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Research paper

Fusion of Classifiers Using Learning Automata Algorithm

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Abstract

Background and Objectives: Sonar data processing is used to identify and track targets whose echoes are unsteady. So that they aren't trusty identified in typical tracking methods. Recently, RLA have effectively cured the accuracy of undersea objective detection compared to conventional sonar objective cognition procedures, which have robustness and low accuracy.
Methods: In this research, a combination of classifiers has been used to improve the accuracy of sonar data classification in complex problems such as identifying marine targets. These classifiers each form their pattern on the data and store a model. Finally, a weighted vote is performed by the LA algorithm among these classifiers, and the classifier that gets the most votes is the classifier that has had the greatest impact on improving performance parameters.
Results: The results of SVM, RF, DT, XGboost, ensemble method, R-EFMD, T-EFMD, R-LFMD, T-LFMD, ANN, CNN, TIFR-DCNN+SA, and joint models have been compared with the proposed model. Considering that the objectives and databases are different, we benchmarked the average detection rate. In this comparison, Precision, Recall, F1_Score, and Accuracy parameters have been considered and investigated in order to show the superior performance of the proposed method with other methods.
Conclusion: The results obtained with the analytical parameters of Precision, Recall, F1_Score, and Accuracy compared to the latest similar research have been examined and compared, and the values are 87.71%, 88.53%, 87.8%, and 87.4% respectively for each of These parameters are obtained in the proposed method.

Introduction

Underwater objective classification and cognition technology have become a research issue due to the detection and extension of oceans and seas [1]. Sonar determines the distance and direction of underwater targets utilizing sound. Sound waves emitted from the target are detected by it and analyzed to calculate range information. It should also be said that sonar measurements are not affected by turbidity or reduced light and color, thus making it a good complement to a camera. Because of the relative ease of undersea propagation compared to other patterns of radiation, acoustic waves have been widely used for undersea discovery and other points [2], [3].

The point estimation of the target position is usually done by thresholding the normalized data and announcing the diagnosis when the threshold is crossed. Due to the sufficient and high signal-to-noise ratio (SNR) of the target echo, this approach is reliable and efficient. Because the target echoes are most likely in the survival threshold process, and connecting only the detected target positions does not require a large number of calculations. A low echo level, either due to reduced source level or low target power, makes detecting and tracking the conventional pulse active sonar less reliable.

The recognition of such targets requires a lower threshold at the cost of more false detections.

In reference [1], an identification and classification algorithm are proposed to solve this problem. This research has proposed a lightweight target detection model for small samples using the improved YOLOV4 algorithm. The improved image feature extraction network in this paper has greatly reduced the number of network parameters, and the parameters of the feature fusion module have been improved. However, this algorithm has difficulty in detecting small targets in the image and detecting targets with unusual sizes. Many researchers have enhanced and proposed various reinforcement learning algorithms (RLAs) for sonar objective classification and cognition [4]. Williams planned a feature classification and exploitation and network with only ten convolution layers for sonar objective classification. The training network proposed in this paper has increased the amount of training data images for learning. In this research, image feature integration has been used and its performance has been displayed only in the form of an AUC diagram [5]. Valdenegro-Toro et al. used a convolutional neural network (CNN) to detect the object of an undersea sonar image, and after training the network, the average detection rate in test sets reached 90% [6]. A sonar objective cognition procedure based on a shallow CNN has fault cognition and insufficient model strength. Ferguson et al proposed the use of a deep CNN to detect the sound of an undersea ship in a shallow water ambiance. In this article, a data augmentation technique is introduced, and the criterion for comparing data integration performance at the feature level is the precision parameter [7].

Huo et al. proposed a classification method for sonar target detection based on semi-synthetic data training and transfer learning for small sample sonar datasets. Experiments indicate that transfer training and semi-synthetic training can help increase model cognition accuracy [8]. In reference [9], a hybrid dragonfly algorithm is proposed to train a multi-layer perceptron (MLP) neural network to design a classifier in solving complex issues and to distinguish true targets from fake objectives in sonar applications. In this paper, by combining DA and ChoA algorithms, the researchers were able to achieve a suitable classification rate and execution time compared to the separate performance of each algorithm.

Researchers have developed many related algorithms, such as the combined probability filter algorithm, which can effectively filter the confusion in the data with the object's motion characteristics [10]. In another algorithm, fuzzy least squares regression for filtering is combined with joint probability data fusion (DF) filtering to achieve efficient target tracking [11]. Also, the new multi-sensor probabilistic hypothesis density filter algorithm can combine data from different sensors and overcome the problems of statistical information loss [12]. Environment-based performance is emphasized to obtain the most expected benefits in reinforcement learning (RL), which is one of the main branches in the field of machine learning (ML). A new data tracking and communication network structure is also developed in this field based on RL networks [13].

Various scattering mechanisms affect object-specific information in a received signal in a sonar system. Collected signals are contaminated by noise, reverberation, and confusion in the ocean environment. ML methods are traditionally used for feature exploitation and classification of active sonar data but lack interpretation. This may lead to a decrease in the confidence of the algorithm, and the reasoning of the classifier becomes unknown. Explainable artificial intelligence (AI) is a field that increases the transparency of ML algorithms by making them humans interpretable. Data fusion is the process of combining data or information to create improved estimates or predictions of the state of an entity [14]. Information obtained from a source may be unreliable or insufficient to determine accuracy. Therefore, it is necessary to use multiple data sources to increase the reliability and quality of information provided to decision-makers.

DF is especially important in many applications where a large amount of data must be fused and then intelligently combined. On the other hand, data aggregation in wireless sensor networks has a special meaning and place. So that in a wireless sensor network, a huge amount of data comes from nodes, sensors, and different input channels, and certain data must be collected before sending these data to some other nodes, outputs, sink nodes, etc. are data aggregations. Finally, sensor data fusion is done to obtain advanced quality information with appropriate integrity so that the decisions made based on these data and the integrated fused information are very reliable. Which should be more accurate about the overall situation, the target situation, the process, and the scenario of interest by reducing the uncertainty. DF should be done logically and with proper understanding of data processing methods and related methods [15].

ML is a subset of AI where a machine learns how to complete a given task without explicitly planning how to do it, by feeding it plenty of training data and building a good model to predict the true values for recent similar data. A common definition is also provided for ML. It is called a computer program that learns from experience according to a set of tasks and performance criteria. If its function in the tasks is the same as the measured efficiency and enhances with experience [16]. In supervised ML, a dataset is given to the learning algorithm along with labels that indicate how much the correct output should be for the given data. Algorithms such as support vector machine (SVM), k-nearest neighbor (KNN), random forests (RF), and artificial neural networks (ANN) are examples of this learning.

Using six ML algorithms such as KNN, SVM, RF, decision tree (DT), extreme gradient boosting (XGboost), and ensemble methods, Krishna et al. conducted research with the help of sonar data to find sea mines. The Ensemble method is the combination of RF, XGboost, and Voting Classifier. Comparative results including Accuracy, Precision, Recall, and F1-score for all these algorithms are presented in this paper [30]. In this research, Wang et al presented a method of identifying active sonar targets based on multi-domain transformations and precision-based fusion networks. The results of the experiments show that by using multi-domain transformations, active sonar echoes can be accurately detected. Improved by 10.5% compared to single domain methods. Also, the findings show that in a high-level feature space by combining features of multiple transformations, more informative and effective results are obtained for active sonar echoes. In addition, the identification performance of different fusion models such as the early fusion model with resnet (R-EFMD) as the backbone of multi-domain attention-based feature extractor (MAFE), early fusion model with swin transformer (T-EFMD) as the backbone of MAFE, late fusion model with resnet (R-LFMD) as the backbone of single domain feature extractor (SFE) no attention-based feature extractor (AFE) module, and late fusion model with swin transformer (T-LFMD) as the backbone of SFE no AFE module has been compared [31].

Ahmed et al. investigated an underwater audio signal classification model with deep learning method. A regular neural network is also implemented to classify audio as input features. Comparing the performance of this classifier and the general results of the presented models is promising [32]. Yang et al. implemented a spatial attention deep convolutional neural network for marine mammal call detection. This method tends to use spatial attention (SA) to help the deep convolutional neural network (DCNN) to achieve better detection performance. Time-frequency image recognition-DCNN (TFIR-DCNN) is designed at the beginning of this method. Then, SA is added to the TFIR-DCNN to help the TFIR_DCNN focus on the location of call features in the time and frequency domains. Favorable marine mammal contact detection test results have been reported [33]. Tian et al. designed a collaborative learning model for underwater acoustic target recognition. In this research, firstly, a light multiscale residual deep neural network (MSRDN) is implemented using light network design techniques, where 64.18% of the parameters and 79.45% of the floating-point operations (FLOPs) from the original MSRDN are reduced in accuracy. It decreases a little. Then, a combined model of wave representation and time-frequency-based models was presented. The results of deterministic experiments prove that the performance improvement of the proposed methods from mutual deep learning has advantages such as favorable recognition accuracy [34].

