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*Araştırma Makalesi / Research Article*

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## **A Comparative Study of Artificial Neural Networks and Naïve Bayes Techniques for the Classification of Radar Targets**

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### **Abstract**

The classification of radar targets is one of the most important study topics, especially in the defense and automotive industries. However, in most of the studies in the literature, raw radar signals are used. Raw radar signals may be subject to ambient noise and signal modulation effects. This may make it difficult to classify radar targets. In this study, instead of using raw data, Fourier-based features extracted from Radar Cross-sectional Area have been used. These extracted features are then input to two types of classifiers, ie, Naive Bayes (NB) and Artificial Neural Networks (ANN) for the classification of radar targets. In addition, both classifiers were trained with different algorithms and their performances were compared. In the ANN-based classifiers, the best accuracy was found that 96.69% with using Bayesian regularization and back propagation training function. On the other hand, the best accuracy with the NB classifier was achieved at 93.95% using Epanechnikov Kernel Distribution. The result presented here demonstrates that Fourier transform based feature extraction can be used effectively in radar target classification applications.

**Keywords:** Artificial neural networks, naïve bayes classifier, radar cross section, radar target classification.

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## **Radar Hedeflerinin Sınıflandırılması için Yapay Sinir Ağları ve Naïve Bayes Tekniklerinin Karşılaştırmalı Bir Çalışması**

### **Öz**

Radar hedeflerinin sınıflandırılması, özellikle savunma ve otomotiv endüstrilerinde en önemli çalışma konularından biridir. Ancak, literatürdeki çalışmaların çoğunda ham radar sinyalleri kullanılmaktadır. Ham radar sinyalleri ortamdaki gürültü ve sinyal modülasyon etkilerine maruz kalabilmektedir. Bu durum radar hedeflerinin sınıflandırılmasını zorlaştırabilir. Bu çalışmada, ham veri kullanmak yerine, Radar Kesit Alanından çıkarılan Fourier tabanlı özellikler kullanılmıştır. Bu çıkarılan özellikler daha sonra radar hedeflerinin sınıflandırılması için iki tür sınıflandırıcıya, yani Naive Bayes (NB) ve Yapay Sinir Ağlarına (YSA) girdi olarak verilmiştir. Ayrıca, her iki sınıflandırıcı farklı algoritmalar ile eğitilmiş ve performansları karşılaştırılmıştır. YSA tabanlı sınıflandırıcıda, en iyi doğruluk, Bayesian regülasyon ve geri yayılma eğitim fonksiyonu kullanılarak 96.69% olarak bulunmuştur. Diğer taraftan, NB sınıflandırıcı ile en iyi doğruluk Epanechnikov çekirdek dağılımı kullanılarak 93.95% olarak elde edilmiştir. Burada sunulan sonuç, Fourier dönüşüm temelli öznelik çıkarımının radar hedef sınıflandırma uygulamalarında etkili bir şekilde kullanılabileceğini göstermektedir.

**Anahtar kelimeler:** Yapay sinir ağları, naïve bayes sınıflandırma, radar kesit alanı, radar hedef sınıflandırma.

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### **1. Introduction**

In recent years, there is an increasing attention in classification of radar targets over the past few years. A vast majority of these researches focus on two fields: automotive industry and defense industry. In the automotive market, because of higher safety demand in road traffic, the advanced driving assistance systems (ADAS) are becoming inevitable. Radar sensors commonly used in ADAS systems to decelerate the vehicle when approaching the obstacles and accelerate current velocity as soon as traffic

