Acadlore Transactions on AI and Machine Learning
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A Novel Machine Learning Approach for Optimizing Radar Warning Receiver Preprogramming

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Received: 08-12-2024 **Revised:** 10-08-2024 **Accepted:** 10-15-2024

Citation: M. Demircan and A. G. Pakfiliz, "A novel machine learning approach for optimizing radar warning receiver preprogramming," *Acadlore Trans. Mach. Learn.*, vol. 3, no. 4, pp. 202–213, 2024. https://doi.org/10.56578/ataiml030402.

Abstract: Radar warning receivers (RWRs) are critical for swiftly and accurately identifying potential threats in complex electromagnetic environments. Numerous methods have been developed over the years, with recent advances in artificial intelligence (AI) significantly enhancing RWR capabilities. This study presents a machine learning-based approach for emitter identification within RWR systems, leveraging a comprehensive radar signal library. Key parameters such as signal frequency, pulse width, pulse repetition frequency (PRF), and beam width were extracted from pulsed radar signals and utilized in various machine learning algorithms. The preprogramming phase of RWRs was optimized through the application of multiple classification algorithms, including k-Nearest Neighbors (KNN), Decision Tree (DT), the ensemble learning method, support vector machine (SVM), and Artificial Neural Network (ANN). These algorithms were compared against conventional methods to evaluate their performance. The machine learning models demonstrated a high degree of accuracy, achieving over 95% in training phases and exceeding 99% in test simulations. The findings highlight the superiority of machine learning algorithms in terms of speed and precision when compared to traditional approaches. Furthermore, the flexibility of machine learning techniques to adapt to diverse problem sets underscores their potential as a preferred solution for future RWR applications. This study suggests that the integration of machine learning into RWR emitter identification not only enhances the operational efficiency of electronic warfare (EW) systems but also represents a significant advancement in the field. The increasing relevance of machine learning in recent years positions it as a promising tool for addressing complex signal processing challenges in EW.

Keywords: Emitter identification; Radar warning receiver; Machine learning; Classification algorithms; Support vector machine; Neural network; k-Nearest Neighbors

1 Introduction

In the early 20$^{\text{th}}$ century, radar and EW technologies became critical and indispensable features of the battlefields. These technologies are mainly used to enable friendly elements to hide or disguise themselves, their maneuvers, and intentions, as well as to prevent using weapons that the enemy can use. Radar-guided weapon systems have also made significant technological progress using and developing EW technologies. Radar technology and radar-guided weapons have taken their place as important key features on the battlefield by providing the capabilities to detect, track, and destroy enemy targets. Although EW technologies are not a direct weapon system, considering the wars in which they are used, they can be seen to harm enemy elements and sometimes affect the course of wars. The extensive usage of radar-guided weapons and the rapid development of radio frequency (RF) technologies are essential milestones in the defense industry [1].

Radar guidance is widely used in missile guidance systems and offers the ability to respond effectively to the enemy's EW and physical threats. Although this is considered a very important advantage, the widespread use of these technological advances allows enemies to improve their EW technologies and capabilities. Every EW threat creates a new electronic countermeasure against them. Thereby, it is seen that the techniques and tactics used in EW technology are often learned with considerable losses in battles. The most important feature that can produce an advantage at this point is to reveal different and superior features to the enemy's technology.

Radar-guided threats can be used to deactivate and neutralize units. For instance, high-speed anti-radiation missile (HARM)-type missiles cruise toward their target as long as enemy elements transmit radar signals. With this type of missile, the target is destroyed or disabled by interrupting the radar emission. To respond to such threats and other anti-air artillery (AAA) and surface-to-air missile (SAM) threats, self-protection systems began to be included in aircraft in the mid to late 20$^{\text{th}}$ century [1]. These self-protection systems are electronic countermeasure systems that protect mother platforms against enemy weapon system radars. While the threats increase the system's complexity in parallel with the technology race, they also reveal that developing more complex and effective EW systems is necessary to ensure the safety of military units [2]. RWR systems are inseparable parts of self-protection EW systems used in air and sea platforms. These are precious military assets, such as fighters (air intercept and bombers), cargo aircraft, strategic bombers, helicopters, navy warships, and, recently, middle- and large-scale Unmanned Aerial Vehicles (UAVs) in fighter, logistic, and reconnaissance roles. This situation makes RWRs more valuable and forces them to be more capable.

In addition to radically changing the nature of warfare in the 20th century, EW technologies are a crucial element that significantly increases the military capability of an army. For this reason, innovations and threats in the defense industry that can provide input to EW technologies should be closely monitored. New strategies and technologies should be constantly developed to counter these innovations. Otherwise, the risk of losing the competitive edge on the battlefield can be very high. For this reason, EW technologies have become a critical political area in which military experts, defense industry experts, and politicians are focused. This technological race requires a continuous effort for countries to create and strengthen their defense strategies in the context of EW and to be ahead of rival countries on future battlefields.

The identification friend or foe (IFF) system is among radar technologies. It is necessary to effectively use this system to detect the enemy element, thereby allowing the friendly element to survive and operate. As a method primarily used in RWR, the signals are then deinterleaved and labeled into clusters using RF, signal amplitude, Direction of Arrival (DOA), and Time Difference of Arrival (TDOA) parameters. The signal identification process primarily depends on accurate measurements of radar parameters. Since almost all radars have different operating modes to adapt to the target range, an essential part of the identification process is to include all signals emitted by recorded radars in different operating modes. Detection, deinterleaving, labeling, and identification of signals received from another radar transmitter are carried out in the RWR. To perform these operations, a receiver subsystem (Rx) inside the RWR and a signal processor compare the received signals with the emitter library [3].

