İSTANBUL UNIVERSITY
CERRAHPAŞA

ORIGINAL ARTICLE
Electrica 2025; 25: 1-15

Cognitive Electronic Warfare Application to Emitter Identification Process in Airborne Radar Warning Receiver Systems

İclal Çetin Taş[1], Ahmet Güngör Pakfiliz[2]

[1]Department of Computer Engineering, Başkent University Faculty of Engineering, Ankara, Türkiye
[2]Department of Electrical and Electronics Engineering, Turkish Aeronautical Association University Faculty of Engineering, Ankara, Türkiye

Cite this article as: İ. Çetin Taş and A. G. Pakfiliz, "Cognitive electronic warfare application to emitter identification process in airborne radar warning receiver systems," *Electrica*, 2025, 25, 0182, doi: 10.5152/electrica.2025.24182.

WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *RWR subsystems are central to Cognitive Electronic Warfare (CEW) architectures, yet conventional rule-based processing pipelines often face limitations in accurate emitter identification and range estimation under dense and dynamic RF conditions.*

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study empirically demonstrates that machine-learning-driven emitter identification can achieve near-perfect classification performance, outperforming traditional deterministic methods in complex electromagnetic environments.By integrating regression-based distance estimation, the study shows that CEW-oriented RWR systems can achieve high-precision range prediction (MAPE = 1.6%), highlighting the potential of adaptive learning models to enhance the intelligence, robustness, and responsiveness of next-generation electronic warfare systems.*

Corresponding author:
İclal Çetin Taş

E-mail:
icetintas@baskent.edu.tr

Received: December 4, 2024
Revision Requested: June 12, 2025
Last Revision Received: August 22, 2025
Accepted: September 11, 2025
Publication Date: November 25, 2025

DOI: 10.5152/electrica.2025.24182

ABSTRACT

Cognitive electronic warfare (CEW) will soon replace conventional electronic warfare (EW) systems in the operational area. Although the CEW concept is utilized on various platforms, it has primarily emerged in military air platforms. Radar warning receiver (RWR) applications are essential in the CEW concept. Effective RWR systems accurately identify radar emitters in complex and dynamic environments, which is critical for situational awareness of air vehicle systems. systems provide information to countermeasure systems, increasing operational success by neutralizing enemy radar and defense systems. To sense the threats and apply appropriate countermeasures, such as jamming or dispensing chaff, requires a quick response and accurate RWR processes. RWR processes are summarized as receiving, signal detection, deinterleaving, labeling, and emitter identification. This study investigates the application of machine learning (ML) techniques to the emitter identification process. The research demonstrates significant improvements in emitter identification accuracy and distance determination by using ML algorithms. The findings suggest that CEW strategies incorporating adaptive learning models can enhance RWR system performance in identifying and categorizing emitters, even in dense Radio frequency (RF) environments. In the trials, it is observed that while the decision tree, ensemble bagged, and support vector machines achieved 100% success in the classification step, the Gaussian method was the most successful, with a mean absolute percent error of 1.6 in the distance calculation step using regression. These results suggest a promising direction for developing more intelligent and resilient EW systems.

Index Terms—Classification, electronic warfare, machine learning, radar warning receiver (RWR), regression

I. INTRODUCTION

The conventional operation of current airborne self-protection electronic warfare (EW) systems uses defined preprogrammed radar warning receiver (RWR) processes in a similar sequence. However, the potential of machine learning (ML) methods to revolutionize this process is immense [1]. These methods can scan the predefined bands, determine the signal activities, deinterleave and label the signals, and constitute an active emitter track list with unprecedented accuracy and speed. They can then compare it with the active emitter track list using the emitter identification data and identify threat radars, offering a hopeful future for RWRs [2].

Once the emitter type is identified, an appropriate preprogrammed electronic countermeasure (ECM) technique is selected and applied to effectively neutralize, deceive, or avoid the threat posed by the emitter. These ECM methods include preset noise, repeater noise, deception jamming, chaff dispensing, towed or expandable decoys, and evasive maneuvering [2]. The noise-based techniques have become less effective as radars advance from fixed analog systems to programmable digital versions with unpredictable behaviors and flexible waveforms. Deception-based methods are more effective against modern radars; moreover, jamming with cognitive electronic warfare (CEW) is an emerging technology to neutralize radar systems [3]. The need for new jamming approaches is evident as radars are expected to pose an even more significant challenge in the future, with their ability to detect surroundings and adjust their transmissions and signal processing to optimize performance and reduce interference.

The capability to detect and apply appropriate countermeasures to new and undefined radar threats in tactical environments has recently been studied. This can be achieved primarily due to the potential of ML in EW. Cognitive electronic warfare systems are enabling a shift from today's manual-intensive, lab-based pre-programming development approach to an adaptive, in-the-field systems approach. These conceptual systems will achieve this by developing novel ML algorithms and techniques that can rapidly detect and characterize new radar-guided threats, dynamically synthesize new countermeasures, and provide accurate battle damage assessment based on over-the-air observable changes in the threat.

Cognitive electronic warfare is a concept that encompasses various applications of EW, and in this study, the focus is on RWR units, a part of self-protection EW (SPEW) systems. The most common RF parts of the SPEW systems are RWR, self-protection jammer (SPJ), and chaff part of the countermeasure dispenser system (CMDS). The CEW applications are summarized as follows [4]:

- Radar warning receiver systems aim to detect, intercept, identify, and locate radar-guided threats.
- Self-protection jammer systems use RF energy to degrade or deny the adversary's radar-guided systems' detection and tracking performances.

Radar warning receiver functions can be categorized under general processes such as signal detection, classification, and identification. The primary operational RWR requirement, which drives new technological developments, is to obtain immediate and accurate information about environmental threat emitters. For this purpose, RWRs conduct signal detection, deinterleaving, signal labeling, and emitter identification (EID). Signal detection is closely related to receiver (Rx) capabilities, and technological advancements in RF components are crucial. Additionally, adaptive and intelligent scanning methodologies [5] and digital Rx in RWR systems also increase detection capabilities [6, 7].

Joshi et al. demonstrated how frequency-domain features extracted via spectral analysis can successfully differentiate between hazardous and non-hazardous zones, underscoring the potential of such techniques in cluttered or ambiguous signal scenarios. Motivated by this perspective, the present study focuses on applying spectral and temporal analysis techniques within RWR systems, where the timely and accurate deinterleaving of interleaved radar pulse sequences is essential. By adapting spectral processing methodologies to identify and group emitter pulses, this work aims to enhance emitter recognition accuracy and support real time ECM decision-making. Thus, the proposed approach extends the advantages of spectral analysis from ground penetrating radar applications to the domain of airborne EW systems [8].

Deinterleaving is another essential and much-studied part of the RWR process. The conventional methods for deinterleaving radar signals are based on these pulse description words (PDWs). Some methods were implemented using image processing techniques, such as connected component labeling-based clustering [9]. Additionally, artificial intelligence (AI)-dependent methods were developed for deinterleaving [10, 11]. Utilizing AI in the deinterleaving process has contributed significantly to the CEW concept. After deinterleaving, the signals are labeled and grouped. This process turns deinterleaved signals into potential threat tracks. The signal labeling process is intermediate and highly straightforward. Thus, not much novelty can be found in the scientific literature.

Emitter identification is the last and maybe the most critical part of the process. The published literature contains a wealth of research on EID. One prominent conventional method for the EID process is parameter matching [12], which involves comparing signal characteristics obtained by measurement with a known radar database to identify radar emitter attributes. Another prevalent method for EID is based on a statistical approach. Moreover, some methods present a combination of various statistical methods that are applied and modified to meet the requirements [13]. These methods have the advantage of giving prompt responses and are straightforward to implement. However, they are overly reliant on prior knowledge and need to improve their adaptive structure skills.

With the development of the CEW concept, the utilization of AI algorithms in the EID process has increased [14, 15]. Moreover, neural networks [16], support vector machine (SVM) [17], extreme learning machines [18], k-nearest neighbor (KNN) [19], intuitionistic fuzzy information tri-training classification [20], and deep learning algorithms [21] have been presented theoretically in the EID process. Although numerous academic studies have been conducted, CEW's operational engagement remains limited and is still under development. Moreover, there has not been a study on determining both threat identification and range estimation together by using ML techniques. In this study, the focus is on this part of the CEW concept.

The literature survey reveals that studies on ML techniques applied to RWR processes are predominantly conceptual and theoretical. The novelty of this study lies in proposing a practical solution with improved performance. The most effective ML methods in threat radar identification and range detection are suggested. For this purpose, ML techniques are utilized for classification and regression in the EID process, which is part of the SPEW systems' CEW concept. The contribution to the RWR process is the application of ML to obtain decision support, as shown in Fig. 1.

A realistic pulse radar data set (or emitter library) is strived to be generated, and the performance of different classification and regression step methods is assessed to create methods for projecting the design of SPEW systems that can be used in actual operations.

This study improves broadcaster detection and range estimation in complex and dynamic RF environments by integrating ML techniques into RWR systems. The main contributions are as follows:

- The dataset used in the study was designed to reflect realistic radar scenarios and optimized through preprocessing steps. This approach provides a more comprehensive and reproducible database compared to existing studies in the literature.
- Adaptive learning models strengthen CEW systems, making them more resilient, intelligent, and capable of effectively responding to diverse threats.
- The accuracy and reliability of broadcasters were improved using decision tree (DT), ensemble, and SVM algorithms.
- Innovative regression approaches were applied to increase the accuracy of broadcaster range determination.