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density allows it. There is a strong relation between ADAS technology and radar targets classification because the more accurate classification of obstacles, the more robustness on cruise controls systems. Global status report on road safety, published by World Health Organization, emphasized that the amount of road traffic deaths has reached 1.35 million [1]. For that reason, the classification of radar targets correctly is important. Machine learning based algorithms are commonly used to distinguish from pedestrian to vehicle and predict the vehicle category because these algorithms show high classification performances. In 2017, Capobianco et al. [2] used a Convolutional Neural Networks (CNN)-based method called DeepRadarNet to classify 6 different vehicles using frequency-modulated continuous wave (FM-CW) radar signals. They reached 96.1% accuracy in classifying the vehicle categories on the highway. Choi et al. [3] compared Naive Bayes (NB) and support vector machine (SVM) methods in terms of radar target classification. They obtained data from four humans, four bicycles and four cars. The recognition success rate of NB and SVM is achieved in [3] respectively 85% and 92%. In a similar vein, Nanzer and Rogers describe a Bayesian expression for the classification of humans and vehicles using micro-Doppler signals from a scanning Beam Radar and it has been reached near or above 90% accuracy [4]. Severino et al. [5] offered a micro Doppler-based method for identifying pedestrian in near field (0 - 15m) using radar sensors. SVM method was used to differentiate pedestrian and non-pedestrian targets. In addition, SVM's classification performance and speed were compared using three different kernel functions (gauss, polynomial and linear), and the best classification result was 99.5% with the Polynomial kernel.

Classification of targets from radar cross section is also an important study topic for defense applications specially dealing with airborne weapon systems. Military application radars are used in aircrafts as an airborne warning and control systems, investigating the enemy aircraft and tracking them. The classification of the target class has notable effect on threat estimation.

The neural networks and probabilistic based methods are commonly used in most modern radar systems. Kim et al. [6] use the convolutional neural networks model with combined Doppler images and obtain 94.7% accuracy. Zaied et al. [7] applied Deep learning techniques to classify Synthetic aperture radar (SAR) and Inverse Synthetic aperture radar (ISAR) images with the weights given by auto-encoder. They also evaluated the effect of the addition of convolution layers and hidden layers on the performance of the network. They acquire 97.65% as a classification percentage for a training time of 47 seconds with the ISAR database. Zhou et al. proposed a method based on deep convolution neural networks (DCNN) to classify the polarimetric SAR image [8]. In the classification of the Synthetic Aperture Radar (AIRSAR) data set, 92.46% accuracy was achieved by DCNN method.

On the other hand, there are some works recommended probabilistic approaches such as Hidden Markov Model (HMM) and Naïve Bayes based methods in the literature [9,10]. Kouemou and Ortiz compare three kinds of HMM methods using radar signals from five classes of real targets and the best mean classification rate is achieved on HMM with discrete outputs (DHMM) methods [10]. Leung and Wu find that the percentage of true track classified by the Bayesian and Dempster-Shafer approaches is 85.37 and 92.68, respectively [10].

As in the studies [2-10] mentioned above, most of the works in the literature use raw radar signals. However, raw signals are sampled in a dynamic process where numerous factors such as noise and signal modulation effect are combined. Therefore, it may not be appropriate to classify radar targets directly obtained by raw signals. Feature selection is one of the methods used to remove irrelevant or unnecessary information. It is also often used as it increases accuracy in classification problems.

The aim of this study is to identify and classify targets by using features extracted from Radar Cross Section (RCS) information in two different machine learning methods such as Naive Bayes and Artificial Neural Networks (ANN). In this study, unlike other studies in the literature, the features derived from the RCS information by Fourier Transform will be used for the first time to classify radar targets. The aim of using Fourier Transform is to design angle-independence classification system.

## 2. Material and Method

In this section, the theoretical background of machine learning algorithms such as Artificial Neural Networks (ANN) and Naive Bayes (NB) is briefly explained.

## 2.1. Artificial Neural Networks

Artificial neural networks, in the most general form, is a method constructed to imitate the way the brain performs a particular task or function. The ANN is commonly applied by using electronic components or is simulated in software in computer [11]. ANN consists of input, output and hidden layers. The ANN network proposed in this study has 3 hidden layers. Hyperbolic tangent sigmoid function was chosen as the activation function in the hidden layers and Softmax function was chosen as the activation function in the output layer.

There are several learning algorithms to train ANN networks. In this study, Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM) and Bayesian Regularization Backpropagation (BRB) learning algorithms were used to train ANN. These learning methods differ in the way they use the gradient to update the weights of the constructed ANN and are known as variations of the Backpropagation algorithm.

