0,86	0,82	0,66	0,78	0,70
		Optimized Forest	0,83	0,90	0,87	0,75	0,96	0,96
		Random Tree	0,75	0,81	0,78	0,58	0,79	0,69

8. Conclusions

It is important to know the type of buried object before excavation is carried out, especially in archaeological sites. Some buried objects require precise excavation to be removed without damage. In addition, the automatic detection of the buried object in field studies directs the field study. It saves time and money. In the study, a artificial intelligence based measurement system was designed for the detection of buried metallic and non-metallic objects. With this proposed system, metal and non-metallic objects were classified quickly and automatically, regardless of the shape and depth of buried objects. Decision tree algorithms, one of the popular classification algorithms, were used to select the artificial intelligence method to be integrated into the designed system. Two different attribute selection methods and metaheuristic search algorithms were used to make fast detections with high accuracy. Then the performances of the algorithms were evaluated. As a result of the performance evaluation, it was understood that the PCA method increased the success of all classification algorithms more than the CFS method. Therefore, it is more appropriate to use the PCA method with classification. The highest metric values were obtained in the hybridization of the random tree algorithm with PCA. The accuracy value obtained in this hybridization is 95.8%. The lowest rms value was also obtained with this hybridization. When the metric values of the classes are examined separately, the metric values of the non-metallic class are higher than the metallic class. This Hybrid is more successful in detecting non-metallic objects. The results obtained in this study using an experimental setup are promising for field studies.

9. Author Contribution Statement

Author contributions The author designed the experiments, prepared the samples and carried out the experiments. Processed the data. Interpreted the results and wrote manuscript.

10. Ethics Committee Approval and Conflict of Interest

There is no conflict of interest with any person/institution in the prepared article.

11. References

[1] G. Grandjean and D. Leparoux, "The potential of seismic methods for detecting cavities and buried objects: experimentation at a test site," Jour. of App. Geoph., vol. 56, no. 2, pp. 93-106, 2004.
[2] J. D. Ducut et al., "A review of electrical resistivity tomography applications in underground imaging and object detection," Disply., vol. 73, p. 102208, 2022.
[3] S. Jazayeri, A. Klotzsche, and S. Kruse, "Improved resolution of pipes with full waveform inversion," 2017.
[4] W. Van Verre, L. A. Marsh, J. L. Davidson, E. Cheadle, F. J. Podd, and A. J. Peyton, "Detection of metallic objects in mineralized soil using magnetic induction spectroscopy," IEEE Trans. on Geosc. and Rem. Sens., vol. 59, no. 1, pp. 27-36, 2020.
[5] K. Ho, P. D. Gader, and J. N. Wilson, "Improving landmine detection using frequency domain features from ground penetrating radar," in IGARSS 2004. 2004 IEEE International Geoscience and Remote Sensing Symposium, vol. 3, IEEE, pp. 1617-1620, 2004.
[6] D. J. Daniels, Ground penetrating radar. Iet, 2004.
[7] L. E. Besaw and P. J. Stimac, "Deep convolutional neural networks for classifying GPR B-scans," in Detection and sensing of mines, explosive objects, and obscured targets, vol. 9454, SPIE, pp. 385-394, 2015.
[8] S. Lameri, F. Lombardi, P. Bestagini, M. Lualdi, and S. Tubaro, "Landmine detection from GPR data using convolutional neural networks," 25th European Signal Processing Conference (EUSIPCO), IEEE, pp. 508-512, 2017.
[9] H. M. Alshamy, J. W. A. Sadah, T. R. Saeed, S. A. Mohammed, G. M. Hatem, and A. H. Gatan, "Evaluation of GPR Detection for buried objects material with different depths and scanning angles," in IOP Conference Series: Materials Science and Engineering, vol. 1090, no. 1, IOP Publishing, p. 012042, 2021.
[10] H. A. Gaber, A. M. Abudeif, M. A. Mohammed, G. Z. AbdelAal, and K. K. Mansour, "Archaeological prospecting on the site of Osirion-Abydos using High Resolution Ground Penetrating Radar Technique, Sohag District, Egypt," Sohag Jour. of Scie., vol. 7, no. 2, pp. 115-122, 2022.
[11] S. Saleh, "Detection of archaeological ruins using integrated geophysical surveys at the Pyramid of Senusret II, Lahun, Fayoum, Egypt," Pure and Appl. Geophy., vol. 179, no. 5, pp. 1981-1993, 2022.
[12] X. Liang, D. Hu, Y. Li, Y. Zhang, and X. Yang, "Application of GPR underground pipeline detection technology in urban complex geological environments," Geofl., 2022.

