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ORIGINAL RESEARCH

Study on metal mine detection from underwater sonar images using data mining and machine learning techniques

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Abstract

Ocean mines are the major threat to the safety of great vessels and other living beings in the marine life. It is a self-contained explosive device placed in water to destroy ships or submarines. Due to various factors like variations in operating and target shapes, environmental conditions, presence of spatially varying clutter, compositions and orientation, detection and classification of sonar imagery with respect to underwater objects is a complicated problem. It is well known that many post processing techniques in image processing have done to receive high resolution images to distinguish the objects. However the mentioned technique needs a special method to detect the metal from the usual sub bottom materials mainly rocks. Hence the data collection made in simulated environment locating metals in rock bed and collected with the sonar and the distinguished features of metals from rock have been identified with the totally different approach called intruder detection technique using data mining/machine learning. This paper proposes a novel approach for discriminating and detection of objects in underwater environment with accuracy of 90% (full feature set) and 86% (selected feature set). Hence, it is quite revealing that the new technique is better in classification of mine like objects in underwater, justified with samples of sonar data sets.

Keywords Uwcns/UWSNs · Mine detection · Machine learning · Data mining · KNN classifier · Gradient booster · Decision tree · SVM

1 Introduction

The detection and classification of underwater mines has become extremely essential for security and safety of harbor, ports, open sea and mine warfare. Side scan sonar is a proven tool for detection of underwater sonar images which are symbolized by partitioning the data sets based on the information generated from the ground truth. Sonar images are obtained by sweeping a side scan sonar camera which is as a payload in moving sensor nodes in the underwater communication network/sensor networks (Geethalakshmi et al. 2011; Rao et al. 2009). Simple scenario of the threat detect system probably a mine in underwater is illustrated in Fig. 1. The algorithm is designed for real-time execution in which it is capable of detecting seabed-bottom objects and vehicle-induced image artifacts (Dura et al. 2005; Szymczak et al. 1998). On the application of the image processing and machine learning techniques, the proposed study showed some novel features in distinguishing metal mines from rock.

1.1 Metal mine detection methods

Various mine detection techniques are already reviewed with particular emphasis on signal and image processing methods using sonar imagery (Phung et al. 2019). Based on the target, mines are classified into two types; anti-tank mine and anti-personnel mine. The assumption made by most mine detection techniques is that the system consists of signal processing circuits with sensors and decision processes. Ground penetration radar (GPR), infrared and ultrasound sensors are

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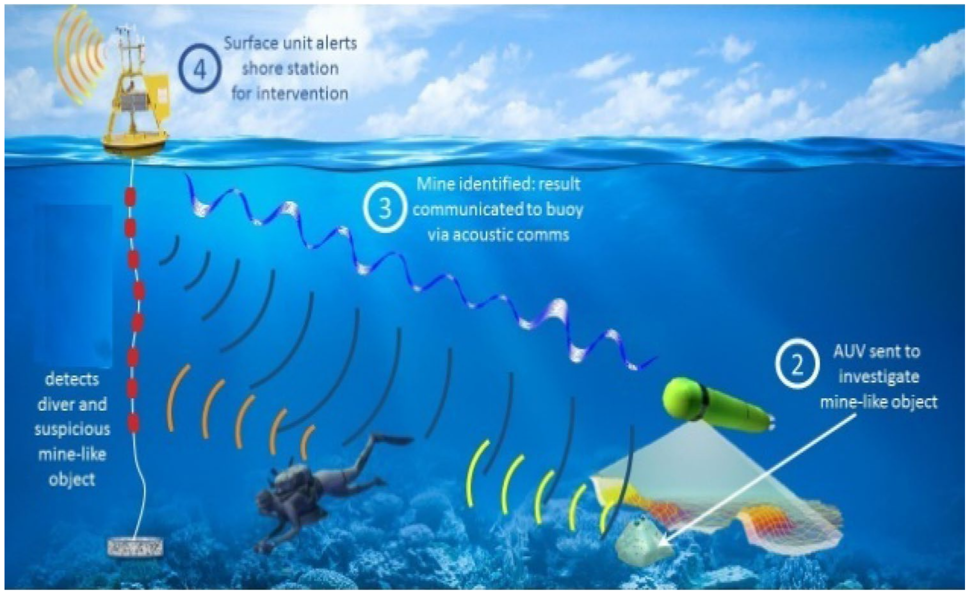

Fig. 1 Threat detect system in underwater network scenario. Courtesy: IMDEA Networks Institute & Phys.org

used and reviewed (Gu et al. 2013). The decision and signal processing comprises with all image processing technique where the Image Segmentation helps to extract metal mine from rock like materials from other competing signals.