The paper is organized as follows: Section 2 provides a general understanding of the EID and its role in the RWR process. Section 3

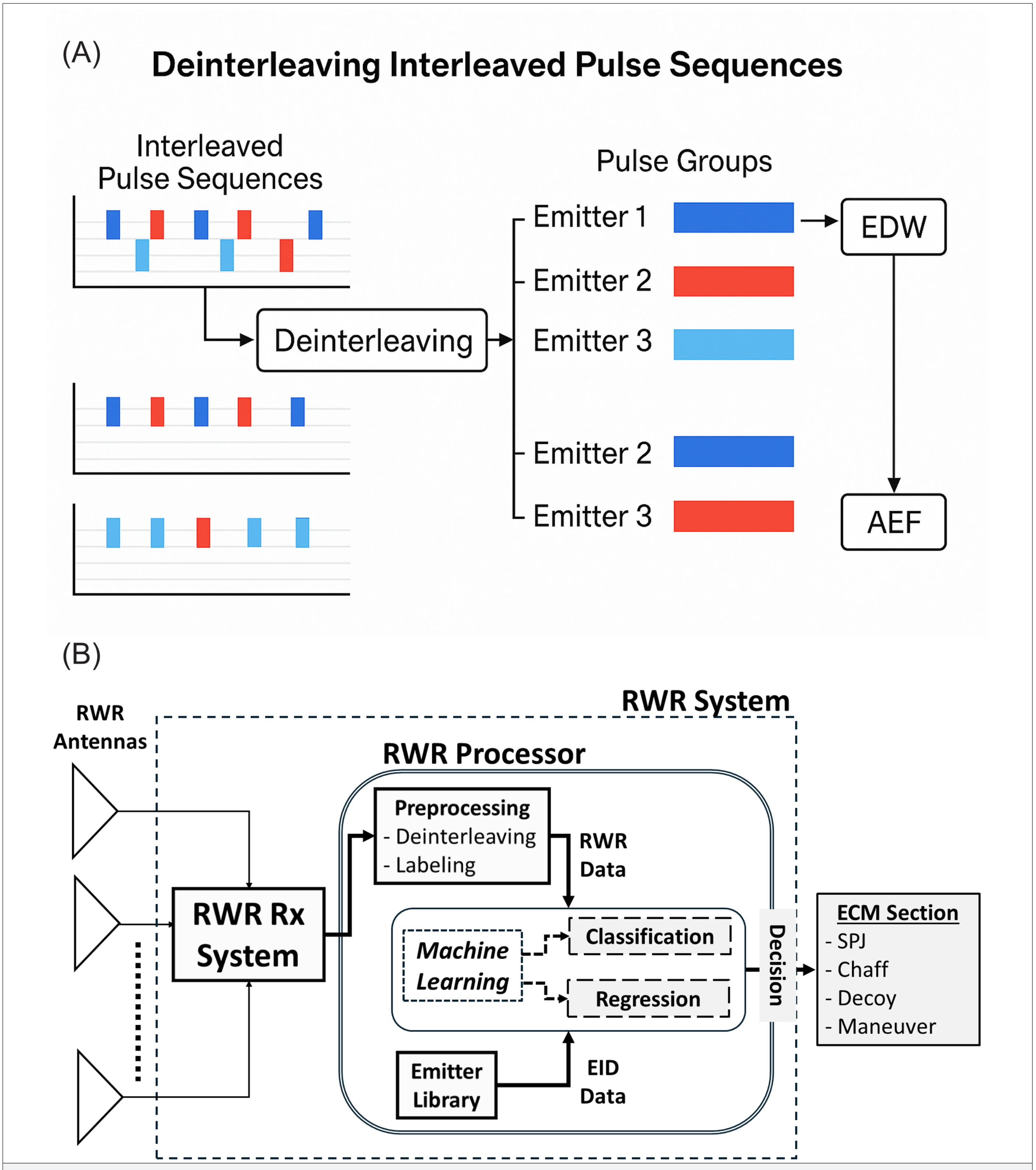

Fig. 1. (a) Radar warning receiver details. (b) The contribution to the radar warning receiver process.

presents the ML methods that are used in this study. Section 4 gives the experimental research and performance of different techniques. The paper concludes with a summary in Section 5.

II. EMITTER IDENTIFICATION PROCESS

The RF part of airborne SPEW systems comprises a passive RWR and countermeasures (CMs) subsystems, including SPJ, towed or expandable decoys, and CMDS systems. These systems depend on the RWR information to maneuver or utilize different CMs. The RWR subsystem is the most fundamental part of all SPEW systems and the emerging point for the CEW concept. Quick, clear, and accurate RWR data enables pilots, crew, and the airborne platform to take the proper precautions, which can be considered lifesaving. These precautions might be conducted manually by pilots, such as evasive maneuvering, decoy usage, manual, or semi-automatic chaff dispensing. On the other hand, they can be automatic CMs, activated by the RWR information, such as preset or repeater noise jamming, deceptive jamming, or automatic chaff dispensing.

Fig. 1 summarizes a general RWR process. Although there may be variations in different applications, the figure demonstrates the compulsory functions. Radar signals in the electromagnetic environment are detected by the Rx unit, which comprises an antenna group, signal processing components, and various sub-Rx units. The RF signals are processed in the Rx. At the end of the Rx process, radar pulses are defined by PDWs, which include radio operating frequency, time of arrival, direction of arrival, pulse repetition interval, pulse width, intra-pulse bandwidth, and pulse modulation. Generally, PDWs express interleaved sequences. Deinterleaving is necessary to separate these sequences and extract the pulse sequences from individual radar transmitters. Deinterleaving interleaved pulse sequences is a critical technology in radar signal processing because modern radar environments are often dense and complex, and multiple emitters transmit overlapping signals. Effective separation is an essential criterion in EW systems. It enables the separation and identification of individual emitter sources, which is necessary for accurate threat assessment, situational awareness, and real time decision-making in EW systems.

The deinterleaving process produces pulse groups belonging to different emitters in the environment. These pulse groups are referred to as the emitter descriptor word (EDW). Each EDW is further processed to determine the active emitter file (AEF) at the time being. The AEF process is achieved during the mission. There is another process for SPEW systems, known as pre-programming. This process identifies possible radar threats in the mission region, and the operational methods for RWR and CMs are defined. The list of threats in the mission region is called the emitter library. The obtained AEF and emitter library data are compared for possible matches. This process involves the EID, and a performance analysis for the EID is proposed.

After the EID process, active emitter tracks are identified, and the established emitter list (IEL) is determined. The IEL data is presented to the crew via displays and provides some control capabilities. Pilots may execute evasive maneuvers according to established operational procedures. Also, if defined in the pre-programming, one or more CM systems are automatically engaged in the operation.

III. MACHINE LEARNING METHODS APPLIED TO THE EMITTER IDENTIFICATION PROCESS

Over the last decade, integrating ML techniques into RWR processes has been a trend to increase accuracy and reduce processing time. Especially, the literature has some studies on the EID process [20]. This study presents the application of ML techniques to the EID process of RWR systems using realistic radar data. In this aspect, the study approach takes one more step for real applications. Fig. 2 digests the study's flowchart. In the first stage, a generic EID that was obtained from open sources is established. Then, this information is used with various ML techniques for classification and regression step methods. The classification process is used to predict the type of radar, and regression provides the distance information. Furthermore, the

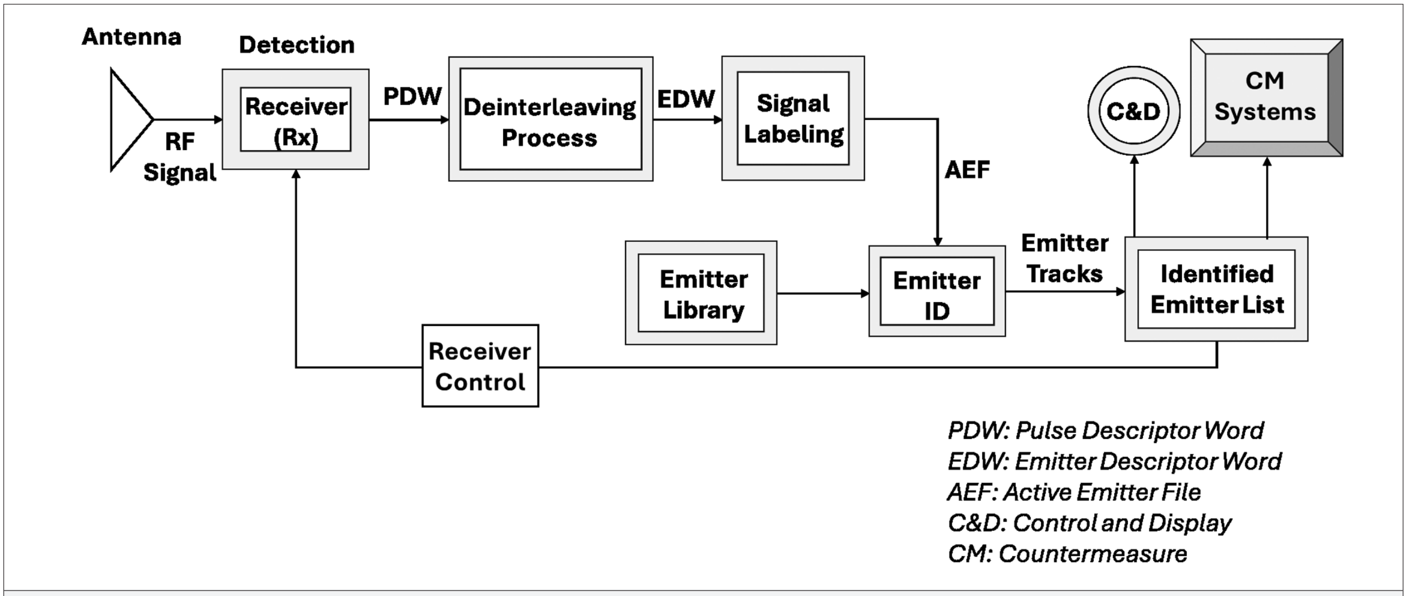

Fig. 2. Radar warning receiver process with its functions.

classification and regression accuracies demonstrate the performance of ML techniques for the RWR operation.