The preprogramming phase of radar identification involves configuring radar systems with predefined parameters and algorithms to detect and classify various radar signals. Specific transmitter identification algorithms are required to identify radar signals under various conditions, including zero-sample scenarios, using parameter learning techniques. The preprogramming phase is processed in an EW support center where radar signals recorded and identified by electronic intelligence systems are analyzed. Libraries are created in these centers to be loaded onto platforms for specific regions before missions, and pulse descriptors for radars are continuously optimized and updated.

The density of interleaved radar signals at an active battlefield creates a problematic environment for RWR systems to identify signals accurately. Therefore, signals must be interleaved, labeled, and identified in the signal processor using their signal parameters [3, 4]. Conventional RWR systems use their signal parameter comparison algorithms within these problematic environments. Since the comparison algorithm is configured in preprogramming, in some cases, radars with very similar signal parameters cannot be distinguished and can be identified as false emitters. The primary motivation of this study is to optimize the precision of the identification algorithm by using machine learning algorithms in the preprogramming phase and thus create an identification algorithm that can prevent incorrect identifications. For this purpose, several machine learning algorithms that can successfully identify radars with signal parameters similar to those mentioned in this study were used to compare with each other in terms of accuracy and agility performances.

Modern RWR systems have been developed with various emitter identification methods. Within these methods, new algorithms are used to overcome complex signal environments in which multiple emitters operate. Against these developments, modulation types and methods have been changed to counter jamming and identification. Linear frequency modulation, phase shift keying, and frequency shift keying are used in most emitters. These modulation types can be used in the same and different operating modes on the radars. Therefore, using these modulating features in emitter classification is not applicable [5].

Current studies have combined conventional methods with innovative methods to improve identification performance. Apart from using resemblance coefficients of emitter signals in essential functions, Wang et al. [5] also used rectangular, composite, triangular, and Gaussian sequences. They discovered that a combination of composite and Gaussian functions is superior to other functions in terms of aggregation within a class and seperability among classes.

Identifying emitters in the RWR can be performed using machine learning algorithms and mathematical models [6]. While existing studies approach a specific radar problem with a single and specific solution, this study approaches the emitter identification problem with multiple algorithm solutions. It includes comparing the performance of these algorithms relative to each other. In this way, the ease of applying machine learning algorithms, especially in radar and emitter identification problems, was examined. The results show that more than one algorithm solution can be used with sufficient algorithm optimization. Among the methods of identifying radar emitters, machine learning is expected to be an effective method. Determining the most effective method for emitter identification using multiple machine learning methods is aimed at obtaining an effective alternative, which reduces the processing load of RWR and makes more accurate decisions compared to the currently used methods. In this study, a signal library was created before the simulation study, and the algorithms were trained using a labeled data set. For this reason, supervised learning techniques among machine learning algorithms were used. As a result of preliminary tests, supervised learning algorithms and methods that can be applied to the radar signal and transmitter identification problem are as follows: SVM, KNN, DT, the ensemble learning method, and neural networks. These algorithms can identify pulse radar signals deinterleaved by RWR systems on aircraft. Signal parameters were defined in the algorithms to identify the signal emitters.

A previously defined radar signal library is presented for machine learning methods to identify deinterleaved radar signals. The radar parameters were determined for all radar emitters to be used in the simulation with this library. First, accuracy tests were carried out with machine learning algorithms suitable for this study, and the algorithms' performance was evaluated.

In the second part of the study, machine learning algorithms whose accuracy performance is deemed appropriate were applied to the simulation of a complex signal environment with the number of radar signals determined by the algorithm. After experiments with different radar signals, these results were evaluated by showing accuracy test results and simulation results.

The primary purpose of this study and its contribution to the literature is to create a machine learning model that can perform pulsed radar signal identification operations with high accuracy and reduce the processing volume in the RWR. In addition, a prime objective is combining different machine learning algorithms as a multifunction model to achieve two identification tasks.

2 Theoretical Background

The main task of RWRs is to detect and identify all signals in the environment in which they are used and to determine whether there may be a threat. The fundamental function blocks used in performing this task in the RWR have been defined [1]. These fundamental function blocks receive the signal, deinterleave, label, identify, and provide information to the electronic countermeasure system. In the first block, the parameters of the received signals are measured, and the signals are deinterleaved and labeled. In the following block, the signal emitter is identified by comparing the signal parameters in the emitter library with the measured parameters. The identified emitter is shown to the pilot as information, and if it is evaluated as a threat, electronic countermeasure action is applied automatically or manually. These basic function blocks and flow directions are shown in Figure 1.