Motivation and Innovation

In this work, the data fusion problem in sonar data classification is considered due to its importance in various applications such as navigation and marine surveillance. However, we must mention that the mechanism of learning automata has not been used in this field yet. We intended to check whether using mechanisms related to learning automata can be effective and efficient in data fusion at the decision level. Although data integration at the level of data, decision, and feature has been used in the problem of sonar data classification. But until now, the use of a machine learning method such as learning automata to increase the ability to classify targets has been neglected. In this article, we measured the remarkable performance of the proposed method for 5 different objectives with Precision, Recall, F1_Score, and Accuracy indicators. Noise and acoustic interferences make the act of identification difficult in the vast and diverse oceanic and marine environments. In most marine devices, target detection is done by human operators, and with the development of this method in detecting most different targets, the speed and accuracy of identification can be increased and human errors can be reduced in these cases.

Algorithms

To increase the accuracy of the classification of complex problems, it is possible to use a combination of classifications that use the same learning algorithm but with different complexities and parameters. Hybrid classifications use the fusion of several classifiers. In fact, these classifiers each build their own model on the data and save this model. Next, for the final classification, a vote will be held between these classifications, and the class that gets the most votes will be the class that has had the greatest impact on the classification. The goal of AI is to train computers to do the things that persons currently do better, and without a doubt, learning is the most significant of those targets [17].

K-Nearest Neighbor

In the KNN, an objective is classified by the majority of its neighbors' votes, and the target is classified into the class that is most general between its KNNs [18]. KNN is a classification algorithm and there are mainly two phases in classification. The first phase is learning, in which a classification is made using the training data, and in the second phase, the evaluation of the classifier is done. Fig. 1 shows a simple KNN structure [19].

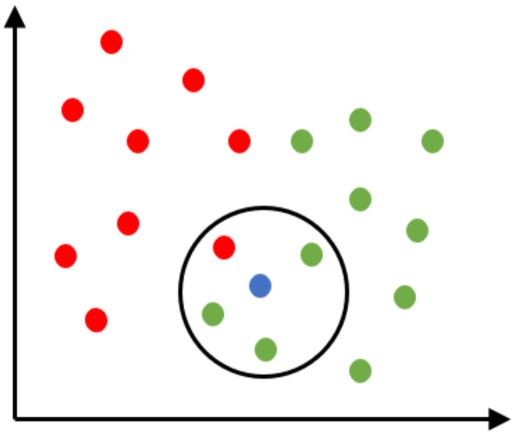

Fig. 1: A simple KNN classification.

As presented in Fig. 2. The new unlabeled data computes the distance of each of its neighbors according to the K value. Then, it specifies the class that contains the maximum number of nearest neighbors to it [20].

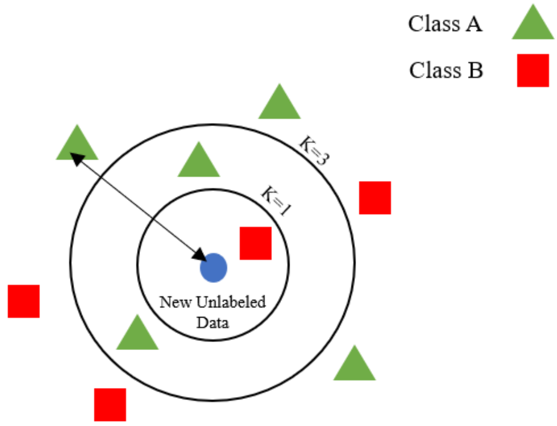

Fig. 2: New unlabeled data.

After collecting KNN, we simply select most of them to predict the training sample class. Agents that affect the operation of this algorithm are K value, Euclidean distance and parameter normalization. For a precise understanding of the algorithm's performance and according to the set of training data shown in (1), the steps are as follows.

$$\begin{Bmatrix} (x(1), y(1)), (x(2), y(2)), \ldots \\ \ldots, (x(m), y(m))\} \end{Bmatrix} \quad (1)$$

First, the training set is stored, and then the Euclidean distance for each new unlabeled data among two points x and y in all training data points is calculated using (2).

$$d = \sqrt{\sum_{k=1}^{N} (x_k - y_k)^2} \quad (2)$$

KNNs are determined, and the maximum number of nearest neighbors is assigned to a class. After saving the training, all the parameters should be set to normal, so that the calculations become easier. The value of K affects the algorithm because it can be used to create the boundaries of each class. The best solution is selected first by checking the data. Larger solutions of K are more accurate because they decrease the net noise, but this is not guaranteed [21].

Multi-Layer Perceptron

ANNs are structures inspired by brain performance. These networks can compute model performance estimation and manage non-linear and linear functions by learning from data generalizing and their relationships to unsighted situations. One of the most main ANNs is MLP. It is a potent modeling tool that exerts a supervised learning method using data samples with certain outputs. This method creates a non-linear function model that makes it possible to predict the output data from the given input data [22].

In order to comprehend MLP, a short description on single layer perceptron (SLP) and single neuron perceptron has been prepared. The first type is the simplest ANN and has only one output to which all inputs are linked, and the values of x_i, w_i and y are inputs, weighting of the neuron and predictive binary class respectively, which are described in Fig. 3 of the steps of weighting, summation and transfer function. Also, Fig. 4 shows its simplified model and the transfer function is calculated in (3).

Fig. 3: Perceptron steps: weighting, sum and transfer steps.

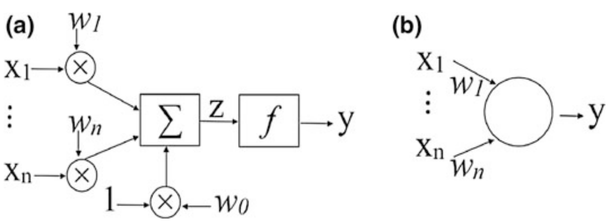

Fig. 4: Perceptron models: a) steps. b) Simplified.

$$y = f(z) \ and \ z = \sum_{i=0}^{n} w_i x_i \quad (3)$$

x_0=1, y is the output and w_0 is the bias or threshold value. The transfer function has different forms such as unit step, linear, and sigmoid. Fig. 5 shows an example of the linear and nonlinear functions, which detaches the data into two classes. A Function can be represented by the dot product among the input and the weight vectors in (4).

$$\sum_{i=0}^{n} w_i x_i = 0 \quad (2)$$

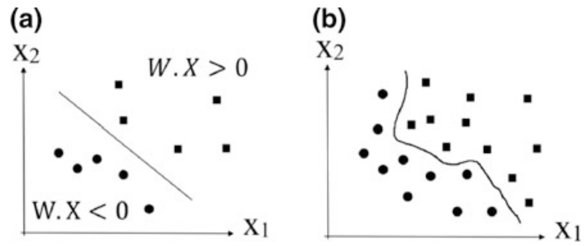

Fig. 5: Input patterns: a) linear. b) nonlinear.

Connecting many perceptrons in parallel creates a SLP structure that is used for different outputs. Fig. 6 represents an example where output and input layers are presented in a multi-class situation that can be linearly separated. The SLP does not solve separable nonlinear problems, which can be seen in Fig. 5. In this case, which is also shown in Fig. 6, a response can be found by appending any number of layers in a sequential order and making a MLP structure [23]. Any connection among neurons has its own weight, and SLP has the same activation function. Hinging on the performance, the output layer can be various functions [24].

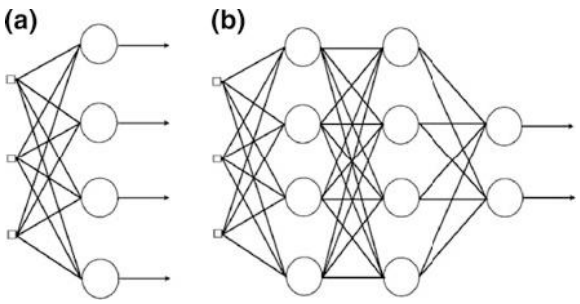

Fig. 6: Layer structure: a) SLP. b) MLP.

Learning Automata Algorithm

Automatic learning is an easy model for adaptive decision-making in anonymous stochastic ambiances. Allegedly, its performance can be supposed identically to the learning method by a living organism in such ambiances. General instances of such positions are cases where an inexperienced person learns to perform the right motions or an individual who finds the best track from home to the office. The structure efforts various operations and chooses new operations based on the response of the environment to the past acts. The structure of such adaptive selection of operations and decisions is indicated by learning automata. The learning problem the appropriate operation is complicated by the verity that ambiance responses are not entirely reliable because they are stochastic and the corresponding probability distribution is anonymous.

