# Prediction of Fishing Activities based on Machine Learning Techniques using AIS and VMS data

PIC2 - Master in Telecommunications and Informatics Engineering
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**Abstract** Illegal, Unreported and Unregulated (IUU) fishing equates to approximately 11-19% of reported global fisheries production and leads to losses of roughly $10-23.5 billion in value yearly. This work aims to combat this issue by developing two models for the classification of fishing activities from AIS and VMS data. It utilizes two deep learning concepts namely Convolutinal Neural Networks (CNN) and Long Short-Term Memory with a Fully Convolutional Network (LSTM-FCN) for classifying fishing gears and predicting fishing activity. The data used for the training and testing of the models is supplied by the Portuguese Navy and encompasses around 12000 vessels monitored in Portuguese waters from December 2021 up until December 2023. Both models are then evaluated and interpreted accordingly. In this manner, this work provides a way to aid in monitoring, identifying, and classifying fishing vessel activities.

**Keywords** — fishing gear type classification, automatic identification system, deep learning, machine learning, illegal fishing

*I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa (https://nape.tecnico.ulisboa.pt/en/apoio-ao-estudante/documentos-importantes/regulamentos-da-universidade-de-lisboa/).

# Contents

# Resumo

A pesca ilegal, não declarada e não regulamentada (INN) equivale aproximadamente a 11-19% da produção piscatória global relatada e leva a perdas de 10 a 23,5 mil milhões de dólares em valores anuais. O presente trabalho visa minorar este problema através do desenvolvimento de dois modelos de machine learning, focados na classificação das atividades piscatórias, a partir de dados AIS e VMS. Propõe-se o desenvolvimento de dois modelos baseados em aprendizagem profunda: (i) Redes Neuronais Convolucionais; (ii) Memória Longa de Curto Prazo com uma Rede Totalmente Convolucional.
Pretende-se com esta metedologia por um lado, classificar as artes de pesca e por outro lado prever a atividade de pesca. Os dados utilizados para o treinamento e teste dos modelos são fornecidos pela Marinha Portuguesa e abrangem cerca de 12000 navios monitorizados em águas portuguesas num arco temporal de dezembro de 2021 até dezembro de 2023. Desta forma, este trabalho permite alavancar um meio para auxiliar na monitorização, identificação e classificação das atividades das embarcações piscatórias, com vista a uma otimização de processos.

## Acronyms

- **ML** Machine Learning.
- **DL** Deep Learning.
- **RF** Random Forest.
- **SVM** Support Vector Machine.
- **MLP** FMultilayer Perceptron.
- **ANN** Artificial Neural Network.
- **CNN** Convolutional Neural Network.
- **LSTM** Long Short-Term Memory.
- **LSTM-FCN** Long Short-Term Memory with Fully Convolutional Network.
- **AIS** Automatic Identification System.
- **VTS** Vessel Traffic Services .
- **VMS** Vessel Monitoring System .
- **IUU** Illegal, Unreported, and Unregulated.
- **FAO** Food and Agriculture Organization of the United Nations.
- **EZZ** Exclusive economic zone.
- **IMO** International Maritime Organization.
- **MONICAP** Monitorização Contínua das Atividades de Pesca.
- **GMM** Gaussian Mixture Model.
- **EU** European Union.
- **RNN** Recurrent Neural Network.
- **1D** One Dimensional.
- **GFW** Global Fishing Watch
- **CVVP** Center Fisheries Control and Monitoring Centers

# Nomenclature

| | |
|---|---|
| $G$ | Gini-index |
| $p_{mk}$ | Proportion of training observations in the mth region from the kth class |
| $D$ | Cross-entropy |
| $op, k$ | Ouput layer |
| $zp, k$ | Hidden layer |
| $E_p$ | Sum of the erros at each neuron in a pattern p |
| $\delta$ | Error Signal |
| $C_t$ | Cell state |
| $f_t$ | Forget gate |
| $i_t$ | Input gate |
| $b_x$ | Bias |

# 1 Introduction and Motivation

Mar
Mar!
E é um aberto poema que ressoa
No búzio do areal...
Ah, quem pudesse ouvi-lo sem mais versos!
Assim puro,
Assim azul,
Assim salgado...
Milagre horizontal
Universal,
Numa palavra só realizado.

*Miguel Torga*

Fishing is an essential economic activity that is practiced all across the globe. It plays an important role in many countries, contributing significantly to their economy and serving as a crucial source of food supply. The Food and Agriculture Organization (FAO) reports that fish accounts for around 30 percent of all animal protein consumed globally [1], making it an important food source for millions of people everywhere. In 2018 96.4 million tonnes of catches was recorded, in both marine and inland fisheries. With such astonishing values, it is no surprise that the global commercial fishing market size was $221 billion in value in 2021 and employs over 40 million people worldwide. However, the fishing industry faces a big challenge embodied in the form of illegal, unreported, and unregulated (IUU) fishing practices. These IUU fishing activities have catastrophic economic and, more importantly, environmental consequences. Yearly IUU fishing equates to approximately 11-19% of reported global fisheries production and leads to losses of roughly $10-23.5 billion in value. These activities lead to overfishing, causing severe damage to marine ecosystems and threatening their sustainability. Dealing with IUU fishing is crucial for the longevity of maritime resources and the sustainable management of fisheries.
To deal with this problem various monitoring systems were developed and enforced on fishing vessels by world authorities. The European Union, for example, requires that all fishing vessels larger than 15m carry such a monitoring system [2]. Two commonly used systems are Vessel Monitoring Systems (VMS) and Automatic Identification Systems (AIS) which report the location, speed, and course of the vessel among other information.

## 1.1 Motivation

The monitoring of fishing vessels through AIS and VMS generates large quantities of data, as most commercial fishing vessels are required to adopt them. The European Union has the fourth-largest fishing fleet globally with over 83000 vessels alone. Even though an abundance of data is available there have been limited academic efforts to create systems that utilize this data to predict the occurrence of illegal, unreported, and unregulated fishing. The FAO states that one of the key aspects of addressing fishing longevity and sustainability is to deal with this problem [3]. Gear identification has been identified as a valuable tool for dealing with this issue. By leveraging VMS and AIS data, various machine learning systems can be developed to detect suspicious fishing activities to assist in the fight against IUU fishing. Such systems analyze temporal and geographical data, vessel behavior, and other information to identify potential illegal fishing practices. By improving monitoring capabilities and therefore aiding maritime authorities, these technologies have the potential to significantly decrease IUU fishing and its serious impacts on marine ecosystems and economies.

## 1.2 Objectives

The main objective of this master's thesis is to develop two machine learning models to classify fishing activity based on AIS and VSM data supplied by the Portuguese Navy. Portugal has the third-largest Exclusive Economic Zone(EZZ) in the EU [4] [5] and the 20th-largest worldwide, illustrated in Fig. 1. This project aims to, in the future, help authorities deal with the common issue of illegal, unreported, and unregulated (IUU) fishing at the

Portuguese south coastline, as seen in Fig. 20, by creating two distinct models, one capable of classifying between the different gear types and another that can detect when fishing activity is being performed. These models will be trained and tested with data collected from over 12000 vessels from December 2021 up until December 2023 related to fishing activity carried out in Portuguese waters as well as some other locations.

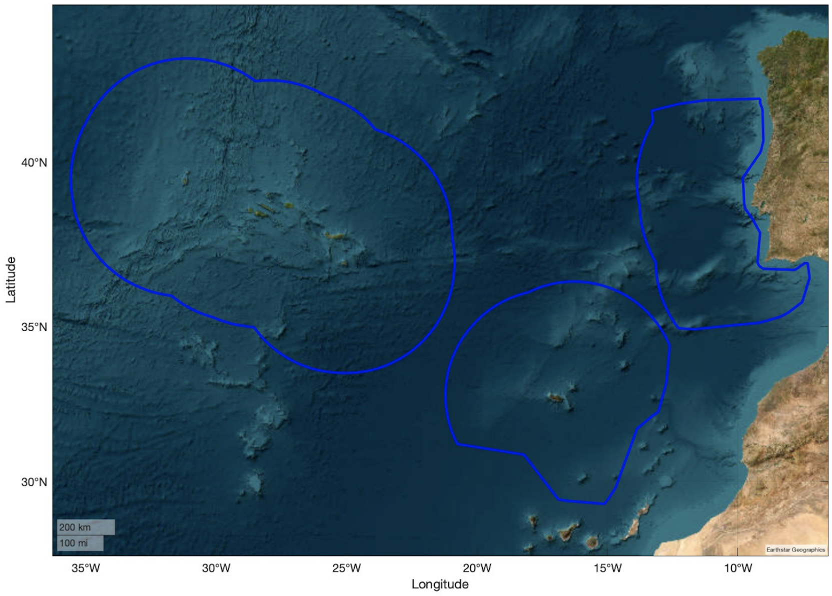


**Figure 1:** Portugal´s Exclusive Economic Zone

## 1.3 Outline

This document is structured the following way. The current section presents the motivation and the objectives for this work.