A. Emitter Identification Definition

The radar EID dataset is created using open-source, well-accepted databases for radar and EW [22] and [23]. In these sources, no exact values are provided; instead, intervals or approximate values are given. In this study, the generic radar parameters are made as close as possible to the real radar counterparts. Nine features in the EID database are used. A portion of the EID dataset is presented in Fig. 3 as an example. For the study, an EID database was prepared that included 756 lines.

The first column is dedicated to radar nomenclature, and the remaining nine columns are used as predictors. The features include technical parameters in a radar receiver system. Table I contains descriptions of the features. Here, it would be beneficial to mention the receiver (Rx) amplitude column. This information is not generated from open-source data but instead extracted from other parameters. The ranges and related Rx power amplitudes are calculated in MATLAB by using the one-way radar in (1), as follows:

$$P_{RWR} = \frac{P_{Tx} G_{Tx} G_{RWR} c^2}{\left(4\pi f R\right)^2} \tag{1}$$

where P_{Rx}: Radar emitted power at the RWR Rx (W)

P_{Tx}: Radar transmitted peak power (W)

G_{Tx}: Radar transmitter (Tx) antenna gain (unitless)

G_{RWR}: Radar warning receiver antenna gain (unitless)

c: Speed of light ($3\text{x}10^8$ m/s)

f: Radar operating frequency (Hz)

R: Range between the radar and RWR (m)

The P_{Tx}, G_{Tx}, and f values are taken from the EID database. The ranges are selected from four different values: 40, 20, 10, and 5 km, which are similar to those found in practical applications. In fact, in various systems, Rx power levels can be calculated for different distances. However, some milestones must be selected for

Radar\Parameter	Frequency (GHz)	Pulse Width (µs)	Gain (dB)	Range (m)	Peak Power (kW)	PRF (kHz)	Rx Amplitude (dBm)	Beamwidth (degree)	Scan Type
AN/TPS-63	1,23	41,00	30,00	40000,00	100,00	0,38	-11,28	5,40	1,00
AN/TPS-63	1,23	41,00	30,00	20000,00	100,00	0,38	-5,26	5,40	1,00
AN/TPS-63	1,23	41,00	30,00	10000,00	100,00	0,38	0,76	5,40	1,00
AN/TPS-63	1,23	41,00	30,00	5000,00	100,00	0,38	6,78	5,40	1,00
AN/TPS-63	1,40	41,00	32,00	40000,00	100,00	0,38	-10,40	4,35	1,00
AN/TPS-63	1,40	41,00	32,00	20000,00	100,00	0,38	-4,38	4,35	1,00
AN/TPS-63	1,40	41,00	32,00	10000,00	100,00	0,38	1,63	4,35	1,00
AN/TPS-63	1,40	41,00	32,00	5000,00	100,00	0,38	7,65	4,35	1,00
AN/TPS-63	1,23	41,00	30,00	40000,00	100,00	0,30	-11,28	5,40	1,00
AN/TPS-63	1,23	41,00	30,00	20000,00	100,00	0,30	-5,26	5,40	1,00
AN/TPS-59	1,22	180,00	40,00	40000,00	46,00	0,18	-4,58	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	20000,00	46,00	0,18	1,43	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	10000,00	46,00	0,18	7,46	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	5000,00	46,00	0,18	13,48	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	40000,00	46,00	0,63	-4,58	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	20000,00	46,00	0,63	1,43	1,73	1,00
AN/TPS-59	1,22	180,00	40,00	10000,00	46,00	0,63	7,46	1,73	1,00
AN/FPS-117	1,22	100,00	43,00	40000,00	24,60	0,25	-4,30	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	20000,00	24,60	0,25	1,72	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	10000,00	24,60	0,25	7,74	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	5000,00	24,60	0,25	13,76	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	40000,00	24,60	1,10	-4,30	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	20000,00	24,60	1,10	1,72	1,20	1,00
AN/FPS-117	1,22	100,00	43,00	10000,00	24,60	1,10	7,74	1,20	1,00
Pantsir S2	2,60	200,00	35,00	40000,00	75,00	0,25	-14,00	3,00	2,00
Pantsir S2	2,60	200,00	35,00	20000,00	75,00	0,25	-8,00	3,00	2,00
Pantsir S2	2,60	200,00	35,00	10000,00	75,00	0,25	-2,00	3,00	2,00
Pantsir S2	2,60	200,00	35,00	5000,00	75,00	0,25	4,00	3,00	2,00
Pantsir S2	2,60	200,00	35,00	40000,00	75,00	0,50	-14,00	3,00	2,00
Pantsir S2	2,60	200,00	35,00	20000,00	75,00	0,50	-8,00	3,00	2,00
AR-325 Commander	2,70	200,00	42,00	40000,00	135,00	0,27	-4,80	1,40	1,00
AR-325 Commander	2,70	200,00	42,00	20000,00	135,00	0,27	1,21	1,40	1,00
AR-325 Commander	2,70	200,00	42,00	10000,00	135,00	0,27	7,23	1,40	1,00
AR-325 Commander	2,70	200,00	42,00	5000,00	135,00	0,27	13,25	1,40	1,00
AR-325 Commander	2,70	200,00	42,00	40000,00	135,00	1,40	-4,80	1,40	1,00
AR-325 Commander	2,70	200,00	42,00	20000,00	135,00	1,40	1,21	1,40	1,00
1L117 Big Bar	3,10	1,20	42,00	40000,00	700,00	0,38	1,14	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	20000,00	700,00	0,38	7,16	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	10000,00	700,00	0,38	13,18	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	5000,00	700,00	0,38	19,20	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	40000,00	700,00	0,75	1,14	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	20000,00	700,00	0,75	7,16	1,37	1,00
1L117 Big Bar	3,10	1,20	42,00	10000,00	700,00	0,75	13,18	1,37	1,00
S-400 Radar 92N6E	11,00	25,00	43,00	5000,00	250,00	0,50	4,73	1,22	9,00
S-400 Radar 92N6E	11,00	25,00	43,00	40000,00	250,00	1,00	-13,33	1,22	9,00
S-400 Radar 92N6E	11,00	25,00	43,00	20000,00	250,00	1,00	-7,31	1,22	9,00
S-400 Radar 92N6E	11,00	25,00	43,00	10000,00	250,00	1,00	-1,30	1,22	9,00
S-400 Radar 92N6E	11,00	25,00	43,00	5000,00	250,00	1,00	4,73	1,22	9,00
SA-8 Radar GECKO	6,00	10,00	35,00	40000,00	90,00	1,00	-20,50	3,00	6,00
SA-8 Radar GECKO	6,00	10,00	35,00	20000,00	90,00	1,00	-14,50	3,00	6,00
SA-8 Radar GECKO	6,00	10,00	35,00	10000,00	90,00	1,00	8,46	3,00	6,00
SA-8 Radar GECKO	6,00	10,00	35,00	5000,00	90,00	1,00	-2,44	3,00	6,00
SA-8 Radar GECKO	14,50	10,00	40,00	40000,00	90,00	10,00	-23,17	1,73	7,00

Fig. 3. Various sections of the generic emitter identification database, for example.

TABLE I. DATASET DETAILS

Feature	Explanation	Range
Radar nomenclature	Radar type - classification target	1–28
Frequency	The operating frequency of the radar - predictor	1.215–16 (Hz)
Pulse width	The duration of time a radar pulse is transmitted - predictor	0.1–1200 (μs)
Gain	The radar's antenna gain - predictor	30–45.5 (dB)
Range	The distance at which the RWR receiver detects a radar threat - regression target	5000–40000 (km)
Peak power	The peak Tx power level emitted by a radar - predictor	2–1500 (W)
PRF	The number of pulses transmitted by the radar per second - predictor	0.146–125 (Hz)
Rx amplitude	The strength of the signal power received by the radar - predictor	−13.82 to 59.9 (V)
Beamwidth	The angular width of the radar antenna beam - predictor	1–5.54 ()
Scan type	The radar antenna scan pattern - predictor	1–10 1: Circular 2: Sectoral 3: Raster 4: Helezonic 5: Conical 6: Spiral 7: Lobe Switching 8: Beam on target 9: Monopulse 10: Track-While-Scan (TWS)

PRF, pulse repetition frequency; RWR, radar warning receiver; Rx, receiver; Tx, transmitter.

establishing the database. For this study, the RWR Rx antenna gain is selected as 3.16 (or 5 dB).

