Computationally efficient vessel classification using shallow neural networks on SAR data

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Abstract

Synthetic aperture radar (SAR) is an active radar system that is mounted on a moving platform, simulating a longer antenna length than the physical antenna real length. Similar to a conventional radar, electromagnetic waves are sequentially transmitted and the backscattered echoes are collected by the radar. With the proper signal processing, this kind of system is able to provide high resolution microwave images of a desired target area by synthesising a larger antenna aperture, in virtually all-weather conditions. Nowadays SAR systems have been extensively used for remote sensing. It has various applications such as Earth surface monitoring, charting and military applications. Since it is weather independent and is able to operate whether it is day or night, SAR can be a more reliable source when compared with optical imagery [1].

Ship detection and recognition in SAR images has become an important research topic in recent years. This paper presents a computationally efficient algorithm for the classification of vessels in Synthetic Aperture Radar (SAR) images using Neural Networks (NN) with a reduced number of hidden layers, also called *Shallow Neural Networks* (SNN). Here the use of SNN for vessel classification will be divided into two main steps: feature extraction and classification. Feature extraction aims to lessen the burden deep neural networks cause on computational resources by extracting key features beforehand from the SAR image. The low computational requirements make this implementation compatible with onboard vessel systems and real time applications. The classification is implemented using a SNN that uses parameters obtained from feature extraction algorithms to classify the vessel present in the radar image.

In this paper feature extraction processes data from the Open SAR Ship dataset [2] in order to obtain the vessel's various features, such as ship length, width, mean, standard deviation and the number of scatter points present on the vessel.

Keywords: Vessel classification, Synthetic Aperture Radar, neural networks, SAR image processing.

1 State of the art

Ship detection and identification has received unprecedented attention due to its significant application value such as fishery management, ship rescue, maritime traffic control, and battlefield awareness [3]. Synthetic aperture radar (SAR) is an advanced active microwave sensor that can simultaneously achieve high resolution and wide swath [1]. Due to the prominent capacity of all-day and all-weather imaging, it has been extensively used for marine surveillance such as ship detection and identification among other applications. However, there still remain some difficulties on SAR ship detection, such as near coast ships due to imperfect land masks. Moreover, it is quite difficult to satisfy the requirements for both high-speed and high-accuracy detection in SAR images.

SAR images are different from optical images, and the microwave imaging mechanism is more complicated. The recognition of SAR image objects is difficult and requires strong domain knowledge. SAR ocean images are heterogeneous and contain ships, upwelling, breaking waves, and many artifacts such as radio frequency interferences (RFIs) and azimuth ambiguities. Quite often the texture and grey information between the ships and the false alarms are indistinguishable. Moreover, the background of the SAR inshore image is more complex due to the impact of multiple interferences from land, which also greatly increases the difficulty of detection.

A lot of research has been devoted to ship detection and identification in SAR images for decades [1]. Traditional methods could be roughly divided into three categories including threshold methods, statistical methods, and transformation methods [4]. They generally use a-priori knowledge to extract features manually through a series of candidate regions. Among these traditional methods, the constant false alarm rate (CFAR) [5] and its improved versions based on threshold are frequently used in the SAR field. As for CFAR detectors, an appropriate statistical model is selected to match the probability density function (PDF) of the ocean clutter, and then an adaptive threshold is calculated with a typical probability of false alarm (PFA). The key to CFAR ship detection is the statistical model of the ocean clutter.

In general, the most commonly used model in real applications are mainly based on Gauss, K, Rayleigh, and Weibull distributions [6]. The most popular CFAR method is the cell-averaging CFAR with the Gaussian distribution [6]. Nevertheless, land, islands, or some artefacts such as RFI and azimuth ambiguities will affect the final performance of CFAR detectors. These interferences will lead to a massive number of false alarms even if the statistical model accurately matches the real sea state. In order to deal with these problems a land mask can be used to reduce the number of false alarms in the SAR image.

In terms of vessel identification, the present methods used for classification in SAR automatic target recognition (ATR) systems consist of Artificial Intelligence (AI), machine learning (ML) techniques and other methods that do not use ML in the process but the results can be applied to ML. These are template-based methods [7], Statistical methods [8], Sparse representation-based methods [9] and phase-based methods [9]. These methods alone can create state-of-the-art results but when combined they can reach even higher levels of utility in RS and SAR target identification. Template based methods involve using a reference image (template) of a known target to identify similar objects in a SAR image. The process consists of a thoughtful cross-correlation between the template and the image, which pinpoints the position with the highest correlation value. This method is efficient and can detect with great success similar shapes, but it can fail in detecting targets with different orientations or with variations in scale [10].