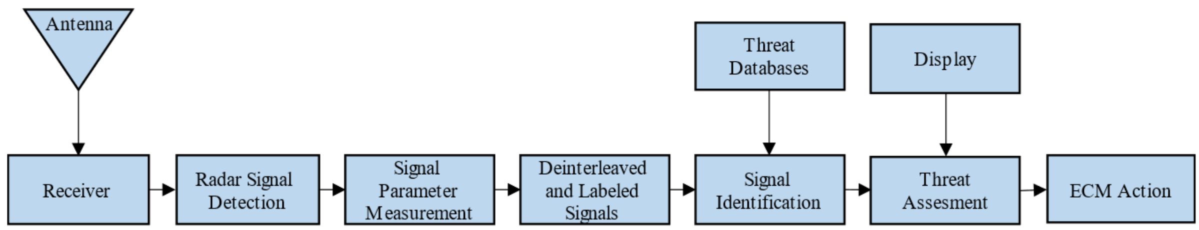


Figure 1. Diagram of RWR functions

Identification of radar signals is one of the main functions of the RWR, as shown in Figure 1. However, some factors can cause the performance of the RWR processor to decrease. The identification of signals depends on how accurately the parameters of these signals are measured by the subsystems connected to the RWR and included in the calculations. In addition to this problem, many radars in the measurement environment may have overlapping signals and similar tasks [3]. Although the parameters of the received signals are deinterleaved, these signals may be emitted from radars operating in frequency bands that are very close to each other. Figure 2 shows the individual and interleaved visuals of the signals emitted by five radars operating with different pulse repetition frequencies.

When deinterleaving the signals from each other before identifying the emitter, some of the signal parameters, such as DOA, Time of Arrival (TOA), etc., are directly used in RWR, and some of the parameters in the incoming signal are included in the deinterleaving process with some calculations. Radar equations are necessary for operations such as finding the output power of the signal from the threat radar and finding the distance.

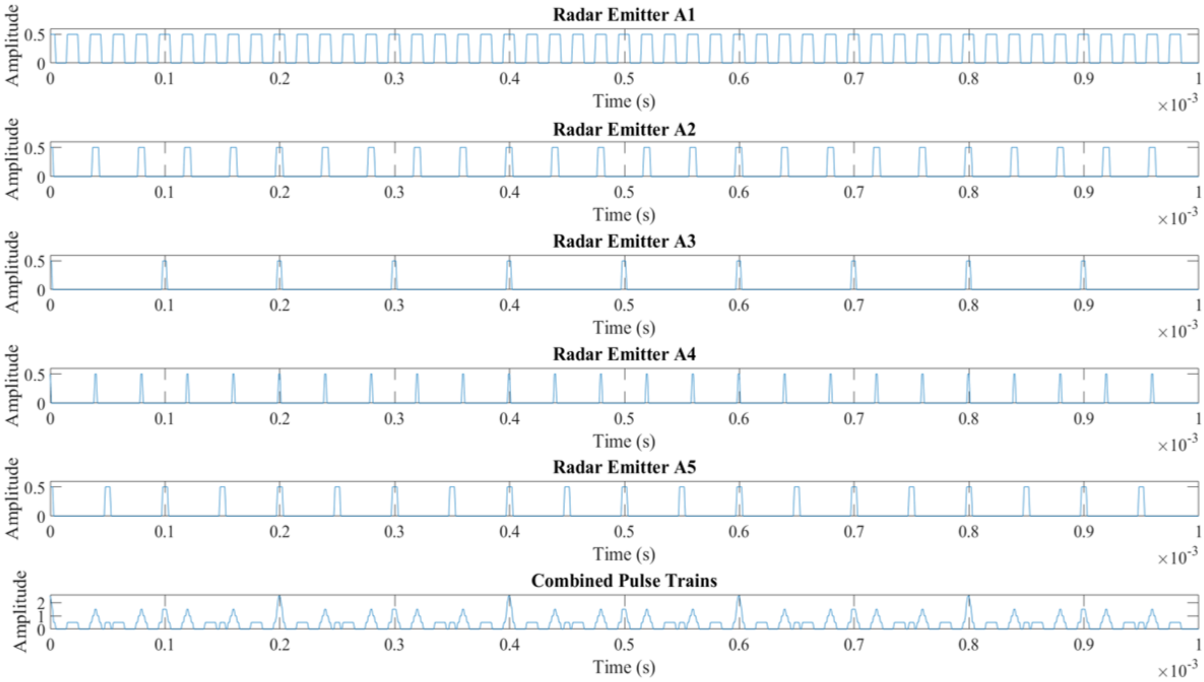
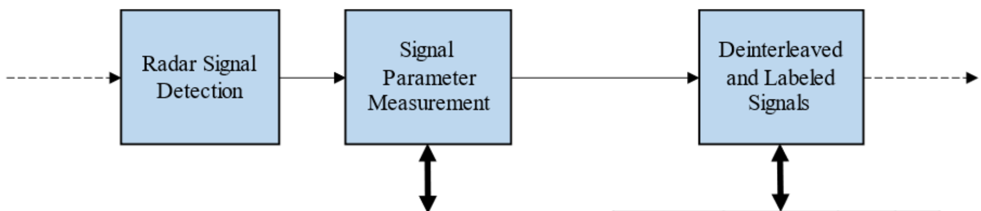


Figure 2. Individual and interleaved waveforms of pulsed signals

The signals received in the signal identification phase have not yet been identified but they can be deinterleaved. Figure 3 shows tables of signal parameters that are input and output of the deinterleaving phase.