Two-dimensional images are obtained by array of sensor that electronically scans a horizontally narrow beam to insonify an arc in a set direction is used to detect mine-like objects floating in the water column or resting on the seabed (Milenkoski et al. 2015; Raza et al. 2011). During the formation of the image, any movement of the sensor array, or objects in the environment is assumed negligible. The image is generated rapidly within the order of a few seconds. Under the critical conditions, the metal mines may be efficiently classified from other objects (Khaledi et al. 2014).

1.2 The challenges in metal mine detection

The underwater environment is very complex with changing sea environment. The unique shape with low target strength and magnetic signature make this kind of mine very difficult to detect. On the course of time, the metal mines are coated with rust which can affect the identification. So image analysis alone find quite difficult to distinguish metal mine from mine like objects like rocks, other metal parts. Hence this paper propose a new technique which gives hand with Image processing and machine learning prediction classifier like Decision Tree, Gradient Boosting and K-Nearest Neighbours Classifier to distinguish metal mine from rock (Juma et al. 2015; Salo et al. 2018). Data Mining is about automating the process of searching for patterns in the data and classification is similar to the clustering, but requires that the analyst know ahead of time how classes are defined. This new approach gives a better accuracy when compared with existing techniques (Modi and Acha 2017; Fong et al. 2014).

2 Method of practices on study and system overview

The concepts of Artificial intelligence proposed a new line in research era for last few years. System developed with signal Image processing and bioinformatics was widely tested for many defence applications, space exploration, power, weather predictions and fore-casting etc.

2.1 Classifier performances

In this section, we examine different machine learning techniques that include a single classifier and hybrid classifier. For each technique, we identify its strengths and weaknesses. The performance of a classifier depends immensely on the characteristics of the data to be classified by using various methods. The efficiency to distinguish rock from mine will decide the performance of the classifier. Single machine learning classifier can be used to address the problem of object detection. Researchers have used machine-learning techniques such as Support Vector Machine (SVM), Self-Organizing Maps (SOM) and K-Nearest Neighbor (KNN) to resolve this problem and the results shows significant achievements and progress in meeting the goal. The most widely used classifiers based upon the dataset are decision trees; support vector machines (SVMs), perceptrons, neural networks, k-nearest neighbor classifiers, and radial basis function classifiers (Chen et al. 2019; Fong et al. 2018; Juma et al. 2015; Peddabachigari et al. 2007).

- Supervised: All data is labelled and the algorithms learn to predict the output from the input data.
- Unsupervised: All data is unlabeled and the algorithms learn to inherent structure from the input data.
- Semi-supervised: Some data is labelled but most of it is unlabeled and a mixture of supervised and unsupervised techniques can be used.

3 Evaluating and performance analysis of the classifier

The following section gives a brief discussion on different prediction algorithms. Their performance evaluation is studied based on the tests carried out with samples of sonar data sets containing both mine and rock on sea beds.

3.1 Decision tree classifier

Strengths: A decision tree classifier is not sensitive to mislabelled data, handles irrelevant features, and is computationally efficient in training and prediction. It performs best when the training set is an accurate representation of the population. But it sometimes tends to overfit to the training data, resulting in a drop in accuracy and performance on the test data. That is, it does not generalize well. Given that this is essentially a binary classification problem with a large, mixed (numerical and categorical) feature set, the decision tree is an apt classifier. It can handle irrelevant features and is scalable (Shah et al. 2015; Fister et al. 2013).

3.2 Gradient boosting classifier

This classifier has parameters that can be tuned to prevent overfitting to the test data and, hence, generalizes well. It predicts fast and performs best when its parameters are well tuned. And, given that it's an additive boosting ensemble technique that utilizes a regression tree at each stage, gradient boosting classifier should be expected to perform better than a decision tree on data sets where decision trees do best. Sometimes it needs careful tuning and is slow in training, and tends to be slower the larger the training data set (Lawrence et al. 2004; Zhang et al. 2019).