SCG algorithm is based on second order information from the network and updates its weights and biases along the conjugate gradient direction using a step size scaling mechanism [12].

Similar to the SCG algorithm, LM uses second order information from the network, but acts as the steepest descent (SD) or Gauss-Newton (GN) method, depending on the value of the mediating factor. When the value of the mediation factor (the distance between the predicted and the experimental result) is zero, the LM algorithm becomes the GN method using the approximate Hessian matrix. When the value of the mediation factor is large, the LM algorithm becomes the SD algorithm with a small step size [13].

In BRB algorithm, in order to decrease the adverse effects of large weights on the network output and to provide a softer response, the penalty term consisting of the squares of all network weights is added to the objective function. That is, the BRB algorithm lessens a combination of squared errors and weights, then determines the right combination in order to generate a network that generalizes well [14].

## 2.2. Naïve Bayes Method

A naïve Bayes classifier is a probabilistic machine learning model that's used for classification task. The principle of this classifier is based on the Bayes' theorem. Bayes' theorem is expressed mathematically as the equation (1) [15].

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B|A_1)P(A_1) + \dots + P(B|A_n)P(A_n)} \quad (1)$$

where  $A_1, A_2, \dots, A_n$  are set of mutually exclusive events together form the sample space  $S$  and  $B$  is any event from the sample space, such that  $P(B) > 0$ .

The reason of this classifier called naïve is that a naïve Bayes classifier assumes that the presence of a particular feature of class is unrelated to the presence of any other feature. When modelling a probability distribution with a naïve Bayes classifier, we are faced with the problem of how to deal with continuous variables. One approach is assuming the continuous values are distributed according to a Gaussian distribution. Other approach is using kernel density estimation for modelling each conditional distribution [16]. Kernel density estimation, also termed the Parzen-Rosenblatt window method is a statistical technique that create a smooth curve given a set of data.

Let  $x_1, x_2, \dots, x_n$  be  $n$  independent observations from the random variable  $X$ . The aim of density estimation is to approximate the probability density function  $f$  of  $X$ . The kernel density estimator  $\hat{f}_h(x)$  for the estimation of the density value  $f(x)$  at point  $x$  is defined as:

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) \quad (2)$$

where  $K$  denoting a kernel function

Apart from the Gaussian kernel, two types of kernel functions are used in this study. Epanechnikov kernel function and triangular kernel function are expressed respectively in equation (3) and in equation (4)

$$K(u) = \frac{3}{4}(1 - u^2)I(|u| \leq 1) \quad (3)$$

$$K(u) = (1 - |u|)I(|u| \leq 1) \quad (4)$$

### 3. Generation of Training and Test Sets

#### 3.1. Synthetization of RCS Data

Radar Cross Section (RCS) term is defined by IEEE standard radar definitions that a measure of the reflective strength of radar target [17]. RCS of a specified target can be described as a function of target aspect angle (except for a sphere). Change of RCS over aspect angle was modelled in this paper using physical optic methods. While synthesizing RCS data, three different geometric shaped objects were used as targets.

These 3 targets evaluated from:

- Circular Plate Targets (CPT) with radii varying from 10cm to 40 cm
- Rectangular Plate Targets (RPT) with area varying from 0.08 m<sup>2</sup> to 0.60 m<sup>2</sup>
- Truncated Cone Plate Targets (TCPT) with heights (the distance from the nose to the tail) from 10 cm to 20 cm, top surface radii from 10 cm to 30 cm and base surface radii from 20 cm to 60 cm.

The RCS models for targets were adapted from [18] and [19]. The RCS model of circular thin plate target used in this work when viewing nearly broadside condition is showed in equation (5).

$$\sigma = \frac{4\pi A^2}{\lambda^2} \quad (5)$$

where  $\sigma$  is RCS of target, A is physical area of the plate,  $\lambda$  is wavenumber. The RCS of a circular plate other than broadside aspects was computed using equation (6).

$$\sigma = \frac{4\pi^2 A^2 \cos^2 \theta}{\lambda^2} \left[ 2 \frac{J_1(kd \sin \theta)}{kd \sin \theta} \right]^2 \quad (6)$$

where J<sub>1</sub> is first order Bessel function, d is diameter of circular plate, k is wavenumber and equal to  $2\pi/\lambda$ .

