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Modeling Naval Mine Warfare with Machine Learning Algorithms

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Mines are a weapon that can change the naval operating environment and force the enemy to change their operational plan or clean up to a level where their forces can operate. For this reason, the measures to be taken against the mines in the hands of the enemy force are very important for the survival of the operation to be carried out. In this context, the use of machine learning algorithms in the planning of measures against possible landmines is discussed in this study. In this direction, firstly, synthetic data to be used in the study was produced, then predictions were made with five different machine learning using these data and the performances of the algorithms were compared. As a result of the calculations, it was seen that the best result was obtained with the ANN algorithm, and therefore, in the first step, "Mining Probabilities of the Channels" followed by the " Number of Ships to be Commissioned in Channels" were determined using the ANN algorithm. In the last step, the required number of ships was calculated based on the results obtained in the previous steps by using Linear Programming. In the conclusion part of the study, the effects of the change in channel mining probabilities on the amount of need were examined and the gains obtained with the developed model were mentioned. In addition, case studies that can be done in the following period for mine warfare were also discussed.

Keywords *– Naval Operations, Sea Mine, Machine Learning, Regression, Linear Programming, ANN Regression, SVR, Decision Tree Regression, Random Forest Regression.*

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I. INTRODUCTION

Mines are important weapons that can change the balance of power in the naval operational environment. The possibility of mines being trapped in any area in the naval operational environment will force the adversary to change their combat plan(s) or to clean up against these threats to a level where their forces can operate. Similarly, if certain sea areas under the control of our country are trapped with mines of various characteristics, this will hinder our dominance in the seas and the protection of our national interests. Therefore, the mine is a force multiplier.

Mines are usually trapped in sea areas called channels at port exits to confine the opposing force to its area. However, the mines were used in history for the purpose of defense against an all-out enemy attack, which was intended to land a landing operation from the sea and to occupy Istanbul by crossing the straits during the Dardanelles Naval War and created a great surprise effect.

Although the mine threat cannot completely stop naval operations, it may delay for a long time or cause other forms of action to be applied. For this reason, it is very important to be ready at any time against a mine-laying operation by the enemy force against the channels that are in our areas of responsibility and that we will use to bring our surface/underwater elements to the operation area. In this study, the gains to be obtained by using machine learning algorithms in planning for the situation will be mentioned and a planning will be made according to a sample scenario.

II. LITERATURE REVIEW

As mentioned above, sea mines have been weapons that directly affect the results of wars throughout history. For this reason, various studies have been carried out for the planning of mine warfare in various periods. Especially in recent studies, it is seen that artificial intelligence algorithms are also used. Case studies discussed in this context are presented in Table 1.

Table 1. Similar Studies in Literature.

Name of the Study	Scope of the Study	Used Models
Application of Artificial Intelligence Techniques in Naval Mine Warfare Planning [1].	The scope of this study is to explore the application of artificial intelligence (AI) techniques in naval mine warfare planning. The study aims to investigate how AI can enhance the effectiveness and efficiency of mine warfare planning by leveraging advanced computational algorithms and decision support systems. It examines various AI techniques and their potential for improving mine detection, classification, localization, and neutralization strategies in naval operations.	Artificial Neural Networks (ANN) Genetic Algorithms Fuzzy Logic Systems Expert Systems
Artificial Intelligence-Based Decision Support System for Naval Mine Warfare Planning [2].	The scope of the study aims to develop an artificial intelligence-based decision support system specifically designed for naval mine warfare planning. The study focuses on leveraging AI techniques to enhance the efficiency, accuracy, and effectiveness of mine warfare planning processes, ultimately improving naval operational capabilities and reducing potential risks.	Support Vector Machines Genetic Algorithms
Machine Learning Approaches for Naval Mine Warfare Planning [3].	The scope of the study focuses on exploring the application of machine learning techniques in naval mine warfare planning. The objective is to develop efficient and accurate models that can aid in decision-making processes, enhance situational awareness, and optimize mine countermeasure operations. The study investigates various machine learning algorithms and their suitability for addressing the challenges associated with mine warfare planning.	Convolutional Neural Networks (CNN) Recurrent Neural Networks (RNN) Support Vector Machines (SVM) Reinforcement Learning (RL)
Intelligent Systems for Naval Mine Warfare Planning and Execution [4].	The study aims to develop intelligent systems for naval mine warfare planning and execution. It focuses on utilizing artificial intelligence techniques to enhance the effectiveness and efficiency of mine warfare operations. The research investigates the application of advanced algorithms and decision support systems to support decision-making processes, optimize resource allocation, and improve situational awareness in mine warfare planning and execution.	ANN Genetic Algorithms
A Review of Artificial Intelligence Techniques for Naval Mine Warfare Planning [5].	The fifth study, conducted by Roberts and Thompson in 2019, provides a comprehensive review of various artificial intelligence techniques employed in naval mine warfare planning. The study aims to evaluate and compare the effectiveness and applicability of these techniques in enhancing mine warfare planning processes within naval operations. The review encompasses a wide range of AI methodologies and their specific applications within the field, addressing both theoretical aspects and practical implementation considerations.	ANN Genetic Algorithms
Deep Learning Approaches for Naval Mine Warfare Planning [6].	The scope of this study is to explore the application of deep learning techniques in naval mine warfare planning. The study aims to investigate the effectiveness of deep learning models in mine detection, classification, and threat assessment, and their potential for improving the accuracy and efficiency of mine warfare planning.	Generative Adversarial Networks (GANs) RNN RL CNN
Evolutionary Algorithms for Naval Mine Warfare Planning [7].	The scope of the study focuses on the application of evolutionary algorithms in naval mine warfare planning. It aims to explore the effectiveness of evolutionary algorithms as a decision support tool for optimizing mine warfare planning strategies. The study investigates how evolutionary algorithms can assist in tasks such as route planning, resource allocation, and mission sequencing in naval mine warfare operations.	Genetic Algorithm Particle Swarm Optimization Ant Colony Optimization (ACO)
Fuzzy Logic-Based Decision Support System for Naval Mine Warfare Planning [8]	The study focuses on the development and implementation of a fuzzy logic-based decision support system for naval mine warfare planning. The aim is to utilize fuzzy logic techniques to enhance the decision-making process in the planning phase of mine warfare operations. The study aims to improve the effectiveness and efficiency of mine warfare planning by providing decision support based on fuzzy logic principles.	Defuzzification Techniques Fuzzy Logic Model:
Neural Network Models for Naval Mine Warfare Planning [9].	The study focused on the application of neural network models in naval mine warfare planning. The study aimed to investigate the effectiveness of neural networks in predicting minefield characteristics, optimizing mine clearance operations, and enhancing decision-making processes in mine warfare planning. The researchers aimed to compare different neural network architectures and evaluate their performance in various mine warfare scenarios.	CNN Radial Basis Function Neural Network (RBFNN) RNN Feedforward Neural Network (FNN)
Multi-objective Optimization in Naval Mine Warfare Planning Using Genetic Algorithms [10].	The study focuses on the application of multi-objective optimization techniques in naval mine warfare planning using genetic algorithms. The study aims to develop an efficient decision support system that can simultaneously optimize multiple objectives in mine warfare planning, such as minimizing risk to naval vessels, maximizing the area covered for mine detection, and minimizing the time required for mine clearance operations.	Genetic Algorithm
This Study	With this study, considering the factors affecting the planning of mine warfare, it will enable the development of a new model that will enable the planning to be carried out in a way that is far from subjective values and gives results close to reality.	KNN Regression Decision Tree Regression Random Forest Regression SVM Regression ANN Regression Linear Programming