3.3 K-nearest neighbors classifier

In this method the training time is negligible and adapts to new data (when such data become available). Depending on the choice (or tuning) of K, KNN can identify complex decision boundaries without (in contrast to decision trees) overfitting to the test data. And, on data sets where decision trees do best, it should be expected to perform better than a decision tree but worse than a boosting algorithm such as a gradient boosting classifier. However, the challenges faced by KNN are prediction is slow, and is slower when the data set is larger in the database. On a large data set with a large number of features (such as that of this problem) a classifier capable of identifying complex decision boundaries, such as an SVM, is likely to be very slow to train; and the cumulative computing performance in terms of training and prediction time is likely to be very slow (Peddabachigari et al. 2007). The KNN algorithm could be the best tradeoff between cumulative computing time and classification accuracy.

3.4 Metrics and the naive predictor

Accuracy as a metric for evaluating a particular algorithm's performance might seem appropriate. However, for an intrusion detection system it is imperative to catch as many attacks as possible. Therefore, an algorithm's ability to precisely predict attacks is less important than its ability to *recall* them. That is, the algorithm needs to be capable of detecting as many attacks as possible, even at the cost of some false alarms.

F-beta score is a metric that considers both precision and recall:

$$F\beta = \left[(1 + \beta 2) percision\ recall\right] / \left[\beta 2\, percision) + recall\right] \tag{1}$$

When $\beta > 1\beta > 1$, more emphasis is placed on recall. Choosing $\beta = 1\beta = 1$, this is called the *F1score* (or F-score for simplicity.

Accuracy It measures how often the classifier makes the correct prediction. It's the ratio of the number of correct predictions to the total number of predictions (the number of test data points).

Precision It is the proportion classified as attacks that actually are attacks. It is the ratio of true positives to all positive classifications by the algorithm:

$$Precision = (True\ Positive / (True\ Positives + False\ Positives) \tag{2}$$

Recall (sensitivity) The proportion of totals attacks that are classified by the algorithm as attacks. It is the ratio of true positives to all the positives in the sample:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{3}$$

Dataset formulation The data set has 208 samples with 61 features each. The Table 1 shows the data set for one sample and its probability value.

From the sample of records, categorical to numeric conversion using Dummy Variables (Features) is done by one hot encoding method. The resultant 61 features are listed below.

['S1', 'S2', 'S3', 'S4', 'S5', 'S6', 'S7', 'S8', 'S9', 'S10', 'S11', 'S12', 'S13', 'S14', 'S15', 'S16', 'S17', 'S18', 'S19', 'S20', 'S21', 'S22', 'S23', 'S24', 'S25', 'S26', 'S27', 'S28', 'S29', 'S30', 'S31', 'S32', 'S33', 'S34', 'S35', 'S36', 'S37', 'S38', 'S39', 'S40', 'S41', 'S42', 'S43', 'S44', 'S45', 'S46', 'S47', 'S48', 'S49', 'S50', 'S51', 'S52', 'S53', 'S54', 'S55', 'S56', 'S57', 'S58', 'S59', 'S60', 'Target'].

After one hot encoding, standardization of numerical features using Z-Score is done and data set for 61 features is listed in Table 2.

Based on the deviation from the mean value and probabilities of occurrence, the splitting of dataset is done (Javaid et al. 2019). The normal derived data set which is nothing but Rock and Attack Datasets are supposed to be metal mine data. Tables 3 and 4 depicts the two datasets i.e. Rock data and Mine dataset.

Table 1 Data set formulated from sonar images of underwater scenario

Samples	P value
S1	0.02
S2	0.0371
S3	0.0428
S4	0.0207
S5	0.0954
S6	0.0986
S7	0.1539
S8	0.1601
S9	0.3109
S10	0.2111
...	...
S52	0.0027
S53	0.0065
S54	0.0159
S55	0.0072
S56	0.0167
S57	0.018
S58	0.0084
S59	0.009
S60	0.0032
Target	R

Table 2 Standardization of numerical features using Z-score

Samples	0	1	2	3	4
S1	− 0.399551	0.703538	− 0.129229	− 0.835555	2.05079
S2	− 0.040648	0.42163	0.601067	− 0.64891	0.856537
S3	− 0.026926	1.055618	1.723404	0.48174	0.111327
S4	− 0.715105	0.32333	1.172176	− 0.719414	− 0.312227
S5	0.364456	0.777676	0.400545	− 0.987079	− 0.292365
S6	− 0.101253	2.607217	2.093337	− 1.149364	− 0.672796
S7	0.521638	1.522625	1.96877	− 0.193816	− 0.013735
S8	0.297843	2.510982	2.85237	− 0.084747	1.317299
S9	1.125272	1.318325	3.232767	− 1.000852	1.510531
S10	0.021186	0.588706	3.066105	− 0.610469	1.77222
S52	− 1.115432	− 0.522349	1.017585	− 0.137365	− 1.073812
S53	− 0.597604	− 0.256857	0.836373	− 1.009341	− 0.75378
S54	0.680897	− 0.843151	− 0.197833	0.557326	− 0.060532
S55	− 0.295646	0.015503	1.231812	− 0.111785	0.241793
S56	1.481635	1.901046	2.827246	− 0.16106	− 1.174638
S57	1.763784	1.070732	4.120162	− 0.488635	− 0.107456
S58	0.06987	− 0.472406	1.30936	− 0.549875	− 0.4879
S59	0.171678	− 0.444554	0.252761	− 0.639154	0.447361
S60	− 0.658947	− 0.419852	0.257582	1.03464	0.576375
Target	R	R	R	R	R