Section 2 explains the theoretical fundamentals for the understanding of this project.

Section 3 presents all the work related to the topic of classification of fishing activities and other related aspects.

Section 4 describes and proposes the work to be carried out in the thesis.

Section 5 describes all the phases that will be carried out to develop the project and divides each of them into their respective time window.

Finally Section 6 presents the conclusions drawn from this intermediate report.

# 2 Background

This section describes various topics and aspects that are fundamental for the understanding of the developed work.
First of all the different classification models are described and explained, highlighting their practical advantages. These are divided into two sections: Machine Learning models and Deep Learning models.
After that a short description of the two main monitoring and identification systems, used for tracking vessels, is made.
And finally the various fishing arts are explained to understand the different aspects and characteristics that distinguish them.

## 2.1 Machine Learning Models

In this subsection an overview of three ML models is made. These models include RF (Random Forest), SVM (Support Vector Machine), and MLP (Multilayer Perceptron). All these models can be used for regression and classification problems, however, they will be explained from a classification point of view seeing as this work only deals with classification.

### 2.1.1 Random Forrest

To understand how RF works, two concepts must be introduced: decision trees and bagging.
*Decision trees* are a type of supervised learning algorithm used both for regression and classification tasks, where data is continuously split into branches based on feature values. Continuing with the tree analogy each internal node represents a decision based on a feature, each *branch* represents an outcome of that decision, and each *leaf* node represents a final prediction [6]. A classification tree predicts that each observation belongs to the most commonly occurring class of training observations in the region to which it belongs. The process of growing a tree is called recursively binary splitting. Before each decision, i.e. before a split is made, a criterion is used to evaluate the split. For this task two common measures are used: The *Gini-index* is a measure of total variance across K classes and is defined by

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk})$$

where $\hat{p}_{mk}$ represents the proportion of training observations in the mth region (or leaf) that are from the kth class. As such *Gini-index* is also referred to as node purity. Node purity measures how homogeneous the nodes are concerning the target variable. Therefore a node is pure when all the data points are classified correctly under one category. An alternative to the *Gini-index* is *cross-entropy*:

$$D = -\sum_{k=1}^{K} \hat{p}_{mk} \log \hat{p}_{mk}$$

When pruning a tree one of these two approaches is used to minimize impurity. However, these types of decision trees suffer from high variance.
*Bagging* or *bootstrap aggregation* is a procedure used to reduce the variance of a statistical learning method, in this case, decision trees. Bagging consists of constructing $B$ classification trees using $B$ bootstrapped training sets, from the original training set. Each different tree will be trained on different subsets and therefore make slightly different predictions. Then a *majority vote* is taken where the overall prediction is the most commonly occurring class among the $B$ predictions, as seen in Fig. 2.

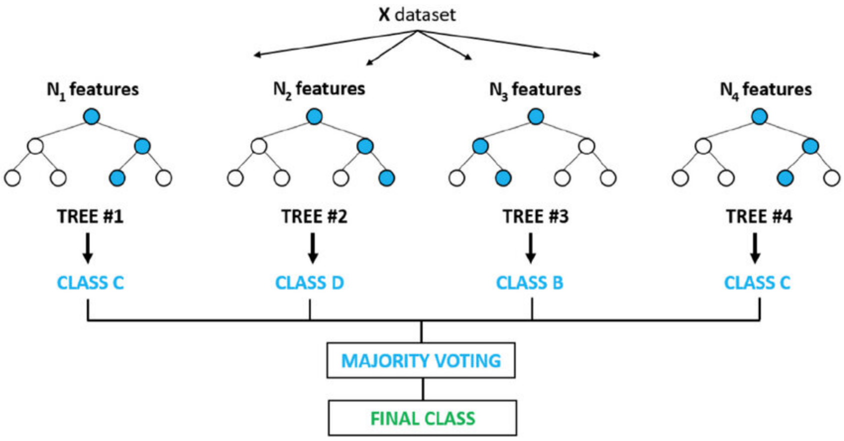


**Figure 2:** Random Forest Majority Voting

*Random forests* provide an improvement over the bagging technique by introducing a feature that *decorrelates* the various trees. As before a number of trees is built on bootstrapped training samples. However, each time a split occurs, when growing the tree, a random sample of $m$ predictors are chosen as split candidates from the full set of $p$ predictors. Therefore when building a random forest, at each split in the tree the algorithm can only consider predictors out of that random sample. This will lead to a more diverse choice of predictors throughout the trees so that one common strong predictor does not keep getting chosen by all trees. Typically random forests use $m = \sqrt{p}$ predictors. Random forests are consequently only a variation of bagging where $m \neq p$.

### 2.1.2 Support Vector Machines

In this subsection Support Vector Machines (SVM) will be explained. SVMs are used for classification problems due to their solid performance in a variety of settings and are often considered one of the best "out of the box" classifiers. In order to comprehend how an SVM functions, two concepts are going to be introduced: *maximal margin classifier* and *support vector classifier*. An SVM is an extension of both these classifiers to accommodate non-linear class boundaries.

*Maximal margin classifiers* construct a classifier based upon a *separating hyperplane* which separates the training observations perfectly according to their class labels. A *hyperplane* in a p-dimensional setting is defined in the following way:

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p = 0$$

Where $X$ is a point in that $p$-dimensional space. We can think of the hyperplane as dividing the p-dimensional space into two halves, and therefore if $X$ satisfies

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p > 0$$

then it lies on one side of the hyperplane. And consequently the same for the other side of the hyperplane.

$$\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p < 0$$

In the case where a separating hyperplane exists, we can use it to construct a classifier: a test observation is assigned a class depending on which side of the hyperplane it is located. However, if the data can be separated using a hyperplane, infinite hyperplanes exist, as seen in Fig. 3 on the left. Maximal margin classifiers use the *maximal margin hyperplane* which is the separating hyperplane that is farthest from the training observations, as seen in Fig. 3. on the right.

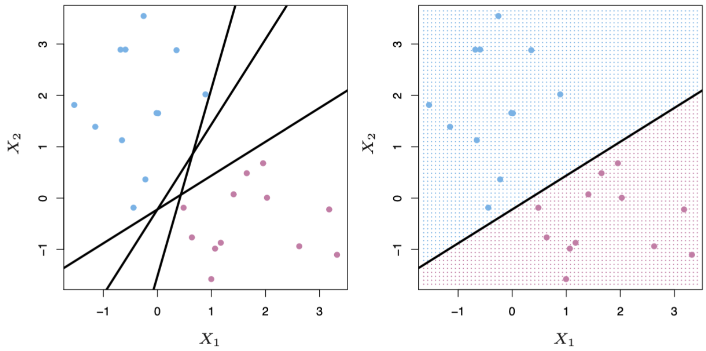


**Figure 3:** Hyperplanes and Maximal Margin Hyperplane.

Even though maximal margin classifiers are often successful, they also often lead to overfitting when $p$ is large. As mentioned before maximal margin classifiers are a very natural way to perform classification with the condition that a separating hyperplane exists. However, this is in many cases not true.

*Support vector classifiers* construct a hyperplane that almost separates the classes, using a so-called *soft margin* allowing some training observations to be on the incorrect side of the hyperplane [6]. We allow this margin for error in the interest of more robust individual observations and better classification of most of the observations. *Support vectors* are observations that lie exactly on that margin, as seen in Fig. 5 where observations lie exactly on the dashed line. Let´s introduce $C$ as a non-negative tuning parameter and *slack variables* $\epsilon_i, \ldots, \epsilon_n$ that allow individual observations to be on the wrong side of the margin or the hyperplane. $C$ can be interpreted as the budget for the amount that the n observations can violate the margin, this can be seen in Fig. 5 with the growth of $C$. Obliging to the following

$$\epsilon_i \geq 0, \quad \sum_{i=1} \epsilon_i \leq C,$$

if $C = 0$ then there are no violations of the margin, however with the increase of $C$ more observations are allowed to enter the margin and consequently the margin widens. Practically speaking when $C$ is close to zero the classifier classifier is highly fitted to the data, which may have low bias but high variance. On the other hand, when C is larger we obtain a classifier that is potentially more biased but may have lower variance.