III. MATERIALS AND METHOD

3.1. Data Definition and Preprocessing

Since the real data, which is the input of the study, is "CONFIDENTIAL" within the scope of the National Security of our country, synthetic data produced according to a certain assumption were used in the study instead of the real data in question. In this direction, it was assumed that planning would be made for 10 channels and synthetic data were created for the following variables for each channel, and based on these data, the mining probabilities of each channel were tried to be estimated by machine learning algorithms.

✓ Depth; Depth is one of the most important factors that show whether the enemy force will mine in that channel. The depths at which sea mines can be effective are limited. Therefore, the deeper the channel is, the less likely it will be mined. In this context, random depth values between 25 and 500 meters were assigned to the channels considered in the study. The channel depth information resulting from the assignment is presented in Table 2.

Table 2 Depth Information of Channels.

Channel Nu	Depth (meter)
Channel 1	226
Channel 2	129
Channel 3	33
Channel 4	354
Channel 5	427
Channel 6	122
Channel 7	190
Channel 8	275
Channel 9	381
Channel 10	80

Then, each channel was given a score between 0 and 5 according to the depth of the channel. Channels with lower depth values scored close to 5, while channels with higher depth values scored close to 0. Depth-Score Values used in this context are presented in Table 2.

Table 3 Depth-Score Table.

Depth (meter)	Score
25-100	5
100-200	4
200-300	3
300-400	2
400-500	1
500+	0

One of the important factors affecting the possibility of mines in the channel is the enemy force platforms (plane/submarine/ship) detected in the channel. In this context, while creating the data set, it was assumed that the number of platforms determined for 365 days in each channel was recorded and synthetic data was created. Details regarding the said data are explained in the following articles.

✓ Number of Frigates Detected in the Channel; frigates in the hands of enemy forces will be able to be actively used in mine-laying activities. In this context, the number of frigates detected in each channel was determined by assigning random values with an average of 5 and a standard deviation of 3, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of frigates detected in the channel. The Detected Frigate Number-Point Values used in this context are presented in Table 4.

Table 4 Number of Frigates Detected-Score Table.

Number of Frigates Detected	Score
7+	5
6-7	4
4-6	3
3-4	2
1-3	1
0-1	0

✓ Number of Corvettes Detected in the Channel; Corvettes in the hands of enemy forces will be able to be actively used in mine dumping activities. In this context, the number of corvettes detected in each channel was determined by assigning random values with an average of 5 and a standard deviation of 3, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of corvettes detected in the channel. The Detected Number of Corvettes-Point Values used in this context are presented in Table 5.

Table 5 Number of Corvettes Detected-Score Table.

Number of Corvettes Detected	Score
7+	5
6-7	4
4-6	3
3-4	2
1-3	1
0-1	0

✓ Number of Assault Boats Detected in the Channel, gunboats in the hands of enemy forces will be able to be actively used in mine-pouring activities. In this context, the number of torpedo boats detected in each channel was determined by assigning random values with an average of 10 and a standard deviation of 4, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of torpedo boats detected in the channel. The Number of Detected Assault Boats-Point Values used in this context are presented in Table 6.

Table 6 Number of Detected Assault Boats-Score Table.