Table 3 Splitting of dataset into rock database sets

Samples	0	1	2	3	4
S1	− 0.399551	0.703538	− 0.129229	− 0.835555	2.05079
S2	− 0.040648	0.42163	0.601067	− 0.64891	0.856537
S3	− 0.026926	1.055618	1.723404	0.48174	0.111327
S4	− 0.715105	0.32333	1.172176	− 0.719414	− 0.312227
S5	0.364456	0.777676	0.400545	− 0.987079	− 0.292365
S6	− 0.101253	2.607217	2.093337	− 1.149364	− 0.672796
S7	0.521638	1.522625	1.96877	− 0.193816	− 0.013735
S8	0.297843	2.510982	2.85237	− 0.084747	1.317299
S9	1.125272	1.318325	3.232767	− 1.000852	1.510531
S10	0.021186	0.588706	3.066105	− 0.610469	1.77222
…	…	…	…	…	…
S52	− 1.115432	− 0.522349	1.017585	− 0.137365	− 1.073812
S53	− 0.597604	− 0.256857	0.836373	− 1.009341	− 0.75378
S54	0.680897	− 0.843151	− 0.197833	0.557326	− 0.060532
S55	− 0.295646	0.015503	1.231812	− 0.111785	0.241793
S56	1.481635	1.901046	2.827246	− 0.16106	− 1.174638
S57	1.763784	1.070732	4.120162	− 0.488635	− 0.107456
S58	0.06987	− 0.472406	1.30936	− 0.549875	− 0.4879
S59	0.171678	− 0.444554	0.252761	− 0.639154	0.447361
S60	− 0.658947	− 0.419852	0.257582	1.03464	0.576375
Target	R	R	R	R	R

Table 4 Splitting of dataset into mine database sets

Samples	0	1	2	3	4
S1	0.86922	4.453171	− 0.395191	1.470905	0.189054
S2	− 0.320448	5.944643	0.1175	2.070019	− 0.761438
S3	0.400875	6.836142	0.30175	2.837251	0.672163
S4	1.575054	8.025419	0.525847	1.486723	1.381156
S5	1.840498	5.878863	− 0.238231	1.236007	− 0.729042
S6	1.462435	1.264006	− 0.29629	0.244726	0.227766
S7	1.621588	1.031055	− 0.026714	− 0.540997	1.185177
S8	− 0.682765	− 1.52211	1.599828	− 0.519134	0.304906
S9	− 0.452175	0.126137	− 0.486044	0.276854	1.063461
S10	− 0.040712	0.110677	− 1.345038	1.129378	1.707339
…	…	…	…	…	…
S52	− 0.553564	2.37023	0.590982	− 0.470324	1.142445
S53	0.311055	1.461076	1.063538	2.199362	1.773428
S54	0.708358	0.612247	0.694628	− 0.019341	− 0.225294
S55	− 0.422934	1.231812	2.787556	0.637801	0.934806
S56	0.642812	− 1.209589	0.136023	1.831144	1.935997
S57	2.006353	0.481638	2.838015	2.6301	− 0.800509
S58	0.937513	0.736096	2.238977	− 0.348457	4.609501
S59	4.096105	1.598742	1.793342	0.544661	0.755477
S60	7.450343	3.306038	0.616224	1.313583	1.811697
Target	M	M	M	M	M

Table 5 34 significant features for α = 0.05

Samples	P value	t score (squared)
S11	0	47.49584
S12	0	37.45753
S49	0	29.00431
S10	0	27.1313
S45	0	26.82002
S48	0	25.06096
S9	0	23.73868
S13	0	22.34355
S46	0.00001	21.22195
S47	0.00001	20.62787
…	…	…
S3	0.00542	7.90126
S8	0.00617	7.65746
S58	0.00774	7.23425
S54	0.00826	7.11257
S50	0.00919	6.91566
S34	0.01298	6.28087
S14	0.02328	5.2249
S42	0.03778	4.37118
S53	0.04094	4.23142
S19	0.04651	4.01131