*Support Vector Machines* are an extension of support vector classifiers that enlarge the feature space in a specific way using *kernels*. As seen before support vector classifiers are an approach for binary classification, if the boundary between the two classes is linear. In practice sometimes non-linear boundaries may appear, and in those cases, a linear classifier would do very poorly, as seen in Fig. 4.

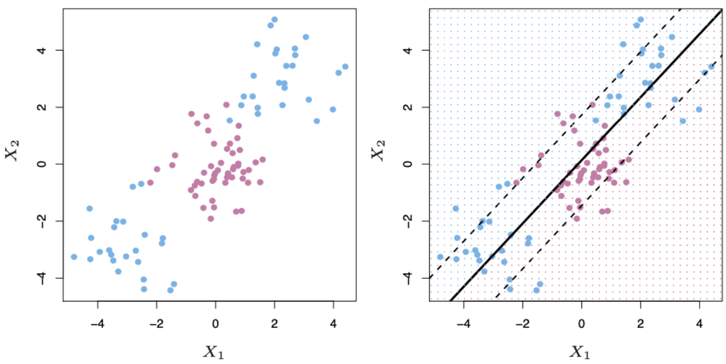


**Figure 4:** Two classes with non-linear boundary.

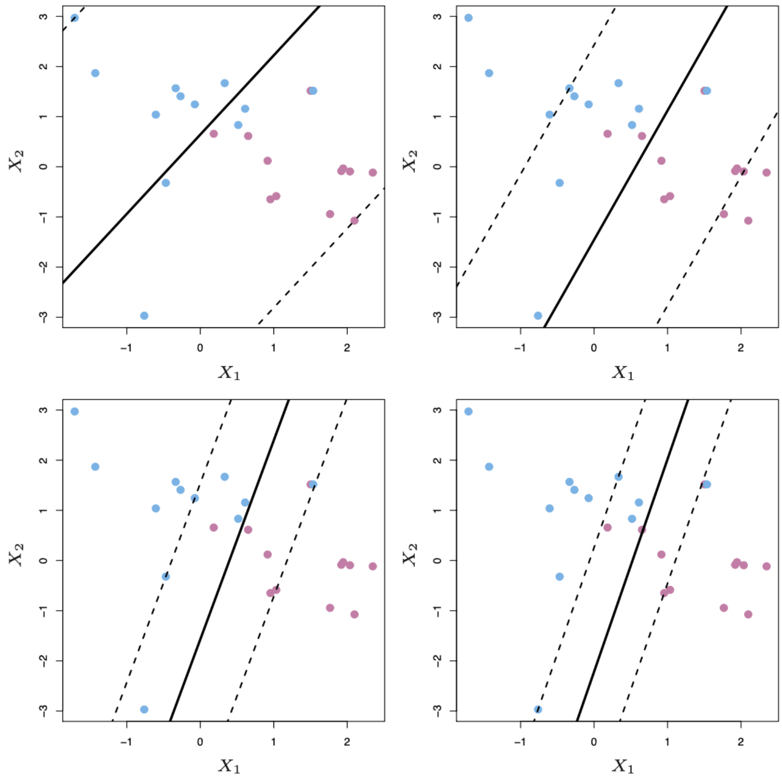


**Figure 5:** Variations of tuning parameter $C$

Through the use of *kernels*, we can enlarge our feature space to accommodate a non-linear boundary between classes. A kernel is a function that quantifies the similarity of two observations. When a support vector classifier is combined with a non-linear kernel this is known as a Support Vector Machine. Various types of non-linear kernels exist, in Fig. 6. [6] on the left a *polynomial kernel* of degree 3 is used and on the right, a *radial kernel* is applied to the same problem.

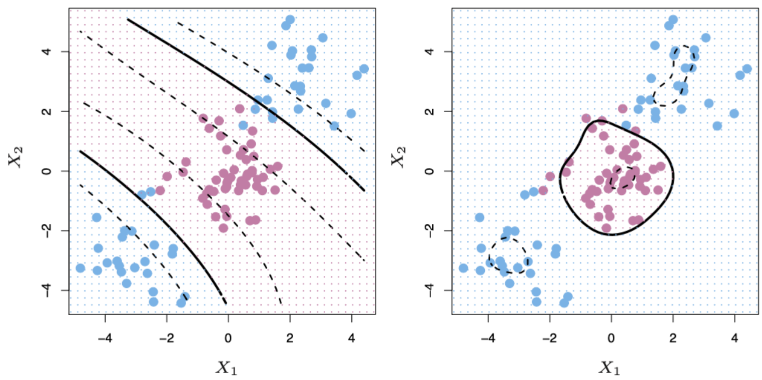


**Figure 6:** Left: *SVM with polynomial kernel of degree 3.* Right: *SVM with radial kernel.*

### 2.1.3 Multilayer Perceptron

*Multilayer Perceptrons* (MLP) are a class of artificial neural networks that excel in the modeling of complex data patterns. Through their layered structure, the use of nonlinear activation functions, and the concept of

backpropagation MLPs transform input data into meaningful outputs. In this section, the structure of MLPs as well as the learning algorithm will be explained. Other considerations regarding the validation of models, the preprocessing of data, and the over-fitting of networks will be described.
An MLP is structured into three layers (input, hidden, and output) composed of nonlinear computational elements called neurons as seen in Fig. 7. [7].

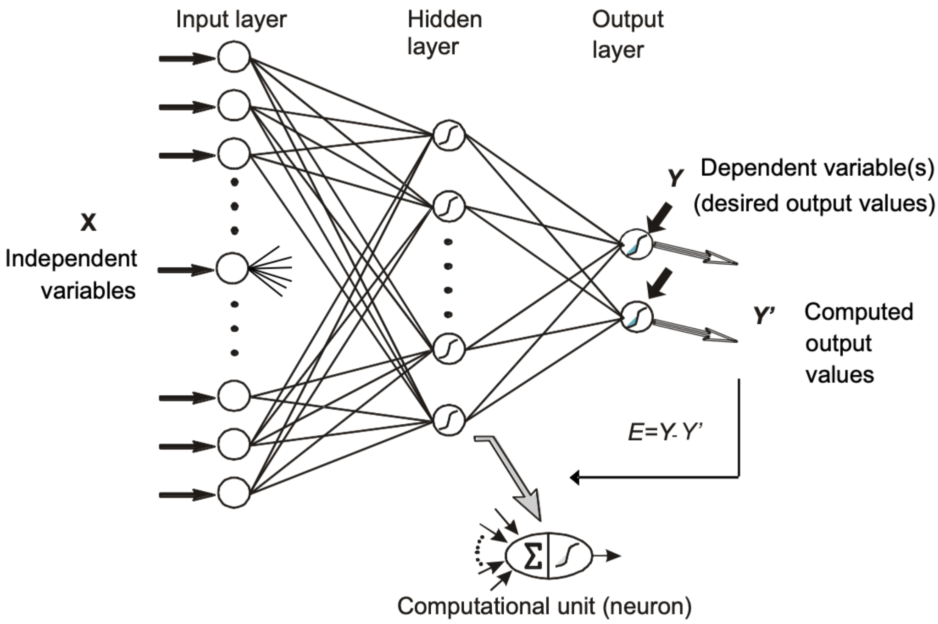


**Figure 7:** Structure of an MLP.

The information flows from the input to the output layer passing through the hidden layer. All neurons between two layers are fully connected. These connections are represented as weights in the learning process. When information flows through the layers the various weights contain the knowledge of the network and play a central role in the propagation of the signal. The number of neurons in the input layer is equal to the number of the independent variables of the model however in the output layer the number of neurons is the same as the number of dependent variables which can be only one or many more. The choice of the number of hidden layers and the number of neurons in them are dependent on the complexity of the model and are important parameters in the development of a successful MLP.
The learning algorithm of an MLP is divided into two steps, a *forward-propagation* part and a *backward-propagation* part. The learning of an MLP consists of minimizing errors between the desired target values and the values computed by the model. If a wrong choice is given then the weights are updated to minimize the errors in the hope that in the future the network will give better results.
The *forward-propagation* phase begins at the input layer with an input pattern, where the weights are initialized as small random numbers. The input of a neuron $j$ of the adjacent hidden layer for a pattern $p$ is calculated as the sum of each output of the input layer multiplied by the weight of each correspondent connection. An activation function is applied to calculate the output of neuron $j$ of the hidden layer $z_{p,j}$ and the output of neuron $k$ of the output layer $o_{p,k}$ as follows:

$$f(\mathrm{NET}) = \frac{1}{1 + \exp(-\lambda \mathrm{NET})}$$

Where $\lambda$ represents the activation function coefficient and $NET$ is expressed by either $z_{p,j}$ or $o_{p,k}$:

$$z_{p,j} = f\left(\sum_i x_{p,i} v_{p,ji}\right) \quad , \quad o_{p,k} = f\left(\sum_j z_{p,j} w_{p,kj}\right)$$