Emitter X	4,9	0,4	0,83	2
Emitter X	4,9	0,41	0,86	2
Emitter X	4,91	0,43	0,9	2
Emitter X	4,91	0,44	0,93	2
Emitter X	5,2	1	0,36	2,4
Emitter X	5,2	5	0,3	2,7
Emitter X	5,2	1,03	0,36	2,4
Emitter X	5,2	5	0,3	2,7
Emitter X	5,2	1,05	0,36	2,4
Emitter X	5,21	1,08	0,36	2,4
Emitter X	5,21	5	0,3	2,7
Emitter X	5,21	5	0,3	2,7
Emitter X	5,45	0,1	0,75	1,6
Emitter X	5,46	0,12	0,78	1,6
Emitter X	5,47	0,15	0,83	1,6
Emitter X	5,48	0,16	0,86	1,6

Emitter 1	4,9	0,4	0,83	2
Emitter 1	4,9	0,41	0,86	2
Emitter 1	4,91	0,43	0,9	2
Emitter 1	4,91	0,44	0,93	2
Emitter 2	5,2	1	0,36	2,4
Emitter 3	5,2	5	0,3	2,7
Emitter 2	5,2	1,03	0,36	2,4
Emitter 3	5,2	5	0,3	2,7
Emitter 2	5,2	1,05	0,36	2,4
Emitter 2	5,21	1,08	0,36	2,4
Emitter 3	5,21	5	0,3	2,7
Emitter 3	5,21	5	0,3	2,7
Emitter 4	5,45	0,1	0,75	1,6
Emitter 4	5,46	0,12	0,78	1,6
Emitter 4	5,47	0,15	0,83	1,6
Emitter 4	5,48	0,16	0,86	1,6

Figure 3. Deinterleaved signals

In this algorithm, the identification process is carried out by using the signal parameters in the emitter library and machine learning algorithms previously trained and validated. In the parameters to be used in the process, frequency, PRF, and beam width have a higher determining weight than others in the signal identification process, and other parameters, such as pulse width, help to increase the accuracy percentage in identifying emitters in close frequency ranges [3]. The signal parameters used in the deinterleaving and identification processes and their discrimination levels are given in Table 1. These parameters are either measured from emitted signals or derived from other signal parameters in conventional radar equations which are shown in Eqs. (1)-(5). Among these parameters, signal frequency, PRF, beam width, and scanning time have a critical impact on the emitter identification process.

Table 1. Discrimination levels of signal parameters in deinterleaving and identification

Signal Parameters	Extraction of the Parameter	Impact Level in the Deinterleaving Process	Impact Level in the Identification Process
Frequency	Measurement	High	High
PRF	Derivation	High	High
Pulse width	Derivation	High	Medium
Pulse amplitude	Measurement	Medium	Low
Beam width	Derivation	Low	High
Direction/angle of arrival	Measurement	High	Low
TOA	Measurement	High	Low
Scanning time	Derivation	Low	High

The main purpose of the study is to show that signal identification processes can be effectively applied in machine learning algorithms. The signal parameters specified are used to evaluate which algorithms are more suitable for this type of radar emitter identification process.

The literature contains various studies on the problem of identifying radar signals. Since identification problems can be solved as classification problems, they can be solved with machine learning and deep learning methods [6].

It has been shown that results can be obtained with high accuracy, especially in studies using ANNs. Cain et al. [7] managed to deinterleave radar signals and identify emitters using pulse width, frequency, pulse repetition interval, and arrival time parameters. In the multi-layer learning model, a modified version of the ANN model, high accuracy was achieved by training the extensive data set in different layers of the data set with multiple simple models instead of a single complex algorithm [8]. The layers used in this algorithm increased accuracy by constantly updating the algorithm's node weights. One of the most significant advantages of this algorithm is that it can be used in problems with very high data input through the reduction in computational load [9].

Several studies also have used a hierarchical classifier structure to ensure high accuracy in identifying radar emitters. Zhang et al. [10] combined the similarity coefficient classifier, SVM, binary tree architecture, and the linear classifier based on Mahalanobis distance. They showed that the simple model has less training time and achieves high accuracy. Considering the inspiring results of these studies, this study aims to achieve a classification accuracy of at least 95%.

In RWR, the Eqs. (1)-(5) and their derivatives are used to measure and derive the signal parameters given in Table 1.

The radar range equation is as follows:

$$P_{RX} = \frac{P_{TX} G_{TX} G_{RX} \lambda^2}{(4\pi R)^2} \tag{1}$$

where, P_{RX} is the received power, P_{TX} is the transmitted power, G_{TX} is the gain of the transmitting antenna, G_{RX} is the gain of the receiving antenna, λ is the wavelength of the radar signal, and R is the range between the radar and the target.

The equation for the Direction Finding (DF) is as follows:

$$\Delta\phi = \frac{2\pi d}{\lambda} \sin(\theta) \tag{2}$$

where, $\Delta\phi$ is the phase difference, d is the distance between antennas, λ is the wavelength, and θ is the angle of arrival of the signal.

The equation for the TDOA is as follows:

$$TDOA = \frac{d1 - d2}{c} \tag{3}$$

where, $d1$ and $d2$ are the distances to the radar source, and c is the speed of light.

The equation for the pulse width is as follows:

$$\Delta\mathrm{R}=\frac{\mathrm{cPW}}{2} \tag{4}$$

where, ΔR is the range resolution (meters), c is the speed of light $\left(\approx 3\times 10^{8}\ \mathrm{m/s}\right)$, and PW is the pulse width (seconds).

$$PW = T_{off} - T_{on} \tag{5}$$

where, PW is the pulse width (seconds), T_{on} is the time when the pulse starts, and T_{off} is the time when the pulse ends.