3.5 Statistical analysis

Identification of statistically significant deviations in features between Rock and Mine datasets using t test was carried out and 34 significant features was identified from 61 features for an alpha level of 0.05 and P Value with highest probability was identified and listed below in Table 5. The feature-wise mean, median, mode, and distribution comparison between rock and mine datasets is obtained by the measures of central tendency is listed in Table 6.

[‘S1’, ‘S2’, ‘S3’, ‘S4’, ‘S5’, ‘S8’, ‘S9’, ‘S10’, ‘S11’, ‘S12’, ‘S13’, ‘S14’, ‘S19’, ‘S20’, ‘S21’, ‘S22’, ‘S34’, ‘S35’, ‘S36’, ‘S37’, ‘S42’, ‘S43’, ‘S44’, ‘S45’, ‘S46’, ‘S47’, ‘S48’, ‘S49’, ‘S50’, ‘S51’, ‘S52’, ‘S53’, ‘S54’, ‘S58’].

3.6 Feature-wise distributions

The feature-wise distributions for the samples S4, S9, S10, S11,S19, S20, S37, S45, S44, S53, S54, and S58 is shown in the Fig. 2. The X-axis and Y-axis represents the sensors output and probability density (P values) for rock and mine data set.

3.7 Simulation results

Simulation of the dataset was carried all the three classifier, in which 80% of the data was used for training and remaining 20% for testing. The detailed result analysis is discussed in following session.

The training set is as follows.

Training set has 166 samples.
Testing set has 42 samples.

3.7.1 Algorithm evaluation with full feature set and with selected feature set (statistically significant features only)

The simulation results and the performance metrics trained for 166 samples for both Full Feature Set and Selected Feature Set (Statistically Significant Features) for the Gradient Boosting Decision Tree and K-Neighbours Classifiers are given in Tables 7 and 8 respectively. The Gradient Boosting Classifier provides high accuracy of 90.47% for the complete feature set and the accuracy of 85.7% for selected feature set with less false negative ratio (FNR) is obtained from the comprehensive test discussion. The proposed system with gradient classifier gives very high prediction ratio thus trained well to make very good distinction between metal mine from rock.

The Feature importance determined by Gradient Boosting Classifier using full feature set and selected feature set for first five most predictive features (statistically significant) for first five most predictive features is analysed in the Figs. 3 and 4. The Table 9 gives the feature importance with respect to P-value and t-Scored determined by t test.

Out of 208 samples of record, a total number of metal cylinders (Mines) are found to be 111 and the number of normal records (Rocks) is found to be 97. Hence, from the prediction methods, the occurrence of Mines is around 53.37% and rock is around 46.63%.

4 Conclusion

There is some concurrence between significant features determined by statistical analysis and machine learning (using both the full feature set and selected set of

Table 6 Feature-wise mean, median, mode, and distribution comparison between rock and mine datasets