$v_{p,ji}$ and $w_{p,kj}$ are the weights of the connections between neuron $i$ of the input layer and neuron $j$ of the hidden layer and between neuron $j$ of the hidden layer and neuron $k$ of the output layer for pattern $p$, respectively. As said before the learning algorithm changes the weights $v_{p,ji}$ and $w_{p,kj}$ to minimize the errors. The sum of the errors in each neuron in a pattern p is calculated as:

$$E_p = \frac{1}{2} \sum_k \left(d_{p,k} - o_{p,k}\right)^2$$

where $d_{p,k}$ is the target value of neuron $k$ in pattern $p$. One iteration of the forward-propagation phase starts at the input layer and ends at the output layer, passing through the hidden layers. In each successive layer every neuron sums its inputs and applies an activation function to compute its output. The final layer, i.e. the output layer, of the network produces the estimated target value.
In the *backward-propagation* phase neurons are back-propagated for the appropriate weight adjustments. The error signal at neuron $k$ of the output layer for a pattern $p$ is given by $\delta_{p,k(o)}$ and calculated the following way:

$$\delta_{p,k(o)} = o_{p,k} \left(1 - o_{p,k}\right) \left(d_{p,k} - o_{p,k}\right)$$

The adjustment of the weights is then done as shown here:

$$\Delta w_{p,kj}(t+1) = \eta \delta_{p,k(o)} o_{p,k} + \alpha \Delta w_{p,kj}(t)$$

$$w_{p,kj}(t+1) = w_{p,kj}(t) + \Delta w_{p,kj}(t+1)$$

Where $\eta$ is the learning rate coefficient, and $\alpha$ is the momentum coefficient. The choice of these values depends on the problem at hand. A large learning rate leads to instability and unsatisfactory learning on the other hand a small value can lead to excessively slow learning. The adjustment of weights of the neurons of the hidden layer is done the same way except for the error signal $\delta$ which is calculated the following way:

$$\delta_{p,j(h)} = z_{p,j}(1 - z_{p,j}) \sum_k \delta_{p,k(o)} w_{p,kj}$$

The learning process of a model is followed by a training test phase to assess the performance of the model. The test phase is divided into two steps: validation and test. Here the most appropriate model has to be selected from rival contenders. The dataset is subdivided into three different parts: training, validation, and testing. The various models are evaluated using the validation dataset, and the best-performing model is selected. Then, the accuracy of the selected model is estimated.
When over-fitting happens a network develops a good memory for specific data, it is important to avoid this as the model loses generalization and is not usable with datasets that were not used to train the network. Two main factors can be attributed to over-fitting namely: the number of epochs and the number of hidden layers. These values are chosen by trial and error using the training and test datasets.

## 2.2 Deep Learning Models

The term Deep Learning or Deep Neural Network refers to Artificial Neural Networks (ANN) with multiple layers. In this subsection two DL models will be described. These models include CNNs (Convolutional Neural Networks) and LSTM-FCN (Long Short-Term Memory with Fully Convolutional Networks).

### 2.2.1 Convolutional Neural Networks

One of the most popular deep neural networks is the Convolutional Neural Network. Its name originated from the mathematical linear operation between matrices called convolution. CNNs are commonly used in wide applications and have excellent performance in image classification and, more relevant to this work, in multi-variable time series classification. This subsection will first describe the main architecture of a CNN and explain the various operations regarding multi-variable time series classification.
The architecture of a CNN typically has three layers: a convolution layer, a pooling layer, a fully connected layer, and a non-linearity layer [8]. An illustration of a CNN can be seen in Fig. 8:

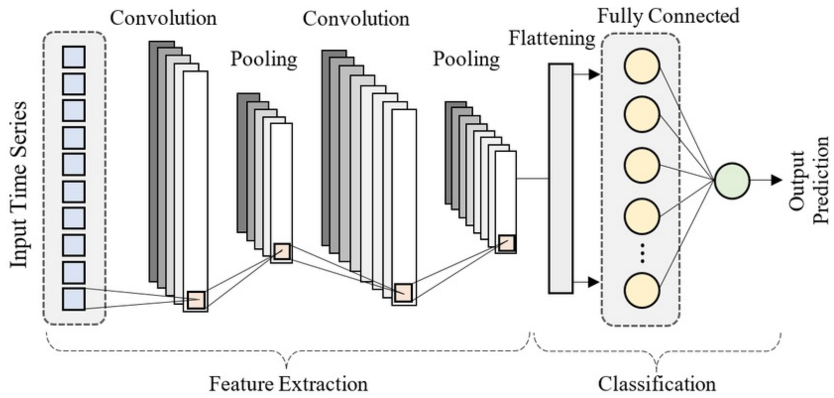


**Figure 8:** Schematic diagram of a basic convolutional-neural network (CNN) model for time series data forecasting.

The *convolution layer* is the core concept of a CNN. This layer performs convolution operations on the input data with convolution filters or kernels. The output of these layers is an activation map or feature map that highlights patterns from the input. Multiple convolutional layers can be stacked, which allows the CNN to learn increasingly complex and abstract features from the input data.
The *pooling layer* will be the link between two consecutive convolutional layers. It aims to reduce the number of parameters and computation loads by making down-sampling representations. Various pooling operations can be used such as max-pooling or average-pooling. The pooling layer is also very helpful in reducing over-fitting and computation weight. Fig. 9 shows a 2D feature map being down-sampled with a max-pooling operation:

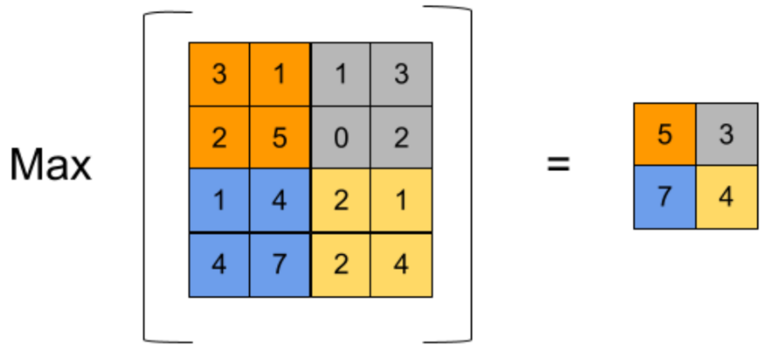


**Figure 9:** Max-pooling operation on 2D activation map.

The third layer is the *fully connected layer*, also called the convolutional output layer. This layer is similar to a standard ANN, like the MLP seen in the previous section, only these ANNs can have multiple hidden layers. It receives an input signal and is responsible for the classification or regression tasks. Ultimately the goal of a CNN is to feed the high-level features extracted by the previous layers to the fully connected layer so they can be trained and map the inputs to the correct output.
Sometimes a *non-linearity layer* can be added after the convolutional layer. This is done by activation functions that introduce non-linearity to the model. The use of introducing non-linearity is to help solve non-linear problems and enable the stacking of multiple convolutional layers. Many activation functions are available, however the most popular are the sigmoid and ReLU function. The sigmoid function limits the output to be between 0 and 1 and is mathematically represented in the following way:

$$f(x)_{\text{sigm}} = \frac{1}{1+e^{-x}}$$

The ReLU function is commonly used in CNNs as it requires a low computational load. ReLu converts all inputs into positive numbers and can be represented this way mathematically:

$$f(x)_{\text{ReLU}} = max(0, x)$$

When dealing with multi-variable time series classification the input signal will be a 1D signal as opposed to a 2D signal in image classification. After several convolutional and pooling operations the initial time series is represented in a combination of feature maps. The output layer will receive as input a new time series which is the combination of those feature maps [9].

