# HYPERPARAMETERS ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR CLASSIFICATION OF MARINE TARGETS IN SAR IMAGES

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***ABSTRACT***

*Due to the extensive coastal area of Brazil, pattern recognition techniques based on artificial intelligence can search for targets at sea faster for surveillance, rescue, or illicit combat activities. This article presents a hyperparameter analysis of machine learning techniques to classify targets in SAR images. We considered a data set with vertical horizontal polarization SAR images from Campos Basin, Rio de Janeiro, to classify oil platforms and ships. The classification attributes are extracted through a convolutional neural network VGG-16 pre-trained with the ImageNet data set. Then, four machine learning techniques are evaluated, random forest, decision tree, k-nearest-neighbors, and logistic regression. As a metric for assessing the classifiers, accuracy (Acc) and area under the curve (AUC) are used. The grid search technique is used to identify the best combination of parameters of the classifiers with the highest Acc and AUC. Finally, the best result is the logistic regression classifier.*

***Key words –*** *Machine Learning, Image Classification, Hyperparameters, Synthetic Aperture Radar.*

## 1. INTRODUCTION

The Brazilian coast has an extensive area of approximately 4.5 million km$^2$. It is well known that the traffic of boats along the coastal roads impacts the economy of the country. It is challenging to monitor all the activities of exports and imports, and, therefore, maritime surveillance needs to be improved. Orbital SAR systems prove to be an interesting strategy for this type of application [1]. Nowadays, many SAR systems are orbiting the Earth, e.g., ERS-1, ERS-2, ENVISAT, and Sentinel-1 series from the European Space Agency; the Canadian systems RADARSAT-1, RADARSAT-2; the Italians COSMO-SkyMed; the German TERRASAR-X and TANDEM-X, and the Chinese GAOFEN-3 SAR systems. Those systems provide SAR images for research and customers all around the world. In particular, SAR systems have advantages over optical systems. For example, SAR systems are characterized by an active sensor that not dependent on sunlight; it can work day and night, generating images in unfavorable weather conditions.

Due to the formation process, it is difficult to visually identify targets in SAR images. Ships appear as bright spots because of high backscattering values, while water surfaces with low backscattering values appear with darker [2] areas. In addition, SAR images are characterized by speckle noise, also known as multiplicative noise, which is generated by the variation of backscattering on non-homogeneous surfaces. This phenomenon makes it even more difficult to detect and classify targets in SAR images. One of the possible solutions for those tasks is to use advanced methods of artificial intelligence (AI), such as machine learning, which permits automating and generating automatic image recognition. Recent studies indicate that machine learning (ML) and deep learning (DL) techniques are efficient tools to detect ships from SAR images [3–6].

ML is a branch of AI that can be divided into subclasses: supervised, unsupervised, and reinforcement learning [7]. Among the algorithms that can be used, the following stand out: Neural Networks, Support Vector Machine, logistic regression (LR), random forest (RF), decision tree (DT), and k-nearest neighbors (kNN). In target classification, performance indicators depend on identifying the most appropriate adjustments of hyperparameters weights. Among the techniques that allow better optimization of hyperparameters, it stand out random search [8, 9], genetic algorithms [8, 10], and grid search [8, 11–13]. The random and grid search techniques quickly arrive at the optimal solution compared to the genetic algorithm [8]. Grid search is a technique widely used [13], which provides increased accuracy of classifiers after its use [8]. In this work, the grid search technique is considered.

The region of interest for the research is concentrated in the Campos Basin, located in the state of Rio de Janeiro. The region is characterized by an area of 120,000.00 km$^2$ and stands out for its national oil production [14], being the second largest national producer, according to the ANP Bulletin [15]. Therefore, in the Campos Basin, a large concentration of platforms and ships are our targets of interest. Thus, this article aims to use hyperparameters analysis through the grid search function to evaluate the performance of ML techniques in the classification of SAR images.