Number of Detected Assault Boats	Score
14+	5
11-14	4
8-11	3
6-8	2
3-6	1
0-3	0

✓ Number of Submarines Detected in the Channel, submarines in the hands of enemy forces will be able to be actively used in mine dumping activities. In this context, the number of submarines detected in each channel was determined by assigning random values with an average of 2 and a standard deviation of 1, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of submarines detected in the channel. The Number of Detected Submarines-Point Values used in this context are presented in Table 7.

Table 7 Number of Detected Submarines-Score Table.

Number of Detected Submarines	Score
3+	5
2-3	4
1-2	2
0	0

✓ Number of Aircraft Detected in the Channel, aircraft in the hands of enemy forces will be able to be actively used in mine-pouring activities. In this context, the number of aircraft detected in each channel was determined by assigning random values with an average of 10, a standard deviation of 2 and accepted as conforming to the normal distribution (total of 3650 data were created). Then, a score was made according to the number of aircraft detected in the channel. The Number of Detected Aircraft-Score Values used in this context are presented in Table 8.

Table 8 Number of Detected Aircraft-Score Table.

Number of Detected Aircraft	Score
12+	5
10-12	4
7-10	3
5-7	2
3-5	1
0-3	0

✓ Number of Amphibious Ships Detected in the Channel; Amphibious ships in the hands of enemy forces will be able to be actively used in mine-laying activities. In this context, the number of detecting amphibious ships in each channel was determined by assigning random values with an average of 3 and a standard deviation of 2, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of amphibious ships detected in the channel. The Number of Detected Amphibious Ships-Point Values used in this context are presented in Table 9.

Table 9 Number of Detected Amphibious Ships-Score Table.

Number of Detected Amphibious Ships	Score
5+	5
4-5	4
3-4	3
2-3	2
1-2	1
0	0

✓ Number of Autonomous Vehicles Detected in the Channel, autonomous vehicles in the hands of enemy forces will be able to be actively used in mine dumping activities. In this context, the number of autonomous vehicles detected in each channel was determined by assigning random values with an average of 8 and a standard deviation of 2, which were considered to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of autonomous vehicles detected in the channel. The Number of Detected Autonomous Vehicles-Point Values used in this context are presented in Table 10.

Table 10 Number of Detected Autonomous Vehicles-Score Table.

Number of Detected Autonomous Vehicles	Score
8+	5
7-8	4
6-7	3
4-6	2
2-4	1
0-2	0

✓ Number of Civil Boats Detected in the Channel, civilian boats in the hands of enemy forces can be actively used in mine dumping activities. In this context, the number of civilian boats detected in each channel was determined by assigning random values with an average of 20, a standard deviation of 3 and accepted to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of civilian boats detected in the channel. The Detected Civilian Boat Number-Point Values used in this context are presented in Table 11.

Table 11 Number of Detected Autonomous Vehicles-Score Table.

Number of Civil Boats Detected	Score
21+	5
17-21	4
14-17	3
8-14	2
5-8	1
0-5	0

✓ Number of Auxiliary Class Ships Detected in the Channel, auxiliary class ships in the hands of enemy forces will be able to be actively used in mine laying activities. In this context, the number of auxiliary classes detected in each channel was determined by assigning random values with a mean of 9, a standard deviation of 2 and accepted to fit the normal distribution (total of 3650 data were created). Then, a score was made according to the number of auxiliary class ships detected in the channel. The Number of Detected Auxiliary Class Ships-Point Values used in this context are presented in Table 12.

Table 12 Number of Detected Autonomous Vehicles-Score Table.

Number of Detected Auxiliary Class Ships	Score
9+	5
8-9	4
7-8	3
5-7	2
2-5	1
0-2	0

By using the scores obtained from the data explained above and the formula (1), the mining probabilities of each channel for the data collection day were calculated and added to the data set.

$\forall\ p_i^k$:

$$p_i^k = \frac{\left[\sum_k \left(x_{ij}^k * w_j\right)\right]}{5} \quad (1)$$

k : Indicates the day on which the mining probability is calculated.

i : The mining probability refers to the calculated channel.

j : It expresses the parameter that affects the probability of mining.

x_{ij}^k : It represents the score of the i channel for the j parameter on day k.

w_j : It expresses the effect (weight) of the parameter j on the probability of being mined. (The weight values in Table 13 were used in the calculations.)

p_i^k : It expresses the probability that channel i is mined on day k.

Table 13 Parameter Weight Values Used in the Study.

Parameter	Weight
Depth	0,3
Number of Frigates Detected	0,04
Number of Corvettes Detected	0,04
Number of Detected Assault Boats	0,04
Number of Detected Submarines	0,04
Number of Detected Aircraft	0,04
Number of Detected Amphibious Ships	0,1
Number of Detected Autonomous Vehicles	0,15
Number of Civil Boats Detected	0,15
Number of Detected Auxiliary Class Ships	0,1

3.2. Creating the Model

3.2.1. Determining Channel Mining Probabilities

Based on the values explained so far, a data set consisting of a total of 3650 rows has been created. By making use of the aforementioned data set, the performances of the algorithms were compared using the machine learning algorithms in Figure 1, and then the mining probabilities of each channel were calculated according to the data in Table 14 with the algorithm that showed the best performance.

