A Hybrid Model for Detection and Classification of Fishing Activity: A Context-Based Approach

1st Pablo Rangel
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
pablo.rangel@marinha.mil.br

2nd Vinícius Maravalhas de Abreu Nunes
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
viniciusmaravalhas@hotmail.com

3rd Matheus da Rocha Salazar
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
matheussalazar78@gmail.com

4th Reinaldo Albuquerque Simões
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
reinaldo.ab00@gmail.com

5th Luiza Morgado de Castro Rosa
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
luizamorgg@gmail.com

6th José Gomes de Carvalho Júnior
Digital Systems Group
Brazilian Navy Research Institute
Rio de Janeiro, Brazil
junior.carvalho@marinha.mil.br

***Abstract*—Fishing activity matters to the entire world because it affects the economy, ecosystems, and human sustainability. Detecting and classifying fishing activity is a challenge that has been the focus of some studies over the years, but many of them are limited to using solutions without considering context information. These works show solid classification results but are limited to the classification task only. In general, most of them assume a fishing activity is in progress. Hence, these works have not explored the potential of false fishing detections, leading to misclassifications and forcing the fitting of detections into one type of fishing technique. Our hypothesis is that geographic context information can improve the detection of fishing activity and the classification of different types of fishing. Therefore, individual and collective information were extracted from a public labeled database used in related works. Individual information is the kinematics of each vessel, while collective information is the geographic fishing areas. The model adopts a stacking ensemble strategy, with the first level being a kinematic classifier and the second level a correlation model with geographic context. The solution presented effectively fills the identified gaps and demonstrates robust results.**

***Index Terms*—Fishing activity, Detection, Classification, DBSCAN, CNN, Fuzzy Logic**

I. Introduction

Fishing activity is an important part of human culture. It supports millions who rely on the sea for their livelihoods. Fishing activity also has a profound effect on marine ecosystems and the worldwide economy [1]. Due to these concerns, the International Maritime Organization (IMO) requires some fishing vessels to install fully operational Automatic Identification System (AIS) equipment. This equipment sends information collaboratively, allowing the monitoring of fishing activity. The transmitted data includes kinematics, activity status, destination, vessel type, country, and other useful information. However, there are many problems with the reliability of AIS data. For instance, vessels engaged in illegal activities, such as predatory fishing, often disable AIS or transmit false information.

The literature has highlighted the necessity of methods based on kinematic behavior [2]–[4], regardless of collaborative information. Some studies have experimented with different techniques for the classification of each fishing method [5]. However, the adoption of different approaches carries the inherent limitation of requiring prior information, resulting in a loss of generality as a consequence.

Although kinematic data alone may produce good results for detection and classification tasks, our hypothesis is that using context-based will improve accuracy values. This process of combination is the key of the fusion process in the higher layers of the JDL model [6]–[9]. Several studies in the literature have incorporated collaborative information (such as vessel type and size) into the context-based fusion process. However, this information is not reliable as we previously explained.

This work aims to provide a context-based approach that operates independently of collaborative information. It achieves this by combining kinematic data from a sensor (e.g., radar) with geographic and temporal context information. The proposed approach involves a detection and classification process based on position and speed, enabling the analysis of trajectory behavior and correlating it with fishing spots extracted from a historical and labeled database. The model adopts a hybrid architecture, with each process employing a specific technique. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was chosen to extract fishing spots, while a Convolutional Neural Network (CNN) was utilized for classification based on a trajectory represented as an image. Additionally, Fuzzy Logic (FL) was employed to combine the CNN output with the output of DBSCAN (fishing spots). The results are presented in comparison with recent studies that have utilized the same database and criteria.

The following sections present the domain characterization,

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our objectives and hypotheses, related works, the methodology adopted, the results obtained, and our conclusions and future work.

II. Domain definition

Fishing activity involves several methods based on the targeted species and the vessel's size, load capability, and technologies. It operates under restrictions and regulations concerning environmental protection and commercial interests.

There are many methods for fishing. However, due to limitation of labeled data available, this work focuses on four types of methods [10]: fixed gear, drifting longline, purse seine and trawl.