3 Proposed Method

Machine learning methods identify emitters with signal parameters similar to those of the recommended method. While performing the identification process, it is also ensured that the proposed algorithm predicts which mission the radar is on according to test signal parameters. The machine learning and conventional algorithms mentioned in the introduction were compared to evaluate their performance.

RF, signal width, PRF, and beam width, which are the parameters deinterleaved in the RWR, were used to identify radar emitters [6]. Example signals defined in the emitter library are shown in Table 2 [11]. The parameters of the signals in the radar signal library are called pulse identifier words. While creating the radar signal library for this study, radars with different missions and signal parameter ranges were included by utilizing various sources. The platform, which uses the algorithms that are the output of the study, was designed specifically to target air platforms, and, therefore, the radars added to the library were selected to pose a threat to air platforms. Radars with different missions whose parameters were used in creating the library are as follows: early warning radars that operate in the L band (1-2 GHz), air surveillance radars that operate in the S band (2-4 GHz), air defense radars that operate in the$C$ band, weapon control radars and air interceptor radars that operate in the X band (8-12 GHZ). Data from a total of 24 radars, covering each frequency band mentioned, were included in the study. Considering the operating modes of these radars and the operating ranges of the parameters, 60 signal samples for each radar were created and the signal library was completed by obtaining 1,440 signal modes.

The radars used in this study can be used in different tasks by changing these parameters according to their operating modes. To reflect this, all operating modes of the radars used and the parameter ranges used in these modes were included in the signal library. In addition, the mission of the radars detected was identified according to the PRF parameters with the same classification algorithm and shown as the operating mode. According to the scenario applied in this study, these operating modes were selected as tracking and searching.

Table 2. Signal examples in the emitter library

Radar No.	Frequency (GHz)	Width (μs)	PRF (Hz)	Beam Width ($^{\circ}$)
Radar 2	1.22	180.00	0.18	3.200
Radar 3	1.22	100.00	0.25	3.400
Radar 6	2.90	1.00	0.71	1.400
Radar 7	3.10	9.00	0.50	1.550
Radar 9	2.90	1.00	0.50	1.000
Radar 10	3.00	10.00	1.00	1.000
Radar 12	5.20	1.00	0.36	2.400
Radar 13	5.20	1.00	0.36	1.400
Radar 14	5.20	5.00	0.30	2.700
Radar 17	9.30	5.00	0.39	1.300
Radar 18	9.38	0.20	0.18	2.400
Radar 20	9.00	0.26	1.75	1.000
Radar 23	9.00	0.25	1.50	2.400

The Classification Learner application in the R2023a version of the MATLAB program was used to train machine learning algorithms. This application trains models based on selected parameters to classify input data. There are various classification algorithms within the application, and it allows them to be configured.

The primary features of the algorithms to be used are that they are suitable for a high number of input data. In addition, they have functions that can define non-linear relationships between parameters and have a high processing speed (observations/second) without increasing the processor load. The algorithms used in this study aim to complete the iterations with the 5-fold cross-folding method to prevent overfitting and improve the accuracy.

SVM algorithms are generally preferred in problems with nonlinear interference between data points and many data inputs. In this algorithm, classification is defined with a plane, a linear line for sets with a small number of data inputs. SVM algorithms appear to be particularly effective for classification tasks, regression, and detection [12]. In contrast, the algorithm used in this study first creates a hyperplane to make a multidimensional classification. This hyperplane can be optimized using kernel functions to be equally distant from the nodes of two different classes of data [6].

The one-vs-one multiclass method was chosen for the hyperparameters of SVM, and the box constraint level was set relatively high to increase the accuracy. Since there is no noise in the data, it was evaluated that this high box constraint level would not cause overfitting. A linear kernel function was used, and, as a result, no classification errors were observed.

KNN algorithms classify points in the data set according to their close neighborhood relationships and can be used in the identification problem with this classification [13]. The k value determined before learning in the algorithm indicates how many nearest neighbors of any data point can be used as the classification reference for that point [14]. KNN is often used in scenarios where the decision boundary is irregular or the data distribution is not well defined. It is especially useful for classification tasks with nonlinear decision boundaries [15].

Since there is no noise in the data set, the number of neighbors was chosen as one, using this advantage in KNN as in SVM. The distance metric was determined as a city block operating in coordinate difference logic. With the assumption that data points that are close in coordinates are similar, the distance weight was determined inversely, and learning was completed with 1% classification error.

DT algorithms divide the data set into subsets based on input parameters. Since the parameters used in the study are numerical, the condition that separates these clusters is a value range [16]. With these conditions, comparisons are made depending on the conditions at every distinction, from the input data considered as the root to the leaf part of the algorithm given as the classification result [17]. During the training of machine learning algorithms, hyperparameters of DT algorithms were determined. The twoing rule was determined as the separation criterion and the maximum number of branches was determined as 150. The learning process was then completed with 131 branches and 5% classification errors.

Ensemble learning algorithms are obtained by selecting an algorithm from other methods and optimizing it with various techniques. In this study, bag and boost methods were used to increase the validation and accuracy of DT algorithms. Among these methods, random undersampling boost (RUSBoost) is intended to benefit optimization by reducing the number of samples in the input data [18]. Adaptive Boosting (AdaBoost) tries to correct the method metrics by checking the validation result of the weights in the decision nodes of the algorithm in each iteration compared to the previous iteration. Bagging was determined as the ensemble learning method and 17 base DT models were used with random samples taken from the data library. The maximum number of branches in DTs was determined as 85 to prevent overfitting. Each base model completed the learning model by sampling two of the parameters in the data set and a 2% classification error was obtained.