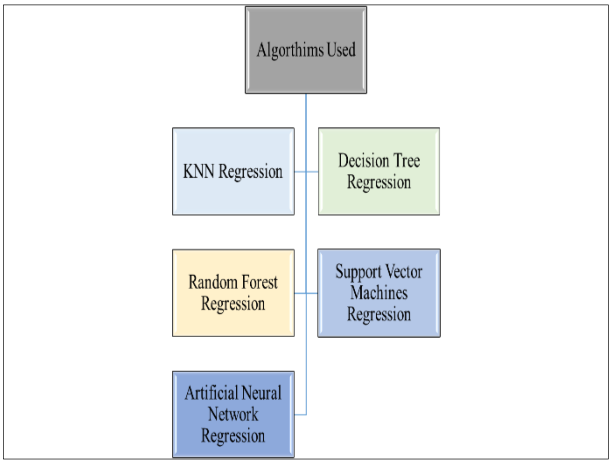

Figure 1 Algorithms Used in the Study.

Brief information about the algorithms used in the study is explained in the following articles.

3.2.1.1. KNN Regression

K-Nearest Neighbors (KNN) regression is a non-parametric algorithm used for predicting continuous values. It is a variant of the KNN algorithm, which is commonly used for classification tasks. In KNN regression, instead of classifying data points into categories, the algorithm predicts the numerical value of the target variable based on the values of its nearest neighbors [11].

The main idea behind KNN regression is to find the K nearest neighbors of a given data point in the feature space and use their values to predict the target variable. The "K" in KNN represents the number of neighbors considered for making predictions. These neighbors are determined based on a distance metric, typically Euclidean distance, which measures the similarity between data points [11].

To make a prediction using KNN regression, the algorithm calculates the average (or weighted average) of the target values of the K nearest neighbors. The predicted value is then assigned to the data point. The choice of K can have a significant impact on the model's performance. A smaller value of K will result in a more flexible model with potentially higher variance, while a larger K will lead to a smoother prediction surface with potentially higher bias [11].

One advantage of KNN regression is its simplicity and interpretability. It doesn't make any assumptions about the underlying data distribution, making it suitable for a wide range of problems. Additionally, KNN regression can capture complex relationships between features and the target variable. However, it can be computationally expensive, especially when dealing with large datasets, as it requires calculating distances between all pairs of data points [11].

KNN regression can be further improved by applying various techniques such as feature scaling, dimensionality reduction, and tuning the value of K. Additionally, selecting an appropriate distance metric and handling missing data are also important considerations [11].

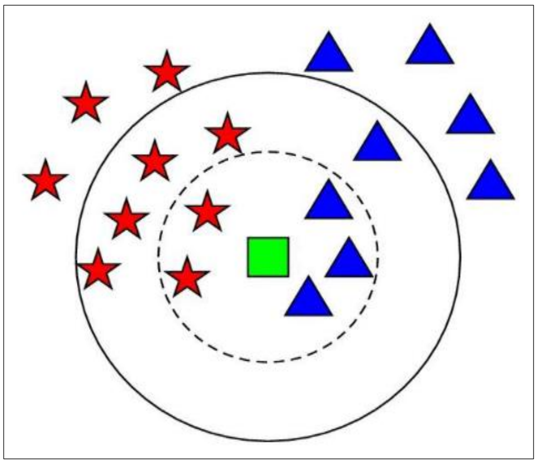

Figure 2 Visual Expression of KNN Algorithm.

3.2.1.2. Decision Trees Regression

Decision tree regression is a popular non-parametric algorithm used for predicting continuous values. It is based on the concept of a decision tree, where the data is split into partitions based on the values of the input features. Each partition corresponds to a leaf node of the tree, and the average (or weighted average) of the target variable within that partition is used as the prediction for new data points falling into that leaf [4].

The decision tree regression algorithm begins with a single node representing the entire dataset. The feature that best splits the data is selected based on a criterion such as minimizing the mean squared error (MSE) or maximizing the coefficient of determination (R-squared). The data is then split into two branches based on a threshold value of the selected feature. This process is recursively applied to each resulting partition until a stopping criterion is met, such as reaching a maximum depth or minimum number of samples in a leaf node [4].

One advantage of decision tree regression is its ability to capture non-linear relationships between the features and the target variable. The resulting model can be easily visualized and interpreted, making it useful for understanding the underlying patterns in the data. Decision trees are also robust to outliers and can handle a mixture of numerical and categorical features. Additionally, decision trees can be combined in ensemble methods such as random forests to further improve predictive performance [4].

However, decision tree regression has some limitations. It is prone to overfitting, especially when the tree becomes too deep or when the dataset has noise or irrelevant features. Regularization techniques such as pruning or setting a minimum number of samples required to split a node can help mitigate overfitting. Decision trees are also sensitive to small changes in the data, which can lead to different tree structures. Therefore, it's important to consider the stability of the results and to use techniques such as cross-validation to assess model performance. [4]

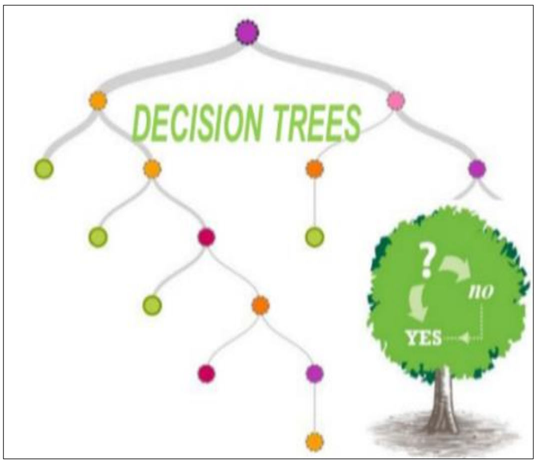

Figure 3 Decision Tree Algorithm Example Display.