Statistical methods take place by using mathematical models to extract features from SAR images for target identification. One of the most used methods is Principal Component Analysis (PCA) [4] its goal is to lower the size of high dimensional SAR images by finding the principal components that compose the data, in other words, to identify which are the directions in the feature space that explain the most amount of variance in the data. With this PCA can objectively retain only the most important information from the SAR image and this information can be used later on ATR ML methods [8].

Sparse representation-based methods involve representing the SAR image as a sparse linear combination of basis functions and identifying or classifying the object by its sparse representation of the image [4]. Despite this classification method proving its performance in pattern recognition its disadvantage of time consuming can be a challenge, especially in the case of features with huge dimensions. In order to overcome this challenge it is possible to implement a feature vector with reduced dimension making the algorithm run smoothly and with better time consuming perspectives [11].

Phase-based methods take advantage of the phase information in SAR images to perform target recognition. In terms of detection and classification, this method does not bring great results but in the RS field of Co-registration which consists of the adjustment of the position and orientation of the images so that they are precisely overlapped with each other this method makes great advancements. The last mentioned method allows the improvement of the images and can enhance the detection and classification of targets [9].

In recent years the most used techniques for pattern extraction and insights involve machine learning [4], and its use has been growing in remote sensing data exploration. A great number of machine learning algorithms have been applied to remote sensing problems, which can be attributed to two basic tasks, classification and regression. Machine learning can be explained as a branch of AI that focuses on the development of algorithms and statistical models that enable computers to learn from data. The objective of machine learning is to enable computers to make predictions and identify patterns, without the need for explicit programming. In order to use this process the model needs to be trained using a large data set that represents the problem at hand, the model is then tested in making decisions and predictions in new, unseen situations of the same kind. With the training, the model can improve its accuracy over time through the process of trial and error and also from data feedback. There are three main types of machine learning: supervised learning, unsupervised learning and reinforcement learning [12]. In supervised learning, the model is trained on a labelled data set where the correct output is known for each input. Unsupervised learning is the process in which the model is not given any labelled data, and must find patterns and relationships within the data on its own. In reinforcement learning, the model receives feedback in the form of rewards or penalties as it interacts with its environment, and must learn from this feedback to make better decisions over time.

2 Introduction

Ship target interpretation in SAR images has become an important research topic in recent years. With the improvement of SAR image resolution, the performance of traditional automatic target recognition (ATR) methods increases gradually. This thesis aims to implement a computationally efficient technique for the classification of vessels in Synthetic Aperture Radar (SAR) images using Artificial Intelligence (AI). The major handicap of AI based techniques is the huge computational requirements. Herein, we will perform feature extraction before proceeding to classification using NN. Feature extraction aims to lessen the burden deep neural networks cause on computational resources by extracting key features beforehand, making the implementation compatible with onboard vessel systems. The classification of vessels is implemented using a shallow neural network that uses parameters obtained from feature extraction to classify the vessels present in the radar image.

In recent publications classifying problems are mostly resolved with the help of Deep Neural Networks (DNN). The problem with this approach is that DNNs demand high computational power in order to have results in a useful time. Some problems don't need an overly powerful DNN, they can be resolved with a shallow neural network and pre-processing techniques that acquire the best of the given data.

In this paper, feature extraction uses data from the Open SAR Ship dataset [2] as a base data set for the research. The main features extracted for the classification of ships in SAR images are the length, width, mean, standard deviation and bimodality coefficient of the ship. The first step in feature extraction is identifying the pixels from the ship in this paper, two distinct methods for this goal were created. The Global threshold algorithm uses, as the name suggests, a threshold to identify if a pixel is from a ship. The other uses a Cell Averaging Constant False Alarm Ratio (CA-CFAR) [13] algorithm to identify these pixels. Having the pixels from the vessel, the SAR image can be binarized and the length and width may be extracted from the image.

To extract the length and width of the ship, two approaches were taken into account. A more general approach utilizing the pre-existing *region props* function in MATLAB and a more specific approach using the center and angle of the ship to create lines in both the ship directional axis (length) and the perpendicular axis (length) to acquire the dimensions of the vessel.