Samples	mean_mine	mean_rock	median_mine	median_rock	mode_mine	mode_rock
S1	0.253983	− 0.29064	− 0.098709	− 0.395191	− 0.377751	− 0.835555
S2	0.216164	− 0.247363	− 0.095392	− 0.432977	− 0.064979	− 0.518133
S3	0.179666	− 0.205597	− 0.136484	− 0.392121	− 0.389513	0.476523
S4	0.2343	− 0.268116	0.017401	− 0.407022	0.148821	− 0.479195
S5	0.207745	− 0.237729	− 0.007261	− 0.498072	− 0.281538	− 0.189511
S8	0.176973	− 0.202516	− 0.058849	− 0.441439	0.061814	− 0.256619
S9	0.300494	− 0.343864	0.0711	− 0.614746	0.0711	− 0.880617
S10	0.318904	− 0.364931	0.121117	− 0.610469	0.202404	− 0.610469
S11	0.404638	− 0.463039	0.22047	− 0.668602	− 0.175344	− 1.074991
S12	0.366676	− 0.419598	0.270361	− 0.704342	0.270361	− 0.704342
S13	0.292419	− 0.334624	0.160676	− 0.539068	0.145031	− 1.165211
S14	0.147025	− 0.168245	0.073939	− 0.239326	0.018173	− 0.239326
S19	0.129195	− 0.147842	0.071837	− 0.453871	− 0.620947	− 0.453871
S20	0.209506	− 0.239744	0.458946	− 0.420374	− 0.176882	− 0.420374
S21	0.226931	− 0.259684	0.516878	− 0.341605	1.519998	1.519998
S22	0.188235	− 0.215403	0.473719	− 0.098622	1.471889	− 0.098622
S34	− 0.160797	0.184005	− 0.333499	− 0.011415	− 0.894437	− 0.011415
S35	− 0.212829	0.243546	− 0.486913	0.010556	− 0.486913	2.349744
S36	− 0.251606	0.28792	− 0.575924	0.314068	− 0.730013	2.334674
S37	− 0.195427	0.223633	− 0.528576	0.259859	− 0.528576	1.092583
S42	0.134751	− 0.154199	− 0.002931	− 0.34632	− 0.002931	− 0.34632
S43	0.218818	− 0.2504	0.070375	− 0.420758	− 0.658752	− 0.248393
S44	0.255932	− 0.292871	− 0.078025	− 0.402158	0.336354	− 0.449537
S45	0.317281	− 0.363074	− 0.062356	− 0.441826	− 0.062356	− 0.802786
S46	0.285688	− 0.326921	0.033445	− 0.557804	− 0.972426	− 0.82424
S47	0.28203	− 0.322735	− 0.059404	− 0.484796	− 0.483643	− 0.920564
S48	0.307865	− 0.352299	0.14576	− 0.567304	0.14576	− 0.715056
S49	0.328411	− 0.375811	0.107929	− 0.541685	1.53262	− 0.541685
S50	0.168476	− 0.192792	− 0.07512	− 0.361208	− 0.155811	− 0.801345
S51	0.274091	− 0.313651	0.086084	− 0.448158	− 0.197732	− 0.448158
S52	0.269834	− 0.308779	− 0.022911	− 0.480729	− 0.491134	− 0.751258
S53	0.132623	− 0.151764	− 0.086484	− 0.37044	− 0.512418	− 0.441429
S54	0.170778	− 0.195427	− 0.184103	− 0.293944	− 0.856881	− 0.417516
S58	0.172184	− 0.197035	− 0.14704	− 0.425926	− 0.673823	− 0.704811

statistically significant features). However, while using only the selected feature set results in some reduction in training and prediction time, there is also a drop inaccuracy and F-scores. Hence, the decision to drop features requires trading off between training /prediction time and accuracy. From the detailed comparison of classifiers performance, the Gradient Booster classifier gives better accuracy in prediction as well discrimination of metal mine from rock.