The correlation matrix is one of the best methods for examining the relationships between dataset features. In the correlation matrix, the matrix elements take values between −1 and 1, indicating the strength and direction of the linear relationship between the two parameters. A high positive correlation of 0.7551 exists between the Radar Parameter and Frequency, as well as Gain and Rx Amplitude. This indicates that both pairs of parameters are closely related; when one increases, the other also increases in value.

There is a negative correlation between Beamwidth and Gain and Rx Amplitude and Frequency, which indicates that the two parameters move in opposite directions. Low correlation coefficient values are observed between the pulse repetition frequency (PRF) and other parameters, suggesting that PRF has a weak relationship with these parameters.

B. Classification Step Methods

1) K-Nearest Neighbors:

The KNN algorithm is used in regression and classification problems in supervised ML models, where predictions are made based on the similarities of observations. Euclidean distance, Manhattan distance, Minkowski distance, and Hamming distance metrics can be used to measure distances in the KNN algorithm; in this study, Euclidean distance was preferred [shown in (2)].

$$x = \sqrt{\sum_{i=1}^{k} \left(x_i - y_i\right)^2} \tag{2}$$

The KNN algorithm identifies k observation units closest to the observation unit in question [24, 25]. These k observation units and their dependent variables are then used to predict the relevant observation (Fig. 4). This process is critical in real-world scenarios because radar signal data are often complex, noisy, and nonlinear. By considering the nearest neighbors, KNN adaptively captures local patterns and variations in the data, providing robust predictions even in the presence of noise or outliers. Its nonparametric nature allows it to operate effectively without prior assumptions about data distribution, making it suitable for practical applications such as emitter detection in dynamic operational environments.

All continuous-valued features are scaled to the range [0, 1] using min-max normalization to provide a fair contribution to the Euclidean distance calculation, given the distance-based nature of the algorithm. During the classification process, the nearest k neighbors for each sample are determined, and label estimation is made by the majority voting method. The value of k is set to 10. It is optimized by a cross-validation method. The nonparametric structure of the KNN algorithm is preferred as a suitable classifier for emitter detection from radar signals, mainly because it does not require prior knowledge about the data distribution.

2) Decision Tree and Ensemble Bagged:

A DT is a fundamental and widely used method in ML due to its simplicity and interpretability. They work by recursively splitting a dataset into subsets based on the value of input features, creating a tree-like structure where each node represents a test on an attribute and each branch represents the outcome of the test. The process continues until a stopping criterion is met, such as a maximum tree depth or a minimum number of samples per leaf [26].

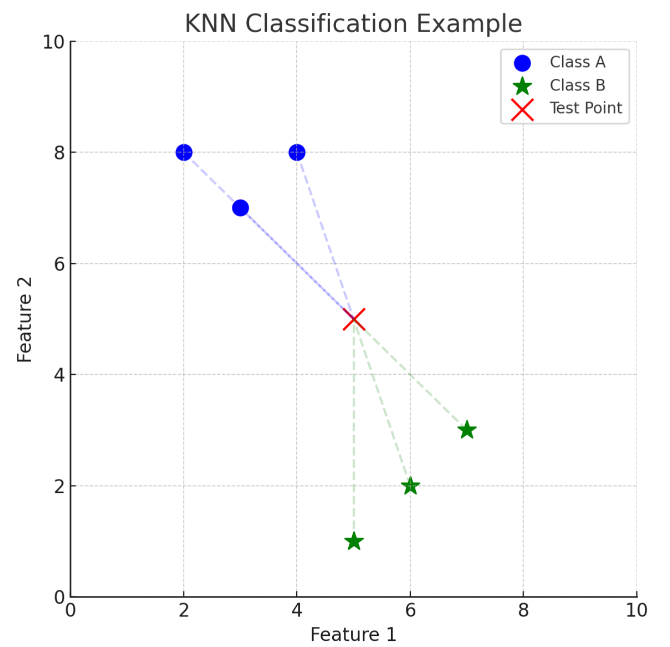

Fig. 4. K-nearest neighbor classification methods approximation (k=6).

Decision trees offer several advantages, including interpretability, the ability to handle nonlinear relationships, and the ability to determine feature importance. The resulting model is easy to understand and visualize, which is crucial for applications that require transparency. Decision trees can also capture nonlinear relationships between features and the target variable. Decision trees indicate which features are most important for prediction.

However, they also have some limitations, like overfitting and instability. Ensemble methods such as Random Forests and Gradient Boosting are often used to mitigate these issues. These methods combine multiple DTs to create a more robust and accurate model. For example, Random Forests build multiple trees using random subsets of the data and features and then combine their predictions to improve generalization [27].

In the task of identifying broadcasters based on radar parameters, the DT algorithm was preferred due to its advantages, including the explainability and transparency of its decision rules. The tree structure was created by determining the feature that provides the most information gain for classifying the target variable as the root node, and then dividing it according to the Gini index criteria in the subsequent branches. To prevent overfitting of the model, parameters such as maximum depth, minimum number of samples, and pruning were optimized experimentally.

To further enhance the performance and generalizability of DTs, the ensemble bagging (bootstrap aggregating) method was also used in this study. The Bagging approach is based on combining the outputs of these models by creating multiple DTs on different random subsets of the training data. In classification problems, it aims to increase the success rate by combining the predictions of the trained trees from each subset with the majority vote. It increases the accuracy and stability of the model by reducing the tendency of DTs to overfit. It also offers lower variance compared to a single DT. This study consists of 30 medium-sized DTs trained on data subsets created by the bootstrap sampling method. Splitting operations in each tree were performed according to the Gini diversity index criterion; the default minimum number of samples for leaf nodes was set to 1. The complexity of the trees was controlled with a limited number of splits (MaxNumSplits), and the decision mechanism was structured according to the principle of equal weighted majority voting of all trees. With this structure, it was aimed to benefit from the features of providing a balanced and reliable model performance in terms of both high classification accuracy and prevention of overfitting.

3) Support Vector Machines:
An SVM is a supervised learning algorithm often used in classification and regression analyses. The primary goal of SVM is to identify a hyperplane that optimally separates data points into distinct classes [28]. This hyperplane is the plane that makes the most significant separation between classes and maximizes the distance, which is referred to as the margin. When separating the data with this plane, SVM uses the data points closest to the decision boundary, called support vectors. These vectors are critical points that increase the model's generalization ability.

An SVM can also work effectively on nonlinear datasets. In this case, kernel functions, such as linear, polynomial, radial basis function, and sigmoid functions, are used. Kernel functions transform the data into a higher-dimensional space, making it linearly separable. The choice of kernel functions has a significant impact on the model's performance and is often determined by the characteristics of the dataset. One of the basic assumptions of SVM is that all examples in the training set are independently and identically distributed [29].

Support vector machine performs effectively on high-dimensional datasets and has high generalization ability, meaning it does not overfit the training data. Thanks to its kernel functions, it can also model nonlinear boundaries. However, training time and memory usage may increase for large data sets. Hyperparameter selection is complex and can significantly affect the model's performance. An SVM is a powerful and flexible algorithm that performs better when used correctly and with carefully tuned parameters. However, its complexity and the sensitivity of its settings require users to be careful and knowledgeable.

C. Regression Step Methods
1) Gaussian Process Regression:
Gaussian regression, also known as GPR, is a powerful and flexible method used in statistical ML [30–32]. It models the behavior of a particular function or system and makes predictions based on observed data. This method is beneficial for complex and high-dimensional data.

Gaussian regression is a continuous random process in which each point is associated with other points through a covariance function, typically represented by a covariance matrix. Gaussian regression assumes that all possible function values fit a Gaussian distribution; the function value at any point follows a standard distribution with the values of other points. The covariance function identifies dependencies or similarities between data. The commonly used covariance function in this study is the Gaussian kernel. The covariance function is a parameter that calculates the similarity between two data points based on their distance.

For this study, the GPR method is applied for distance estimation from continuous outputs based on radar parameters. The statistical nature of GPR provides advantages against noisy signals encountered in EW environments by providing not only point estimation but also an uncertainty range regarding the estimation. The model is trained with a rational quadratic GPR configuration, and a constant basis function and a rational quadratic kernel function are used. With the isotropic kernel preference, an equal variance assumption is made in all directions, and kernel scale, signal standard deviation, and sigma parameters are automatically optimized. In addition, optimization of numerical hyperparameters is enabled, and input data is standardized before modeling. This structure provides a strong representation of nonlinear relationships in particular and contributes to obtaining high model accuracy even in low sample scenarios. Gaussian regression is used because it is expected to be an effective approach in estimating emitter parameters from radar signal data.