3.2.1.3. Random Forest Regression

Random Forest regression is a powerful ensemble learning algorithm that combines the predictions of multiple decision trees to make accurate predictions on continuous target variables. It is an extension of decision tree regression, where a collection of decision trees, known as a forest, is created using bootstrapped samples from the training data. Each decision tree is trained independently on a subset of features and data points. The final prediction is obtained by averaging (or taking the weighted average) of the predictions made by all the trees in the forest [13].

Random Forest regression addresses some of the limitations of decision tree regression, such as overfitting and high variance. By aggregating the predictions of multiple trees, random forest regression reduces the impact of individual trees that may overfit the training data. This ensemble approach provides more robust and stable predictions by capturing a wider range of patterns in the data. Additionally, random forests can handle both numerical and categorical features and are less sensitive to outliers compared to single decision trees [13].

The randomization aspect of random forest regression plays a crucial role in its effectiveness. Firstly, during the construction of each decision tree, a random subset of features is considered for splitting at each node. This ensures that each tree focuses on different aspects of the data, leading to a diverse set of trees. Secondly, the bootstrapping process introduces randomness by sampling the training data with replacement. This means that each tree is trained on a slightly different subset of the data, further promoting diversity among the trees [13].

Random Forest regression provides important advantages, including robustness, scalability, and interpretability. It can handle large datasets efficiently and is less prone to overfitting compared to individual decision trees. The ensemble of decision trees also enables the estimation of feature importance, allowing for the identification of influential variables in the prediction process. Moreover, random forests can be used for missing value imputation and can handle high-dimensional data [13].

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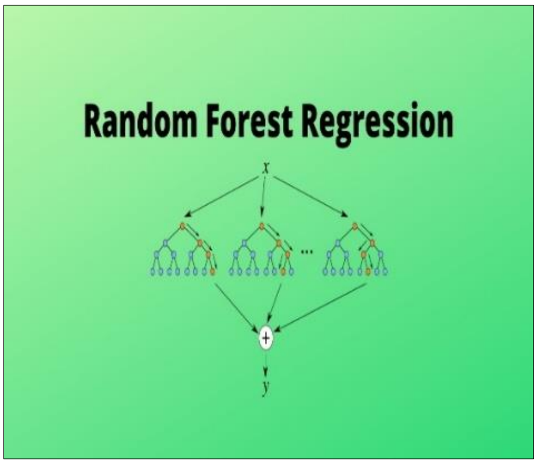

Figure 4 Random Forest Algorithm Example Display

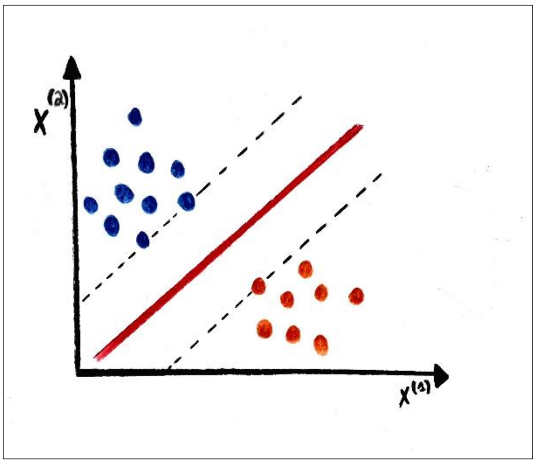

Figure 5 SVR Algorithm Example Display.

3.2.1.4. Support Vector Machines Regression

Support Vector Machine (SVM) regression is a machine learning algorithm that is commonly used for solving regression problems. It is an extension of the SVM algorithm, which is primarily used for classification tasks. In SVM regression, the goal is to find a hyperplane that maximally fits as many data points as possible within a certain margin, while also minimizing the prediction error [14].

In SVM regression, each data point is represented as a vector in a high-dimensional feature space. The algorithm aims to find the optimal hyperplane that separates the data points while maximizing the margin between the hyperplane and the closest data points, known as support vectors. The decision function of the SVM regression model is defined by a linear combination of support vectors, with weights determined during the training process [14].

The unique characteristic of SVM regression is the use of a loss function called ε-insensitive loss. This loss function allows for a certain tolerance (ε) around the predicted value, such that any prediction falling within this tolerance is considered accurate. This flexibility helps the model handle outliers and noise in the data, as they have less impact on the final prediction [14].

One of the key advantages of SVM regression is its ability to handle non-linear relationships between the features and the target variable. This is achieved by applying kernel functions, such as radial basis function (RBF), which transform the data into a higher-dimensional space. The transformed data is then separated by a hyperplane in this new space, allowing for non-linear decision boundaries in the original feature space [14].

SVM regression has several other benefits, including its ability to effectively handle high-dimensional data and the existence of a regularization parameter (C) that controls the trade-off between maximizing the margin and minimizing the prediction error. Additionally, SVM regression has a solid theoretical foundation and is less prone to overfitting compared to some other regression algorithms [14].

As seen in the graphic plane, we have two data groups and want to classify them by labeling them. When the support vector machine regression algorithm is applied, we get the parallel line passing through the middle. The points where the similar range drawn on the graph intersects are the support points [14].

3.2.1.5. Artificial Neural Networks Regression

Artificial Neural Network (ANN) regression is a powerful machine learning technique used for solving regression problems. It is inspired by the structure and function of biological neural networks in the human brain. ANN regression models consist of interconnected artificial neurons, organized in layers, that process input data and generate predictions [15].