For the rectangular plate, formula of normal-incidence RCS is same as circular one, equation (5). When aspect angle not equal to zero, equation (7) is used for computing RCS of rectangular plate target [18].

$$\sigma_{total} = \frac{b^2}{\pi} \left| \sigma_1 - \sigma_2 \left[ \frac{1}{\cos \theta} + \frac{\sigma_2}{4} (\sigma_3 + \sigma_4) \right] \sigma_5^{-1} \right|^2 \quad (7)$$

where  $\sigma_{total}$  is total RCS of rectangular plate target and b is the half of the short edge.  $\sigma_{total}$  term is derived from  $\sigma_1, \sigma_2, \sigma_3, \sigma_4$  and  $\sigma_5$ . Computation of these terms is showed in equation (8).

$$\sigma_1 = \cos \cos(ka \sin \theta) - j \frac{\sin(ka \sin \theta)}{\sin \theta} \quad (8)$$

$$\sigma_2 = \frac{e^{j(ka - \frac{\pi}{4})}}{\sqrt{2\pi}(ka)^{\frac{3}{2}}}$$

$$\sigma_3 = \frac{(1 + \sin\theta)e^{-jkasin\theta}}{(1 - \sin\theta)^2}$$

$$\sigma_4 = \frac{(1 - \sin\theta)e^{jkasin\theta}}{(1 + \sin\theta)^2}$$

$$\sigma_5 = 1 - \frac{e^{j(2ka - \frac{\pi}{2})}}{8\pi(ka)^3}$$

where a is the half of the long edge and k is wavenumber.

Geometry of truncated cone target is showed in Figure 1.

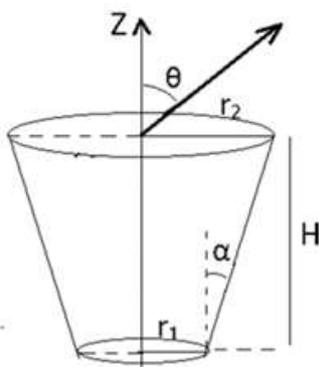


Figure 1. Geometry of Truncated Cone

In the Figure 1, alpha is lateral tilt angle and tangent of lateral tilt angle is computed using equation (9).

$$\tan \alpha = \frac{(r_2 - r_1)}{H} \tag{9}$$

In the normal incidence case, equation (10) is used when computing RCS of truncated cone targets.

$$\sigma_N = \frac{8\pi \left( z_2^{3/2} - z_1^{3/2} \right)^2 \sin\alpha}{9\lambda(\cos\alpha)^4} \tag{10}$$

where z<sub>2</sub> is z-coordinate value of top surface of truncated cone and z<sub>1</sub> is z-coordinate value of bottom one.

For aspect angle other than zero, RCS of truncated cone target was modelled in this paper using equation (11).

$$\sigma = \frac{\lambda z \tan\alpha \left( \frac{\sin\theta - \cos\theta \tan\alpha}{\sin\theta \tan\alpha + \cos\theta} \right)^2}{8\pi \sin\theta} \tag{11}$$

After modelling these targets, random noise was added in accordance with equation (12).

$$n = a * r * \sqrt{S} \tag{12}$$

where n is noise, S is standard deviation, alpha is scale factor and r is random number vector scaling between 0 and 0.01. When computing standard deviation, equation (13) was used.

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^N |\sigma_i - \mu|^2} \quad (13)$$

where N is number of the element and  $\mu$  is mean value of the set.

### 3.2. Feature Extraction and Dataset Creation from RCS Models

After defining the targets that are going to be combined into data sets, these models were used in order to generate simulated radar data. In Table 1, all features used in this paper are specified.