All methods are characterized by the shape of the trajectory and the sequence and variation of speeds, indicating two phases of fishing activity: setting and hauling. In the setting phase, the gear is deployed according to the desired amount of fishes and technique used. In the hauling phase, the vessel's crew retrieves the deployed gear while managing the caught fishes.

Drifting longline fishing is a method that consists of a main line up to a hundred kilometers long, with hooks attached at regular intervals [11]. This technique, also classified as an angling technique, can be applied to pelagic or demersal fishing. Generally, vessels performing this type of fishing follow straight trajectories, varying speeds according to the phase. In the setting phase, a vessel navigates at speeds between 9.5 knots and 11 knots, while in the hauling phase, the vessel maintains an average speed of 6 knots.

Purse seine fishing is a method that involves using a surrounding net to capture a school of fish by encircling them from the bottom up to the surface [10]. The vessel deploys the net in a circular trajectory at a high speed, typically averaging around 10 knots, to ensure the capture of as many fish many as possible. The radius of the trajectory may increase according to size and load capability of the vessel. During the hauling phase, which usually takes several hours, the vessel stays stationary. Sensors typically indicate low speeds (2 knots or less) during this phase.

Another type of fishing is called trawling, which involves dragging one or more nets to capture fish while a vessel is in motion. This method can be practiced either at the surface (pelagic) or depth (demersal). A vessel engaged in trawling maintains a constant speed, typically lasting from 2 to 5 knots. The duration of trawling periods can vary widely (3 to 5 hours), depending on the vessel's capabilities and the expected amount of fish captured [12]. In this case, considering our definition, we consider only the hauling phase.

The last type of fishing is called fixed gear. Unlike the previously mentioned methods, which are classified as mobile gear fishing, fixed gear methods involve the use of stationary equipment, such as traps. One example of a fixed gear method similar to those in the mobile gear category is longline fishing. The main difference lies in the use of gear as traps. After hours or even days, fishing vessels return to retrieve the fishes caught with the trap [10].

III. Objective and hypotheses

Our goal is to provide a model capable of detecting whether a vessel is engaged in fishing activity and, if so, classifying the specific method being applied.

Mapping the kinematic behavior of each fishing method is an important aspect of our detection and classification approach. As previously explained, each type of fishing method has its own pattern of speed and course in setting and hauling phases, which requires a rigorous process of data filtering. Our premise is based on the ability to provide distinctive information to our image-based model by creating colored segmented lines of the trajectory according to speed intervals. To perform this image classification, we employed a Convolutional Neural Network (CNN) on images representing kinematics behavior, with distinct colors representing phases of fishing activity.

However, we believe that this alone is not sufficient to avoid false positives, especially because we are attempting to perform detection and classification at two levels of granularity: determining whether a vessel is engaged in fishing activity and, if so, identifying the specific method being used. The domain of vessels not engaged in fishing activity is larger than the opposite case, presenting a significant challenge. The inherent imbalance in data and the possibility of non-fishing vessels with similar kinematic behavior to fishing vessels, make classification difficult and increase the likelihood of false positives.

This hypothetical scenario leads us to consider a hybrid model, fusing the output of image classification with context-based information, such as distance from vessel to typical regions of certain fishing methods. Therefore, an important aspect is to understand the intrinsic agglutination of fishing vessels according to targeted species. Species vary from place to place, influenced by local marine ecology conditions [13]. Regulations dictate that fishing methods should be chosen to minimize harm to the environment and other marine species. Even so, it is possible to detect a vessel engaged in illegal activity using prohibited fishing methods.

This is the reason to believe that we can observe the clustering of vessels engaged in a specific fishing method in particular spots, regardless regulations or laws. Identifying these fishing spots may be useful to increase the accuracy of the model after the kinematic classification. This work considers the actual data rather than static regions of fishing under any formal regulation.

We used DBSCAN algorithm to identify fishing spots for each fishing method explored in this work. We presuppose that, as non-supervised clustering algorithm, DBSCAN is capable of creating groups based on the density of vessels in regions for each fishing method.

Finally, we used FL to fuse image classification output with the fishing spots. The idea consists of expressing, in vague terms, the intuitive concept that as a vessel gets closer to a certain type of fishing spot, the likelihood of performing a specific fishing method should be higher.