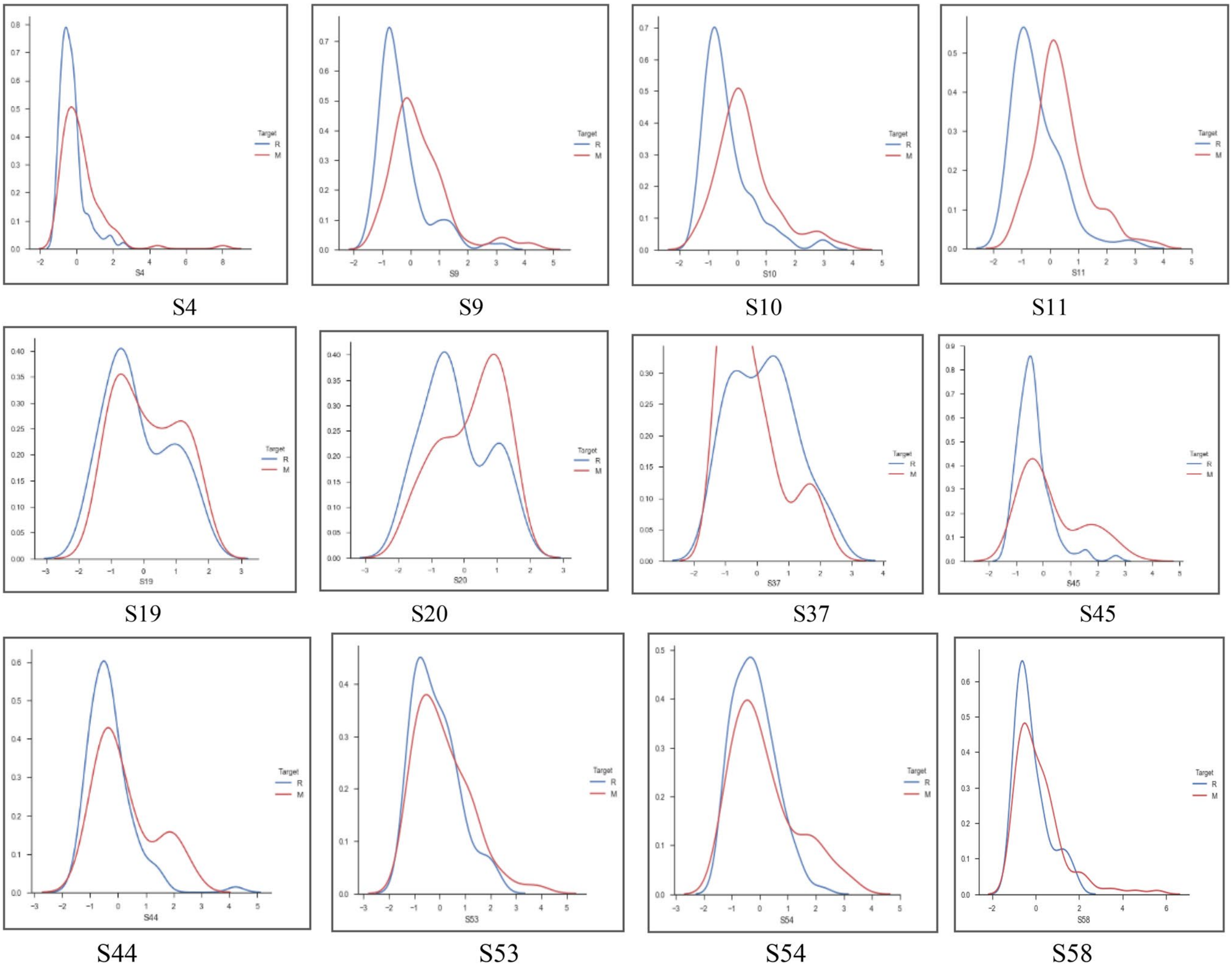

Fig. 2 Feature wise distribution of selected sample (rock & mine)

Table 7 Algorithm evaluation with full feature set

Metrics	Decision tree classifier	Gradient boosting classifier	K-neighbors classifier
FNR_Test	0.095238	0.047619	0.047619
FNR_Train	0.000000	0.000000	0.044444
acc_test	0.785714	0.904762	0.809524
acc_train	1.000000	1.000000	0.885542
f_test	0.808511	0.909091	0.833333
f_train	1.000000	1.000000	0.900524
pred_time (s)	0.000000	0.001000	0.005000
train_time (s)	0.005000	0.136000	0.002000

Table 8 Algorithm evaluation with selected feature set

Metrics	Decision tree classifier	Gradient boosting classifier	K-neighbors classifier
FNR_Test	0.333333	0.142857	0.095238
FNR_Train	0.000000	0.000000	0.033333
acc_test	0.642857	0.857143	0.857143
acc_train	1.000000	1.000000	0.903614
f_test	0.651163	0.857143	0.863636
f_train	1.000000	1.000000	0.915789
pred_time (s)	0.000000	0.001000	0.003000
train_time (s)	0.004000	0.116000	0.001000