After acquiring the length and width the next parameters are the statistical values obtained from processing the ship pixels, these parameters are mean, standard deviation and the bimodality coefficient [14]. These parameters are acquired by using their mathematical equation on the pixels. The bimodality coefficient is a very important parameter because it can be a major factor in deciding what type of ship it is since it can identify if the data has two distinct peaks or clusters of values, suggesting the presence of two separate distributions within the data. It can unveil if the vessel has one or more scatter points present.

With the parameters obtained beforehand, a SNN is now trained to classify three different types of vessels: Cargo, Tanker and Fishing. Using the preprocessed parameters the shallow network is capable of classifying these three types of ships with high accuracy.

3 Proposed approach

This chapter presents every implemented component of the project, starting with an explanation of the binarization algorithms used on the project, length and width acquisition, mathematically calculated parameters like standard deviation, mean and number of scattering points as well as an explanation of the SNN used for the project. The diagram of the project is shown in Figure 1.

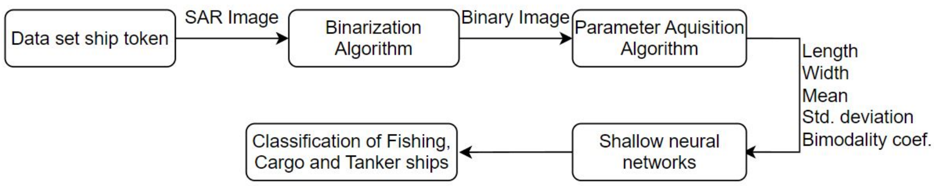


Figure 1: Block diagram of the project.

3.1 SAR image binarization

A binarization algorithm is a technique employed in image processing to transform an image into a binary representation of itself, where every pixel is shown with only two values: 1 and 0 (black and white).

Dividing an image into sections of interest based on the intensity is the main purpose of binarization. Binarization algorithms can be divided into three categories Threshold selection, Pixel Classification and Output image creation

- **Threshold Selection**: The first step is to choose a threshold value that will be used in order to classify pixels as either pixels of interest or background. The threshold value can be selected based on various methods, such as statistical analysis of pixel intensities, global or local histogram analysis or by simple trial and error.
- **Pixel Classification**: Each pixel's intensity value is compared to the chosen threshold. If the pixel value is greater than or equal to the threshold, it is classified as a pixel of interest; otherwise, it is classified as background.
- **Output Image Creation**: Based on the pixel classified as of interest, a

new binary image is generated, where the detected pixels values are replaced by "1" (white) and the background pixels by 0 (black).

During the development of the thesis, an algorithm was created to binarize the SAR images that uses the Constant False Alarm Ratio (CFAR) to detect the pixels from the vessel.

3.1.1 CFAR binarization

This subsection is divided by a brief explanation of the implemented Cell Averaging CFAR (CA-CFAR) algorithm and afterwards how it is used to binarize the ship token.

CA-CFAR is an algorithm that uses the mean from the background to declare a pixel as a ship candidate if its intensity is above the threshold. For that, it uses two boxes (figure 2), both surrounding the pixel being classified to determine if it’s a pixel of interest and, therefore a part of a ship.

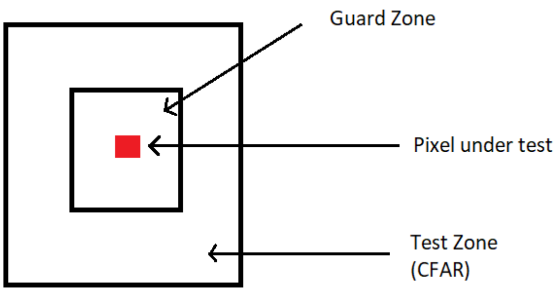


Figure 2: CFAR algorithm idea

There is a larger box and a small one (figure 2). The larger box is the outer limit of pixels and the small box is the guard zone. The pixels in between these boxes are called the Test Zone and they will be used for the calculation of the mean and used for the equation 2 to define if the pixel being tested is a pixel of interest [15].

In this project the dimensions of the outer and inner box are selected by an adaptive limit. This method was chosen due to the fact that every image from the data set has varying dimensions ranging from 9x9 for some Fishing vessels to 204x204 Cargo and Tanker ships and because of this peculiarity the same outer and inner box sizes can’t be used for every token or else the detection would heavily downgrade since the test zone could be inside the limits of the ship causing the algorithm to detect false negatives. In order to keep a good detection the ratio between small and medium images is kept the same.