### 2.2.2 Long Short-Term Memory with Fully Convolutional Networks

This subsection will first explain the architecture of an LSTM-FCN and its components and after describe how an LSTM block works. *Long Short-Term Memory Fully Convolutional Network* (LSTM-FCN) is a model that aims to enhance the traditional FCN model by incorporating an LSTM component. This integration allows the model to capture temporal dependencies in the data, resulting in improved robustness and performance [10]. An FCN is a modified CNN, seen in the previous subsection, which only contains convolutional layers. An *LSTM-FCN* is a fully convolutional network augmented with an LSTM block, this combination leverages the efficient processing capabilities of FCNs while also capturing temporal information through the LSTM block. Typically an LSTM-FCN has the following architecture:

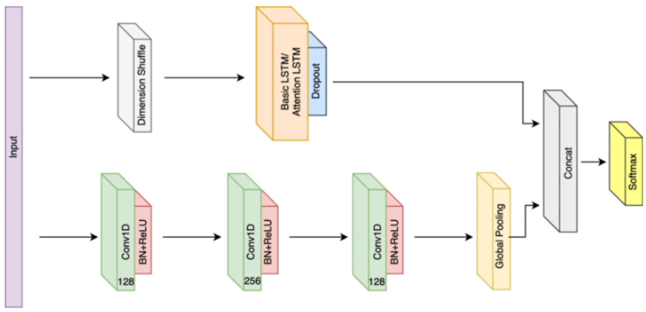


**Figure 10:** LSTM-FCN Architecture.

As seen in Fig. 10 the time series input is fed a series of convolutional blocks. Each convolutional block consists of a convolution layer, identical to the CNN explained in subsection 2.2.1, followed by batch normalization and a ReLU activation function. After this, a global average pooling layer is applied. Simultaneously the time series input is inserted into a dimension shuffle layer, which transforms the input into a multivariate time series with a single time step. This multivariate time series is fed into an LSTM block and after into a dropout layer. Finally, the output of the global pooling layer and the LSTM block are concatenated and passed onto a softmax classification layer [11].

*LSTMs* are a type of Recurrent Neural Network (RNN) that addresses the vanishing gradient problem over the traditional RNNs. The vanishing gradient problem refers to the issue where gradients diminish or explode during the backpropagation phase of the learning process, affecting the training of deep neural networks and not allowing the network to remember longer contexts in the sequential data. LSTM-RNNs address the vanishing gradient by incorporating gating functions into their state dynamics. An LSTM block has the following structure:

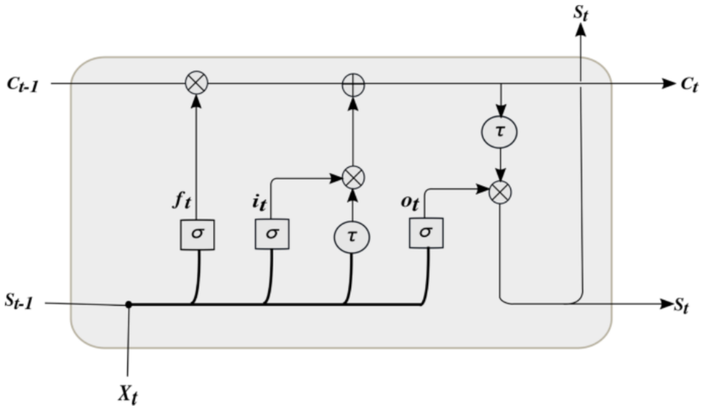


**Figure 11:** LSTM block structure

An LSTM block can be divided into four units: a cell state, an input gate, a forget gate, and an output gate. The *cell state* ($C_t$) serves as the memory block, retaining information over arbitrary time intervals. The gates control the flow of information in and out of the cell. The *input gate* ($i$) determines which of the input values will be updated in the cell state, i.e. which of values should be used to change the memory. The *forget gate* ($f$) decides which parts of the previous cell state $C_{t-1}$ will be forgotten. And finally, the *output gate* ($o$) controls the parts of the current cell state that are fed to the next layer. These four components work together to update and maintain the cell state. Let´s define $f_t$ as the forget gate, $i_t$ as the input gate, $C_t$ as the cell state, and $o_t$ as the output gate all at time step $t$. The following math equations will be made by each unit:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \Big\} \quad \textit{forget gate}$$

Where *sigma* is the sigmoid function, which outputs a value between 0 and 1 where 0 means a high forget rate and 1 means a high retain rate. $W_f$ represents the weight matrix for the forget gate, $x_t$ the current input , $h_{t-1}$ the output of previous step and $b_f$ the bias for the forget rate.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad , \quad \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad \Big\} \quad \textit{insert gate}$$

Here $\tilde{C}_t$ represents a filtered version of the input to be potentially added to the actual cell state.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad \Big\} \quad \textit{cell state update}$$

When updating the cell state $C_t$ the previous cell state $C_{t-1}$ is multiplied by the forget gate output $f_t$ to determine how much will be retained from the old state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad , \quad h_t = o_t \cdot \tanh(C_t) \quad \Big\} \quad \textit{output gate}$$

Finally, the output gate controls the parts of the cell state that are output to the next layer, used in the next cell's input gate, or used in the final prediction.
In conclusion by incorporating LSTM blocks within the fully convolutional layers of the LSTM-FCN model, the model can effectively capture temporal dependencies in the data. The fully convolutional layers perform local feature extraction, while the LSTM blocks preserve and propagate information over time, allowing the model to understand long-term patterns and detect dependencies in sequential data.

## 2.3 AIS and VMS

This subsection gives a brief introduction to the two main identification and monitoring systems used worldwide for the tracking of fishing vessels. A comparison is also made between the two systems from a data perspective.

### 2.3.1 AIS

*Automatic Identification System* (AIS) is a tool employed by Vessel Traffic Services (VTS) aimed to enhance safety and navigation in the maritime domain. As a refined tracking system, AIS serves as a complement to traditional marine radar, which provides vital information for collision avoidance and vessel monitoring. Ships equipped with AIS transponders transmit data at regular intervals which include their precise location, speed, and navigational status. These details are broadcasted through VHF transmitters, ensuring effective communication with VTS authorities. AIS was initially designed for terrestrial applications with a range of approximately 20 miles, accounting for the curvature of the Earth. However, as maritime operations expanded into more remote waters, the need arose for extended signal coverage. Through low-orbit satellites, vessels can relay their AIS signals to these orbiting platforms, enabling continuous tracking and accurate positioning across vast open sea areas.Its widespread adoption, through the enforcement made by worldwide authorities, has revolutionized the maritime industry enabling close monitoring and advanced collision avoidance.

### 2.3.2 VMS

*Vessel Monitoring System* (VMS) encompasses a range of technologies used to gather data on fishing vessels. Governments and environmental organizations use VMS primarily for the management of fisheries. The applications of VMS data however extend beyond fisheries, with various entities leveraging its use for research, enforcement, and various other purposes. One significant advantage of VMS is its powerful impediment effect. The knowledge that fishing operators are being monitored through VMS acts as a strong disincentive against Illegal, Unreported, and Unregulated (IUU) fishing activities. This knowledge of surveillance fosters a sense of accountability and among operators, reducing the likelihood of non-compliant behavior. VMS provides precise information on the locations, vessel velocity, and heading of monitored fishing vessels. The transmission of data occurs through satellite communication, providing global coverage regardless of the vessel's geographic location. Another advantage is the reliability of VMS reports compared to relying solely on information given by vessel operators. While operators may sometimes provide inaccurate or intentionally misleading information, VMS data offers a trustworthy source of information.

### 2.3.3 AIS vs VMS

While the use of VMS devices is mandated only for some fleets in individual nations, the International Maritime Organization (IMO) has made the carrying of an AIS transponder mandatory for all vessels larger than 300 gross tons or carrying passengers (SOLAS Chapter V) [12]. The European Union also requires that all fishing vessels bigger than 15m must carry an AIS device [2]. From a data processing point of view, VMS makes analyzing a vessel's trajectory and activity incredibly hard since information is transmitted in intervals of a few minutes which have high variance. The data set provided to us for this research was also not labeled which provided another hurdle. On the other hand, AIS offers a more stable transmission at regular intervals where navigational status data is transmitted every 2 to 180 seconds depending on vessel activity. GFW provides an already labeled AIS dataset used in similar works regarding AIS-based fishing activity.

## 2.4 Fishing Arts

In this section, the different fishing arts that appear in most fishing-related datasets will be discussed, along with their behaviors and characteristics. These include drifting longlines, purse seines, trawling, trolling, and fixed gear.

### 2.4.1 Drifting Longlines

Drifting longlines, also known as pelagic longlines, are a type of fishing gear primarily used for catching pelagic species like tunas, sharks, and swordfish. A drifting longline is a type of longline that is not fixed to the seabed and drifts with the current, usually with the boat attached at one end of the longline [13].Drifting longlines usually fish near the surface or in the water column typically in offshore waters. The depth of the hooks therefore influenced by desired catch rates and specific species. Branch lines in drifting longlines are often more than 10 m long and may include a clip, one or more swivels, and a weight. An illustration of a drifting longline can be seen below in Fig. 12.