The rest of this paper is structured as follows. In Section 2, we present characteristics of the Sentinel orbital system, an overview of DL highlighting convolutional neural network (CNN) VGG-16, and the methodology used in the research. Section 3 analyzes and discusses the obtained results. Finally, we end this paper with conclusions and final remarks in Section 4.

## 2. MATERIAL AND METHODS

This section briefly presents some characteristics of the Sentinel mission. In addition, the methodology considered to obtain the targets from SAR images is described.

## 2.1. Sentinel Mission

The Sentinel mission is formed by a constellation of two satellites, Sentinel-1A and Sentinel-1B, launched on April 3, 2014, and April 25, 2016. The system is capable of generating medium and high-resolution images [16]. These systems are at an altitude of approximately 693 km, with a 12-day repetition cycle, generating SAR images in the C-band [16, 17].

Sentinel-1 operates in the 5.405 GHz center frequency, with single (HH or VV) or dual (HH+HV, VH+VV) polarization, using one channel for transmitting (V or H) and two channels for receiving (V and H). where V is the vertical polarization and H is the horizontal polarization, and have 945 kg of the total mass.

## 2.2. Sentinel-1 Image Data set

The data set consists of eight SAR images in VH polarization obtained from the Copernicus project [18]. These are interferometric wide (IW) images, level 1 ground range detected (GRD), high resolution (20 m × 22 m - range × azimuth) images. Based on the SAR images, targets are defined, cut, and transformed into patches. Figure 1 presents two examples of oil platforms and its respective SAR images.

## 2.3. Overview Deep Learning

DL is a subset of ML inspired by the information processing patterns present in the human brain. DL is designed based on layers of artificial neural network algorithms [19]. In recent years, DL has been one of the most used computational approaches in the ML field.

DL has been, in recent years, one of the most used computational approaches in the ML field. One of the reasons for this is its ability to learn from large volumes of [20] data. The ZfNet, VGG, GoogLeNet, Inception-V3, Inception-V4, ResNet, and Xception networks stand out among the DL. CNN is one of the most popular and used DL networks. One of the advantages of this is its ability to detect features without human need.

In [21], a practical CNN project that became known as the Visual Geometry Group (VGG) is proposed. The VGG-16 is formed by 13 convolutional layers, 5 max-pooling, 3 fully connected, and 1 softmax. The composition details of the VGG-16 layers can also be seen in the diagram in Figure 2. In this research, the VGG-16 architecture is composed of the FC7 layer that provides the features to the ML algorithms, as shown in Figure 3. The use of a pre-trained CNN has the following advantages over training a new one: the need for equipment with less computational power because the image is processed only once; less data is needed to achieve high accuracy because the deep layers have activations that can be used to represent the deep features [22]. To perform the classification, we used the widely know methods: RF [11], LR [23], DT [24], and kNN [25].

## 2.4. Methodology

This section presents the methodology. The work is divided into some steps that can be seen through Figure 4.

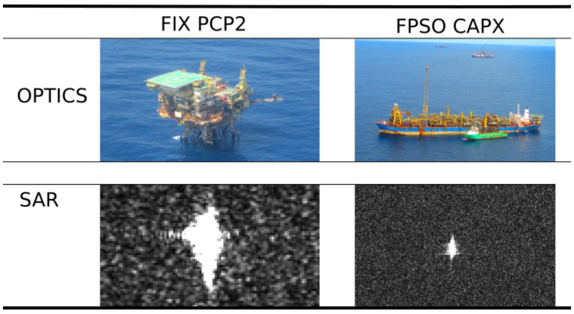


**Figure 1: Optical and SAR images of fix and FPSO oil rigs. Optical and SAR images extracted from [26] and [27], respectively.**