2) Neural Networks:
A neural network is a nonlinear and statistical prediction method mimicking how the human brain processes information. It consists of three primary layers: the input layer, the hidden layer, and the output layer. The input layer is the first layer in the neural network, responsible for receiving raw data and passing it to the intermediate layers. The term intermediate layers used in the network model in this study is used in the sense of the hidden layers of the neural network, and both terms are used synonymously to describe the processing layers located between the input and output layers. Each neuron in the input layer represents a feature or attribute of the input data. This layer acts as a conduit, passing the data to the next set of neurons in the network. The hidden layers are where processing and learning occur [33]. A classical neural network model typically comprises several hidden layers, each with multiple neurons. These hidden layers perform a series of complex transformations on the input data, learning to extract and abstract features critical for accurate predictions.

The number of hidden layers and neurons within each layer can vary depending on the problem's complexity and the network's architecture. These layers are where the network learns to recognize patterns and relationships in the data through the backpropagation process. It involves propagating the error from the output layer back through the network to update the weights of the connections between neurons. This iterative process enables the network to minimize the difference between the predicted output and target values, thereby refining its accuracy over time. The output layer is responsible for producing the computational result. The neurons in this layer combine the features learned in the hidden layers to make a prediction or classification.

Various factors can influence the neural network's performance, including the network's architecture (such as the number of layers and neurons) and the effectiveness of the training process. For example, the total number of hidden layers in a neural network depends on the complexity of the input data and the specific task at hand. The details of the network architecture implemented in this study are shown in Table II.

D. Performance Evaluation Criteria
In this study, a confusion matrix was used. The confusion matrix is a table used to describe the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of the classification algorithm. Performance was compared based on the following metrics by proportioning the values obtained from the confusion matrix. The operation is performed on four numerical values obtained from the matrix. These are true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TP: the observation is predicted to be positive and is positive. FP: the observation is predicted to be positive and is negative. TN: the observation is predicted to be negative, but it is negative. FN: the observation was predicted as negative and positive. Precision [(3)], recall [(4)], accuracy [(5)], specificity [(6)], sensitivity [(7)], and F1-score [(8)] are metrics obtained from the confusion matrix and used for performance evaluation in the literature.

TABLE II. NEURAL NETWORK MODEL PARAMETERS

Model Parameter	Value
Number of fully connected layers	1
First layer size	10
Activation function	Relu
Iteration limit	1000

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$Specificity = \frac{TN}{TN+FP} \tag{6}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{7}$$

$$F1Score = 2x\frac{PrecisionXRecall}{Precision+Recall} \tag{8}$$

To compare method performances, root mean square error (RMSE) (9), mean absolute error (MAE) (10), and mean absolute percent error (MAPE) (11) metrics are used.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{\left(y_i - y_i\right)^2}{n}} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i\right| \tag{10}$$

$$MAPE(\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|y_i - y_i\right|}{\left|y_i\right|} \tag{11}$$

y_i represents the predicted value and y_i represents the real value for all error calculation formulas.

IV. RESULTS AND DISCUSSION

All classification and evaluation analyses were performed using MATLAB version 2025b. The analysis process was conducted on an ASUS ZenBook 14 laptop with 16 GB RAM and an Intel Core i9 processor. The hardware and software infrastructure used provided sufficient performance in data processing and model training processes. The flowchart of the study is shown in Fig. 5.

The classification step, the first stage of this study, aims to determine the type of radars. For this reason, the problem seems to be a multi-class classification problem. In the model evaluation process, the 5-fold cross-validation method was employed to prevent overfitting and to more accurately measure the model's generalizability. Additionally, 10% of the existing data was set aside as test data—completely independent of the training process—to evaluate the model's final performance on an independent dataset. The reliability and generalizability of the model were analyzed in detail through the performance metrics obtained in both the validation and testing stages. One of the most critical performance criteria for determining classification performance is the confusion matrix. Figs. 6–8 show the confusion matrices of the three methods.

As shown in Table III, the methods with the highest classification performance are DTs and SVM. These confusion matrices show that they can separate the classes from each other on the relevant dataset.

This study analyzes radars, a vital piece of equipment in EW. It utilizes a dataset comprising various parameters associated with different types of radar. The study consists of two stages: the first is classification, and the second is regression. In the classification phase, the aim is to determine the type of radar using the features in the dataset. In the second phase, the goal is to calculate the distance of the threat element to the target. The regression step results are presented in Table IV.

K-nearest neighbor, DT, SVM, and ensemble bagged methods were used in the classification phase; SVM, DT, ensemble bagged, NN, and GPR algorithms were evaluated in the regression process in the analysis performed within the scope of the study. Decision trees, SVM, and ensemble methods stood out with their high discrimination ability by reaching a 100% accuracy rate according to the classification results. Decision tree's fast decision-making structure, SVM's discrimination power in high-dimensional data, and the ensemble structure's increasing generalization ability by reducing variance were effective in obtaining these results. K-nearest neighbor lagged behind these models, especially due to data density and neighborhood sensitivity. The lowest error rate was obtained with GPR in regression analyses; this can be explained by GPR's ability to model nonlinear relationships and its ability to express uncertainties statistically. The three methods provided 100% accuracy in classification, making these models the primary consideration in determining the hybrid structure. Time complexity is shown in Table V.

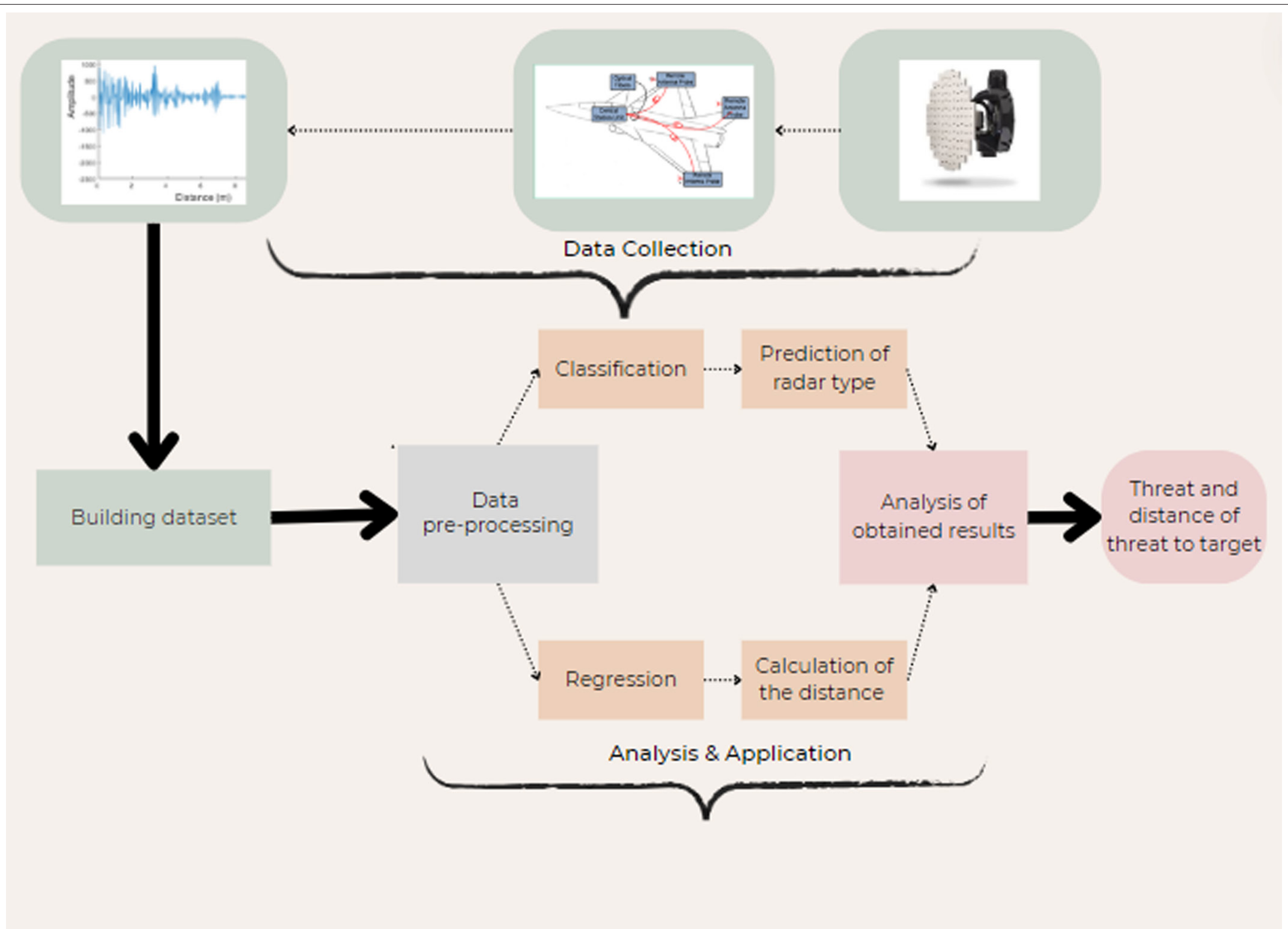

Fig. 5. Flowchart of this study.