This model is effective in many functions related to adaptive decision-making. Hence, it would be attractive to have an algorithm that can learn appropriate selections based on some noisy evaluation of the good choice, which is consistent with the automata model. A classifier must decide on the class label of each pattern input to it in a pattern recognition problem. The law of optimal decision-making can be considered as a learning problem for choosing one of the available actions based on some random feedback about the appropriate of each selection [25].

The learning method in the field of LA is as follows. Every time it cooperates with the environment, it automatically and stochastically selects an action based on a probability distribution. After the ambiance responds to a chosen action, it automatically updates its operation probability distribution. Then, a new operation is chosen according to the updated probability distribution, and the solution of the environment is extracted for this act, and this method is rerun. The updated algorithm for the operation probability distribution is called the RLA [25].

The general method of LA, which is an unsupervised optimization procedure and one of the key parts in adaptive learning systems, is to perform an operation through cooperation with the ambience in terms of receiving a sequence of repeated evaluation cycles with selecting the highest reward compared to other operations. By learning to select the best solution, automata adapt without needing to have detailed data about the pattern of the environment [26]. The cooperation between the environment and LA is shown in Fig. 7. In [27], for the first time, the idea of automatic learning was introduced to model the mechanism of biological learning.

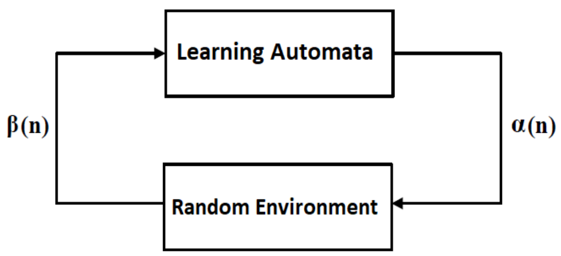

Fig. 7: The cooperation of LA with the environment.

LA is a self-organizing decision-making unit whose performance improves through repeated cooperation with a stochastic environment. A LAA learns how to select the best solution based on the response it receives from the environment. In this process and interaction, repetition number n starts when the automata select the input vector x(n) from the set $X \in R^m$ from the environment. According to the input vector, the automata select one of its possible actions and apply it to the random environment (for example α(n) ϵ α). Then, the stochastic environment classifies the selected α(n) act in the x(n) input vector and estimates an amplification signal of β(n) ϵ β. For this purpose, the automata use the learning algorithm T, the x(n) input vector, the α(n) act, and the β(n) reinforcing signal to update its state. By repeating or continuing this process, the LA learns how to choose the optimal solution [28].

LA is more practical and effective in discovering the exact best solutions for complicated optimization issues. The dimensions of the points are equal to the number of automata used in the LAA. In other words, for the N-dimensional problem, this algorithm contains N automata [29]. Each automata is accountable for exploring one dimension and operates separately in the ambiance. The i-th LA can be defined as the model ⟨x_i, A_i, r, P_i, U⟩ where x_i = {x_i} represents the set of possible positions in the i-th dimension. As well as, x_i is the next state in the dimension i (x_i ϵ [$x_{min,i}$, $x_{max,i}$]), the maximum and minimum amounts in dimension i are $x_{max,i}$ and $x_{min,i}$, respectively. In automatic learning, A_i = {$a_{l,η}$} is the set of possible operations that the LA can perform in the dimension i, $a_{l,η}$ demonstrates that an operation is right (l=2) or left (l=1) moves and η is the length of step. Note that r is a scalar value and represents a reinforcement signal that is generated through the ambiance to demonstrate the quality of the movement x_i during the step in the selected route. As well as, P_i includes two possibilities p_1 and p_2. p_1 and p_2 respectively demonstrate the probability of choosing the right route and the left route in the i-th dimension. Suppose the right route is chosen, and the probability of selecting one cell among k cells located on the route determines the probability p_2. As well as, U is a procedure for calculating the probabilities of operations, P.

In the introduced procedure, each dimension is parted into D cells. This intends that x_i is parted into D subsets, and each subset comprises all dimensional states located in the cell. Thus, D×N cells are generated for the N-dimensional space of exploration where $ω_{c,i}$ is a cell width in the dimension i and is computed using (5).

$$\omega_{c,i} = \frac{x_{max,i} - x_{min,i}}{D} \quad (3)$$

At the beginning of the operation exploration, it must be able to select one of two possible directions to appraise the selection of the best solution in the route. Therefore, the value of $L_2(x_i)$ is determined by the amounts of the k adjacent cells in the right route, where k is a predefined integer amount and $c_{i,j}$ is cell j in dimension i. As well as, j is computed by (6) and the amount of a route can be evaluated by (7).

$$j = floor\left(\frac{x_i - x_{min,i}}{\omega_{c,i}}\right) \quad (6)$$

$$\boldsymbol{L}_l(x_i) = (1-\lambda_1)\sum_{m=1}^{k-1}\lambda_1^{m-1}\upsilon_{l,m}^{*} + \lambda_1^{k-1}\upsilon_{l,k}^{*} \quad (4)$$
$$l = 1,2$$

where $\upsilon_{l,m}^{*}$ represent the variable of the vector m that is placed in the direction of l. Also, λ_1 is computed with the conditions $0 \le \lambda_1 \le 1$ and $(1-\lambda_1)\sum_{m=1}^{k-1}\lambda_1^{m-1} + \lambda_1^{k-1} = 1$, provided that the relation $(1-\lambda_1)\lambda_1^{k-2} \ge \lambda_1^{k-1}$ is established. The two probabilities p1 and p2 are obtained from (8) and (9).

$$p_1\big(L_l(x_i)\big) = \frac{e^{\frac{L_l(x_i)}{\tau}}}{\sum_{s=1}^{2} e^{\frac{L_s(x_i)}{\tau}}} \quad l = 1,2 \quad (5)$$

$$p_2\big(c_{i,j+s}\big) = \frac{e^{\frac{(V(x_i)|x_i\epsilon c_{i,j+s})}{2\tau}}}{\sum_{z=1}^{k} e^{\frac{(V(x_i)|x_i\epsilon c_{i,j+z})}{2\tau}}} \quad (6)$$
$$l = 1,2 \quad s = 1,\dots,k$$

where V(x_i) is the cell value. The τ parameter makes a balance among search and utilization. With selecting a cell, the operation proceeds to the new cell with a step length that can be expressed in the act of η in (10). Thus, when L_1 is chosen, the current dimensional state of x_i changes to $x_i = x_i - η$ and when L_2 is selected, x_i moves to $x_i = x_i + η$.

$$\eta = \omega_{c,i}(\xi + \zeta) \quad (7)$$

where the distance among the former cell and the chosen cell ζ and ξ is a stochastic number (ζ ∈ (0, 1]). Next, an amplification signal is applied to investigate the next state x_i. Just after the dimensional state x_i is transferred to x_i', the i-th variable of the current state $X(x_i)$ is changed by $X(x_i')$. According to (11), the amplification signal is allocated to cell $c_{i,j}$. The amplification signal is used to update the cell value ci, j and is obtained according to (12).

$$r\big(X(x_i')\big) = \begin{cases} 1, & if\ F(X(x_i')) \le F(X_{best}) \\ 0, & otherwise \end{cases} \quad (8)$$

$$V(x_i)|_{x_i\epsilon c_{i,j}} \leftarrow r\big(X(x_i)\big) + \alpha_1 V(x_i)|_{x_i\epsilon c_{i,j}} \quad (9)$$
$$+(1-\alpha_1)\big((1-\lambda_2)L_{max}(x_i) + \lambda_2 L_{min}(x_i)\big)$$

The solution is desirable when r=1 and r=0 indicates an unfavorable answer. Also, L_{max} (x_i) = max {L_1 (x_i), L_2 (x_i)} and L_{min} (x_i) = min {L_1 (x_i), L_2(x_i)} are two estimated path values at x_i. L_{max} (x_i) has a greater impression on the cell value than L_{min} (x_i). Thus, the parameter $λ_2$ must be given in such a way that this relation (1− $λ_2$) > $λ_2$ is true. The weights $α_1$ and (1-$α_1$) show the impression of past evaluations and route values on the new evaluation, respectively. In (13), the relationship among X_{best} and X and is shown.

$$X_{best} \leftarrow \begin{cases} X(x_i'), X(x_i') = [x_i, \dots, x_{i-1}, x_i', x_{i+1}, \dots, x_N] & if\ r = 1 \\ X_{best} & otherwise \end{cases} \quad (10)$$

Methodology

To increase the classification accuracy of complex problems, it is possible to use a combination of classifications that use the same learning algorithm but with different complexities and parameters. Hybrid classifiers use the fusion of several classifiers. In fact, these classifiers each build their own pattern on the data and save this model. Eventually, for the final classification, a vote is held between these classifications, and the class that gets the most votes will be the class that has had the greatest impact on the classification. In this work, we defined coefficients to weight the classifiers, and in order to achieve the best accuracy, we implemented voting and finding the optimal coefficients by automata learning algorithm. We proceeded with this process in five steps. Fig. 8 shows the overall process.