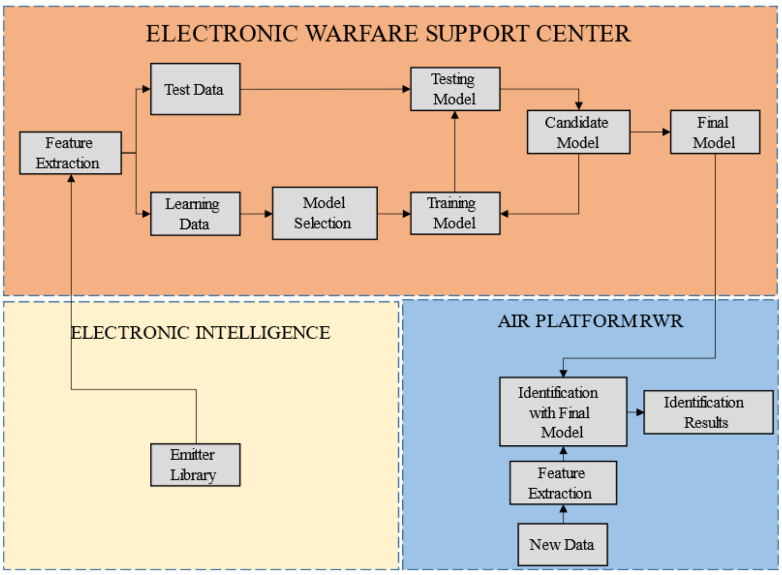


Figure 4. Diagram of the learning and identification model

ANN algorithms are frequently used in pattern identification, prediction, and recognition problems. It enables the classification of the data set by creating an architecture that includes input, hidden, and output layers [19]. The classes are connected by defining the data set parameters given as input nodes and each parameter class as a separate step. The weights of these nodes are determined in the decision algorithm, and the classification process is carried out by establishing latent connections between them [6]. Three fully connected layers have been defined in ANNs. Once the data is given as input and the learning process begins, the first of these layers is shaped to make classification by creating 57 neurons, the second by 132 neurons, and the third by creating 6 neurons. By selecting a low-level regularization factor, overfitting was prevented, and learning was completed with a classification error of 0.06%.

The learning and identification process, in which all the algorithms mentioned above were used, is shown in Figure 4.

4 Implementation of the Method

In the actual applications, the learning and identification steps shown in the model were performed on separate platforms. The learning part was carried out in EW support centers with various algorithms using the signal parameters of previously obtained emitters. The identification part, defined as testing in this study, was performed with actual external radar elements while the aircraft was on mission. Before an aircraft joined a mission, the mission region was pre-programmed and loaded into the aircraft's RWR processor. Looking at these real-world counterparts of the radar identification process, the preprogramming part was optimized to be more precise in the following sections.

An accuracy difference was observed between the machine learning algorithms used due to the compatibility of their parameters with the signal library and validation performance. The time spent identifying radar signals and correctly identifying predicted radars was evaluated as significant performance indicators.

A 5-layer cross-validation method was used in the iteration part of the machine learning stages. In this method, the data set taken as input was divided into five equal parts. Despite being divided, these sets were created by mixing them to represent the integrity of the data set. In each learning iteration of the model, one set was used as test data, and learning was applied to the data represented by the other four sets [20].

In the optimization part, 30 steps and a 5-layer cross-validation method were used to prevent the models from underfitting and overfitting. As shown in the MATLAB screen in Figure 5, the Bayesian optimizer was used and the expected improvement per second plus purchase function was applied in these 30 iteration steps. Additionally, the training period was not restricted, and these periods were included in the results section.

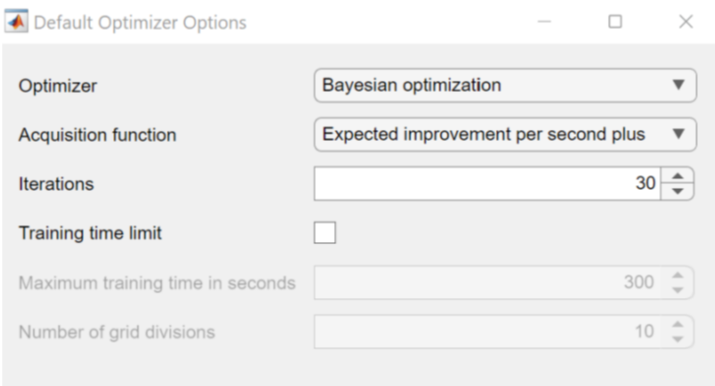


Figure 5. Optimization function selection

As seen in Figure 6, the Model 5 algorithm, which is an optimized model of the SVM algorithm, performs 30 iterations to increase the accuracy level during learning.

The parameters used in the evaluation are the data received during learning and testing. Learning accuracy is the ratio of correctly classified observations to total observations. A high value should be obtained before use since learning accuracy is an indicator that directly affects test accuracy. The validation confusion matrix should be checked before optimizing it for a high validation value. The validation confusion matrix for Model 6, an optimized model of the KNN algorithm, is shown in Figure 7.