Equation 1 is the mathematical explanation for the adaptative limits, It uses the property of all images being squares and by acquiring the dimension of the same ($I_{dimensions}$) adapts the Test zone to better detect the pixel of interest:

$$TestZone(I_{dimensions}) = \begin{cases} \frac{I_{dimension}}{3} & , I_{dimension} \leq 68 \\ \frac{I_{dimension}}{3} & , 68 < I_{dimension} \leq 136 \\ \frac{I_{dimension}}{6} & , I_{dimension} > 136 \end{cases} \tag{1}$$

In order to threshold the program to identify the pixels surrounded by water we used the next equation:

$$x_t > \mu_b t \tag{2}$$

Equation (2) where:

x_t - The pixel being evaluated.

μ_b - Background mean.

t - User defined constant to control false alarm rates.

In the following block diagram (figure 3) the flow of the algorithm is presented, starting from the data set SAR image, until saving the coordinates of every pixel of interest.

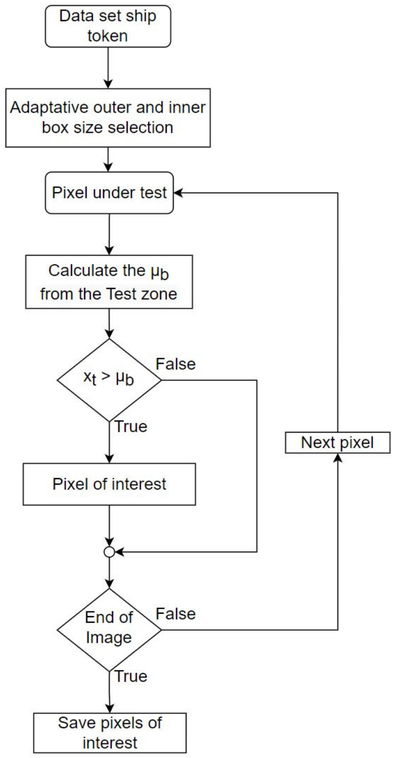
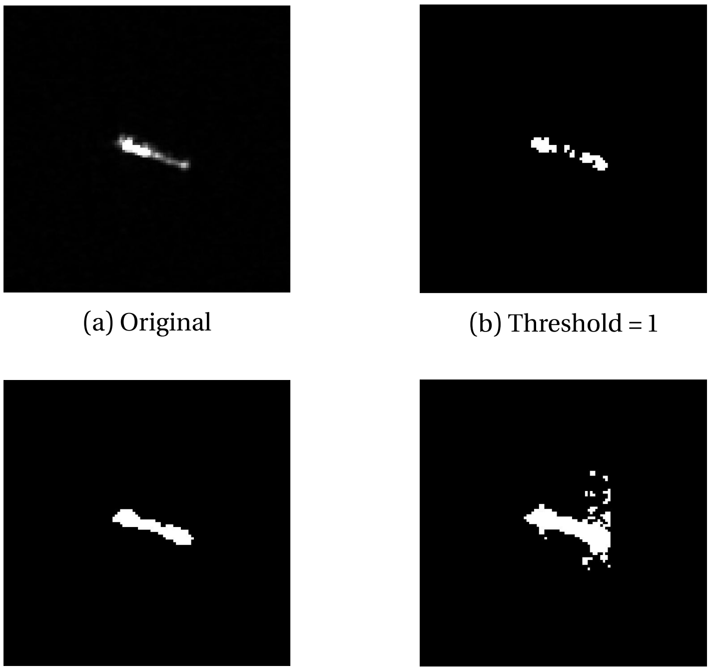


Figure 3: CFAR algorithm Flow Chart

After saving every detected pixel, the binary image is created by using an $I_{dimensions}$x$I_{dimensions}$ bi-dimensional array filled with zeros and replacing the detected pixels location for ones. The outputs for this function, like the Threshold algorithm, are the binarized image and the coordinates of every pixel flagged as of interest.

The user defined constant t was experimentally chosen. To select the best value for "t", with the best false alarm to detection ratio, the following test was carried out (Figure 4). These tests consist of applying different values for t and observing if the binarized images are as close as possible to the original SAR image and how the threshold works on different types of vessel tokens.