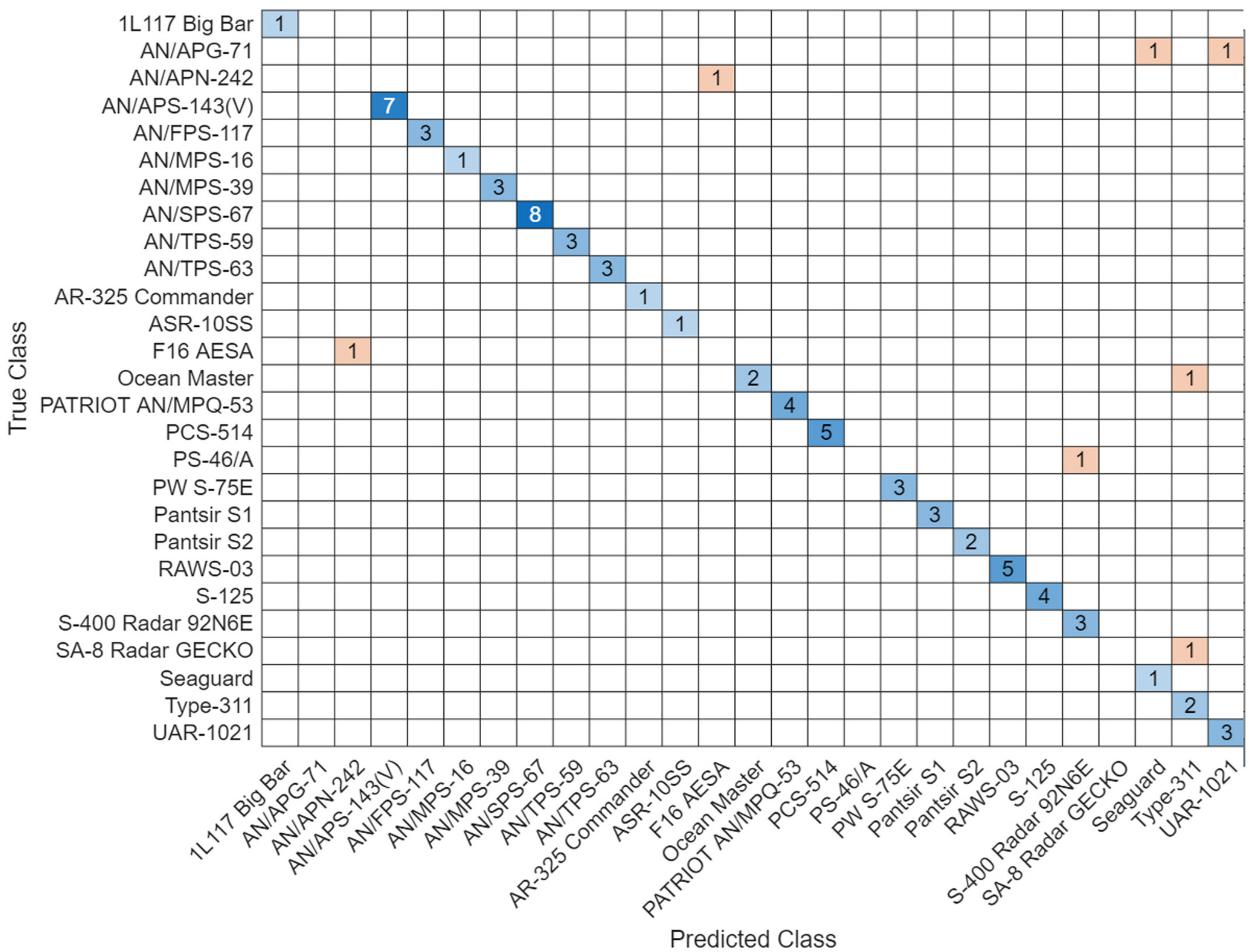

Fig. 6. Confusion matrix of k-nearest neighbors.

Hybrid combinations of other methods were created, and temporal comparisons were made. Each classifier was combined with both its regression counterpart and the GPR that gave the lowest error, and the system response times were evaluated. It was observed that DT-GPR, mainly when used together, has high potential in time-sensitive applications.

As a result of the analyses, the accuracy, error rates, and processing times of the different ML methods used in the classification and regression steps were compared. In the classification stage, DT, SVM, and ensemble methods stood out with 100% accuracy, sensitivity, specificity, and F1 scores. These results demonstrate that these methods provide high reliability, particularly in defense applications with low error tolerance, such as RWR systems.

In the regression stage, GPR stands out with its MAE, RMSE, and MAPE values. Gaussian regression's ability to model nonlinear relationships and express uncertainties statistically demonstrates its success in estimating the threat range.

In terms of time analysis, the DT + GPR structure, which has the lowest total processing time in binary combinations that consider both classification and regression steps, provided both high accuracy and a low error rate in a total time of only 20.69 seconds. This situation shows that the combination of DT's fast decision-making structure and GPR's powerful regression capabilities is quite suitable for CEW systems that are expected to operate in real time.

These results demonstrate that the classification performance of the DT, ensemble bagged, and SVM methods is highly suitable for RWR applications, which do not tolerate any incorrect decisions. Almost always, after an RWR detects a radar threat, it sends the information to the CMs system via the SPEW system's central management unit. At the end of this process, automatic, semi-automatic, or manual CMs are engaged, such as jamming, chaff, and decoys. Incorrect detection of the emitter type would result in the use of unsuitable CMs, potentially leading to pilot casualties and aircraft losses.

The range detection of the threat radars is of utmost importance, especially in adjusting the noise jamming power, generating false targets, engaging decoys, and determining the direction of evasive maneuvering. For range detection purposes, the ML techniques aim to conduct regression processes fast and accurately. The studies show that the GPR model is the most suitable technique for detecting the threat's range in RWRs.

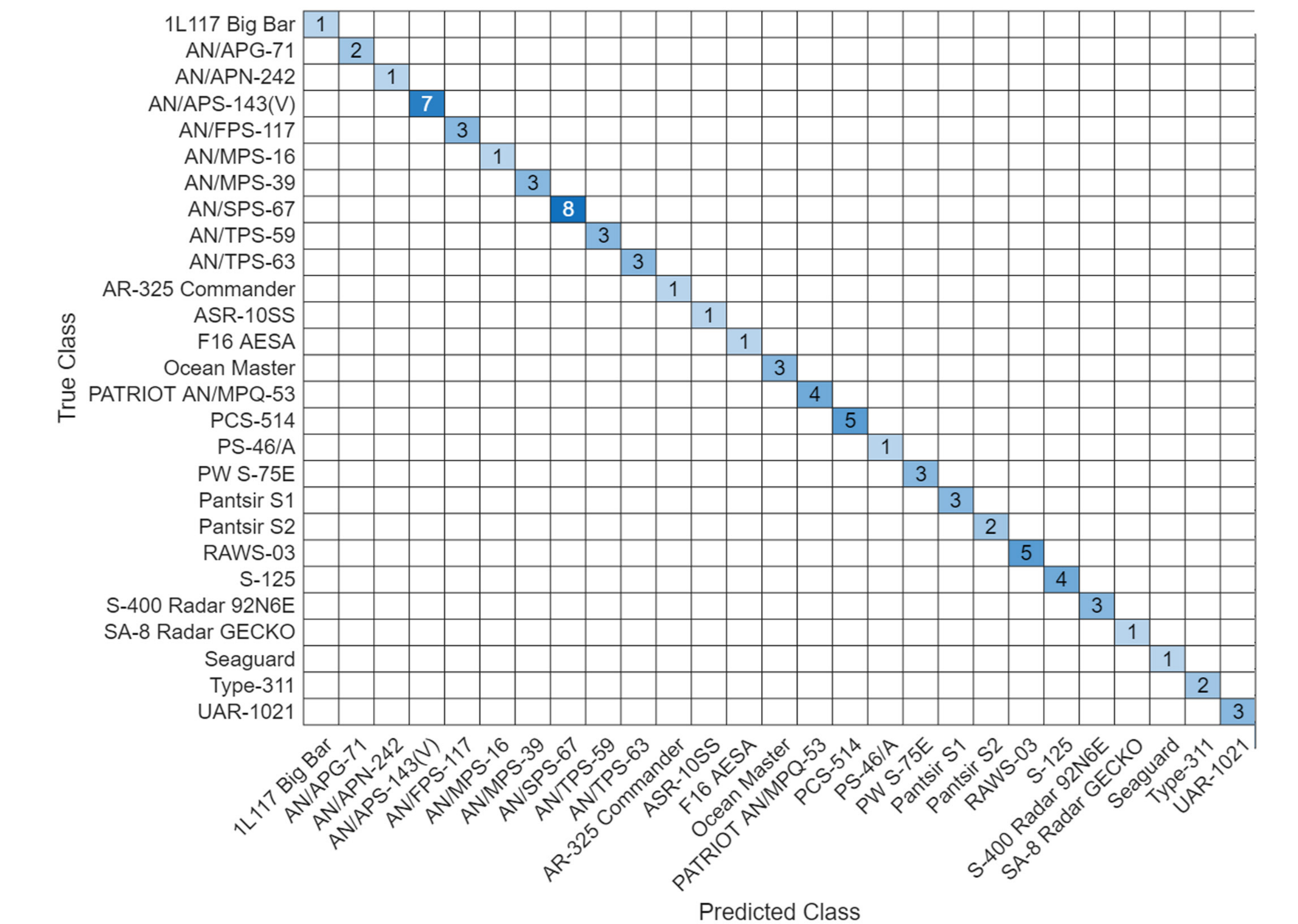

Fig. 7. Confusion matrix of decision tree.