Elements of Feature Vector	
1.	Second-Order Term Coefficient
2.	First-Order Term Coefficient
3.	Second-Order Term Coefficient (in Fourier Domain)
4.	First-Order Term Coefficient (in Fourier Domain)
5.	Variance of Dataset Element (in Fourier Domain)
6.	Index of Greatest Value at Dataset Element (in Fourier Domain)

First step of feature extracting process is generating second order function to change of RCS over aspect angle. When generating second-order function, least squares fitting method was used. Coefficients of unknown terms were constituted first two element of feature vector. Fourier transform of dataset elements were calculated with fast Fourier transform algorithm. Then, second order function of these Fourier domain values was created. Coefficients of second order and first order terms of this function were forming third and fourth elements of feature vectors. Fifth element of feature vector is variance of Fourier domain values. Index of greatest value at RCS Dataset in Fourier Domain was used as sixth element of feature vector.

After defining feature vectors, these vectors were merged under the RCS dataset. Each sample of RCS dataset contains features extracted from RCS data coverage to 30-degree aspect angle. Sampling interval of RCS values was selected 0.5 degree. Starting aspect angle of RCS values corresponding to each sample was chosen different than each other. RCS Dataset contains 2040 circular plate targets sample, 1998 rectangular plate targets sample and 2160 truncated cone targets sample.

## 4. Results and Comparison of the Methods

This section shows various experimental results for classifying radar targets using two different machine learning methods. The performance of the ANN-based method is compared using three different learning algorithms (SCG, LM and BRB). In NB method, performance comparison is made using three different kernel (Gaussian, Epanechnikov and triangular) distribution functions. To provide same conditions for models, the computer experiments were carried out in MATLAB 2017a environment on a PC with Intel Core I5 processors 2.30 GHz with 4 GB RAM and 64-bit Windows 10 operation system. 10-fold cross validation was applied to dataset before training and testing classifiers. In 10-fold cross-validation, the dataset is randomly separated into 10 mutually exclusive subsets (folds) of almost equal size. The performance of each classifier was computed with taking average of each folds' classification accuracy.

Classification accuracies obtained from ANN based classifiers are indicated in Table 2. It can be seen from the Table 2 that the best classification accuracy is found % 96.69 with BRB algorithm. Although LM algorithm obtains four percent lesser classification accuracy than BRB classifier, it is observed during training phase of those classifiers that classification speed of LM classifier is faster than BRB classifier. Furthermore, as shown in Table 2, the accuracy of classification is much worse than other neural networks-based classifiers, although the speed of the SCG algorithm is highest.

Accuracy is a great measure but only when our datasets are distributed symmetrically. Therefore, other confusion metrics are also used to evaluate the performances of the classifiers. As shown in Table 3 and Table 4, all ANN based classifiers obtain good results to distinguish rectangular plate targets. Furthermore, we can observe from these tables, Truncated Cone Target and Circular Plate Target classification performance of BRB classifier is greater than those of LM classifier. This causes difference in classification accuracy of LM classifier and BRB classifier.

**Table 2.** Classification Accuracies and Time of ANN Based Classifiers

	BRB	SCG	LM
Classification Accuracies	% 96.69	% 77.54	% 92.30
Training Time (second)	4.467	2.465	3.758

**Table 3.** Classification Precisions of ANN Based Classifiers

	BRB	SCG	LM
TCPT	% 96.20	% 48.70	% 88.84
RPT	% 99.80	% 99.80	% 99.55
CPT	% 94.17	% 86.67	% 88.87

**Table 4.** Classification Recalls of ANN Based Classifiers

	BRB	SCG	LM
TCPT	% 96.43	% 79.70	% 89.50
RPT	% 99.90	% 99.40	% 98.37
CPT	% 98.36	% 61.28	% 89.22

The resulting classification accuracies of NB based classifiers with Gaussian, Triangular and Epanechnikov kernel distributions are tabled in Table 5. The results clearly show that using kernel Triangular and Epanechnikov kernel with NB classifier affects positively on performance while classifying radar targets. In addition, considering the classification accuracy in Table 6 and the classification recall in Table 7, it can be seen that there is no significant difference between NB classification results having Epanechnikov kernel distribution and triangular kernel distribution. On the other hand, NB with Gaussian kernel distribution demonstrates the lowest sensitivity (44.54%) for the Truncated Cone Target as seen in Table 6, as well as the lowest recall (61.22%) for the Circular Plate Target as seen in Table 7.