(a) Original (b) Threshold = 1

(c) Threshold = 0.4 (d) Threshold = 0.1

Figure 4: Application of the Vessel measurements algorithm with different thresholds.

Comparing the images present in Figure 4 it's possible to perceive that Figure 4b is too high of a threshold since some pixels in the middle of the vessel are not flagged as of interest. Figure 4c shows every section of the boat and not detecting any of the background pixels as part of the ship on the other hand using a threshold of 0.1 (Figure 4d) causes a large number of false detections on the background. One can conclude that the best threshold for a good detection rate is around the value of 0.4 (Figure 4c).

3.2 Vessel measurements algorithm

Now that the binarization of SAR ship tokens is complete, the next step is to obtain the measurements from the specific vessel. To get a good idea of what vessel is present in the image, the length and width parameters are of the most importance. These measurements can provide an easy comparison for the neural network to distinguish big from small ships and to identify what are the average sizes of each ship type.

The algorithm to acquire the measurements of the ship can be explained as follows, we have a binarized image of the ship and the first step is to identify the center and the rotation angle in which the boat is turned. To obtain these parameters a Matlab function named *regionprops* [16] is used, it calculates the centroid and the angle of rotation of the vessel, and with this information, it is possible to measure the length and width of the ship. To calculate these values two algorithms were tried: one algorithm that uses the size of the ship obtained by the *regionprops* function and another one that uses basic mathematics to identify the parameters. Both algorithms only identify the size in pixel so in order to obtain the calculated length of the ship first we have to multiply it by 10 since it is the Sentinel-1 pixel spacing for high-quality GRD images.

$$Length = 10 * P_{Laxys} \tag{3}$$

$$Width = 10 * P_{Waxys} \tag{4}$$

Equation 3 and 4 where:

P_{Laxys} - Pixels under the line on the direction axys.

P_{Waxys} - Pixels under the line perpendicular to the direction axys.

3.2.1 Cluster of pixels identification

Regionprops is a Matlab function that identifies a cluster of pixels, in a binary image, as an object and obtains the radius from the ellipse that covers the cluster area, like presented in Figure 5 [16], and it obtains the angle of the ship by comparing the bigger radius of the ellipse with the x axis.

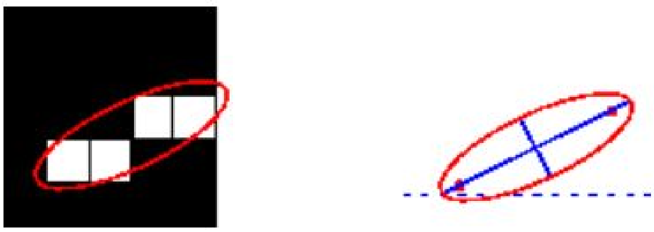


Figure 5: Elipsoid example extracted from [16].

By using the ellipse method to identify the angle of the ship, it can also estimate the length and width of the vessel.

3.2.2 Linear equation algorithm

The algorithm presented in this section is based on the use of the "regionprops" function to obtain the centre and angle of the ship, but it uses a linear equation to determine the ship's directional axis and the perpendicular axis. Using the angle (θ) and the centre of the ship, it's possible to create a line equation similar to 5.

$$y = ax + b \tag{5}$$

This simple equation consists of slope (a) and y-interception (b). The slope can be calculated using $\tan(\theta)$ and b by entering the x and y coordinates of the centre, now we have the equation for the ship's heading axis line. To find the equation for perpendicular line you need to calculate $a_\perp$ and $b_\perp$. It is possible to calculate these parameters using the property of perpendicular lines, given in equation 6.

$$a_\perp = \frac{-1}{a} \text{ Where } a = \text{Slope of ships direction axis} \tag{6}$$

With this property, the value of $a_\perp$ can be easily calculated by using equation 5. The centre coordinates can be used to determine the value of $b_\perp$. Having both the equation we achieve the result present in Figure 6.

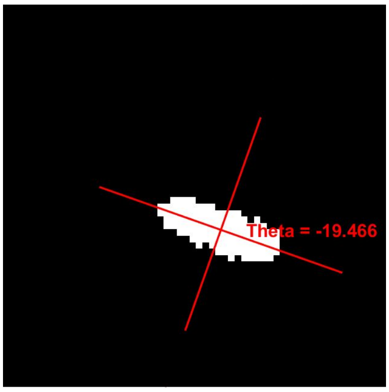


Figure 6: Ship token with the determined lines.