IV. Related works

Some works also base their hypotheses on the usage of kinematic data as the solution of the reliable identification of fishing activity.

A study conducted by de Souza et al. [5] uses different techniques for three types of fishing methods: longline, purse seine and trawl. The authors proposed a Hidden Markov Model (HMM) to deal with trawler vessels. The classification process for longliner vessels uses Lavielle's segmentation algorithm, while for purse seiners, it uses a filter based on speed and time. The authors claim that the variability of fishing pattern is too complex to adopt just one solution. The limitation of their study refers to the necessity of knowing the gear type. Our proposition does not require this information in advance, besides being capable of detecting the fishing activity and classify the fishing method.

A well-known fishing activity dataset is provided by Global Fishing Wath (GFW) [14]. They have also published a model capable of classifying fishing activity considering four fishing methods, based on kinematic behavior. Using a CNN model, the results serve as a baseline for many works for comparisons purposes. For instance, the study by Arastesh et al. [2], presents a framework called "FishNET" as a possible solution for detection and classification of fishing activity. The authors propose a different architecture of CNN to perform trajectory classification. They offer a direct comparison to the study by GFW [14], showing better results for some metrics. We understand that these works fit into a possible discussion on the merit of our paper. We take a different approach by representing vessel trajectories as images. We create images highlighting the variation of speed through colors, a similar approach taken by [15]. In addition to the application of CNN and images representing speed variation and its fishing phase like these works, we propose a context-based information fusion, using both temporal and geographic context. Thus, all results will be compared to them.

A study published by Mujtaba and Mahapatra [16] used a Long Short-Term Memory (LSTM) model, based on kinematic data associated with a timestamp, to create a predictive model for fishing activity, without providing classification of the fishing method itself. However, this work shares the same idea of using geographic and temporal context for the decision-making process.

Recasens et al. [4] created a dataset of fishing activity by combining AIS data with fishing reports and environmental data. Recently, Thakrar and Gonsai [17] presented a fishing dataset also combining different sources, using a similar approach. In these works, the combination of these data sources served as inspiration to incorporate fishing spots datasets as complementary information in our model. As we will explain later, we extract hot spots of each fishing method from the fishing dataset, using the geographic context to improve our model's capability.

Chen et al. [3] extracted fishing spots using Kernel Density Estimation (KDE) and Hot Spot Analysis (HSA). The authors used Gaussian Mixture Model (GMM) and Expectation Maximization (EM) to identify fishing activity behaviors, with speed as key aspect of fishing activity characterization. Their work differs from ours, as we use the fishing spots as complementary information to classify fishing activity. In contrast, the main objective of these authors is to detect fishing activity previously within these spots and compare it to current regulations. The area covered is limited and fishing methods are restricted to gillnet and trawling. Another work with the same objective is seen in [18].

A hybrid model combing FL and other techniques related to this subject was the work of Sylaios, Koutroumanidis and Tsikliras [19]. They present a model to classify fishing areas. We were not able to find a related work using FL with the same the objective as our work.

None of these works use metrics considering imbalanced data. In addition to classical metrics (Accuracy, Precision, Recall and F1-Score), we also provide results using the Matthews Correlation Coefficient (MCC). This is important, as noted by [20], when the classifier needs to deal with a different number of samples per class, which is the case with GFW dataset.

V. Methodology

This work adopts a comparison method to demonstrates its contribution to the data fusion field and practical application. It is challenging to produce a fair comparison without the use of the same datasets. Thus, we created a model and chose to evaluate our results considering only works that used the same dataset. The decision to use only one dataset provider limits the coverage of all fishing methods, as it is confined to what was recorded and verified (labeled).

In this context, all results will be presented in comparison to the results presented in [14] and [2], because the former is the dataset provider and the latter provides a recent comparison for the same data source.

To encourage continuous evolution in addressing this problem, we have made all scripts for generating or converting datasets, as well as the codes to reproduce our results, available at: https://github.com/pablorangel82/detecting-and-classifying-fishing-activity/releases/tag/v1.0.0-fusion2024.

A. *Workflow Description*

This model employs various techniques to address the hypotheses presented in earlier sections. It is structured into two stages: Stage 1 and Stage 2 (Fig 1).