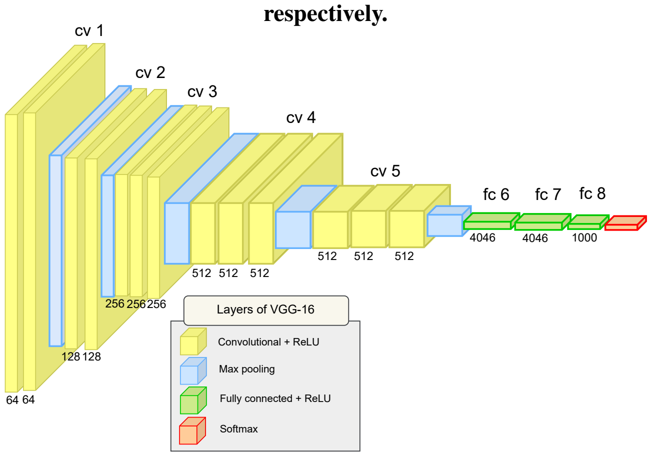


**Figure 2: VGG-16 formation diagram.**

### 2.4.1. *Data set and preprocessing*

The dimensions of the images are (Range × Azimuth): 912 × 596 pixels, 968 × 596 pixels, 939 × 596 pixels, 901 × 596 pixels, 930 × 596 pixels, 944 × 596 pixels, 985 × 596 pixels, 1057 × 596 pixels. SAR images were calibrated using SNAP (Sentinel Application Platform) software. Then, the targets of interest are defined individually, according to their geolocation (latitude × longitude) [28]. Finally, each image patch is saved in TIFF format.

### 2.4.2. *Extraction of features*

Feature extraction plays an important role in ML. In this work, this step is done through CNN VGG-16, which provides data to classifiers through the FC7 layer, as shown in Figure 3.

### 2.4.3. *Formation of train and test samples*

After extracting attributes, the vectorized data set (df-16vh) is formed. Based on this data set, subgroups (bootstraps) are created randomly and with replacement using the bootstrap technique. Each group is developed considering the following proportion of the total of 400 samples: 80% (training) and 20% (test), the same methodology applied by [1, 3, 27].

### 2.4.4. *Tuning parameters and Classification*

In this step, the parameter adjustment is performed through the "grid search" function present in Scikit-Learn [29] which combines the parameters of each classifier. Subsequently, we

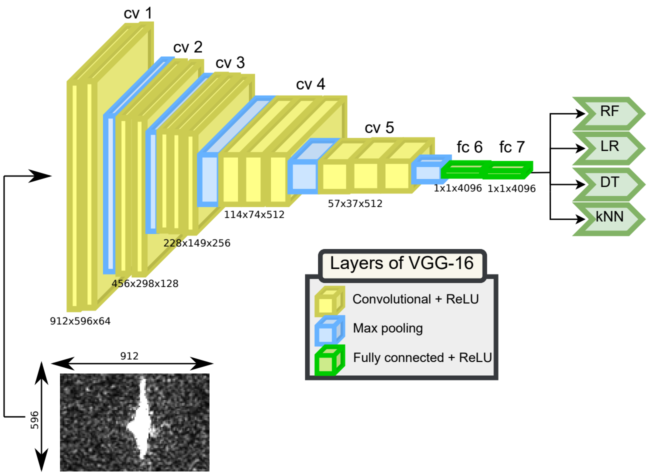


**Figure 3: CNN VGG-16 architecture used for feature extraction.**

apply the LR, RF, DT, and kNN classifiers.

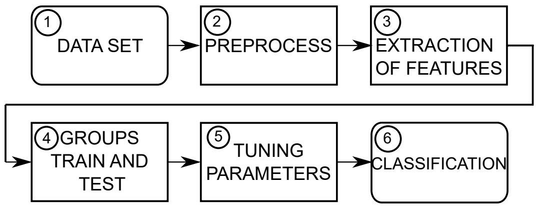


**Figure 4: Methodology.**

## 3. RESULTS

The numerical results are presented, and analyzed in this section. The shape hyperparameter adjustment automation allows for achieving better classification results. Depending on the classification technique, the most suitable adjustment can be very time-consuming due to many existing parameters.