Furthermore, after drawing the lines it is possible to obtain the coordinates and value of the pixels under the line for both the directional axis and the perpendicular axis, making it possible to count the number of pixels with value equal to "one". With this, the algorithm is finished and the number of "one" pixels can be fed to equation 3 and 4 to determine the ship size.

3.3 Statistical aproach

SAR image processing needs a deeper exploration of mathematical parameters to decipher the intricate characteristics of vessels at sea. Among these parameters, standard deviation and mean emerge as indispensable tools in the realm of ship classification, offering an approach to distinguish between ship types.

Classifying ships from SAR imagery is a difficult challenge. Vessels vary in size, shape, orientation, and operational states, contributing to a diverse range of radar signatures. Moreover, environmental factors such as sea state, wind, and the presence of other objects in the scene introduce complexities that must be taken into consideration. Mathematical parameters play a very important role in facilitating this complexity, providing metrics for discriminating between different ship classes in particular for this project differences between Cargo, Tanker and Fishing vessels.

3.3.1 Mean

The main objective of calculating the mean is to measure the central tendency of the vessel and reveal the average intensity of the pixels. With this we obtain a new parameter to enter the network in order to better identify the ship types. The mean of every vessel is calculated using equation 7 having as data all the pixels previously detected as from the ship.

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} a_i \tag{7}$$

The mean can sometimes be a good parameter for vessel classification but must be treated with caution, due to its values depending exclusively on the angle of incidence of the radar electromagnetic waves and the polarization used to acquire the reflected signal.

3.3.2 Standard deviation

While the mean provides information about central tendencies, the standard deviation quantifies the variability or dispersion of radar intensity values within ship regions. This parameter is a powerful tool for capturing the nuances of ship behaviour and conditions. High standard deviations suggest variations in ship radar signatures, which may be indicative of structural differences, damage, or unique operational states. By assessing standard deviation alongside the mean, analysts can discern subtle variations that hold the key to ship classification.

The standard deviation equation is presented at 8.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{8}$$

3.3.3 Bimodality function to identify the number of scatter points

Bimodality refers to a data type where it exists two distinct peaks or clusters of values, suggesting the presence of two separate distributions within the data. This parameter can be very useful for ship classification due to some ships having distinct scatter points. For instance, on tanker ships it's expected to have only 1 on the main bridge (also referred to as pilothouse). This function returns a bimodality flag and a bimodality coefficient and calculates these values using a straightforward approach as it only requires three numbers: the sample size, the skewness of the distribution of interest, and its excess kurtosis.

Skewness is a statistical measure that quantifies the asymmetry or lack of symmetry in the distribution of data. It provides information about the direction and degree of asymmetry in a dataset's distribution. In other words, skewness helps us understand whether the data is skewed to the left (negatively skewed), skewed to the right (positively skewed), or roughly symmetric (approximately normally distributed).

Kurtosis is another important statistical measure that provides information about the shape of the distribution of data. Specifically, kurtosis measures the "tailedness" or the degree to which the data distribution has outliers or extreme values (values significantly far from the mean). It indicates whether the data has heavy tails or light tails compared to a normal distribution.

To identify the number of scattering points equation 9 is used [14] in this equation "s" refers to the skewness of the distribution and k to its excess kurtosis.

$$BC = \frac{s^2 + 1}{k + 3.\frac{(n-1)^2}{(n-2)(n-3)}} \tag{9}$$

The bimodality Coefficient (BC) of the given distribution is then compared to a benchmark value of $BCcrit = 5/9 \approx 0.555$ [17] that would be expected for a uniform distribution higher numbers point toward bimodality whereas lower numbers point toward unimodality.

3.4 The neural network

On this topic, the reasoning behind the decision to use a shallow neural network will be presented. Shallow neural networks offer a compelling choice for a great number of tasks, mainly in the classification of vessels, due to its simplicity and efficiency. A key reason for using shallow networks is their ease of training and interpretation. These networks have a fewer number of layers and input parameters, making them less prone to overfitting and an excellent choice for smaller datasets or when computational resources are limited.

Additionally, shallow neural networks can be easily interpreted since they have less layers than deep neural networks. Furthermore, shallow networks can be quicker to train, deploy, and maintain, making them a pragmatic choice for rapid prototyping and real-time applications.