For Stage 1, during the training phase, the model is divided into two parallel approaches:

1) The individual approach focuses on each vessel's data and includes the following steps:
    a) Each pattern is formed by a temporal sequence of measurement points of a vessel (position and speed) labeled with the same label;
    b) Each pattern is converted into an image by connecting points of the trajectory with lines of different

colors corresponding to the speed of the starting point of the line;

c) The pattern set is divided into three sets: two for training (train set and validation set) and one for testing to evaluate the model;

d) A Convolutional Neural Network (CNN) model is trained using the training set and validation set to classify each sequence of points into five classes (classes include ”not fishing” and the four types of fishing method;

e) A final model for the CNN classifier is obtained;

2) The collective approach considers the entire vessel’s data and involves the following steps:

a) All positions and labels of the dataset are considered without vessel identification;

b) Fishing spots are clustered using DBSCAN;

c) Fishing spots are made with convex hull calculation;

d) A database of fishing spots is constructed.

During the testing phase, each pattern of the test set, represented by images, is presented to the CNN classifier to obtain the probability of belonging to each class (fishing method). Simultaneously, they are provided to a module for evaluating the distance of the image to the nearest fishing spot. The two variables obtained in Stage 1 — probability and distance — are the inputs for Stage 2, which makes the final classification considering the geographic context.

B. Conversion of Kinematic to Image (Trajectory Behavior)

Our model was built and tested using the dataset provided from Global Fishing Watch (GFW) [21], as other works have done. The dataset provided is a vast collection of kinematic data from numerous vessels, acquired from AIS sensors and labeled based on community validation. Each row of the dataset provides an average score indicating fishing activity, ranging from 0 to 1. A value of 0 indicates that the vessel is definitely not fishing. while a value of 1 indicates 100% certainty of fishing activity. This work uses only rows with labels defined as 0 or 1; other values were discarded.

GFW datasets are separated by fishing method, each containing kinematic data. The kinematic data serve as the basis for generating images representing kinematic behavior and fishing spots. Our solution creates images folders, one per fishing method, considering the label *is_fishing* with value of 1. All other rows in all files with value of 0 go to a single folder called ”not fishing”.

An image converter was developed to transform kinematic data into a 256 x 256 image, representing trajectory composed of line segments with colors representing different ranges of speed. Fig. 2 shows an example of an image created with these colors associated with speed ranges.

After generating images, a splitting process was performed to create three datasets. We split 70% of the generated images into one dataset for training, 15% into one dataset for validation, and 15% into one testing dataset.

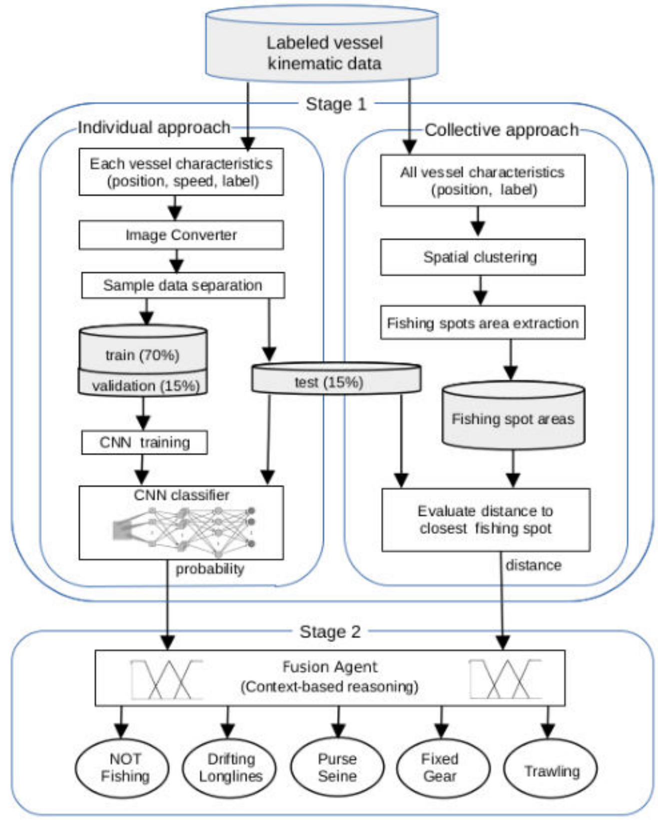

Fig. 1. Workflow process.