[13] A. Dell'Acqua, A. Sarti, S. Tubaro, and L. Zanzi, "Detection of linear objects in GPR data," Signal Proce., vol. 84, no. 4, pp. 785-799, 2004.
[14] Z. Hui-lin, T. Mao, and C. Xiao-li, "Feature extraction and classification of echo signal of ground penetrating radar," *Wuhan University Jour. of Natural Scie., vol. 10, no. 6, pp. 1009-1012, 2005.
[15] C. G. Windsor, L. Capineri, and P. Falorni, "The estimation of buried pipe diameters by generalized hough transform of radar data," Piers Online, vol. 1, pp. 345-349, 2005.
[16] S. K. Sinha and P. W. Fieguth, "Automated detection of cracks in buried concrete pipe images," Autom. in Constr., vol. 15, no. 1, pp. 58-72, 2006.
[17] X. Zhou, Q. Chen, S. Lyu, and H. Chen, "Estimating the Direction and Radius of Pipe from GPR Image by Ellipse Inversion Model," arXiv preprint arXiv:2201.10184, 2022.
[18] L. C. M. Amaral, A. Roshan, and A. Bayat, "Review of machine learning algorithms for automatic detection of underground objects in GPR images," Journal of Pipel. Systems Eng. and Pract., vol. 13, no. 2, p. 04021082, 2022.
[19] S. Li, J. Zhao, H. Zhang, and Y. Zhang, "Automatic detection of pipelines from sub-bottom profiler sonar images," IEEE Journal of Oceanic Eng., vol. 47, no. 2, pp. 417-432, 2021.
[20] T. S. Brandes, B. Ballard, S. Ramakrishnan, E. Lockhart, B. Marchand, and P. Rabenold, "Environmentally adaptive automated recognition of underwater mines with synthetic aperture sonar imagery," The Journ. of the Acoust. Socie. of America, vol. 150, no. 2, pp. 851-863, 2021.
[21] A. Abhinaya, "Using Machine Learning to detect voids in an underground pipeline using in-pipe Ground Penetrating Radar," University of Twente, 2021.
[22] X. Yin, Y. Chen, A. Bouferguene, H. Zaman, M. Al-Hussein, and L. Kurach, "A deep learning-based framework for an automated defect detection system for sewer pipes," Autom. in Constr., vol. 109, p. 102967, 2020.
[23] M. Salucci, L. Tenuti, L. Poli, and A. Massa, "Buried object detection and imaging through innovative processing of GPR data," in 11th European Conference on Antennas and Propagation (EUCAP): IEEE, pp. 1703-1706, 2017.
[24] E. Pasolli, F. Melgani, M. Donelli, R. Attoui, and M. De Vos, "Automatic detection and classification of buried objects in GPR images using genetic algorithms and support vector machines," in IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium, vol. 2: IEEE, pp. II-525-II-528, 2008.
[25] H. Qin, D. Zhang, Y. Tang, and Y. Wang, "Automatic recognition of tunnel lining elements from GPR images using deep convolutional networks with data augmentation," Autom. in Constr., vol. 130, p. 103830, 2021.
[26] M. Dash and H. Liu, "Feature selection for classification," Intelligent Data Analy., vol. 1, no. 1-4, pp. 131-156, 1997.
[27] M. A. Hall, "Correlation-based feature subset selection for machine learning," Ph.D. Thesis, University of Waikato, 1988.
[28] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science: IEEE, pp. 39-43, 1995.
[29] D. Goldenberg, Genetic Algorithms in Search, Optimization and Machine Learning, Reading: Addison Wesley, 1989.
[30] L. M. Schmitt, "Theory of genetic algorithms," Theor. Comp. Scie., vol. 259, no. 1-2, pp. 1-61, 2001.
[31] Z. W. Geem, C.-L. Tseng, and Y. Park, "Harmony search for generalized orienteering problem: best touring in China," in International Conference on Natural Computation*, Springer, pp. 741-750, 2005.
[32] S. Fong, R. P. Biuk-Aghai, and R. C. Millham, "Swarm search methods in weka for data mining," in Proceedings of the 2018 10th International Conference on Machine Learning and Computing, pp. 122-127, 2018.
[33] L. KPFRS, "On lines and planes of closest fit to systems of points in space," in Proceedings of the 17th ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems (SIGMOD). 19, 1901.

[34] G. Holmes, B. Pfahringer, R. Kirkby, E. Frank, and M. Hall, "Multiclass alternating decision trees," in Machine Learning: ECML, 13th European Conference on Machine Learning Helsinki, Finland, August 19–23, Proceedings, Springer, pp. 161-172, 2002.
[35] H. Shi, "Best-first decision tree learning," University of Waikato, 2007.
[36] B. Pfahringer, "Random model trees: an effective and scalable regression method," University of Waikato, New Zealand, 1995.
[37] C. Tan, H. Chen, and C. Xia, "The prediction of cardiovascular disease based on trace element contents in hair and a classifier of boosting decision stumps," Biolog. Trace Element Res., vol. 129, pp. 9-19, 2009.
[38] N. Landwehr, M. Hall, and E. Frank, "Logistic model trees," Machine Lear., vol. 59, pp. 161-205, 2005.
[39] M. N. Adnan and M. Z. Islam, "Optimizing the number of trees in a decision forest to discover a subforest with high ensemble accuracy using a genetic algorithm," Knowledge-Based Syst., vol. 110, pp. 86-97, 2016.
[40] P. Pradham, N. H. Younan, and R. L. King, "Concepts of image fusion in remote sensing applications," in *Image Fusion: Algorit. and Applic., pp. 391-428, 2008.
[41] R. Joshi, "Accuracy, precision, recall & f1 score: Interpretation of performance measures," Retrieved April, vol. 1, no. 2018, p. 2016, 2016.