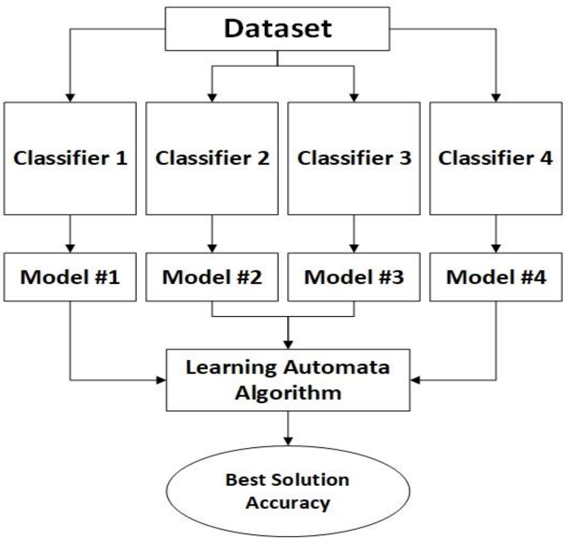

Fig. 8: The overall process of the proposed method.

In the first step, we created and stored sonar data in five classes with specific dimensions and samples.

In the second step, we loaded those data into the introduced classification training algorithm and after running the algorithm, we saved the accuracy results of each of the classification models related to the sonar data. Four classifiers (two KNN classifiers and two MLP classifiers) were used in this research.

In the third step, the stored models and data were loaded into the LA algorithm.

In the fourth step, we created and integrated functions for weighting the categories.

In the last step, to find the best accuracy answer with the majority vote, we ran the LA algorithm to find the optimal coefficients of the classifiers and saved the results.

Data and Device

In this work, a dataset of sonar targets with five different classes and dimensions of 103x129 was used. Also, these targets in different subclasses include different viewing angles and signal-to-noise. The Specifications of targets are demonstrated in Table 1.

Table 1: Specifications of objectives

Class Number	Name	Type of Application
1	MV Barzan	container carrier
2	Front Century	oil tanker
3	Harmoney of the Seas	Cruise
4	Atlas Pishro	passenger ship
5	logistic	Military

This program is implemented on a system with Intel® Core™ i7-6500U CPU (2.50-2.59) GHz processor specifications, 8 GB RAM, and MATLAB R2020b software.

Results and Discussion

In this work, we are going to investigate the improvement of the performance of combining the classifications using the automatic learning algorithm.

Also, to better check the efficiency of the used models, Accuracy, Precision, Recall, F1_Score, and AUC parameters are reported in Table 2. Also, the test charts of each model are shown in Figs 9 to 16.

In the first model, the data was trained by a KNN classifier with a nearest neighbor rate of 3. The performance of model 1 on sonar data with confusion matrix and ROC charts for 5 different classes is shown in Fig. 9 and Fig. 10.

In the second model, the data was trained by a KNN classifier with a nearest neighbor rate of 15. The performance of model 2 on sonar data with confusion matrix and ROC charts for five different classes are demonstrated in Fig. 11 and Fig. 12.

In the third model, the data was trained by an MLP classifier with an input layer of 15. The performance of model 3 on sonar data with confusion matrix and ROC charts for 5 different classes is shown in Fig. 13 and Fig. 14.

In the fourth model, the data was trained by an MLP classifier with an input layer of 15 and a hidden layer of 15. The performance of model 4 on sonar data with confusion matrix and ROC charts for 5 different classes is shown in Fig. 15 and Fig. 16.

Table 2: Machine learning Models performance results

Model Number	Precision (%)					Recall (%)					F1_Score					AUC					Accuracy (%)
	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	
1	77.27	78.94	100	100	69.56	94.44	62.5	90.47	100	80	85	69.76	95	100	74.41	0.99	0.94	0.99	1	0.95	84.46
2	100	70.58	72.72	83.33	56.25	44.44	50	76.19	100	90	61.53	58.53	74.41	90.90	69.23	0.97	0.93	0.93	1	0.91	71.84
3	100	90.47	72.72	60.60	78.26	83.33	79.16	38.09	100	90	90.90	84.44	50	75.47	83.72	0.91	0.88	0.67	0.92	0.92	77.67
4	100	78.94	72	83.33	61.53	50	62.5	85.71	100	80	66.66	69.76	78.26	90.90	69.56	0.75	0.78	0.88	0.97	0.84	75.72

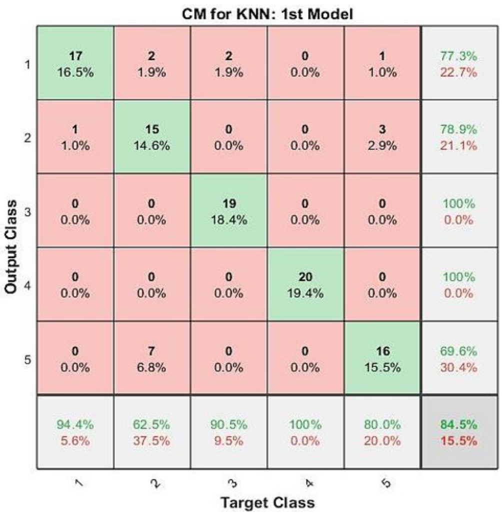

Fig. 9: Confusion matrix chart for KNN - 1st Model.

Fig. 11: Confusion matrix chart for KNN - 2nd Model.

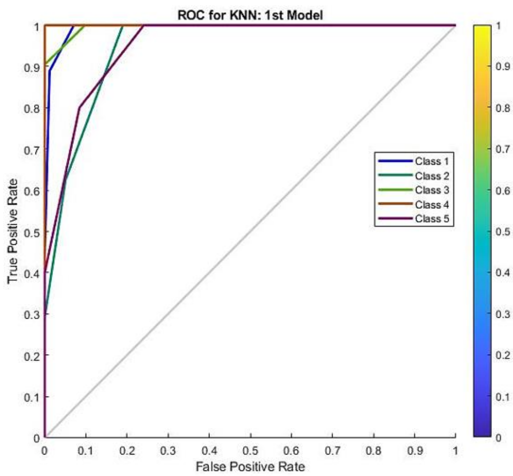

Fig. 10: ROC chart for KNN - 1st Model.

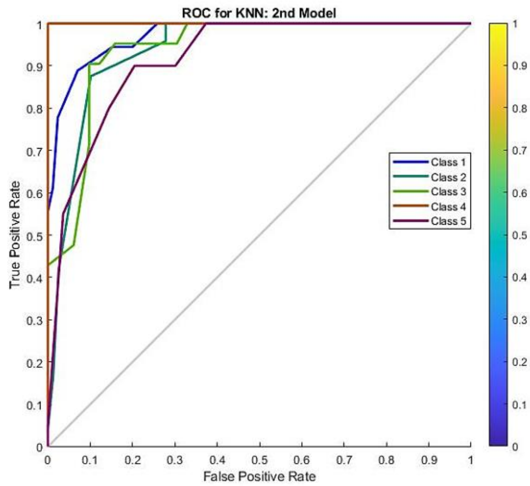

Fig. 12: Roc chart for KNN - 2nd Model.

As described in the work process in the previous sections. The stored models of each class are weighted using the LAA and weighted summation functions in the defined range. To achieve the best accuracy and decision by obtaining the best solutions for the classifications and fusion it by the LA algorithm.

Due to the fact that in this process the effective parameters in the learning automata algorithm are very effective.

The results of Accuracy, Precision, Recall, F1_Score, and AUC are reported separately for the impact of each of the K, D, and N_{femax} parameters.

Fig. 13: Confusion matrix chart for MLP - 3rd Model.

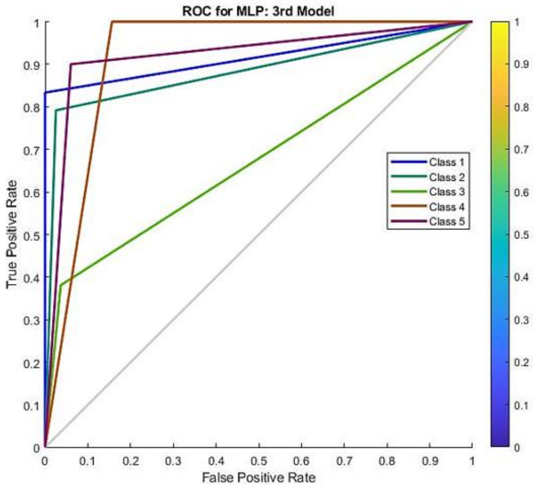

Fig. 14: ROC chart for MLP: 3rd Model.