Initially, the data set to be classified is vectorized by CNN VGG-16, which extracts 4096 features. From the vectorized data set, 50 distinct groups are formed for the training and testing of classifiers. We used the grid search function to identify the best combination of parameters.

The classifications were performed based on the parameters defined by the grid search function and evaluated through the area under the curve (AUC) and accuracy (Acc) metrics. The average of each metric was calculated based on the 50 subgroups (bootstrap) formed from the target features extracted with the VGG-16. Table 1 presents the combination of parameters with best metrics.

The results are shown in Figure 5. It is observed that the classifiers with True Positive Rate closer to 1 have higher AUC and also Acc. Therefore, when analyzing the ROC curve, the best classifier is considered to be the one in which the curve is closest to the y axis.

## 4. DISCUSSION

In short, we can observe that, for all classifications, the optimization with parameter adjustment provided a gain in relation to the default configuration. The comparison of the best result of each classifier is shown in Figure 5. It can be seen that the LR has the highest AUC and Acc, 0.93 and 0.86, respectively. Next comes RF with AUC and Acc, 0.91 and 0.82, respectively.

**Table 1: List of parameters optimized by classifiers.**

| Classifier | Parameter | | | |
|---|---|---|---|---|
| | **C** | **penalty** | **tol** | **solver** |
| LR | 0.2 | l2 | 0.01 | liblinear |
| | **criterion** | **min-samples-split** | **min-samples-leat** | **splitter** |
| DT | gini | 2 | 10 | random |
| | **n-estimators** | **random-state** | **max-features** | |
| RF | 100 | 0 | auto | |
| | **n-neighbors** | **p** | **weights** | |
| kNN | 10 | 1 | distance | |

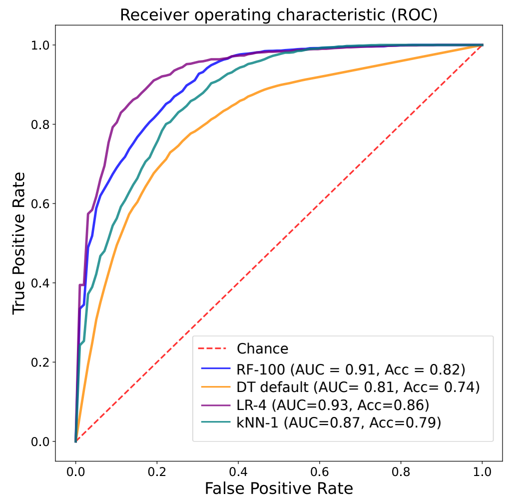


**Figure 5: ROC curve comparing the best AUC and Acc results of the RF, LR, DT and kNN classifiers.**

## 5. CONCLUSIONS

This article analyzed the tuning of parameters to compare machine learning techniques in classifying marine targets in SAR images with VH polarization. The grid search function was used to identify the best combinations of parameters. As a step prior to classification, CNN VGG-16 was used to extract features. The RF, LR, DT, and kNN classifiers were evaluated for AUC and accuracy. The grid search parameter adjustment technique proved efficient because the combinations found provided gains to the classifiers, highlighting the RF with AUC of 0.91, Acc of 0.82; DT with AUC of AUC of 0.81, Acc of 0.74; kNN with AUC of 0.87, Acc of 0.79. For LR, the optimization of parameters did not present gains. Despite this, it was the classifier with the best results of AUC of 0.93, and Acc of 0.86. VGG-16 proved to be efficient because it extracted representative features for ML classifiers. In future works, other CNN techniques, such as ZfNet, VGG-19, GoogLeNet, Inception-V3, Inception-V4, and ResNet, could be considered. In addition, other ML techniques, such as support vector machine, naive Bayes, neural networks, and AdaBoost, could also be evaluated.

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