The confusion matrix results of ANN-based classifier trained with three different learning rules are shown in Tables 8, 9 and 10, respectively, while the confusion matrix results of NB-based classifier with three different kernel distributions are illustrated in Tables 11, 12 and 13, respectively.

It can be seen that the best confusion matrix values for TCPT, RPT and CPT datasets are obtained by BRB algorithm (207.8, 199.4, and 192.1) in ANN-based model (Table 8) and Epanechnikov kernel distribution (199, 196, and 187.3) in NB-based model (Table 12).

**Table 5.** Classification Accuracies of NB Based Classifiers

	BRB	SCG	LM
	NB with Gaussian Kernel	NB with Triangular Kernel	NB with Epanechnikov Kernel
Classification Accuracies	% 78.96	% 93.73	% 93.95
Training Time (second)	1.6	3.943	2.721

**Table 6.** Classification Precisions of NB Based Classifiers

	NB with Gaussian Kernel	NB with Triangular Kernel	NB with Epanechnikov Kernel
TCPT	% 44.54	% 92.36	% 92.13
RPT	% 96.30	% 98.10	% 98.10
CPT	% 98.43	% 90.88	% 91.81

**Table 7.** Classification Recalls of NB Based Classifiers

	NB with Gaussian Kernel	NB with Triangular Kernel	NB with Epanechnikov Kernel
TCPT	% 96.78	% 90.76	% 91.50
RPT	% 100.00	% 100.00	% 100.00
CPT	% 61.22	% 90.88	% 90.80

**Table 8.** Confusion Matrix of ANN Based Classifier used BRB Training Algorithm

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	207.8	0	8.2
	RPT	0.1	199.4	0.3
	CPT	11.7	0.2	192.1

**Table 9.** Confusion Matrix of ANN Based Classifier used SCG Training Algorithm

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	105.2	0	110.8
	RPT	0	199.4	0.4
	CPT	26.8	1.2	176

**Table 10.** Confusion Matrix of ANN Based Classifier used LM Training Algorithm

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	191.9	2.5	21.6
	RPT	0.6	198.9	0.3
	CPT	21.9	0.8	181.3

**Table 11.** Confusion Matrix of NB Classifier with Gaussian Kernel Distribution

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	96.2	0	119.8
	RPT	0	192.4	7.4
	CPT	3.2	0	200.8

**Table 12.** Confusion Matrix of NB Classifier with Epanechnikov Kernel Distribution

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	199	0	17
	RPT	1.8	196	2
	CPT	16.7	0	187.3

**Table 13.** Confusion Matrix of NB Classifier with Triangular Kernel Distribution

		Predicted		
		TCPT	RPT	CPT
Actual	TCPT	199.5	0	16.5
	RPT	1.7	196	2.1
	CPT	18.6	0	185.4

## 5. Conclusion

Different versions of two machine learning algorithms are compared in terms of radar target classification performances. The findings of this study indicate that using BRB training function gives

better performance than using LM and SCG training functions with ANN based classifiers. Also, the results obtained from NB algorithm-based classifiers highlight the importance of using Epanechnikov kernel distribution on classification accuracy.

Computational complexity of machine learning algorithms is especially important issue when working with real time applications. In the future works, in order to compare convenience for real time applications of different kind of classifiers, some comparison metrics state the computational complexity of algorithms will be used. Three types of neural networks training algorithms are investigated in this paper. Future research could examine performances of other neural networks training algorithms. Also, we implement two different kernel functions with NB classifier. Future studies might apply other kernel functions and compare their result with this work.

### **Author's Contributions**

The authors gave final approval of the current version and any revised version to be submitted to the journal.

### **Statement of Conflicts of Interest**

There is no conflict of interest among the authors.