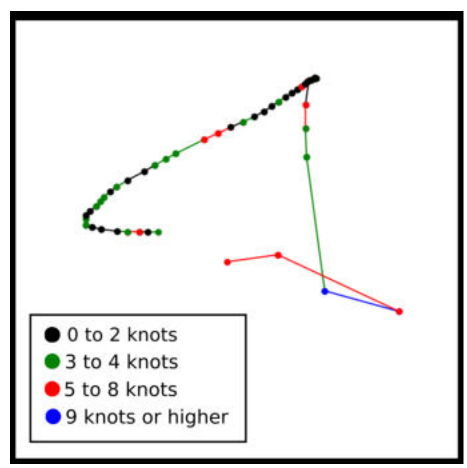

Fig. 2. Image representing a kinematic behavior of a fishing vessel.

The available dataset is imbalanced, particularly concerning the amount of data for purse seine and fixed gear methods. Therefore, an augmentation process was performed by transforming each original image into three additional images rotated 90 degrees successively. While the dataset remains imbalanced, the augmentation process helps decrease the difference in data distribution. The datasets sizes are shown in Table: I.

TABLE I
IMAGE DATASETS

Fishing Method	Number of files				
	Train	***Validation***	***Test***	***Total***	***Percentage***
Drifting longline	1415	304	302	2021	12%
Fixed Gear	2481	532	531	3544	20%
Purse seine	625	134	133	892	5%
Trawl	2625	563	562	3750	21%
Not Fishing	5072	1089	1802	7243	42%

It is important to highlight that the reliability of kinematic data from AIS is not crucial for the model conception in this particular case, as the values were validated. Our criticism about models using AIS data is related to the usage of complementary data, such as vessel type or size, as being feasible information in a decision-make process. Our model does not dependable of secondary AIS information. Kinematic data can be provided from other sensors, such as radars. Thus, the usage of AIS data for training the model and discover of fishing spots is not a problem, as the kinematic GFW dataset is reliable and validated by community.

C. Fishing spots creation process

The same labeled GFW datasets [21] served as the basis for creating fishing spots dataset. Each entry was considered individually, regardless of belonging to the same vessel. We were confident that the agglutination process would not be affected, because the distance between these points was not enough to create another spot.

Hence, DBSCAN algorithm was used to create clusters considering the density of vessels in the geographic places. Only kinematics with the *is_fishing* attribute and a value of 1 were considered.

TABLE II
FISHING SPOT DATASET

Fishing Method	***Total***	***Percentage***
Drifting longline	110	59%
Fixed Gear	19	10%
Purse Seine	27	15%
Trawler	30	16%

An additional conversion was necessary, involving the creation of polygons based on the clusters formed. To perform this task, we calculated the convex hull for each cluster, representing for each one, the smallest polygon possible for it.

A new dataset containing fishing spots was saved in a single file, containing the geographical position of the centroid, the geographic position of the farthest vessel considered in this area (*max_distance*) and the label related to the fishing method. To keep the calculation simple, the *max_distance* is considered as the radius of the fishing spot. Therefore, all fishing spots are considered as circles.

D. Trajectory (image) classifier

The image classifier operates two times within the entire model. In the training process, image datasets for training and validation were presented to a CNN with layered architecture.

The CNN has an input layer which is capable of reading images with dimensions of 256x256 pixels. Convolutional processes are carried out in 4 layers, each with 2 dimensions. The number of filters increases exponentially, starting with 32 and ending with 512. All convolutional layers have a kernel size of 3x3 and stride defined as 1. All layers have the ”ReLU” activation function.

The CNN architecture ends with two fully connected layers, each with 1024 neurons. The output layer has five neurons, each representing one class. The activation function for this layer is ”softmax”, in order to normalize the output to a probability distribution over the fishing classes.

We use stochastic gradient descent (Adam’s version) with default parameters and a learning rate, along with the categorical cross-entropy loss function, to train the network.

The CNN model was executed over 10 epochs, saving the best weights obtained through the iterations.