The test accuracy is similar to the ratio of test entries classified as correct to total entries. It is the most important parameter since the test time does not exceed half a second. This is the performance indicator used in the real world, and it allows the users to take actions that can ensure their survival. The number of misclassifications is also output and used in accuracy calculation. Observation speed is the classification speed the algorithm estimates for new data input. Learning time is the total time the algorithm needs to run to complete the specified iterations. Test time is related to observation speed. To respond quickly to threats, it must be low; therefore, it is one of the most crucial performance indicators. These performance indicators were derived from MATLAB's Classification Learner Application, and the result representation for SVM, neural networks, and KNN algorithms is shown in Figure 8.

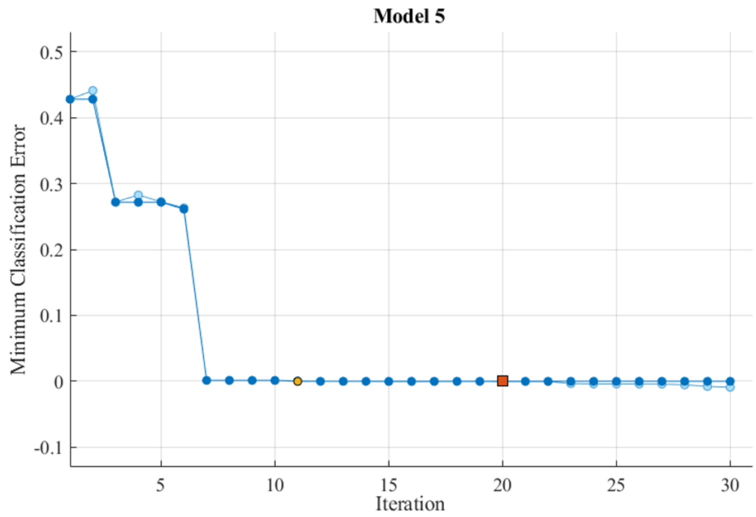


Figure 6. Minimum classification error plot of Model 5

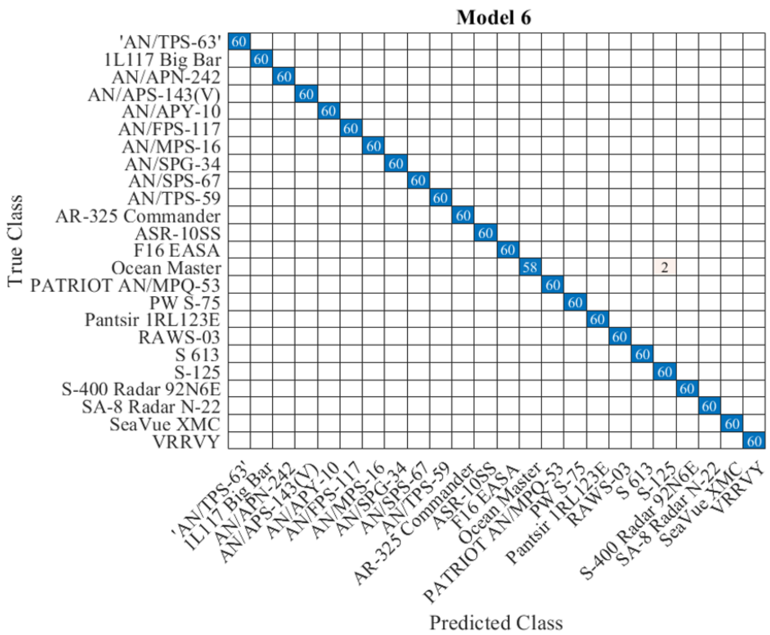


Figure 7. Validation confusion matrix of Model 6

The simulation algorithm is aimed at obtaining an environment where multiple radar signals are mentioned in the earlier sections, which is considered challenging. For this purpose, scenarios were planned to include various numbers of signals in the environment. Along with the emitter identification feature of these algorithms, the feature of defining the mission of the radars was also implemented. After preparing an auxiliary algorithm to use the PRF parameter as a mission definition condition to extract this representation, the results were obtained, as seen in Figure 9. Using the information in Figure 9, it can be inferred that at least two radars in the region are track-while-scan radars. The time to complete the operations using the machine learning algorithms during all these tasks was also recorded and evaluated as a performance indicator.

The threat library was defined in the simulation algorithm as the first step of the test process. Depending on the input of 100 radar signals, the number of signals was randomly determined and defined as the combat environment. The parameters of the signals in the environment were defined and compiled into a table and made ready for processing. The selected machine learning algorithm performs the identification process and creates a table of predicted radars.

According to the value defined in the input for the PRF of the received signals, the current mission of the radars was determined as tracking or searching. Once the results are received, the comparison table shows the number of correctly predicted radars and processing time outputs. Table 3 shows the performance indicators of different algorithms. Table 4 shows the performance metrics of the algorithms applied to this study.