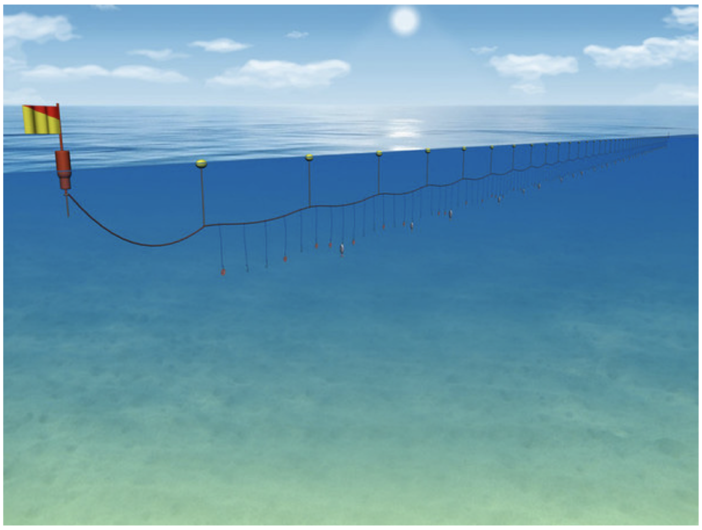

**Figure 12:** A fleet of drifting longlines (LLD 09.32) set near the surface

The movement of this gear type is characterized by slow, continuous movements and slight adjustments to keep the vessel aligned with the current.

### 2.4.2 Purse Seines

A purse seine is a wall of netting designed to encircle a school of fish near the surface and use a purse line to close the bottom of the net. Purse seines use weights, lead lines or chains attached to the footrope, and dense netting materials, to increase the sinking velocity of the net to prevent fish from escaping horizontally [13]. A modern purse is illustrated in Fig. 13. When a target fish school is identified, the vessel maneuvers into a favorable position, and the seine net is prepared for deployment. The vessel follows a course around the edge of the school, attempting to encircle it. With the net fully deployed, ropes attached to the ends of the net are hauled to close the seine around the school. The purse seine is the most important fishing gear in marine capture fisheries in terms of the quantity of fish landed. According to recent Food and Agriculture Organization of the United Nations (FAO) statistics, this gear accounts for about a third of total marine landings.

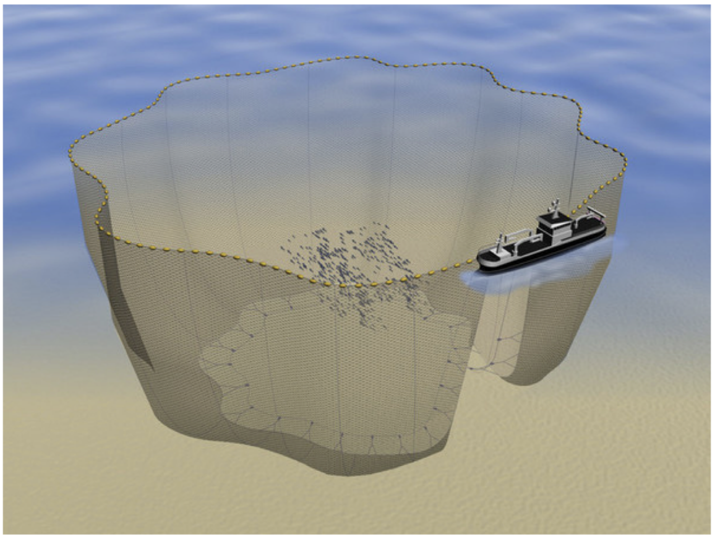

**Figure 13:** Modern purse seine (PS 01.1) encircling a free-swimming fish school.

Concluding the movement of purse seines can be described in two main phases. The first phase is where the school of fish is encircled, and the second phase is where the vessel remains nearly stationary during a waiting period [10].

### 2.4.3 Trawling

A trawl is a cone-shaped body of netting, usually with one cod-end, towed behind one or two boats to catch fish through herding and sieving. There are two main kinds of trawling namely bottom trawls, seen in Fig. 15, and midwater trawls, seen in Fig. 14 [13]. Bottom trawls are towed across the seabed where as midwater trawlers are towed across midwater. Trawls are very versatile and can be used to catch many different species. The towing speed is usually determined by the behavior and swimming capacity of the target species and the power of the boat.

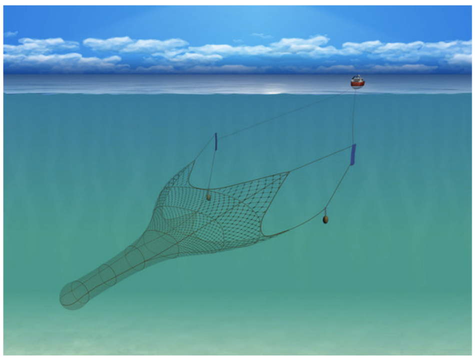

**Figure 14:** A single boat midwater otter trawl.

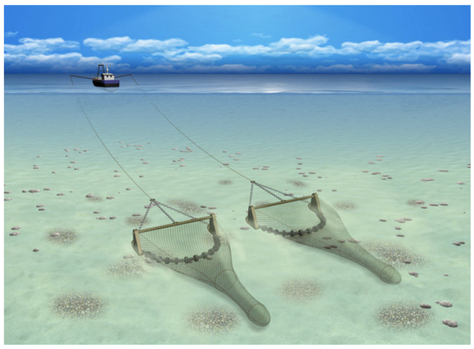

**Figure 15:** Two beam trawls are towed behind a boat on its outriggers.

Trawling speeds typically range from 3 to 5 knots. This fishing art has a big environmental impact, especially in bottom trawling, which has a high bycatch rate of around 56% [13].

### 2.4.4 Trolling

A trolling line is a line with one or more baited hooks (or lures) towed behind a boat, as seen in Fig. 16 [13]. The various lines may be near the surface or somewhat below the surface depending on where in the water column the fish are, which can be adjusted by the amount of weight on each line, the length of the line, and the vessel speed.

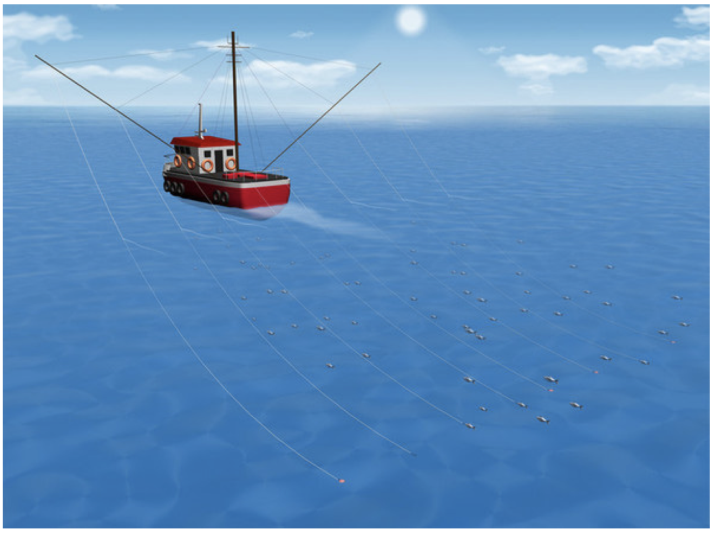

**Figure 16:** Trolling lines towed behind a boat using outriggers.

Trolling is relatively similar to trawling. However, the main difference lies in the speed at which the vessel moves. Compared to trawling, trolling operates at lower speeds.

### 2.4.5 Fixed Gear

Fixed gear encompasses a variety of fishing techniques that utilize stationary, as seen in Fig. 18, or semi-stationary equipment, as seen in Fig. 17 known as traps. They are designed in such a manner that the entrance itself becomes a non-return device, allowing the fish to enter the trap but making it impossible to leave the catching chamber. Fixed gear vessels typically operate at lower speeds compared to other fishing techniques, as they primarily focus on stationary or semi-stationary fishing methods. In terms of course, other fishing arts, where vessels may follow specific paths or make deliberate turns, the movement direction of a fixed gear vessel would be relatively stable. Once the traps are set in their designated locations, the vessel will primarily maintain its position.