Fig. 15: Confusion matrix chart for MLP - 4th Model.

In Table 3, the parameter D = 50 is considered constant and the results are reported by changing the values of K and N_{femax} parameters. Also, the performance of sonar data fusion by LAA is shown using the confusion matrix and ROC charts in Figs 17 to 22.

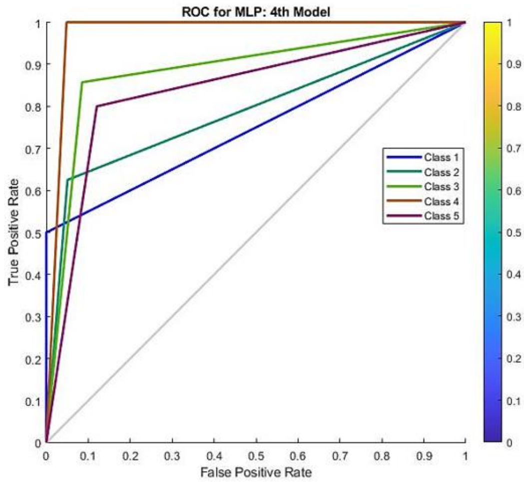

Fig. 16: ROC chart for MLP - 4th Model.

The performance of sonar data fusion by the learning automata algorithm for D = 50, K = 10, and N_{femax} = 5 values is shown in Fig. 17 and Fig. 18.

Fig. 17: Confusion matrix chart for D = 50, K = 10, and Nfemax = 5 parameters in LAA.

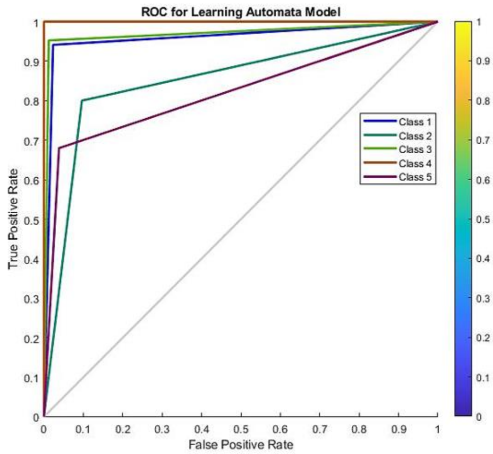

Fig. 18: ROC chart for D = 50, K = 10, and Nfemax = 5 parameters in LAA.

Table 3: LA performance results with the influence of Nfe and K parameters

Run Number	LAP: Nfe	LAP: K	Best Solution: W1	W2	W3	W4	Precision (%): C1	C2	C3	C4	C5	Recall (%): C1	C2	C3	C4	C5	F1_Score: C1	C2	C3	C4	C5	AUC: C1	C2	C3	C4	C5	Accuracy (%)
1	5	10	0	3	0	3	88.88	66.66	95	100	85	94.11	80	95.23	100	68	91.42	72.72	95.23	100	75.55	0.95	0.85	0.97	1	0.82	86.4
2	10	100	4	1	5	3	83.33	66.66	90.47	100	95	93.75	88.88	90.47	95.23	70.37	88.23	76.19	90.47	97.56	80.85	0.95	0.89	0.94	0.97	0.84	86.4
3	15	200	3	1	4	3	88.88	66.66	95	100	85	94.11	80	95.23	100	68	91.42	72.72	95.23	100	75.55	0.95	0.85	0.97	1	0.82	86.4

(The results for D=50 in LAA)

The performance of sonar data fusion by the learning automata algorithm for D = 50, K = 100, and N_{femax} = 10 values is shown in Fig. 19 and Fig. 20.

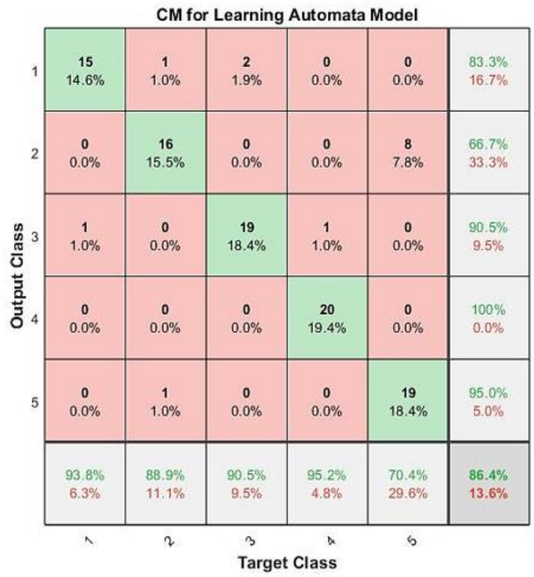

Fig. 19: Confusion matrix chart for D = 50, K = 100, and Nfemax = 10 parameters in LAA.

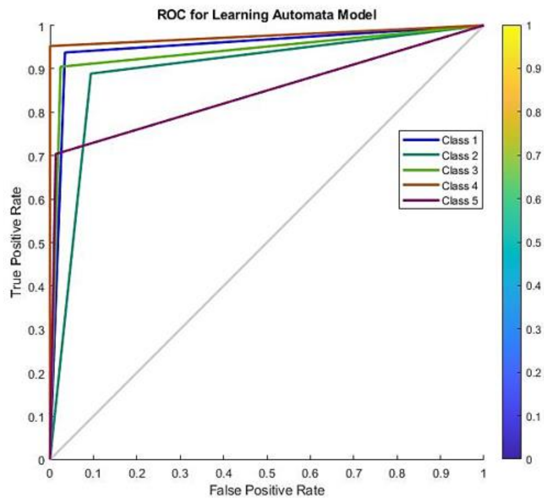

Fig. 20: ROC chart for D = 50, K = 100, and Nfemax = 10 parameters in LAA.

The performance of sonar data fusion by the learning automata algorithm for D = 50, K = 200, and N_{femax} = 15 values is shown in Fig. 21 and Fig. 22.

In Table 4, the parameter K = 100 is considered constant and the results are reported by changing the values of D and N_{femax} parameters. Also, the performance of sonar data fusion by LAA is shown using the confusion matrix and ROC charts in Figs 23 to 28.

The performance of sonar data fusion by the learning automata algorithm for K = 100, D = 10, and N_{femax} = 5 values is shown in Fig. 23 and Fig. 24.

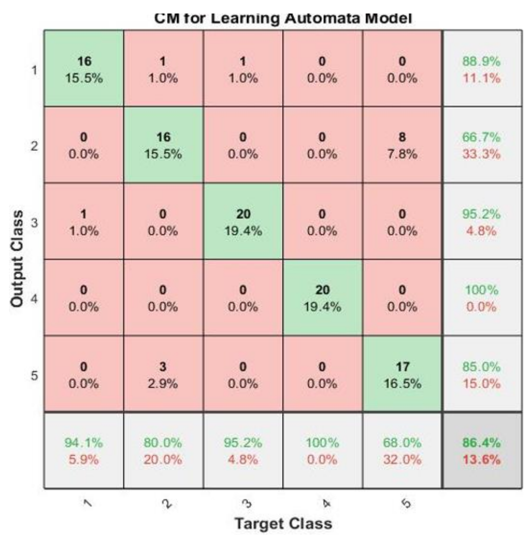

Fig. 21: Confusion matrix chart for D = 50, K = 200, and Nfemax = 15 parameters in LAA.

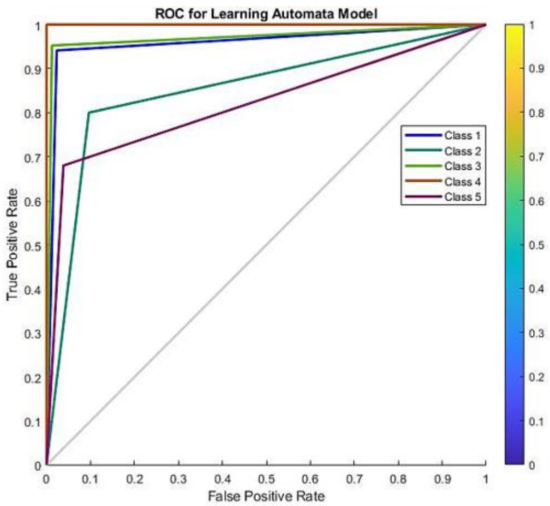

Fig. 22: ROC chart for D = 50, K = 200, and Nfemax = 15 parameters in LAA.