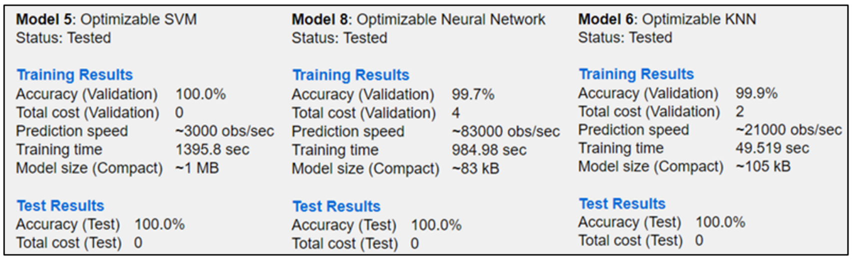
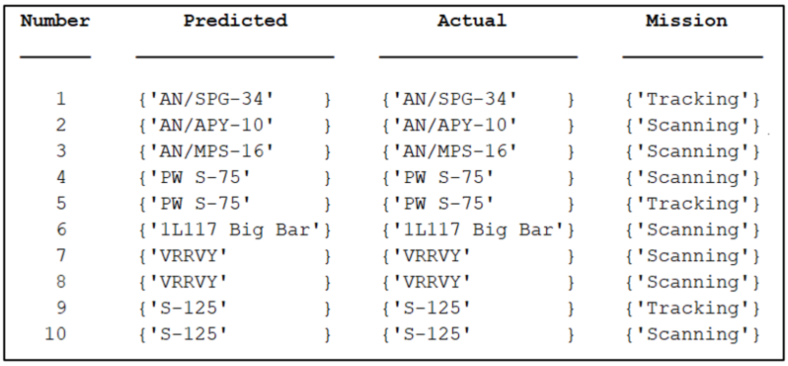


Figure 8. Algorithm performance summaries of SVM, neural networks and KNN



Number	Predicted	Actual	Mission
1	{'AN/SPG-34' }	{'AN/SPG-34' }	{'Tracking'}
2	{'AN/APY-10' }	{'AN/APY-10' }	{'Scanning'}
3	{'AN/MPS-16' }	{'AN/MPS-16' }	{'Scanning'}
4	{'PW S-75' }	{'PW S-75' }	{'Scanning'}
5	{'PW S-75' }	{'PW S-75' }	{'Tracking'}
6	{'1L117 Big Bar'}	{'1L117 Big Bar'}	{'Scanning'}
7	{'VRRVY' }	{'VRRVY' }	{'Scanning'}
8	{'VRRVY' }	{'VRRVY' }	{'Scanning'}
9	{'S-125' }	{'S-125' }	{'Tracking'}
10	{'S-125' }	{'S-125' }	{'Scanning'}

Figure 9. Simulation result of a 10-emitter environment

Table 3. Algorithm performance indicators

	Learning Accuracy (%)	**Observation Speed (obs/sec)**	**Learning Time (sec)**	**Test Accuracy (%)**	**Test Time) (sec)**
KNN	99.9	21000	49.519	100	0.068
DT	99.4	29000	37.794	100	0.049
Ensemble learning method	99.7	4900	166	99.9	0.293
SVM	100	3000	1395.8	100	0.480
ANN	99.7	83000	984.98	100	0.017
Parameter-conditioned conventional algorithm	-	-	-	45	0.22
Short-time Fourier transform [21]	-	-	-	86	N/A
Pulse parameter estimation [21]	-	-	-	88	N/A
Clustering techniques [22]	-	-	-	77.7	4.27
Histogram-based techniques [22]	-	-	-	84.6	120.52
Wavelet detector techniques [22]	-	-	-	76.2	61.85

Table 4. Algorithm performance metrics

Method	**Precision**	**Recall**	**F1-score**	**Accuracy**
KNN	0.9986	0.9986	0.9986	0.9986
DT	0.9828	0.95	0.9661	0.9972
Ensemble learning method	0.9672	0.9833	0.9752	0.998
SVM	1	1	1	1
ANN	0.9833	0.9672	0.9752	0.998

5 Conclusion and Future Work

First, the usability of machine learning algorithms, which perform the learning, validation, and testing processes, in the classification algorithm with specific learning performance indicators was evaluated. The study was conducted primarily to provide higher performance than conventional radar signal classification and identification algorithms in particular performance indicators. It was observed that the processing time results obtained from all machine learning algorithm models tested are at a level that can provide information to countermeasure systems in applications without causing any delay. For this reason, the most distinctive result value in the performance of the algorithm models was determined as the number of correctly identified radars.

In conventional algorithms encountered in the literature, the accuracy seems lower, and the parameters, which can be defined as processor load or time spent during identification, appear to be higher [5, 22]. A parameter-conditioned conventional classification algorithm was also generated in this study. In this algorithm, it was discovered that either the prediction speed or the prediction accuracy could be increased. In addition, while improving the performance of a feature, other performance indicators decreased.

The signal library used in machine learning algorithms creates a challenging radar signal environment for the identification algorithm regarding the closeness of signal parameter values and the identification of more than one radar in similar tasks. However, machine learning algorithms do not consistently differ in accuracy and running time parameters between testing some or all of the signals in the environment because the learning and preprogramming parts, where the primary workload of this study is occupied, are done before the tests.

In comparing machine learning algorithms, two main differences emerged due to the close test accuracies. First, KNN and DT algorithms provide advantages with low learning time. DT and ANN algorithms provide a high advantage in the parameter given as observation speed and directly affect the identification speed. These results confirm this study's goals, such as increasing identification accuracy and prediction speed using machine learning algorithms instead of conventional algorithms. The fact that more than one machine learning algorithm is successful in these two major performance indicators shows that more faultless hybrid algorithm models can be revealed with optimizations in future studies.

This study explains how to identify pulsed radar signals with machine learning methods and the differences and advantages of the machine learning algorithms. In future studies, the radar signal library could be expanded with continuous radar signals. In addition, deep learning methods could be applied to this problem by continuing the emitter identification methods based on ANNs with multiple classification tasks.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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