In ANN regression, the input layer receives the features of the data, and the output layer produces the regression predictions. Between the input and output layers, there can be one or more hidden layers, each consisting of multiple neurons. Neurons in each layer are connected to neurons in the subsequent layer through weighted connections. The weights represent the strength of the connections and are adjusted during the training process to optimize the model's performance [15].

The key idea behind ANN regression is that the neurons in each layer perform a weighted sum of their inputs, followed by the application of an activation function. This activation function introduces non-linearity into the model, allowing it to capture complex relationships between the features and the target variable. Popular activation functions used in ANN regression include sigmoid, tanh, and ReLU (Rectified Linear Unit) [15].

Training an ANN regression model involves an iterative process called backpropagation. During this process, the model's predictions are compared to the actual target values, and the errors are propagated backward through the network. The weights of the connections are updated based on the calculated errors, aiming to minimize the difference between the predicted and actual values. This iterative process continues until the model reaches a satisfactory level of performance [15].

ANN regression offers several advantages. It can handle both numerical and categorical features, making it versatile for various types of data. ANN regression models are capable of learning complex non-linear relationships, making them suitable for capturing intricate patterns in the data. Additionally, ANN models could generalize well to unseen data when appropriately trained [15].

However, ANN regression models can be computationally intensive and require a large amount of training data to avoid overfitting. Proper preprocessing of the data, such as feature scaling and handling missing values, is also important for achieving optimal performance. Hyperparameter tuning, including the number of hidden layers, the number of neurons in each layer, and the learning rate, is crucial for obtaining the best model performance [15].

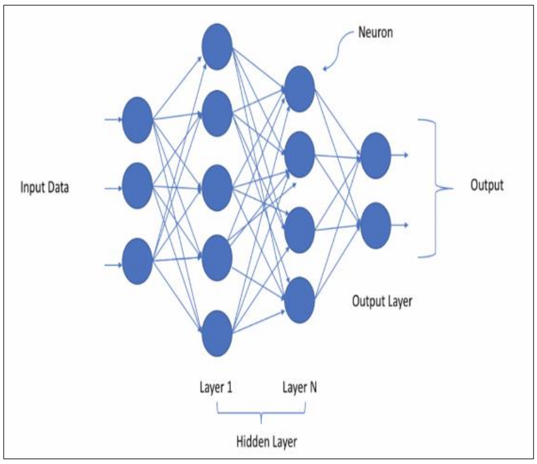

Figure 6 ANN Layers.

3.2.1.6. Comparing Algorithm Performances

Using the created data set, predictions were made with each algorithm and the performances of the models were compared by using the R^2 Score[1]. The R^2 Score values obtained in this context are presented in Figure 7.

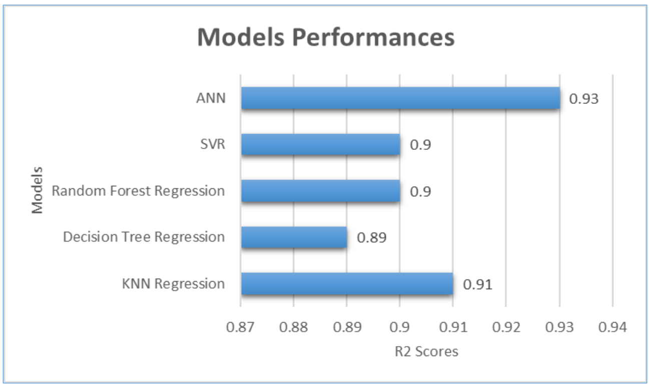

Figure 7 Algorithm Performances

When the data in Figure 7 is examined, it is seen that the best result is obtained with the ANN algorithm. Therefore, the mining probabilities of the channels will be calculated using ANN.

3.2.1.7. Calculation of Mining Probabilities of Channels

In this part of the study, the mining probabilities of each channel will be calculated. In this context, the mining probabilities of each channel were determined by using the ANN algorithm and using the data in Table 14.

Table 14 Data Used for Estimation.

Depth	Frigate	Corvette	Attack Boat	Submarine	Aircraft	Amphibian	Autonomous	Civilian	Assistant Ship
226	5	5	10	2	10	3	8	20	9
129	5	5	10	2	10	3	8	20	9
33	5	5	10	2	10	3	8	20	9
354	5	5	10	2	10	3	8	20	9
427	5	5	10	2	10	3	8	20	9
122	5	5	10	2	10	3	8	20	9
190	5	5	10	2	10	3	8	20	9
275	5	5	10	2	10	3	8	20	9
381	5	5	10	2	10	3	8	20	9
80	5	5	10	2	10	3	8	20	9

The channel mining probabilities calculated based on this information are presented in Table 15.

Table 15 Calculated Channel Mining Probabilities.