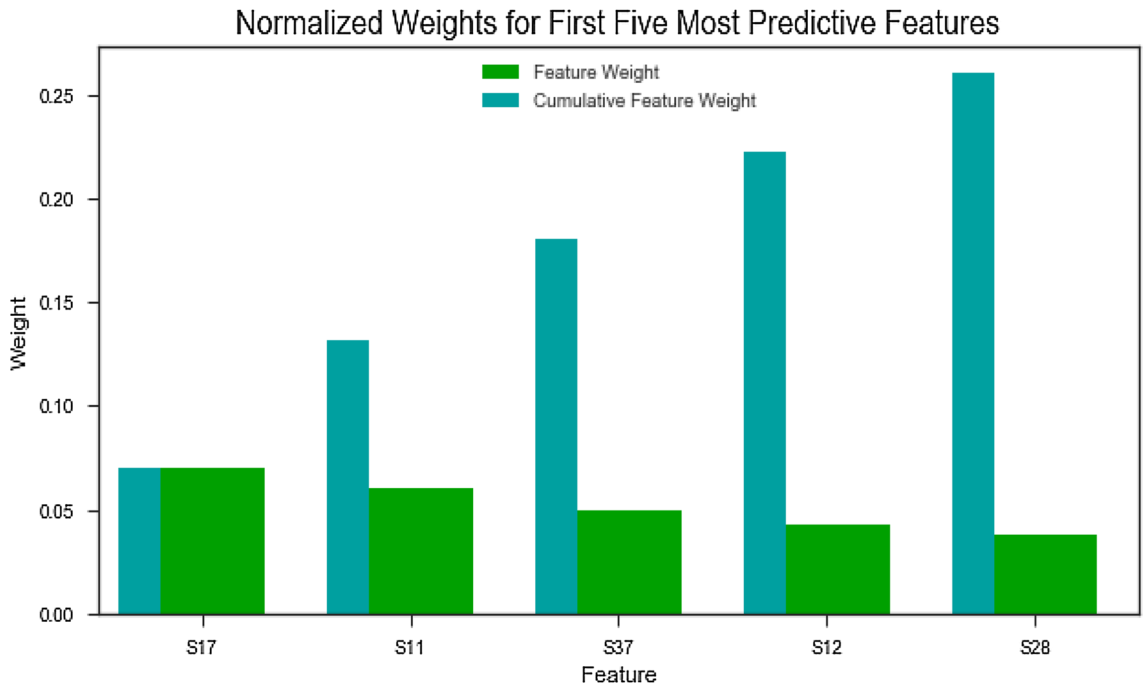

Fig. 3 First five most predictive features—full set

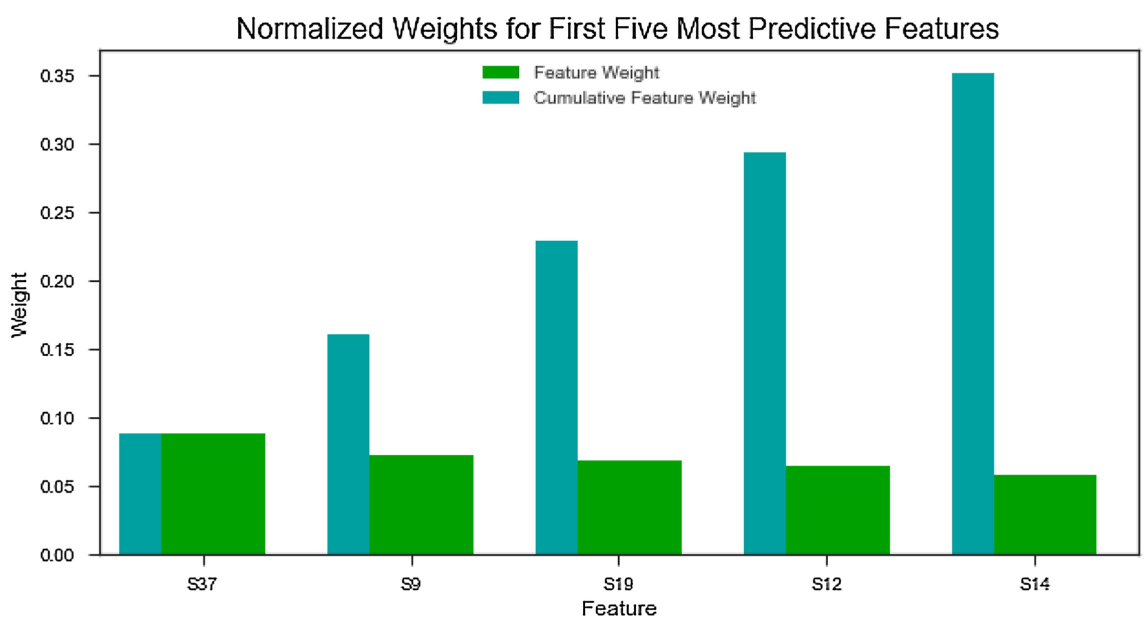

Fig. 4 First five most predictive features for selected set

Table 9 Feature importance determined by t test

Samples	P value	t score (squared)
S11	0	47.49584
S12	0	37.45753
S49	0	29.00431
S10	0	27.1313
S45	0	26.82002
S48	0	25.06096
S9	0	23.73868
S13	0	22.34355
S46	0.00001	21.22195
S47	0.00001	20.62787
…	…	…
S3	0.00542	7.90126
S8	0.00617	7.65746
S58	0.00774	7.23425
S54	0.00826	7.11257
S50	0.00919	6.91566
S34	0.01298	6.28087
S14	0.02328	5.2249
S42	0.03778	4.37118
S53	0.04094	4.23142
S19	0.04651	4.01131

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