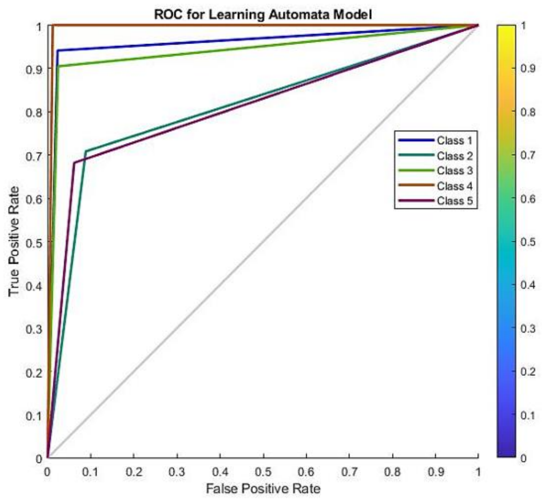

Fig. 24: ROC chart for K = 100, D = 10, and Nfemax = 5 parameters in LAA.

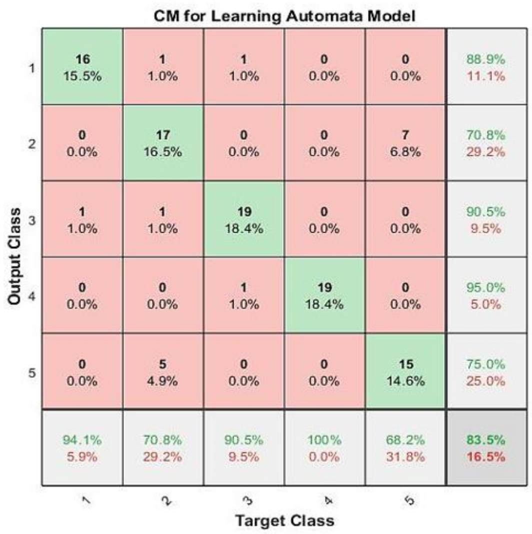

Fig. 23: Confusion matrix chart for K = 100, D = 10, and Nfemax = 5 parameters in LAA.

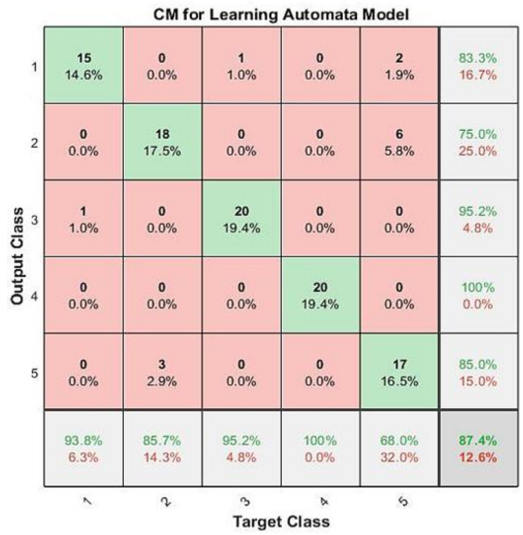

Fig. 25: Confusion matrix chart for K = 100, D = 50, and Nfemax = 10 parameters in LAA.

Table 4: LA performance results with the influence of Nfe and D parameters

The results for K=100 in LAA																										
Run Number	LAP		Best Solution				Precision (%)					Recall (%)					F1_Score					AUC					Accuracy (%)
	Nfe	D	W1	W2	W3	W4	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	
1	5	10	4	3	4	4	88.88	70.83	90.47	95	75	94.11	70.83	90.47	100	68.18	91.42	70.83	90.47	97.43	71.42	0.96	0.81	0.94	0.99	0.81	83.5
2	10	50	2	2	1	3	83.33	75	95.23	100	85	93.75	85.71	95.23	100	68	88.23	80	95.23	100	75.55	0.95	0.89	0.97	1	0.82	87.4
3	15	100	0	5	3	2	83.33	75	95.23	100	85	93.75	85.71	95.23	100	68	88.23	80	95.23	100	75.55	0.95	0.89	0.97	1	0.82	87.4

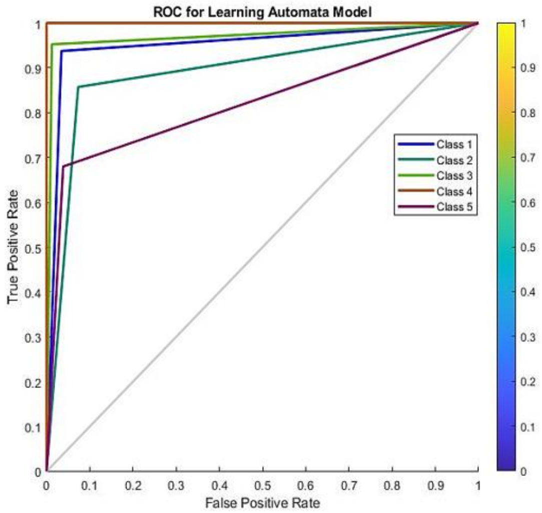

Fig. 26: ROC chart for K = 100, D = 50 and, Nfemax = 10 parameters in LAA.

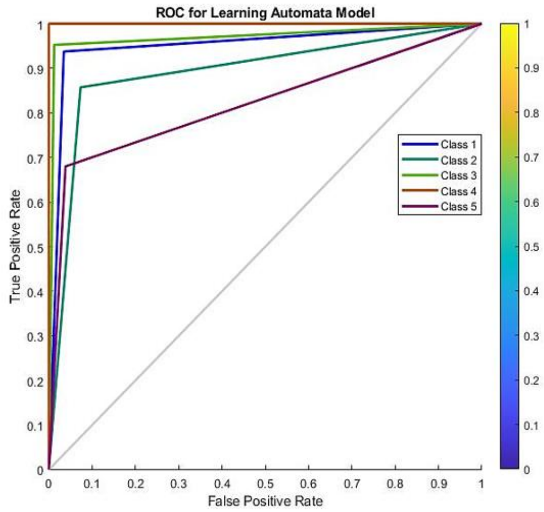

Fig. 28: ROC chart for K = 100, D = 100, and Nfemax = 15 parameters in LAA.

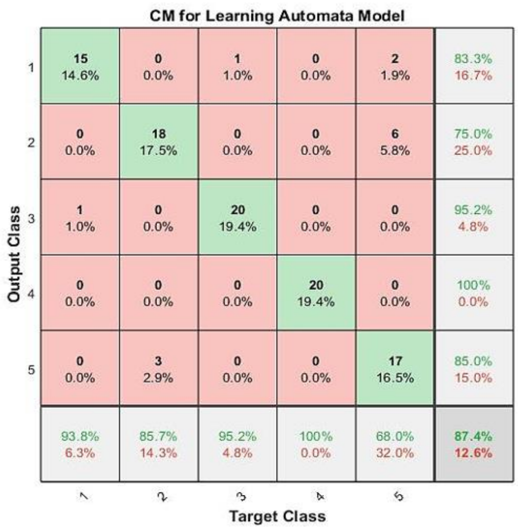

Fig. 27: Confusion matrix chart for K = 100, D = 100, and Nfemax = 15 parameters in LAA.

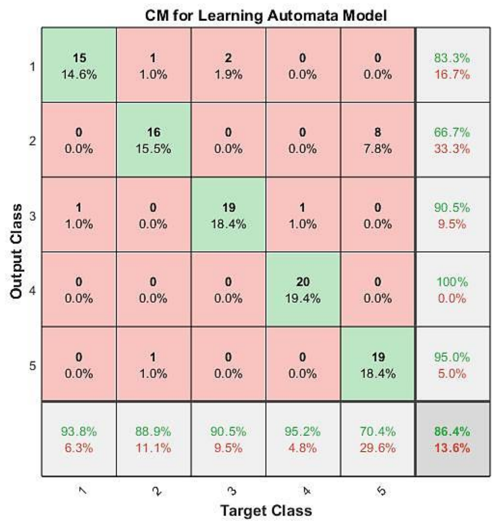

Fig. 29: Confusion matrix chart for Nfemax = 10, K = 10, and D = 10 parameters in LAA.

The performance of sonar data fusion by the learning automata algorithm for K = 100, D = 50, and N_{femax} = 10 values is shown in Fig. 25 and Fig. 26.

The performance of sonar data fusion by the learning automata algorithm for K = 100, D = 100, and N_{femax} = 15 values is shown in Fig. 27 and Fig. 28.

In Table 5, the parameter N_{femax} = 10 is considered constant and the results are reported by changing the values of K and D parameters. Also, the performance of sonar data fusion by LAA is shown using the confusion matrix and ROC charts in Figs 29 to 34.

The performance of sonar data fusion by the learning automata algorithm for N_{femax} = 10, K = 10, and D = 10 values is shown in Fig. 29 and Fig. 30.