Channel Nu	Mining Probability
Channel 1	0,8
Channel 2	0,6
Channel 3	0,55
Channel 4	0,4
Channel 5	0,9
Channel 6	0,35
Channel 7	0,65
Channel 8	0,7
Channel 9	0,75
Channel 10	0,5

The calculated channel mining probabilities are used to determine the priority degrees of the channels. In other words, a mine hunting ship will be planned primarily for the channel where the channel is likely to be mined. In this context, the priority degrees of the channels formed

1 R^2 Score also known as the coefficient of determination, is a statistical measure used to evaluate the goodness of fit of a regression model. It indicates the proportion of the variance in the dependent variable that can be explained by the independent variables in the model. The R^2 score ranges from 0 to 1, where a value of 1 indicates a perfect fit, meaning that all the variance in the dependent variable is accounted for by the independent variables. To calculate the R^2 score, we compare the sum of squares of the differences between the predicted values and the mean of the dependent variable (SSR, sum of squares of regression) with the sum of squares of the differences between the actual values and the mean of the dependent variable (SST, total sum of squares). The formula for R^2 is $R^2 = 1 - (SSR / SST)$. Essentially, R^2 measures the proportion of the total variability in the dependent variable that is captured by the regression model. The R^2 score is commonly used as an evaluation metric for regression models because it provides an intuitive interpretation of the model's performance. A high R^2 score indicates that a large portion of the variability in the dependent variable is explained by the independent variables, suggesting a good fit. On the other hand, a low R^2 score implies that the model fails to capture much of the variation, indicating a poor fit [16].

according to the mining probabilities calculated are presented in Table 16.

Table 16 Priority Levels of Channels.

Channel Nu	Priority Rating
Channel 1	0.13
Channel 2	0.10
Channel 3	0.09
Channel 4	0.06
Channel 5	0.15
Channel 6	0.06
Channel 7	0.10
Channel 8	0.11
Channel 9	0.12
Channel 10	0.08

3.2.2 Determining the Number of Platforms Needed

In this part of the study, the number of mine hunting vessels required for 100% clearing of 10 channels against the mine threat will be calculated. It is assumed that there are 3 types of ships named MWS1 (Mine Warfare Ship 1), MWS2 and MWS3 operating in the channels. In this context, firstly, a data set consisting of mine hunting missions performed in the past with mine hunting ships was created. However, two different approaches were used while creating the data sets. In the first, a data set was created for the situation in which each ship served individually. Then, a second data set was created for the case of more than one ship at the same time. The parameters used in the data sets are explained in the following articles.

- ✓ Depth: The depth values determined in the data sets are the same values used in the mining probabilities.
- ✓ Length: The length values of each channel where the task is performed are entered into the data set. In this context, the lengths of the channels were determined by assigning random values between 5000-15000 miles. The resulting channel lengths are presented in Table 17.

Table 17 Length Information of Channels.

Channel Nu	Channel Length (nm)
Channel 1	10000
Channel 2	7000
Channel 3	5000
Channel 4	9000
Channel 5	14500
Channel 6	11000
Channel 7	8250
Channel 8	6500
Channel 9	10500
Channel 10	15000

- ✓ Width: The width values of each channel where the task is performed are entered into the data set. In this context, the lengths of the channels were determined by assigning random values between 250-600 miles. The channel widths obtained are presented in Table 18.

Table 18 Width Information of Channels.

Channel Nu	Channel Width (nm)
Channel 1	500
Channel 2	300
Channel 3	450
Channel 4	250
Channel 5	350
Channel 6	600
Channel 7	400
Channel 8	300
Channel 9	250
Channel 10	400

In line with this information, in the data set in which a single ship was assigned:

- ✓ 4000 random values suitable for normal distribution with a mean of 5 standard deviations of 2 for MWS1,
- ✓ For MWS2, 4000 random values suitable for normal distribution with a mean of 4 and a standard deviation of 2,
- ✓ For MWS3, 4000 random values were generated, which were in accordance with the normal distribution with a mean of 3 standard deviations of 1.
- ✓ In the data set where more than one ship was assigned, 4000 random values were created according to the following conditions.
- ✓ For MWS3, data with a mean of 2 standard deviations of 1 and a normal distribution were generated.
- ✓ MWS2 için;

```
If (MWS3<=2);
        MWS2== random.randint(2,3)
Else
        MWS2== random.randint(1,2)
```

- ✓ MWS1 için;

```
If (MWS2<=2);
        MWS1== random.randint(2,3)
Else
        MWS1== random.randint(1,2)
```

The model was trained using the prepared data sets and the ANN algorithm, and the number of ships needed in each channel was calculated using the data in Table 19.

Table 19 Forecast Data.

Channel Length (nm)	Channel Width (nm)	Channel Depth (m)
10000	500	226
7000	300	129
5000	450	33
9000	250	354
14500	350	427
11000	600	122
8250	400	190
6500	300	275
10500	250	381
15000	400	80

As a result of the calculations, the number of ships needed in each channel is presented in Tables (20 and 21).

Table 20 Number of Ships Required in Case of Single Ship Assignment.

Channel Nu	MWS1	MWS2	MWS3
Channel 1	7	5	3
Channel 2	4	4	2
Channel 3	6	5	3
Channel 4	6	5	3
Channel 5	8	6	3
Channel 6	7	6	3
Channel 7	6	4	3
Channel 8	6	5	3
Channel 9	6	5	3
Channel 10	6	8	2

Table 21 Number of Ships Required in Case of More than One Ship Deployment.

Channel Nu	MWS1	MWS2	MWS3
Channel 1	3	2	2
Channel 2	2	1	1
Channel 3	2	2	2
Channel 4	2	2	2
Channel 5	3	2	2
Channel 6	3	2	2
Channel 7	3	2	2
Channel 8	2	2	2
Channel 9	3	2	2
Channel 10	2	1	1

The values in Table 21 are the values that occur when ships are sent to the channels at different times. In this context, in order to determine the amount of need in case ships are sent to the channels at the same time, the following mathematical model has been created and the required amounts have been determined in order to calculate the number of ships required to carry out these operations with minimum cost within the scope of all the information obtained so far.