E. Fuzzy Engine

An important premise adopted in this work concerns combining two values as input to the Fuzzy Inference Engine. The first value considered is the probability calculated by the CNN in image-based trajectory classification.

To convert this value into fuzzy sets, we created a fuzzy variable called ”probability” (p), with three immutable sets. These sets are defined with the same domain of probability varying from 0 to 1, but divided according to linguistic concepts (”low”, ”medium” and ”high”). The fuzzy variable ”probability” is defined as follows:

$$low(p) = \begin{cases} 1, & \text{if } 0 \leq p < 0.1 \\ -3.333p + 1.333, & \text{if } 0.1 \leq p < 0.4 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$average(p) = \begin{cases} 3.333p - 1, & \text{if } 0.3 \leq p < 0.6 \\ -3.333p + 3, & \text{if } 0.6 \leq p < 0.9 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$high(p) = \begin{cases} 10p - 8, & \text{if } 0.8 \leq p < 0.9 \\ 1, & \text{if } p \geq 0.9 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The second value refers to the distance of the closest fishing spot associated with the fishing method and its probability input.

In our model, the distance (d) value (measured in meters) is the input for the fuzzy variable ”proximity”. The sets of this variable are interactively defined during the test/classification process, adapted according to the closest fishing spot identified. Fuzzy sets are defined in terms of the radius length defined with a percentage. Thus, considering *r* as the radius

(r) of a fishing spot, we have these sets of the fuzzy variable ”proximity”:

$$close(d) = \begin{cases} 1, & \text{if } 0 \leq d < 0.05r \\ -20d + 2, & \text{if } 0.05r \leq d < 0.1r \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$medium(d) = \begin{cases} 4.4d - 0.2, & \text{if } 0.05r \leq d < 0.275r \\ -4.4d + 2.2, & \text{if } 0.275r \leq d < 0.5r \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

$$far(d) = \begin{cases} 5.714d - 2.428, & \text{if } 0.42r \leq d < 0.6r \\ 1, & \text{if } d \geq 0.6r \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

The output fuzzy variable has three sets (”low”, ”average” and ”high”) defined statically. It shares the same domain as the fuzzy variable ”probability”.

The combination of input variables and output variable produces 9 rules. These rules are designed to reinforce the image classification result to the same class of the closest fishing spot. The idea is that the closer a vessel is to the predicted fishing spot, the more reliable the decision. This work adopts Mamdani Inference. The rules are described as follows in table III.

TABLE III
FUZZY RULES

Rule	***Proximity***	***Probability***	***Conclusion***
1	Close	Low	Average
2	Close	Average	High
3	Close	High	High
4	Medium	Low	Low
5	Medium	Average	Average
6	Medium	High	High
7	Far	Low	Low
8	Far	Average	Low
9	Far	High	Average

F. Fusion Agent

The *Fusion Agent* is responsible for managing the results obtained with CNN, initiating the Fuzzy Inference, obtaining the result and making the final decision about the classification process. The image classification process involves the primary detection of fishing activity. The simple fact that there is a class representing vessels not performing fishing activity allows, by implication, to predict if a vessel is engaged in fishing activity or not.

Therefore, the *Fusion Agent* process does not uses FL when the fishing method predicted by CNN is ”Not Fishing”. Otherwise, the *Fusion Agent* selects the highest probability and its associated fishing method predicted by CNN, initiating a deeper investigation about the confidence of the result. To do so, the *Fusion Agent* examines all fishing spots correlated to the suspected fishing method, identifying the closest spot.

As mentioned earlier, fishing spots are represented as circles. The radius of the closest fishing spot serves as the basis for the fuzzy variable domain of ”proximity”. The *Fusion Agent* calculates the distance to the centroid of selected fishing spot. Both the radius and the distance to the centroid of the fishing spot serve as inputs to the Fuzzy Inference Engine.