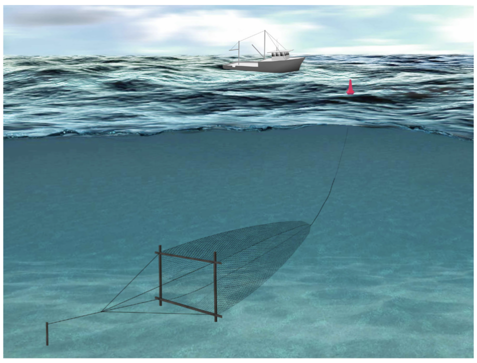

**Figure 17:** A stow net with one anchoring point.

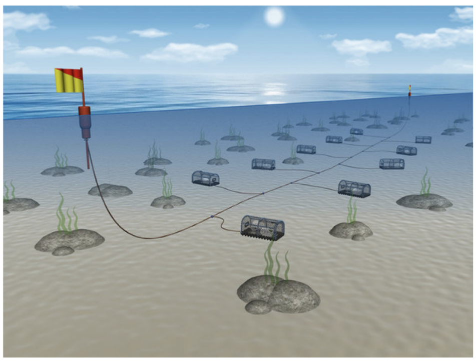

**Figure 18:** A fleet of pots set on the seabed.

## 3 Related Work

This section provides an overview of current and past research works developed for the detection and classification of fishing activities using various machine learning and deep learning techniques.
The research studies selected and described have various approaches and different end goals, but most of them seek to address the common issue of illegal, unreported, and unregulated (IUU) fishing. These efforts are critical to the continuous development of fishing arts and activities monitoring.
It is divided into two main sections, covering works based on machine learning and deep learning techniques:
Firstly, related works were examined that apply traditional machine learning algorithms like Random Forest (RF), and Support Vector Machines (SVM).
Secondly, publications that apply deep learning techniques such as Recurrent Neural Networks (RNNs) with slight variations were examined, i.e traditional Convolutional Neural Networks (CNNs), CNNs with Residual Connection Blocks, Long Short-Term Memory with Fully Convolutional Networks (LSTM-FCN) and Restricted Boltzmann Machines with Autoencoders.

### 3.1 Machine Learning Techniques

In [14] the authors propose a process that achieves the identification of non-compliant data reports aiming to advance the control of fishing activities in Portuguese national waters (continental EEZ, Madeira and the Azores). This process is based on data mining approaches such as Naïve Bayes and Decision Trees. The European Union legislation requires that all coastal EU countries must set up VMS systems that are compatible with each other. In Portugal, the MONICAP system was developed and implemented. This system consists of a continuous monitoring equipment, "blue box", installed on fishing vessels, which records and transmits satellite information (VMS) on the vessel's geographic position, course, and speed to a Center Fisheries Control and Monitoring Center (CCVP). Due to high communications costs, the transmission rate is only one position every two hours however registers occur in the MONICAP local database every 10 minutes. The model described in [14] identifies important variables, statistics and patterns through k-means and other models from VMS data and vessel electronic logbooks. These are then used as input for a Naïve Bayes and Decision Tree model. These two models then detect and report non-conformities in fishing activity.

[15] is a further advancement of the previous work where MONICAP VMS data is used for real-time fishing activity detection. The authors propose a system that receives VMS data every minute and based on data patterns, created on historical data, creates an alarm process that authorities can use to monitor fishing activities more closely. This system is divided into various processes. Using MONICAP each vessel will collect data and store it locally. After using this VMS data various patterns will be identified regarding speed, position, date, and course direction. The third process implements a decision tree classification model for new data, to create alarms based on changes in patterns identified in process 2.

In [16] the authors, explored a method based on traditional machine learning techniques to classify fishing gear based on VMS data from Indonesia with the ultimate goal of identifying Illegal, unreported, and unregulated (IUU) fishing in that area.
Marzuki et al. [16] divides the developed method in three phases. First a Gaussian Mixture Model (GMM) model is used on preprocessed VMS data to extract various features. The features are then used as inputs for the classification. For this classification of the fishing gear, two methods were used, an RF and SVM model. Both methods yielded a high Mean Correct Classification Rate of around 95%.

Kontopoulos et al. [17] proposes a method for real-time classification of vessel activity in streaming activity. The motivation in [17] was MarineTraffic, a website that is flooded by more than 16,000 AIS messages per second received from almost 200,000 vessels globally. In this paper, a method is developed to classify vessel activity from incoming AIS messages and is divided into two main steps.
First of all various features are extracted to capture common observed behavior of fishing vessels. The selected features fall into three areas: vessels' speed, vessels' drifting, and turn frequency. These features are then used

by a Random Forest classifier trained to classify unseen trajectories of such vessels. The choice of using an RF classifier is justified by its high-performance results in the maritime domain [18] but also because it requires fewer data than other algorithms, is less computationally expensive and predictions are easier to interpret.
The architecture used by the developed method is a $\lambda$-architecture with two layers. The first layer is responsible for the construction of the Random Forest classification mode. The second layer consumes AIS messages and classifies vessel trajectories based on the model created from the first layer.

Mazzarella et al. [19] partitions vessel trajectories into stops and moves aiming to identify sections of a single trajectory where the ship is probably fishing. To do so a combination of two algorithms are used, first CB-SMoT focusing on the speed variation of the trajectory and DB-SMoT focusing on the direction of the trajectory. Then a clustering algorithm DBSCAN is used to discover clusters in the data and therefore locate fishing areas based on historical AIS data.

### 3.2 Deep Learning Techniques

Grey et al. [20] compares two models used for the classification of fishing vessels with the intent to determine Illegal, unreported, and unregulated (IUU) fishing. Both models are also evaluated with two different data preprocessing approaches. Both models, although different from each other, utilize Recurrent Neural Networks chosen for their ability to retain memory within sequences. One of the models utilizes a one-dimensional Convolutional Neural Network (CNN). However as the dept of the CNN begins to grow a problem emerges, called the vanishing gradient problem, which prevents learning from happening effectively. To solve this issue residual blocks were developed resulting in a 1D-CNN with Residual Blocks. The second model uses Gated Recurrent Units (GRUs), another option that mitigates the same problem as earlier by introducing update and reset gates. Seeing as AIS signals are highly irregular two different approaches are used to preprocess the data. Linear Interpolation and Zero Padding. Careful evaluation of the four system combinations was made and the GRU with zero-padded test data achieved the highest accuracy of all with 95%.

In [11] the use of long short-term memory fully convolutional networks (LSTM-FCN) for time series classification is described. The proposed method achieves state-of-the-art performance when compared to other FCN methods without requiring heavy preprocessing of data or feature engineering and also dealing with the vanishing gradient problem of RNNs. Seeing as it was developed to enhance the classification of time series in general and yielded good results, it was an inspiration to use it on AIS data.

Kim et al. [21] presents a deep learning-based fishing gear-type identification method from AIS ship movement data and environmental data. The method makes use of CNNs and Fully Connected Neural Networks(FCNN) for feature extraction followed by a second FCNN for the prediction of gear type. It can be divided into three main phases: First contaminated AIS messages are cleaned, removing unreliable and meaningless data. As AIS messages appear to be sampled at random time intervals, linear interpolation is used to compute the interpolated positions at the sampling time resulting in more accurate time intervals. A sliding-window technique is then used to capture trajectories that reflect the patterns of the various fishing gear types.
The next phase deals with the feature extraction module. This model uses both a 1D-CNN and an FCNN. The first one extracts features from records of course change and speed. The second one uses fishing environment data such as tidal current, daylight, water temperature, and water depth.
The last phase consists of the prediction model, where the outputs of the 1D-CNN-based and the FCNN-based feature extraction modules are concatenated and passed to an FCNN with two hidden layers.
Finally to evaluate this work a comparison to another model was made, where very good performance for purse seine, trap, and trawl fishing gear types was observed but somewhat average performance for stow net, longline, and drift gill net fishing gear types.

In the paper [22] a model was developed called FishNet that uses a 1D-CNN to classify vessel trajectories into a fishing or nonfishing class. Arasteh et al. [22] binary classifier achieves a 93% accuracy when classifying unlabeled AIS data. It is described as a 3-stages algorithm to differentiate fishing activities from non-fishing ones. Learning from raw AIS data is not an easy task and as such the first phase is to take original AIS features and transform them into a set of motion-related features that are suitable for discovering dynamic behavioral patterns of fishing activities, independent of space and time. Secondly, a sliding window technique is used to segment data into 2-hour-long sequences. This is done because feeding a classifier model with very long input sequences may decrease performance and also increase the model's complexity and training time. Finally, a 1D-CNN assigns one of two labels to any arbitrary input segment, determining a fishing/non-fishing status.

Jiang et al. [23] was one of the first attempts to use deep learning approaches to automatically find features in AIS data to detect fishing activities. Autoencoders are proposed and built by Restricted Boltzmann Machines to discover features of vessel AIS trajectories that will ultimately characterize the differences between fishing and non-fishing activities.