Objective Function:

$$minz = \sum_{ij} x_i^j * c_j \quad (2)$$

The total ship cost is tried to be minimized.

Constraints:

$\forall i;$

$$x_i^j \geq 1 \quad (3)$$

Constraint to have at least one ship in each channel.

$\forall i, \forall j;$

$$\left[l_i * \left(x_i^j * a_j\right)\right] \geq a_i \quad (4)$$

$$l_i = \frac{p_i}{\sum p_i} \quad (5)$$

Area constraint to clear.

$\forall i, \forall j;$

$$\left[l_i * \left(\sum_{ij} x_i^j * e_i^j\right)\right] \leq t_j \quad (6)$$

Cleaning time limit.

i : Channel index
j : Ship index.
x_i^j : Number of ships j sent to channel i.
c_j : j ship cost[2]
l_i : priority of channel i.
a_j : The maximum area in which the task can be performed during the cleaning period determined by ship j.
a_i : Area of the i channel.
p_i : The probability of mining the i channel.
e_i^j : Minimum number of ships j to be deployed to channel i.
t_j : Time required to clear the i channel[3].

The model was solved with the python program and the number of ships required to clean all channels in a specified time with optimal cost was calculated. The calculation results in question are presented in Table 22.

Table 22 Number of Ships Required to Clean All Channels.

Channel Nu	MWS1	MWS2	MWS3
Channel 1	3	2	2
Channel 2	2	2	2
Channel 3	2	2	2
Channel 4	2	2	2
Channel 5	3	2	2
Channel 6	3	2	2
Channel 7	3	2	2
Channel 8	2	2	2
Channel 9	3	2	2
Channel 10	2	2	2
Total	**25**	**20**	**20**
Total Cost		**2480000000 $**	

According to the values in Table 22, it has been seen that the number of ships in Table 21 will not be sufficient if there is a simultaneous assignment in all channels. In this way, any vulnerabilities can be prevented from occurring. The study has been updated for 3 different cases in order to observe the effect of the change in the mining possibilities of the channels on the change in the amount of need and cost. These are the case where the mining probabilities are assumed equal in all channels, and the two cases where the mining probabilities are determined subjectively at random.

Mining probabilities considered in this context are presented in Table 23. The reason why different values are taken as Case 2 and Case 3 is to show that if the mining probabilities are determined by different people, the probability values will change, and in this case, it will also affect the amount of need. This may result in unnecessary costs.

[2] Ship costs were determined randomly and, in this study, the cost was accepted as 30 million dollars for MWS1, 45 million dollars for MWS1 and 40 million dollars for MWS3.

[3] In this study, the cleaning time was taken into account as 24 hours.

Table 23 Mining Probabilities According to Different Situations

Channel Nu	Mining Probabilities		
	Case 1	Case 2	Case 3
Channel 1	0,75	0.51	0.58
Channel 2	0,75	0.74	0.93
Channel 3	0,75	0.79	0.90
Channel 4	0,75	0.52	0.54
Channel 5	0,75	0.85	0.63
Channel 6	0,75	0.88	0.66
Channel 7	0,75	0.59	0.50
Channel 8	0,75	0.64	0.89
Channel 9	0,75	0.59	0.78
Channel 10	0,75	0.75	0.75

The costs incurred according to the amount of ships calculated according to the 3 different situations in question are presented in Table 24.

Table 24 Number of Ships Required for Different Situations and Total Costs.

Case Nu	Total Number of Ships Needed	Total Cost
Case 1	69	2570000000$
Case 2	85	3250000000$
Case 3	93	3490000000$
This Study	**65**	**2480000000 $**

As can be seen in Table 24, channel mine probabilities play a very important role in determining the amount of need. For this reason, the change in mine possibilities also affects the number of ships, which causes unnecessary costs. In this context, as in this study, the use of machine learning algorithms in the steps that directly affect the amount of needs will produce more cost-effective solutions, and since data-driven calculations are made, personnel replacement will not cause much change in the calculations.

IV. RESULTS

In this study, the number of mine hunting ships that will be needed in a sample scenario has been calculated by using machine learning algorithms in mine warfare planning.

In this context, firstly, the mining probabilities of the channels were tried to be determined. First of all, synthetic data was produced because the data to be used within the scope of the study have the degree of confidentiality. Subsequently, the synthetic data produced was tested with 5 different algorithms and the algorithm with the best performance was determined first. The best end to the calculations made. It was taken with the ANN algorithm with a 93% R^2 score.

Then, using the estimation data set and ANN algorithm, the priority degrees of the channels were calculated according to the probability values of the mining probability of each channel.

Subsequently, the number of ships required for the performance of the cleaning task in each channel was calculated using the ANN algorithm, again on the synthetic data. Finally, a mathematical model was developed based on the data obtained because of the calculations, and the model was solved with python software and the number of ships needed within the scenario was calculated.

In addition, the number of ships was calculated according to different mine probabilities to see the effect of the change in the mining probabilities on the number of ships needed.

As a result of the calculations, it has been seen that the probabilities of channel mines directly affect the amount of need. For this reason, it is considered that calculating the mining probabilities in a data-driven way, as in this study, will provide more cost-effective results.

V. DISCUSSION

This study was carried out to determine the amount of need for mine hunting vessels. However, with the developing technology, it is evaluated that autonomous vehicles can be used in mine warfare as in every field. This may shorten the term of office.

For this reason, it is considered that it would be appropriate to carry out this or similar studies for mine warfare planning, including autonomous vehicles.

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