Considering the fishing method (K), vessel image trajectory (i), the set of predictions calculated by CNN (Pr_V) and the Fuzzy inference result (F_K), the final decision for vessel behavior classification (C_i) is made as follows:

$$C_i = max(F_K, max(Pr_V)) \quad (7)$$

G. Evaluation Metrics

The subject of this paper is a classic multi-class classification problem. The evaluation occurs through the creation of a confusion matrix, allowing the adoption of classical evaluation metrics, such as precision and F1-Score. For multi-class classification problems, we must consider *K* representing an index for a specific class, *i* the current row and *j* the current column in confusion matrix table. Thus, true positives (*TP*), true negatives (*TN*), false positives (*FP*) and false negatives (*FN*) are calculated as:

$$TP_K = C_{ii} \quad (8)$$

$$TN_K = \sum_{i \neq K} \sum_{j \neq K} C_{ij} \quad (9)$$

$$FP_K = \sum_{i \neq K} C_{iK} \quad (10)$$

$$FN_K = \sum_{j \neq K} C_{Kj} \quad (11)$$

As usual in works with classification as the main subject, we will present the results obtained considering classical metrics (Accuracy, Precision, Recall and F1-Score):

$$Accuracy_K = \frac{TP_K + TN_K}{TP_K + FP_K + FN_K + TN_K} \quad (12)$$

$$Precision_K = \frac{TP_K}{TP_K + FP_K} \quad (13)$$

$$Recall_K = \frac{TP_K}{TP_K + FN_K} \quad (14)$$

$$F1 - Score_K = 2 * \frac{Precision_K * Recall_K}{Precision_K + Recall_K} \quad (15)$$

However, as explained before, the image dataset is imbalanced, as there is significant difference between the number of samples for each class. The authors C. Davided and J. Giuseppe [20] claim that classical metrics may offer a biased vision of the results, potentially leading to wrong conclusions. These authors demonstrate an alternative to provide fair evaluations even when the model deals with imbalanced datasets.

Their work analyzes the Matthew Correlation Coefficient (MCC) along with Accuracy and F1-Score metrics, showing significant reasons to calculate MCC as an additional metric.

The MCC metric ranges from -1 to 1. A value close to 1 indicates perfect agreement between expected and recognized outcomes, a value close to 0 indicates results no better than random choice, and a value close to -1 indicates complete disagreement between expected and predicted.

MCC metric was designed primarily to binary classifications. However, MCC can be extended to multi-class classification evaluations [22]. The MCC equation applied in multi-class classification problem is described as:

$$MCC = \frac{\sum_{k=1}^{K} T_k \times C_k - \sum_{i=1}^{K} \sum_{j=1}^{K} T_i \times C_j}{\sqrt{\left(\sum_{k=1}^{K} T_k \times P_k\right) \times \left(\sum_{k=1}^{K} T_k \times N_k\right)}} \quad (16)$$

In this equation:

- K is the number of classes
- T_K is the number of true positives for class K
- C_K is the number of true negatives for class K
- P_K is the number of predictions for class K
- N_K is total number of non-predictions for class K

VI. Results

As we previously contextualized in the "Related Works" section and explained in the "Methodology" section, our model uses the same dataset as these works [2], [14]. The study published by [2] will be cited as "FishNET". The work published by [14] will be cited as "GFW". In this context, our results are shown in comparison to those, considering the precision to 2 decimal places. The values obtained by them are shown in tables IV and V. Our work is cited as "Hybrid Model".

TABLE IV
GFW Metric results [14]

Method/Metric	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Longline	92	94	91	93
Purse seine	78	81	95	79
Fixed gear	95	88	97	90
Trawler	98	94	96	96

TABLE V
FishNET Metric results [2]

Method/Metric	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Longline	92.63	92.23	91.78	92
Purse seine	97.58	96.21	95.34	95.77
Fixed gear	97.62	97.35	97.36	97.35
Trawler	98.27	96.13	95.18	95.65

First of all, we present our results in the confusion matrix (Table VI), in case there is a need for additional metric calculation or even for reproduction or comparison purposes. In this table, the first column represents what is expected as the prediction (E), while the first row represents what is actually predicted (P).

TABLE VI
Confusion Matrix

E/P	*Ll*	*FG*	*NF*	*PS*	*Tl*
Longline (Ll)	293	0	8	0	1
Fixed Gear (FG)	1	500	23	0	7
Not Fishing (NF)	30	8	1036	1	7
Purse Seine (PS)	0	5	22	106	0
Trawlers (Tl)	1	7	12	0	542

As seen in the Table VII, the results obtained are considered solid. Results are marked with two symbols "+" (better) or "-" (worse). The first symbol indicates the result compared to GFW. The second one indicates the comparison with FishNET result. All fishing methods have high accuracy, better than what was observed in GFW and FishNET results. We credit this to our choice to enhance characteristics of trajectory behavior with colors according to speed range.