Since temporal analysis directly affects the reaction time of the system in detecting and classifying radar threats, it is a critical evaluation criterion for real time EW applications. Since radar threats can generally be effective at high speed and in a short time, the algorithms used must provide high accuracy with low processing time, which is of vital importance for the success of the system. During the mission, since the time factor is decisive for pilot safety and mission success, the information provided by the RWR is processed without delay, and the appropriate countermeasures are quickly activated; this comparison is seen as an important performance criterion.

Considering all performance criteria, the DT + GPR combination stands out as the structure that best represents the usability of the proposed system in the operational field.

Despite the promising findings of this study, one of its limitations is that working with datasets that fully reflect all environmental variability and noise in real operational conditions could help analyze multiple cases for possible scenarios. To demonstrate the performance of the proposed method in practical systems in a more comprehensive manner, verification with real field data and evaluation of the algorithms in embedded hardware environments will be beneficial for the development of future studies.

V. CONCLUSION

In this study, an ML-supported method for emitter identification and range estimation processes for RWR systems is proposed. To test the validity of the proposed approach, a comprehensive and synthetic radar pulse dataset was created that realistically simulates operational electromagnetic environment conditions.

Machine learning algorithms were used in the EID process within SPEW systems, which play an important role within the scope of the CEW concept, and their performance was evaluated. While radar types were successfully detected with classification algorithms, target distance was accurately estimated with regression algorithms. While DT and SVM stood out with high accuracy rates in the EID mission, the GPR model exhibited strong adaptability and stability in range estimation.

The obtained results show that ML-based methods can significantly increase the design and operational efficiency of SPEW systems. In particular, the time-efficient operation of these approaches is critical for accelerating decision-making processes in real time applications. The timely activation of countermeasures directly affects the survival chances of both the pilot and the platform. It is thought that

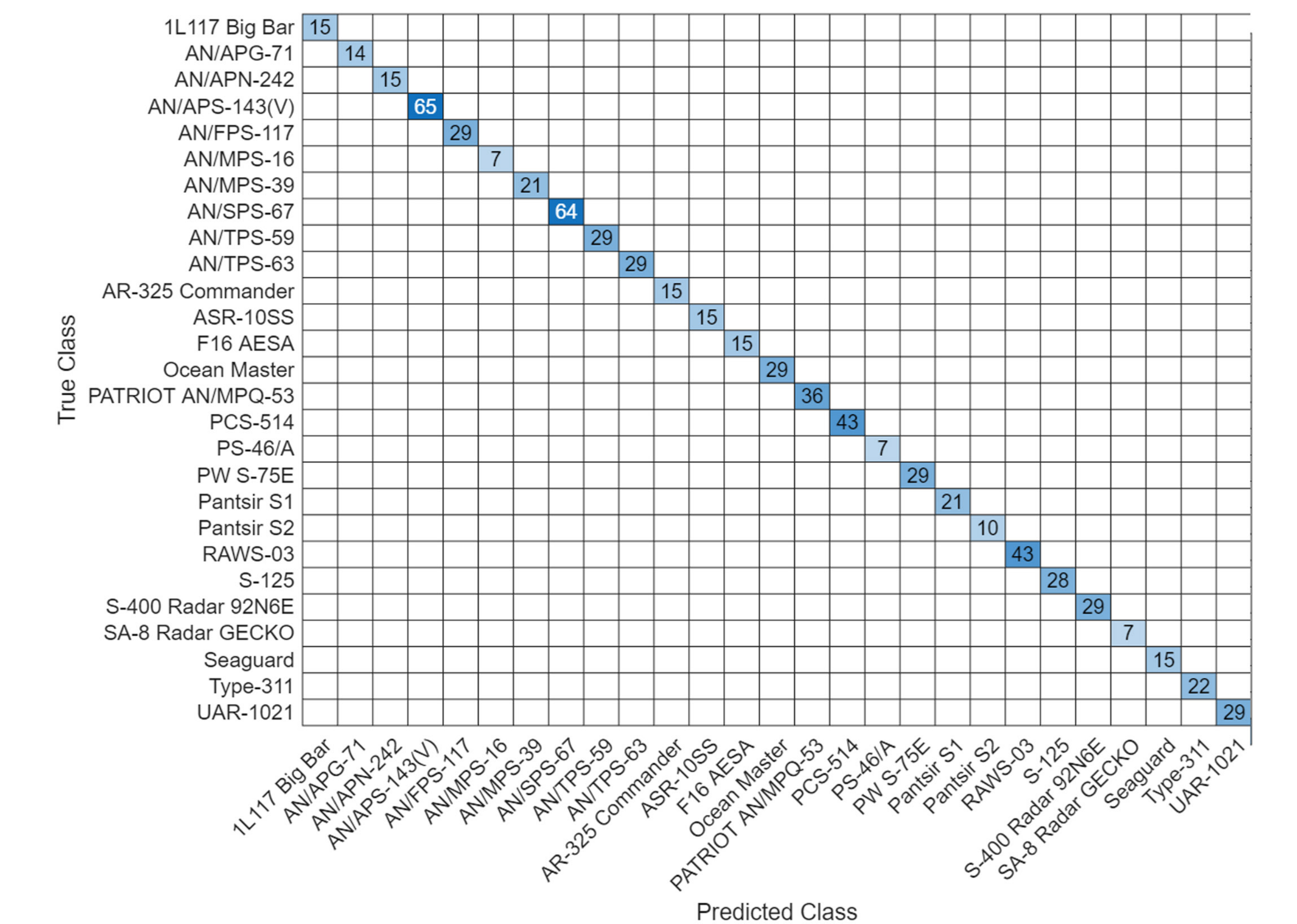

Fig. 8. Confusion matrix of support vector machines.

improvements can be made in the following items within the scope of future studies.

Physical data support: By integrating physical environmental parameters such as ambient temperature, atmospheric pressure, body temperature, and wind speed into the dataset in real time, the system can make more accurate and reliable decisions under variable conditions.

Utilizing various learning approaches and network models for analysis: Specifically, the goal is to enhance performance by integrating deep learning techniques, such as convolutional neural networks (CNNs) and attention mechanisms (attention-based models), into EID and distance estimation processes. It is planned to apply transfer learning techniques so that the system can be used in different geographical regions or on different platforms, and to provide continuous learning capability against new types of threats.

Real time application: The hardware applicability of the algorithms in Field programmable gate arrays (FPGA) or Graphics processing unit-based embedded systems will be tested, and the level of real time operability will be evaluated.

TABLE III. CLASSIFICATION STEP PERFORMANCE METRICS

	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F-1 Score (%)	Accuracy (%)	Time
KNN	81.3	81.3	81.3	81.3	81.3	82.7	26.81
DT	100	100	100	100	100	100	8.03
Ensemble	100	100	100	100	100	100	18.49
SVM	100	100	100	100	100	100	88.51

DT, decision tree; KNN, k-nearest neighbor; SVM, support vector machine.

TABLE IV. REGRESSION STEP ERROR VALUES

	MAE	RMSE	MAPE (%)	Time
DT	276.22	967.66	1.4	2.05
Ensemble	1555.8	2647.3	9.3	12.38
SVM	2782.5	4235.2	155	4.43
GPR	360.76	934.98	1.8	12.66
Neural Networks	712.36	1369.4	5.2	7.70

DT, decision tree; GPR, Gaussian regression; MAE, mean absolute error; MAPE, mean absolute percent error; RMSE, root mean square error; SVM, support vector machine.

TABLE V. TIME SCORES

Model Combination	Total Time (sec)
DT + DT	10.08
DT + Ensemble	20.41
DT + SVM	12.46
DT + GPR	**20.69**
DT + NN	15.73
SVM + DT	90.56
SVM + Ensemble	100.89
SVM + SVM	92.94
SVM + GPR	101.17
SVM + NN	96.21
Ensemble + DT	20.54
Ensemble + Ensemble	30.87
Ensemble + SVM	22.92
Ensemble + GPR	31.15
Ensemble + NN	26.19
KNN + DT	28.86
KNN + Ensemble	39.19
KNN + SVM	31.24
KNN + GPR	39.47
KNN + NN	34.51

DT, decision tree; GPR, Gaussian regression; KNN, k-nearest neighbor; SVM, support vector machine.

Modeling of threat environments: Simulation environments will be developed to test the system's durability and accuracy in scenarios where multiple radar sources are active simultaneously and electronic jamming elements are present.

A. Limitations

The study has some limitations. This section lists these domain-based limitations:

1. Usage of synthetic data: The radar pulse data used in this study were generated in a synthetic environment representative of real-world operational conditions. It should be noted that this may result in the developed models' limited real-world performance.
2. Omission of physical environmental factors in the data: Environmental factors such as ambient temperature, pressure, and wind speed were not included in the data set. The absence of such variables may reduce the model's sensitivity to variable external conditions.
3. Inadequate representation of real-world noise and interference effects: Complex real-world situations such as electromagnetic interference, signal interference, and multi-threat scenarios may present shortcomings in fully integrating the data set.
4. Generalizability issue: The similar characteristics of training and test data may prevent the direct measurement of the developed system's performance on different platforms or under varying geographical conditions.