Neves et al. [10] is the main inspiration for this work. In his work, the author develops various machine and deep learning models for two main goals. First a model capable of classifying between different fishing-gear types and another model able to detect if fishing activity is being performed or not. The training of these models utilizes a labeled AIS dataset supplied by the GFW (Global Fishing Watch). To validate the most successful model a VMS dataset provided by Seatall was used, which represents local fishing activities covering a variety of fishing gears. The machine learning algorithms used were an RF, an MLP and an SVM model. Two deep learning techniques were also utilized which were an CNN and an LSTM-FCN. This work can be divided into three main phases. First, the data processing phase which involves filtering and preparing the data that will serve as input for the various models. Secondly, the model training phase which creates and trains the various models to accurately identify different types of fishing methods and if fishing activity is being practiced or not. For the end-to-end models, a thorough feature engineering step was carried out. In total 28 features were derived from various attributes such as speed, course and time. These features can be summarized into time-based features, speed features, course features, power features, and interaction features. This way the author was able to capture more nuanced relationships between variables and improve the model's ability to identify different patterns and behaviors within the data. Finally, the testing phase where the various models are tested to evaluate their performance. An F1 score was used to measure the accuracy of the various models. This work achieved optimistic results after the development of the models with AIS data. The best-performing model, the LSTM-FCN, was validated with the VMS Seatall dataset obtaining a promising F1 score of 0.84 on unseen data.

# 4 Work Proposal

In this section, the work proposal for the thesis will be presented. The aim of this project is to continue the research initiated in [10] and build upon the findings and methodologies established in that work to further advance the realm of prediction and classification of fishing activities. The approach will involve the development of two deep-learning methods namely a Convolutional Neural Network and a Long Short-Term Memory with a Fully Convolutional Network mentioned in Section 2.2.1 and Section 2.2.2 respectively, in order to classify fishing gears and predict fishing activity. Leveraging past insights mentioned in Section 3, we expect to achieve more refined results.
The ultimate objective of this work is to develop two models that in the future will helping authorities deal with the common issue of illegal, unreported, and unregulated (IUU) fishing at the Portuguese south coastline, as seen in Fig. 19, protected by the Portuguese Navy. This project will work mainly with VMS datasets supplied by the Portuguese Navy related to fishing activity carried out in Portuguese waters as well as some other locations.

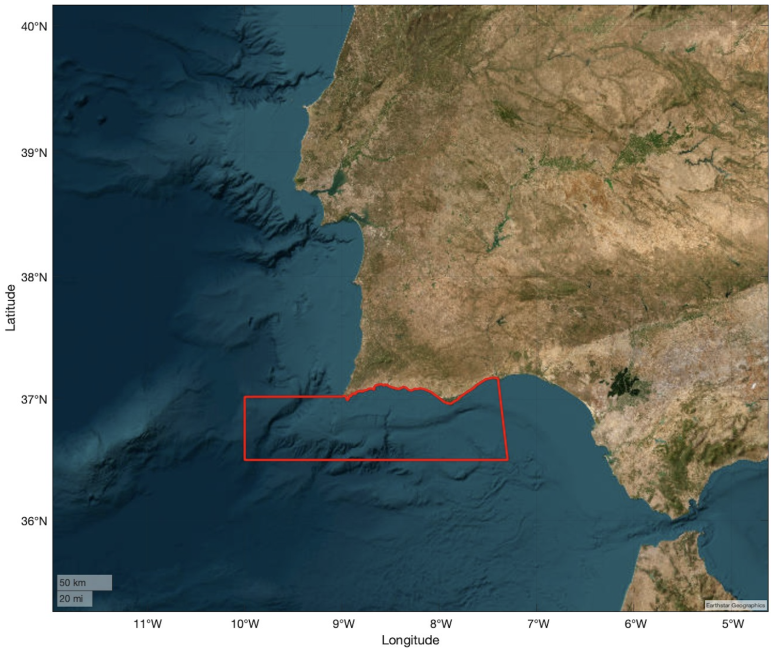


**Figure 19:** Portuguese South Maritime Zone Command

These datasets provide information on more than 12000 vessels collected from December 2021 up until December 2023. Valuable information such as the time, latitude, longitude, speed over ground, course over ground and the fishing gear of vessels is available, among other. An example of vessel trajectories can be seen in Fig. 20. Having new data on fishing vessel activities will drastically improve the training of the models and give a new perspective to the problem at hand. The work will be divided into a development phase and an evaluation phase where the models will evaluated and tested with the dataset provided by the Portuguese Navy. Various evaluation metrics will be used to assess the accuracy and precision of the models as well as precision matrices to visualize the performance of the classification and prediction.

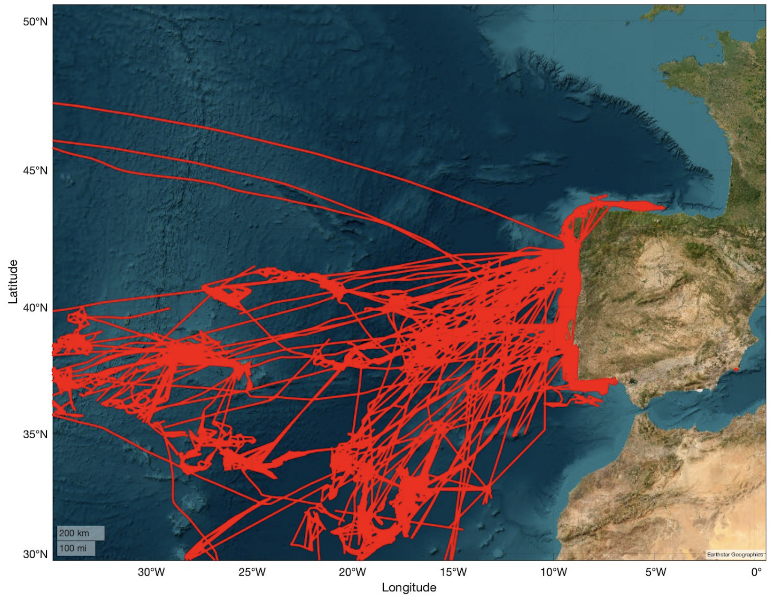


**Figure 20:** Example of vessel trajectories collected January 2022.

# 5 Work Schedule

In this section, the work schedule is proposed for the development of the thesis. This schedule is divided into four phases.
The first phase consists of the pre-processing of the various new VMS datasets supplied by the Portuguese Navy.
In the next phase, the development of both models for the classification and prediction of fishing activities will take place.
Then the testing and evaluation of these models will be carried out, testing different scenarios and utilizing various metrics.
Finally, the end of this development phase will be consolidated in the writing of the thesis, which will address the results obtained, discussions about them, and possible future work. This schedule, Fig. 21, outlines a structured and progressive path towards the successful completion of this thesis, contributing to the advancement of knowledge in the classification of fishing activities based on machine and deep learning techniques.

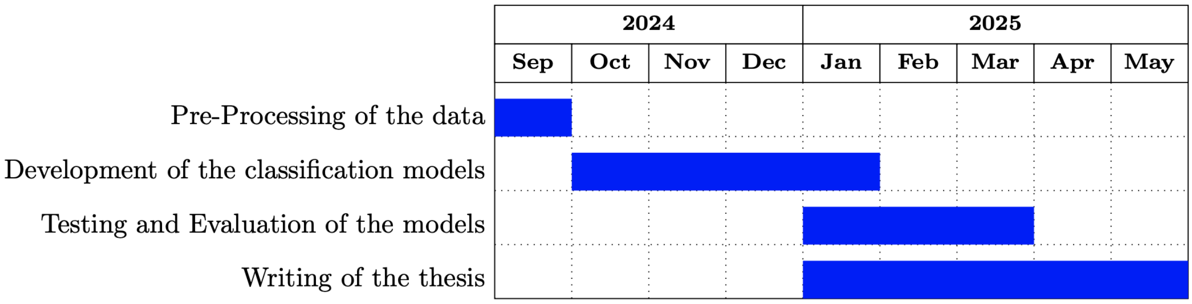


**Figure 21:** Work Schedule for the Thesis

# 6 Conclusion

Illegal, Unreported and Unregulated (IUU) fishing has a big impact on the longevity of maritime resources and the sustainability of fishing activities. Some efforts have been made by world authorities to combat this attack on the fishing market and marine life such as the implementation of vessel monitoring systems. Fishing vessels are required to communicate their location, speed, and course at certain intervals to Center Fisheries Control and Monitoring Centers (CVVP).
With the intention of addressing this big problem that is IUU fishing, the main goal of this thesis is to develop two models, one to classify fishing gears and another to predict fishing activity, to ultimately help authorities monitor this fishing activity along the south coast of Portugal. Two deep learning algorithms will be applied, a CNN and an LSTM-FCN which have been proven to have a good performance at the classification of fishing activities from AIS and VMS data. Both these classification models will be trained and tested with a dataset provided by the Portuguese Navy collected from several vessels across Portuguese waters. Throughout this research, we will describe the development of these models and the choices and variations made to implement them, from the training phase all the way to the evaluation phase. Finally, this study will assess the viability and success of the developed work.

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