### **Statement of Research and Publication Ethics**

The authors declare that this study complies with Research and Publication Ethics.

### **References**

- [1] World Health Organization. 2018. Global Status Report on Road Safety. [https://www.who.int/violence\\_injury\\_prevention/road\\_safety\\_status/2018/en](https://www.who.int/violence_injury_prevention/road_safety_status/2018/en). (Accessed: 21.09.2019).
- [2] Capobianco S., Facheris L., Cuccoli F., Marinai S. 2017. Vehicle Classification Based on Convolutional Networks Applied to FMCW Radar Signals. 1st European Conference on Traffic Mining Application to Police Activities, 25-26 October, Rome, Italy.
- [3] Choi Y., Choi I., Chae D. 2018. Decision-Level Fusion Scheme of SVM and Naive Bayes Classifier for Radar Target Recognition. 2018 International Symposium on Antennas and Propagation, 23-26 October, Busan, South Korea.
- [4] Nanzer J.A., Rogers R.L. 2009. Bayesian Classification of Humans and Vehicles Using Micro-Doppler Signals from a Scanning-Beam Radar. *IEEE Microwave and Wireless Components Letters*, 19 (5): 338-340.
- [5] Severino J.V.B., Zimmer A., Brandmeier T., Freire R.Z. 2019. Pedestrian Recognition Using Micro Doppler Effects of Radar Signals Based on Machine learning and Multi-objective Optimization. *Expert Systems with Applications*, 136 (1): 304-315.
- [6] Kim B.K., Kang H.S., Park S.O. 2016. Drone Classification Using Convolutional Neural Networks with Merged Doppler Images. *IEEE Geoscience and Remote Sensing Letters*, 14 (1): 38-42.
- [7] Zaied S., Toumi A., Khenchaf A. 2018. Target Classification Using Convolutional Deep Learning and Auto-encoder Models. 4th International Conference on Advance Technologies for Signal and Image Processing, 21-24 March, Sousse, Tunisia.
- [8] Zhou Y., Wang H., Xu F., Jin Y. 2016. Polarimetric SAR Image Classification Using Deep Convolutional Neural Networks. *IEEE Geoscience and Remote Sensing Letters*, 13 (12): 1935-1939.
- [9] Kouemou G., Opitz F. 2007. Hidden Markov Models in Radar Target Classification. 2007 IET International Conference on Radar Systems, 15-18 October, Edinburgh, UK.
- [10] Leung H., Wu J. 2000. Bayesian and Dempster-Shafer Target Identification for Radar Surveillance. *IEEE Transactions on Aerospace and Electronic Systems*, 36 (2): 432-447.
- [11] Haykin S.S. 2009. *Neural Networks and Learning Machines*. 3rd ed., Prentice Hall, New York.

- [12] Moller M.F. 1993. A Scaled Conjugate Gradient Algorithm for Fast Supervising Learning. *Neural Networks*, 6 (4): 525-533.
- [13] Hagan M.T., Menhaj M.B. 1994. Training Feed-Forward Networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks*, 5 (6): 989-993.
- [14] Foresee F.D., Hagan M.T. 1997. Gauss-Newton Approximation to Bayesian Learning. *International Conference on Neural Networks*, 12 June, Houston, USA.
- [15] Papoulis A. 1991. *Probability Random Variables and Stochastic Processes*. 3rd ed., McGraw-Hill, New York.
- [16] John G.H., Langley P. 1995. Estimating Continuous Distributions in Bayesian Classifiers. *11th Conference on Uncertainty in Artificial Intelligence*, 18-20 August, Montreal, Canada.
- [17] IEEE Aerospace and Electronic Systems Society. 2017. IEEE Standard for Radar Definitions. <https://ieeexplore.ieee.org/document/8048479>. (Accessed: 25.09.2019).
- [18] Knott E.F. 2012. *Radar Cross Section Measurements*. Springer Science and Business Media, New York.
- [19] Mahafza B.R. 2013. *Radar Systems Analysis and Design Using Matlab*. CRC Press, Florida.