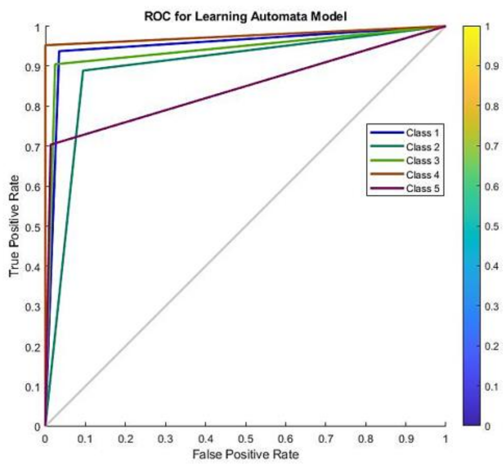

Fig. 30: ROC chart for Nfemax = 10, K = 10, and D = 10 parameters in LAA.

Table 5: LA performance results with the influence of K and D parameters

The results for Nfe=10 in LAA																											
Run Number	LAP		Best Solution				Precision (%)					Recall (%)					F1_Score					AUC					Accuracy (%)
	D	K	W1	W2	W3	W4	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	C1	C2	C3	C4	C5	
1	10	10	1	1	2	2	83.33	66.66	90.47	100	95	93.75	88.88	90.47	95.23	70.37	88.23	76.19	90.47	97.56	80.85	0.95	0.89	0.94	0.97	0.84	86.4
2	50	100	3	5	1	1	88.88	75	80.95	100	75	88.88	72	100	95.23	68.18	88.88	73.46	89.47	97.56	71.42	0.93	0.82	0.97	0.97	0.81	83.5
3	100	200	3	2	4	4	88.88	66.66	95.23	100	85	94.11	80	95.23	100	68	91.42	72.72	95.23	100	75.55	0.95	0.85	0.97	1	0.82	86.4

Fig. 31: Confusion matrix chart for Nfemax = 10, K = 100, and D = 50 parameters in LAA.

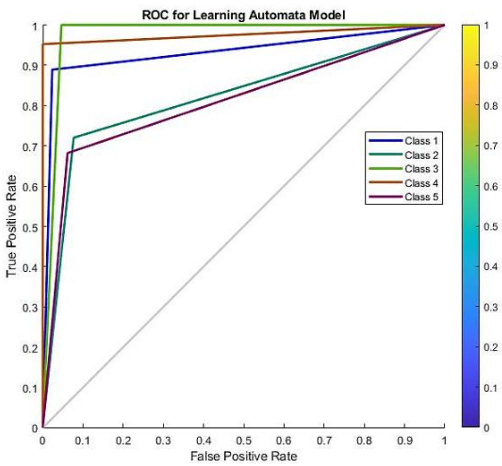

Fig. 32: ROC chart for Nfemax = 10, K = 100, and D = 50 parameters in LAA.

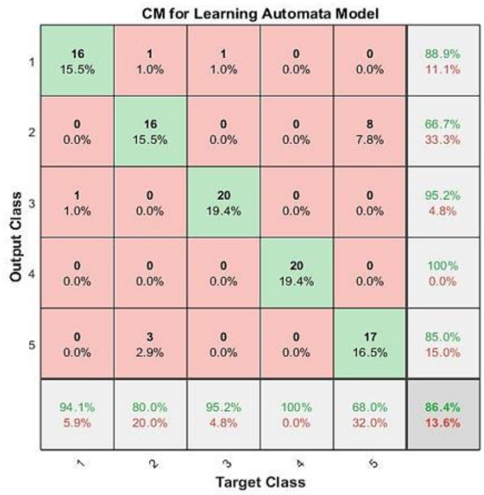

Fig. 33: Confusion matrix chart for Nfemax = 10, K = 200, and D = 100 parameters in LAA.

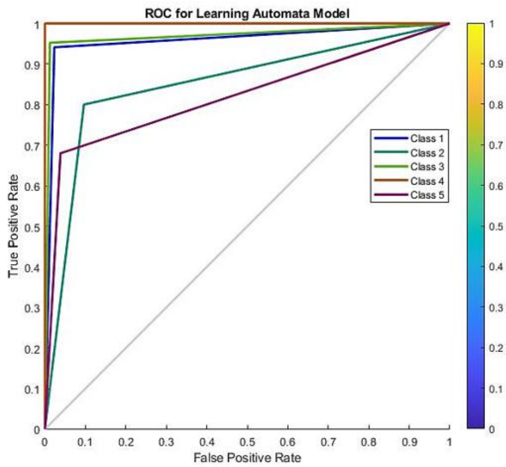

Fig. 34: ROC chart for Nfemax = 10, K = 200, and D = 100 parameters in LAA.

In addition, Table 6 shows the important parameters and computational requirements of introduced models such as SVM, RF, DT, XGboost, ensemble method, R-EFMD, T-EFMD, R-LFMD, T-LFMD, ANN, CNN, TIFR-

DCNN+SA, and joint [30-34]. The results of these models have been compared with the proposed model. Considering that the objectives and databases are different, we benchmarked the average detection rate.

In this comparison, Precision, Recall, F1_Score, and Accuracy parameters have been considered and investigated in order to show the superior performance of the proposed method with other methods. Also, in Fig. 35, the graph of this comparison is illustrated to show the results of each of the model's side by side, and the optimal performance of the data fusion method with the C algorithm is quite evident.

Table 6: Performance comparison of conventional and fused classification models

No.	Model	Precision (%)	Recall (%)	F1_Score (%)	Accuracy (%)
1	SVM	71.4	70	70	83.9
2	RF	70	77.78	73.68	76.19
3	DT	90	75	81.81	80.95
4	XGboost	80	80	80	80.95
5	Ensemble Method	60	75	66.67	71.45
6	R-EFMD	79.27	76.5	77.86	78.25
7	T-EFMD	79.51	81.5	80.49	80.25
8	R-LFMD	78.82	80	79.4	79.25
9	T-LFMD	83.17	86.5	84.8	84.5
10	ANN	63.71	64.58	64.14	65.57
11	CNN	78.47	79.39	78.92	65.57
12	TFIR-DCNN+SA	73.55	66.14	69.65	66.14
13	Joint	79.5	80.12	79.49	79.8
14	**Proposed Method**	**87.71**	**88.53**	**87.8**	**87.4**

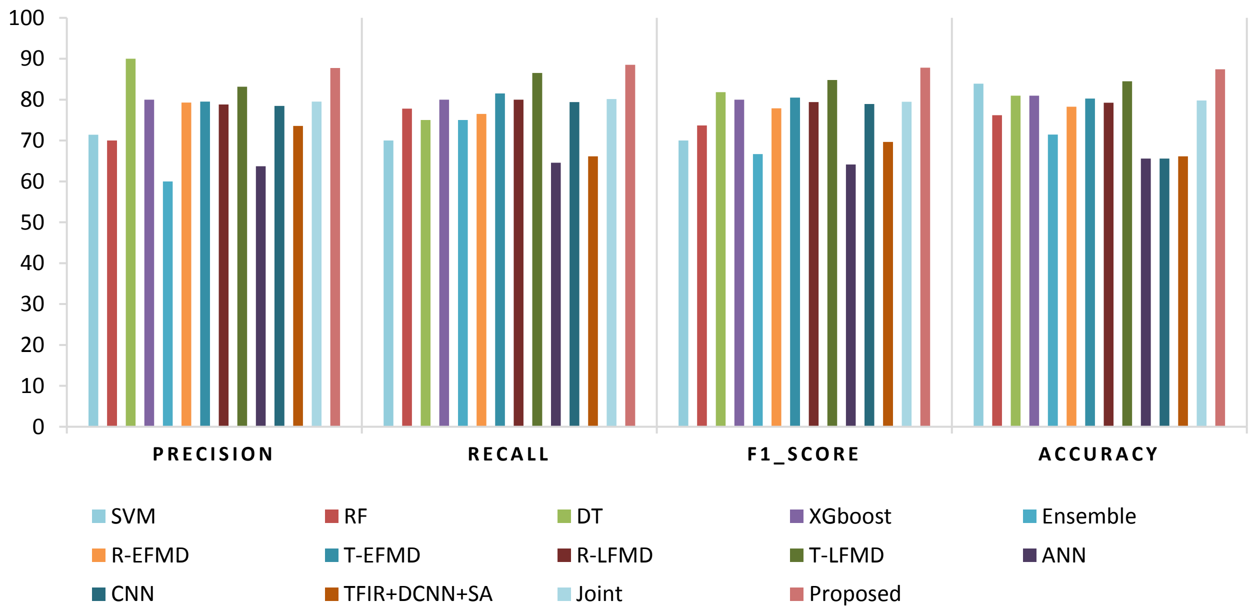

Fig. 35: Functional comparison of Precision, Recall, F1_Score, and Accuracy parameters.