The neural network created for this project in order to classify between Cargo, Tanker and Fishing vessels has the following architecture (Figure 7)

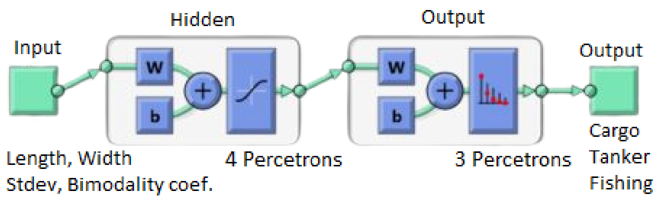


Figure 7: Neural network architecture.

It has 3 hidden layers and 3 output layers and for the input, we use the previously mentioned characteristics of length, width, standard deviation and bimodality coefficient. Every single one of these parameters is obtained by processing the SAR images of every ship individually.

The neural network uses the Scaled Conjugate Gradient (SCG) optimization algorithm for training. This algorithm is used to identify the optimal value of weights and biases in the model which minimizes the number of errors in the classification.

The primary objective of SCG in training a neural network is to adjust the model's parameters during the training process to minimize the error between predicted outputs and the actual target outputs in the training data [18].

The cross-entropy loss function is used to ensure network performance. Cross-entropy is widely used for classification problems [19]. The function for multiclass classification can be translated in equation 10.

$$H(Y,P) = -\sum_{i=1}^{n} Y_i \log(P_i) \tag{10}$$

Where:

Y - Represents the true class labels.

P - Represents the predicted probability of the predicted class.

n - Number of classes.

In this project, the value for n will go up to 3 since we only have three possible outputs Cargo, Tanker or Fishing vessels.

4 Results

In this chapter, the results of the vessel classification algorithm will be presented and analyzed. In order to start the discussion, firstly it's needed to explain the data that will be used in the results.

Due to the data set having a different number of tokens for each type of vessel if we use all ship tokens in the training of the neural network a fatal problem will occur. The network will be highly biased towards the vessel type in which there are more tokens, in this case, Cargo vessels, causing it to only identify this type of vessel. To prevent this biased result, the data set was downsampled to 120 tokens of each type selected for the detection, so that the final data set consists of 120 Cargo, 120 Tanker and 120 fishing vessel tokens. These tokens were not randomly selected since some of the tokens present in the Open Sar Ship data set contain various ships in the same token. For the binarization of the SAR vessel images the algorithm that will be used is the CFAR binarization with a threshold of 0.4. Briefly explained this algorithm uses a cell averaging CFAR to identify if a pixel is part of the vessel and all the pixels flagged by the CFAR are replaced by 1's and the ones not flagged are replaced by 0's, creating the binary image. This algorithm keeps all the pixel values from the ship to be processed to acquire the statistical parameters for the neural network. After obtaining the binary image of the ship the length and width are estimated using the Linear equation algorithm presented in section 3.2.2. Statistical parameters are all obtained by processing the beforehand stored ship pixel values.

In terms of the network used for the classification of vessels, it will have the following distribution (Figure 8): four inputs, one hidden layer and three outputs this number of hidden layers was chosen due to the objective of the paper to greatly minimize the computational requirements to execute the classification network.

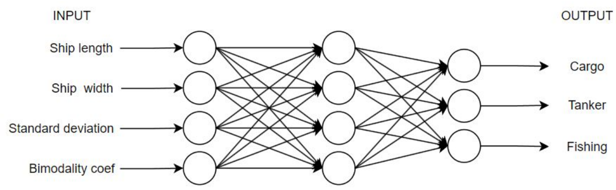


Figure 8: Diagram of the neural network for cargo, tanker and fishing vessels.

This distribution was chosen taking into consideration the number of inputs and the objective of minimising the computational requirements needed to execute the algorithm.

The neural network's classification results were, for the classification of Cargo vessels, an approximate value of 75% ,for the Tanker vessel of around 50% ratio and for fishing vessels, we have a ratio of correct classification of approximately 80%.

These results show that using these parameters the network isn't capable of discerning with good accuracy Tanker vessels but on the other hand we have a very promising result in the classification of fishing vessels and a good result for Cargo vessels as well.