TABLE VII
Our Metric results

Method/Metric	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Longline	98.43 (++)	90.15 (–)	97.02 (++)	93.46 (++)
Purse seine	98.93 (++)	99.07 (++)	79.70 (–)	88.34 (+-)
Fixed gear	98.05 (++)	96.15 (+-)	94.16 (–)	95.15 (+-)
Trawler	98.66 (++)	97.31 (++)	96.44 (++)	96.87 (++)
Not Fishing	95.75	94.10	95.75	94.92

When comparing our results to those of GFW, we observe even better precision values, except for longline fishing method, where GFW achieved a better result. Specifically, the precision values obtained for purse seine, fixed gear and trawlers show a difference of 18.07, 8.15 and 3.31 percentage points higher, respectively. In this case, we credit these high values to the fusion process, considering fishing spots and possible distance to them as valuable assets in decision-making process. When we compare to FishNET results, there is a tie. Our model has better results of precision for purse seine and trawler, while FishNET has better results for longline and fixed gear methods.

Our model demonstrates better recall values for two fishing methods comparing to GFW and FishNET: longline and trawler. Both precision and recall values are influenced by the smaller number of fishing spots extracted for fixed gear and even more for purse seine. The augmentation process was applied solely to kinematic data to generate trajectory behavior images. The augmentation would not bring more spots to balance the dataset. To improve these results, more data from additional locations are necessary.

Our results show better F1-Score for all fishing methods compared to GFW results. When compared to FishNET, our results are worse for purse seine and fixed gear. The result obtained for fixed gear is close, but there is notable difference for purse seine. Once more, we credit this to the smaller number of samples of purse seine fishing spots.

It is important to note that there are no results in the GFW and FishNET works regarding the detection of vessels not engaged in fishing activity. Therefore, it remains important to highlight the results obtained with our model: all values are higher than 94%.

We present our overall results (micro average) compared to FishNET overall results (Table VIII). We were not able to see overall results from the GFW work.

TABLE VIII
OVERALL METRIC RESULTS [2]

Reference/Metric	***Accuracy***	***Precision***	***Recall***	***F1-Score***
Hybrid Model	97.96	94.90	94.90	94.90
FishNET	93.63	93.14	92.78	92.35

The overall results with our model are better in all metrics than FishNET. The MCC result corroborates the model's success. The MCC value obtained was 0.93, which means that the model correctly performs in classification process, even with imbalanced datasets.

VII. Conclusion and Future Works

The results presented are solid and practical application is feasible.

To our knowledge, we have not been able to identify any work using exactly the same approach, especially with the application of FL. The idea of colors representing a range of speed gives to CNN distinguished characteristics for the learning process without the necessity of complex pre-filtering algorithms. Furthermore, we were not able to find any results in related literature using the MCC metric. This makes it difficult to perform a fair comparison on imbalanced datasets. This disparity in the number of samples for fishing methods is reflected not only in the amount of images representing trajectory behavior, but also in the number of fishing spots. Nevertheless, the comparison of overall results and the MCC obtained confirms our hypotheses.

Our contributions extend beyond providing a feasible model for practical objectives. They also broaden the perspective on the approach of hybrid models and how to fuse different outputs to achieve solid results.

The improvement of the model is directly correlated with the improvement of the dataset. This is because the fusion process utilizes the geographic context associated with fishing spots discovered in the earliest stages.To enhance the performance of our model, especially in increasing the metric values for non-fishing activity, we could consider utilizing a dataset adopted by Pedroche et al [23].

We intend to extend our study to include the detection of predatory fishing. Our results take into account the possibility of vessels not engaged in fishing activity, which is beneficial for reducing false positives in real-world scenarios. However, there are still tasks to be completed. We plan to conduct a specific study on the Brazilian coast, fusing data from satellite images, radars, AIS, pre-defined fishing areas and regulations/laws. This model will be further improved to incorporate additional features based on the data sources.

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