Conclusion

In this article, the issue of combining classifications using LAA and sonar data is considered. The used sonar data, which includes 5 types of targets with different capabilities and specifications, were analyzed with the help of LAAs. The interference of sound waves and noise causes many problems in the detection of targets in marine environments. The classification of this data is often done in a traditional and manual way, and the possibility of target identification error is high in this method. By using ML methods and combining them with each other, the accuracy of detecting these targets can be increased. In this research, we first used 4 classification models separately to classify sonar data. Then by combining those classifiers with learning automata algorithm to achieve the best solution and by determining the optimal coefficients for each classifier, we were able to achieve significant results compared to similar works. The results obtained with the analytical parameters of Precision, Recall, F1_Score, and Accuracy compared to the latest similar papers have been examined and compared, and the values are 87.71%, 88.53%, 87.8%, and 87.4% respectively for each of These parameters are obtained in the proposed method.

Some limitations that can be mentioned. The proper setting of learning automata parameters is the proper selection of basic classifiers and the existence of appropriate databases for training basic classifiers. In the future, it is possible to perform tasks such as fuzzing or optimizing the control parameters of learning automata for better convergence, using intelligent methods for the optimal selection of parameters, and using the proposed method in the face of incomplete and missing databases.

Author Contributions

Sajjad Mahmoudi Khah simulated the proposed method in MATLAB. Seyed Hamid Zahiri and Iman Behrvan supervised and consulted in the design, implementation and results of this research. All authors discussed important sections and contributed to the final text.

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Conflict of Interest

The authors announce no potential conflict of interest regarding the publication of this paper. Also, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission and redundancy have been completely witnessed by the authors.

Abbreviations

SONAR	Sound and Range Navigation
DF	Data Fusion
RLA	Reinforcement Learning Algorithm
CNN	Convolutional Neural Network
ML	Machine Learning
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
RF	Random Forest
DT	Decision Tree
XGboost	Extreme Gradient Boosting
R-EFMD	Early Fusion Model with Resnet
T-EFMD	Early Fusion Model with Swin Transformer
R-LFMD	Late Fusion Model with Resnet
T-LFMD	Late Fusion Model with Swin Transformer
SA	Spatial Attention
TFIR	Time Frequency Image Recognition
DCNN	Deep CNN
SLP	Single-Layer Perceptron
MLP	Multi-Layer Perceptron
LA	Learning Automata
LAA	Learning Automata Algorithm
LAP	Learning Automata Parameter
AUC	Area Under the ROC Curve
CM	Confusion Matrix
ROC	Receiver Operating Characteristic

References

[1] X. Fan, L. Lu, P. Shi, X. Zhang, "A novel sonar target detection and classification algorithm," Multimedia Tools Appl.s, 81(7): 10091-10106, 2022.

[2] J. U. ROBERT, Principles of underwater sound for engineers. MCGRAW-HILL., 1983.

[3] S. J. Davey, M. G. Rutten, B. Cheung, "A comparison of detection performance for several track-before-detect algorithms," EURASIP J. Adv. Signal Process., 2008(1): 1-10, 2007.

[4] M. Hassaballah, A. I. Awad, Deep learning in computer vision: principles and applications. CRC Press, 2020.

[5] D. P. Williams, "Underwater target classification in synthetic aperture sonar imagery using deep convolutional neural networks," in Proc. 2016 23rd International Conference on Pattern Recognition (ICPR): 2497-2502, 2016.

[6] M. Valdenegro-Toro, "Best practices in convolutional networks for forward-looking sonar image recognition," in OCEANS 2017-Aberdeen: 1-9, 2017.

[7] E. L. Ferguson, R. Ramakrishnan, S. B. Williams, C. T. Jin, "Convolutional neural networks for passive monitoring of a shallow water environment using a single sensor," in Proc. 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP): 2657-2661, 2017.

[8] G. Huo, Z. Wu, J. Li, "Underwater object classification in sidescan sonar images using deep transfer learning and semisynthetic training data," IEEE Access, 8(1): 47407-47418, 2020.

[9] F. Mousavipour, M. R. Mosavi, "Sonar data classification using neural network trained by hybrid dragonfly and chimp optimization algorithms," Wireless Pers. Commun., 129(1): 191-208, 2023.

[10] Q. Li, L. Song, Y. Zhang, "Multiple extended target tracking by truncated JPDA in a clutter environment," IET Signal Process., 15(3): 207-219, 2021.

[11] E. Fan, W. Xie, J. Pei, K. Hu, X. Li, V. Podpečan, "Improved joint probabilistic data association (JPDA) filter using motion feature for multiple maneuvering targets in uncertain tracking situations," Information, 9(12): 322, 2018.

[12] T. Li, J. Prieto, H. Fan, J. M. Corchado, "A robust multi-sensor PHD filter based on multi-sensor measurement clustering," IEEE Commun. Lett., 22(10): 2064-2067, 2018.

[13] W. Xiong, X. Gu, Y. Cui, "Tracking and data association based on reinforcement learning," Electronics, 12(11): 2388, 2023.

[14] L. Snidaro, J. Garcia-Herrera, J. Llinas, E. Blasch, "Context-enhanced information fusion," Boosting Real-World Performance with Domain Knowledge, 2016.

[15] J. Raol, "Multi-Sensor Data Fusion with MATLAB. 2009," ed: CRC press.

[16] T. M. Mitchell, "Does machine learning really work?," AI magazine, 18(3): 11-11, 1997.

[17] P. Domingos, The master algorithm: How the quest for the ultimate learning machine will remake our world. Basic Books, 2015.

[18] A. K. Bathla, S. Bansal, M. Kumar, "OKC classifier: an efficient approach for classification of imbalanced dataset using hybrid methodology," Soft Comput., 26(21): 11497-11503, 2022.

[19] K. Taunk, S. De, S. Verma, A. Swetapadma, "A brief review of nearest neighbor algorithm for learning and classification," in Proc. 2019 International Conference on Intelligent Computing and Control Systems (ICCS): 1255-1260, 2019.

[20] D. Wettschereck, T. Dietterich, "Locally adaptive nearest neighbor algorithms," Adv. Neural Inf. Process. Syst., 6(1): 184-191, 1993.

[21] M. Sharma, S. K. Sharma, "Generalized K-nearest neighbour algorithm-a predicting tool," Int. J. Adv. Res. Comput. Sci. Software Eng., 3(11): 1-4, 2013.

[22] C. M. Bishop, Neural networks for pattern recognition. Oxford university press, 1995.

[23] H. Taud, J. Mas, "Multilayer perceptron (MLP)," in Geomatic approaches for modeling land change scenarios, Lecture Notes in Geoinformation and Cartography, Mexico City, 451-455, 2018.

[24] K. L. Du, M. N. Swamy, Neural networks and statistical learning. Springer Science & Business Media, 2013.

[25] M. A. Thathachar, P. S. Sastry, Networks of learning automata: Techniques for online stochastic optimization. Springer Science & Business Media, 2003.

[26] F. Hourfar, H. J. Bidgoly, B. Moshiri, K. Salahshoor, A. Elkamel, "A reinforcement learning approach for waterflooding optimization in petroleum reservoirs," Eng. Appl. Artif. Intell., 77(1): 98-116, 2019.

[27] M. L. v. TSetlin, "Automaton theory and modeling of biological systems," 1973.

[28] N. S. Shahraki, S. H. Zahiri, "DRLA: Dimensionality ranking in learning automata and its application on designing analog active filters," Knowledge-Based Syst., 219(1): 106886, 2021.

[29] Q. Wu, H. Liao, "Function optimisation by learning automata," Inf. Sci., 220(1): 379-398, 2013.

[30] B. N. K. Reddy, C. A. Vaithilingam, S. Kamalakkannan, "SONAR based under water mine detection using machine learning algorithms," in Proc. 4th International Conference on Innovative Practices in Technology and Management (ICIPTM): 1-4, 2024.

[31] Q. Wang, S. Du, W. Zhang, F. Wang, "Active sonar target recognition method based on multi-domain transformations and attention-based fusion network," IET Radar Sonar Navig., 2024.

[32] F. Ahmad, M. Z. Ansari, R. Anwar, B. Shahzad, A. Ikram, "Deep learning based classification of underwater acoustic signals," Procedia Comput. Sci., 235(1): 1115-1124, 2024.

[33] H. Yang, Y. Huang, Y. Liu, "Spatial attention deep convolution neural network for call recognition of marine mammal," in Proc. International Conference on Autonomous Unmanned Systems: 2725-2733, 2022.

[34] S. Z. Tian, D. B. Chen, Y. Fu, J. L. Zhou, "Joint learning model for underwater acoustic target recognition," Knowledge-Based Syst., 260(1): 110-119, 2023.

Biographies

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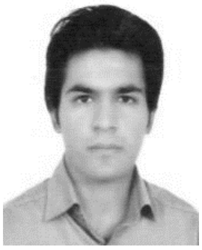

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