To overcome this inaccuracy problem in the classification of Cargo and Tanker vessels, another network with the same characteristics as the one previously presented, but now with 5 perceptrons in the hidden layer, was created to differentiate Cargo from Tanker vessels. The difference between these networks is as shown in Figure 9.

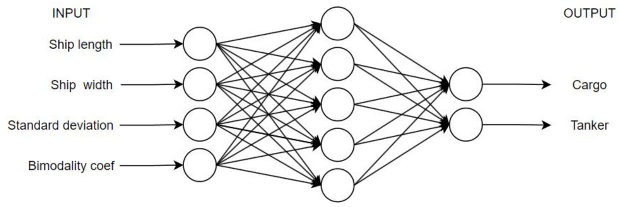


Figure 9: Diagram of the neural network for cargo and tanker vessels.

The characteristic that distinguishes this network from the one previously mentioned is the number of inputs and outputs. By doing various tests using only the length, width, standard deviation and bimodality coefficient the results were not very promising with a successful classification rate of around 63%. Then with the objective of improving the classification, another parameter was selected to be inserted into the network, this parameter was the mean of the pixels from the ship.

Starting with the training of the network by entering into it the input and target vectors of every ship token that was not classified as fishing on the previous network.

The results of the analysis reveal that the second network has better results for the classification of tanker vessels. Having an accuracy ratio which rounds 70% for classifying both vessel types.

By joining these two networks better results were obtained with an overall accuracy for Cargo ships of 75%, for tanker ships 70% and for fishing vessels 80%.

5 Conclusions and Future Work

The objective of this paper was to create a computationally efficient solution to classify vessels from SAR images using a shallow neural network alongside pre-processed inputs, such as length, width, mean, standard deviation and the bimodality coefficient with the objective of obtaining state of the art results using only a fraction of the computational resources that a Deep Neural Network would use. A shallow neural network consists of a machine learning algorithm with a maximum of three hidden layers. All the data employed for implementing this approach was sourced from the Open SAR Ship dataset [2].

Prior to acquiring these parameters, a preliminary processing of the SAR images is required. To start this process firstly the identification of which pixels are from the vessel is of the utmost importance. An algorithm to identify the pixels of the ship and binarize the image was developed. A Cell Averaging Constant Alarm Ratio (CA-CFAR) to identify the pixels of interest was also implemented. Both approaches produce good results but the CA-CFAR is an algorithm that adapts more efficiently to rough sea activity in SAR images.

Feature extraction uses a binarized version of the original ship token, using the pixels extracted beforehand, to obtain the dimensional parameters from the ship token. Two algorithms were tested in order to select the one with the best results, since accurate vessel length and width estimation using SAR data is a very complex topic. These algorithms consist of using the Matlab function *region props* that identifies the centre and angle of the ship, this algorithm can also obtain the length and width of the vessel but due to it being a very generalised function, its outcome isn't the best for this situation. So another algorithm was developed that uses the centre and angle of the ship to create lines in the axis that corresponds to the heading of the ship and the perpendicular one to obtain the corresponding length and width of the vessel. This algorithm has an error of approximately 10 meters due to the resolution of Sentinel-1 GRD images being 20x22 and the pixels spacing 10x10 causing a scatter to overlap the pixels surrounding it. These results were deemed acceptable due to it affecting every vessel the same way.

SAR image processing needs a deeper exploration of mathematical parameters to decipher the intricate characteristics of vessels at sea, statistical parameters are good for unveiling hidden patterns for ship classification. The fundamental parameters acquired in this project are mean, standard deviation and the bimodality coefficient. The bimodality coefficient refers to data in where it exists two distinct peaks of values, suggesting the presence of two separate distributions within the data. This parameter can be very revealing in ship classification due to certain ships exhibit distinctive scatter points.

The previously estimated parameters were used to train a shallow network to differentiate cargo, tanker and fishing vessels. The training of the first network led to the following round-up accuracy rates: 75%, 50% and 80%, for cargo, tanker and fishing vessels respectively. These results show that this network classifies fishing vessels the best and cannot distinguish cargo and tanker vessels with the same accuracy so, in order to improve the detection rates a new network was trained to classify only cargo and tanker vessels. This second neural network had an accuracy rate of approximately 70% for both cargo and tanker vessels. By joining both networks and using the first to classify fishing and cargo ships and the second to classify tanker vessels we came to an improved classification rate of 75% for cargo, 70% for tankers and 80% for fishing ships.

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