B. Future Works

To address limitations and contribute to competency in future work, improvements can be made in the following areas:

- Validation: To assess the reliability of the algorithms, the system's performance will be verified using real time operational data, and benchmark studies will be conducted accordingly.
- Real time implementation: The real time operability of the developed system will be assessed by conducting tests on embedded hardware such as FPGAs and GPUs.
- Integration of physical parameters: The aim is to increase the accuracy and reliability of the decision-making mechanism by integrating environmental variables (temperature, pressure, humidity, etc.) into the system in real time.
- Integration of deep learning methods: The aim is to improve classification and distance estimation performance, particularly through the use of models based on CNN and attention mechanisms.
- Simulation of threat environments: Simulation environments in which multiple radar sources and electronic countermeasures are active will be developed to test the system's resilience and stability in different scenarios.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – İ.C.T., A.G.P.; Design – İ.C.T., A.G.P.; Supervision – A.G.P.; Materials – A.G.P.; Data Collection and/or Processing – A.G.P.; Analysis and/or Interpretation – İ.C.T., A.G.P.; Literature Search – İ.C.T., A.G.P.; Writing – İ.C.T., A.G.P.; Critical Review – İ.C.T., A.G.P.

Declaration of Interests: The authors have no conflicts of interest to declare.

Funding: The authors declare that this study received no financial support.

REFERENCES

1. R. Reddy, and S. Sinha, "State-of-the-art review: Electronic warfare against radar systems," in *IEEE Access*, vol. 13, pp. 57530–57567, 2025. [CrossRef]

2. A. G. Pakfiliz, in *Self-Protection Jammer Systems*. Norwood, MA: Artech House, 2021, ch. 5 and 6.
3. C. Zhang, L. Wang, R. Jiang, J. Hu, and S. Xu, "Radar jamming decision-making in cognitive electronic warfare: A review," in *IEEE Sens. J.*, vol. 23, no. 11, pp. 11383–11403, 2023. [CrossRef]
4. K. Z. Haigh, and J. Andrusenko, ch. 1, *Cognitive Electronic Warfare: An Artificial Intelligence Approach*. Norwood, MA: Artech House, 2021.
5. C. Winsor, and E. J. Hughes, "Optimisation and evaluation of receiver search strategies for electronic support," *IET Radar Sonar Navig.*, vol. 6, no. 4, pp. 233–240, 2012. [CrossRef]
6. R. A. Poisel, *Electronic Warfare Receivers and Receiving Systems*. Norwood, MA: Artech House, 2014. ch. 10.
7. A. De Martino, *Introduction to Modern EW Systems*, 2nd ed. Norwood, MA: Artech House, 2018. ch. 3.
8. U. Joshi, R. D. Garg, N. Sharma, V. K. Joshi, and K. Sharma, "Hazardous zone identification by spectral analysis of ground penetrating radar response," *Electrica*, vol. 24, no. 2, pp. 503–514, 2024. [CrossRef]
9. N. Fişne, and A. G. Pakfiliz, "PRI deinterleaving with connected component labeling-based clustering," *Pamukkale J. Eng. Sci.*, vol. 29, no. 6, pp. 589–595, 2023. [CrossRef]
10. M. B. Kocamiş, A. Orduyilmaz, and S. Taşcioğlu, "Object detection-based deinterleaving of radar signals using deep learning for cognitive EW," *Signal Image Video Processing.*, vol.18, pp. 7789–7800, 2024.[CrossRef]
11. H. Zheng, K. Xie, Y. Zhu, J. Lin, and L. Wang, "A reconstruction bidirectional recurrent neural network -based deinterleaving method for known radar signals in open-set scenarios," *IET Radar Sonar Navig.*, vol. 18, no. 6, pp. 965–981, 2024. [CrossRef]
12. J. Dudczyk, and A. Kawalec, "Identification of emitter sources in the aspect of their fractal features," *Bull. Pol. Acad. Sci. Tech. Sci.*, vol. 61, no. 3, pp. 623–628, 2013. [CrossRef]
13. M. Gupta, G. Hareesh, and A. K. Mahla, "Identification of emitter sources in the aspect of their fractal features," *Def. Sci. J.*, vol. 61, no. 3, pp. 228–234, 2011.
14. P. Li, "Research on radar signal recognition based on automatic machine learning," *Neural Comput. Appl.*, vol. 32, no. 7, pp. 1959–1969, 2020. [CrossRef]
15. S. Guo, S. Akhtar, and A. Mella, "A method for radar model identification using time-domain transient signals," in *IEEE Trans. Aerosp. Electron. Syst.*, vol. 57, no. 5, pp. 3132–3149, 2021. [CrossRef]
16. W. Sun, L. Wang, and S. Sun, "Radar emitter individual identification based on convolutional neural network learning," *Math. Probl. Eng.*, vol. 2021, no. 1, p. 1–8, 2021. [CrossRef]
17. G. Zhang, and X. Li, "A new recognition system for radar emitter signals," *Kybernetes*, vol. 41, no. 9, pp. 1351–1360, 2012. [CrossRef]
18. X. Sun, J. T. Xu, C. M. Jiang, J. Feng, S. S. Chen, and F. J. He, "Extreme learning machine for multi-label classification," *Entropy*, vol.18, no. 6, p. 225, 2016. [CrossRef]
19. Z. T. Yang, Z. L. Wu, Z. D. Yin, T. F. Quan, and H. J. Sun, "Hybrid radar emitter recognition based on rough k-means classifier and relevance vector machine," *Sensors (Basel)*, vol. 13, no. 1, pp. 848–864, 2013. [CrossRef]
20. J. Wang, X. Wang, Y. Tian, Z. Chen, and Y. Chen, "A radar emitter recognition mechanism based on IFS-tri-training classification processing," *Electronics*, vol. 11, no. 7, p. 1078, 2022. [CrossRef]
21. M. Zhu, Z. Feng, and X. Zhou, "A novel data-driven specific emitter identification feature based on machine cognition," *Electronics*, vol. 9, no. 8, p. 1308, 2020. [CrossRef]
22. *Handbook, Electronic Warfare, Shephard Press Publication*. Berkshire, UK: Williams Press, 2008.
23. M. Streetly (Ed.), *Jane's Radar and Electronic Warfare Systems: 2008-2009*. Jane's Information Group, 2008.
24. C. Bao, T. Zhang, Z. Hu, W. Feng, and R. Liu, "Wind turbine condition monitoring based on improved active learning strategy and KNN algorithm," *IEEE Access*, vol. 11, pp. 13545–13553, 2023. [CrossRef]
25. K. Alnowaiser, "Improving healthcare prediction of diabetic patients using KNN imputed features and tri-ensemble model," *IEEE Access*, vol. 12, pp. 16783–16793, 2024. [CrossRef]
26. V. R. Modhugu, and S. Ponnusamy, "Comparative analysis of machine learning algorithms for liver disease prediction: SVM, logistic regression, and decision tree," *Asian J. Res. Com. Sci.*, vol. 17, no. 6, pp. 188–201, 2024. [CrossRef]
27. Z. Azam, M. M. Islam, and M. N. Huda, "Comparative analysis of intrusion detection systems and machine learning-based model analysis through decision tree," *IEEE Access*, vol. 11, pp. 80348–80391, 2023. [CrossRef]
28. D. Valkenborg, A. J. Rousseau, M. Geubbelmans, and T. Burzykowski, "Support vector machines," *Am. J. Orthod. Dentofacial Orthop.*, vol. 164, no. 5, pp. 754–757, 2023. [CrossRef]
29. Y. Yakut, E. Yakut, B. Elmas, and S. Yavuz, "Yapay sinir ağları ve destek vektör makineleri yöntemleriyle borsa endeksi tahmini," *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, vol. 19, no. 1, pp. 139–157. 2014. [Online]. Available: https://dergipark.org.tr/en/pub/sduiibfd/issue/20816/222712.
30. E. K. Nisa, and S. D. Miasary, "Parameter estimation and application of inverse Gaussian regression," *AIP Conf. Proc.*, vol. 3046, no. 1, 2024. [CrossRef]
31. S. Aigrain, and D. Foreman-Mackey, "Gaussian process regression for astronomical time series," *Annu. Rev. Astron. Astrophys.*, vol. 61, no. 1, pp. 329–371, 2023. [CrossRef]
32. J. Wang, "An intuitive tutorial to Gaussian process regression," *Comput. Sci. Eng.*, vol. 25, no. 4, pp. 4–11, 2023. [CrossRef]
33. A. Kurani, P. Doshi, A. Vakharia, and M. Shah, "A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting," *Ann. Data Sci.*, vol. 10, no. 1, pp. 183–208, 2023. [CrossRef]

İclal Çetin Taş received her BSc. degree in Electrical-Electronics Engineering from Çukurova University in 2009. She completed her MSc. and then Ph.D in Electrical and Electronics Engineering at Çukurova University in 2012, 2019 respectively. Her research areas are image and signal processing and artificial intelligence. She is currently working as an Assisant Professor in Department of Computer Engineering at Baskent University.

Ahmet Güngör Pakfiliz received his B.S. degree in Electrical Engineering from Yıldız Technical University in 1991. He then completed his M.S. in Electrical and Electronics Engineering at Middle East Technical University in 1997, followed by a Ph.D. in Electronics Engineering from Ankara University in 2004. His research interests include electronic warfare, radar systems, and signal processing. Currently, he is an Associate Professor in the Department of Electrical and Electronics Engineering at the University of the Turkish Aeronautical Association.