

# Detecting Illegal Fishing with Automatic Identification Systems and Machine Learning

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# Stakeholders



**Sponsor: GA-CCRI**

- **Tara Valladares**
- **Rebecca DeSipio**



**Mentor: Heman Shakeri**



# Introduction

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# Illegal, Unreported, and Unregulated (IUU) Fishing

- Widely defined – fishing outside of local or international regulations
- Critical issue impacting health of marine ecosystem and global security
- Estimated to cost \$10-23 billion annually



# Automatic Identification Systems (AIS)

- Standardized tracking systems outfitted on all vessels
- Continuously transmits user data
- Utilized for maritime monitoring and collision avoidance
- Very available and easy to obtain

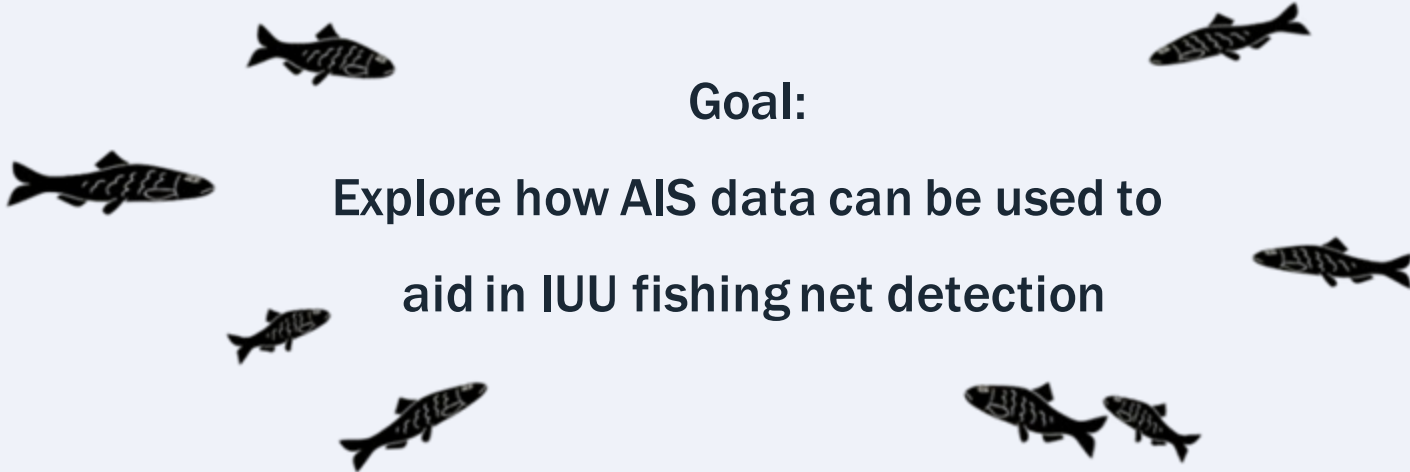


# Motivation

- AIS devices are commonly illegally exploited on fishing nets and buoys to protect large hauls
- Increased need to reform AIS regulations

Goal:

Explore how AIS data can be used to  
aid in IUU fishing net detection



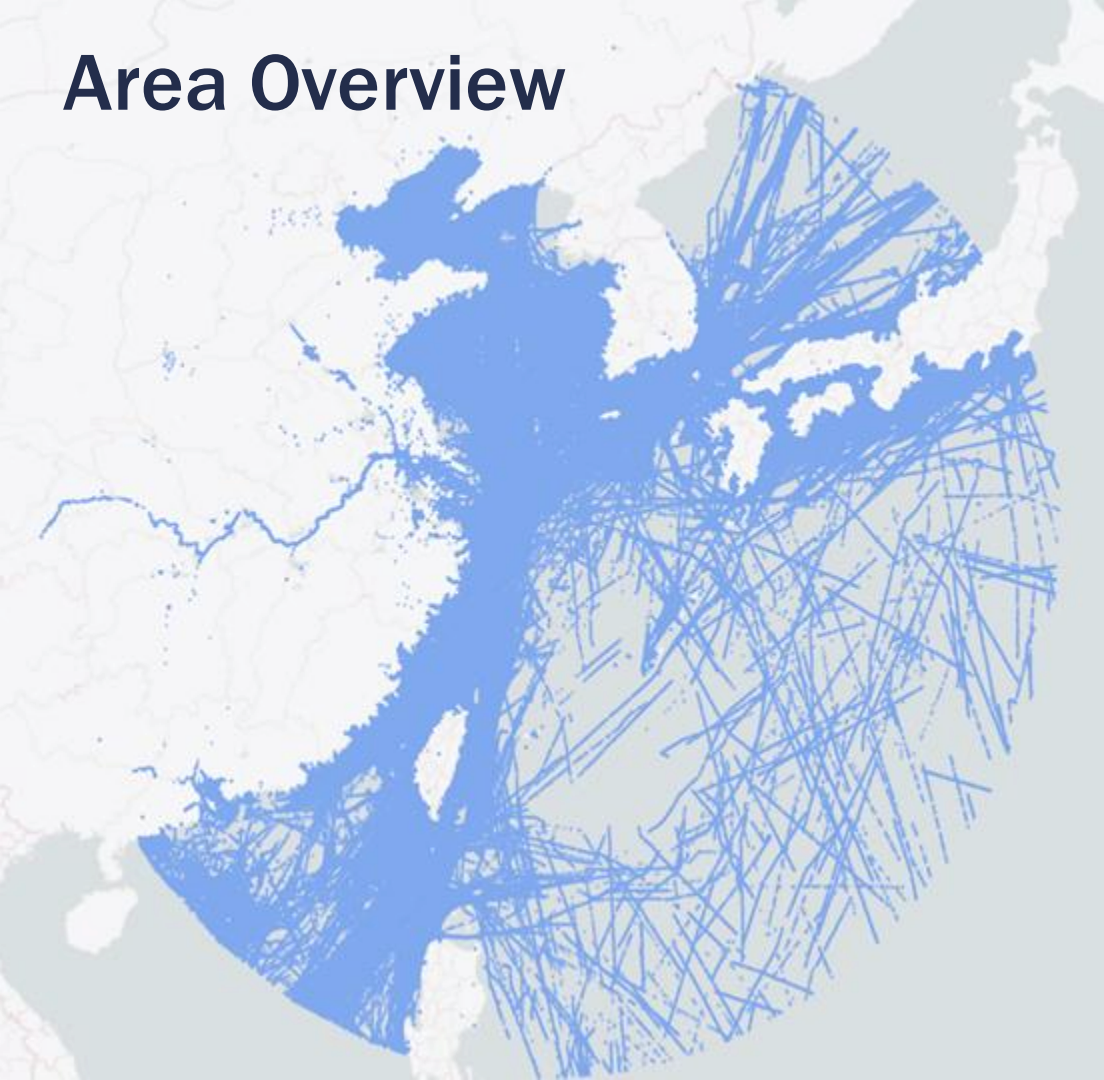
# Data

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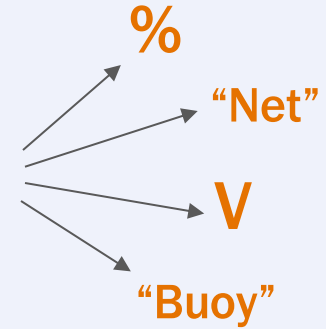
# Area Overview



- **Region of interest:**
  - Southeast Asia
- **Spatial, temporal, and user inputted data**
- **Training set**
  - Around 4 days
  - September 1→5 2023
- **Test set**
  - Around 4 days
  - October 12→16 2023

# Assumptions and Limitations

- Certain naming or positional conventions are suggestive of fishing nets
- Computational limitations led to restricted region of interest and timeframe



# Methodology

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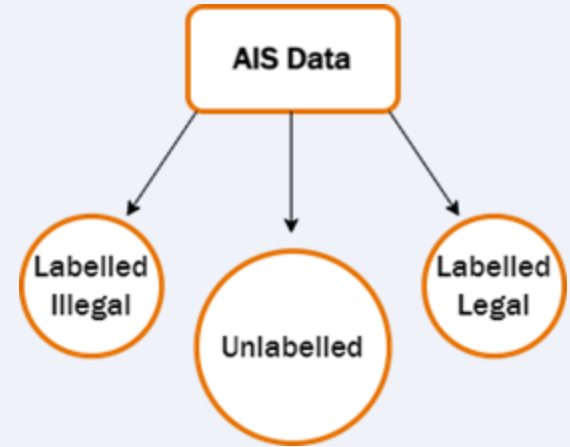
# Pre-Processing

- Aggregate data by distinct device 'trips'
  - Unbroken period of AIS transmission
  - Included scaled parameters for speed, heading, and positioning
- **Red flag**: Indicators of non-standard naming conventions and movement
  - Score from 0→4
  - Used for modelling analysis

<i>net_name</i>	Names including a 'V', '%', 'buoy', or 'net'
<i>mmsi_length</i>	MMSI values not equal to 9 digits
<i>spawn_offshore</i>	Vessels whose first transmission is offshore (1 nautical mile off coastline)
<i>spoof</i>	Devices with unreasonably high calculated speeds ( $\geq 150$ knots)

# Pseudo-Labeling

- AIS dataset is unlabelled
  - Select models utilized pseudo-labels for training
- Pseudo-labelled confident points based on 'red flag' conditions
  - Illegal: Bad *net\_name* and  $\geq 3$  total red flags
  - Legal: No red flags



# Approaches

## 1. Unsupervised clustering

- Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN)

## 2. Semi-supervised classification

- eXtreme Gradient Boosted trees (XGBoost) and Artificial Neural Network (ANN)

## 3. Supervised classification

- ANN

# Models



# Unsupervised Clustering

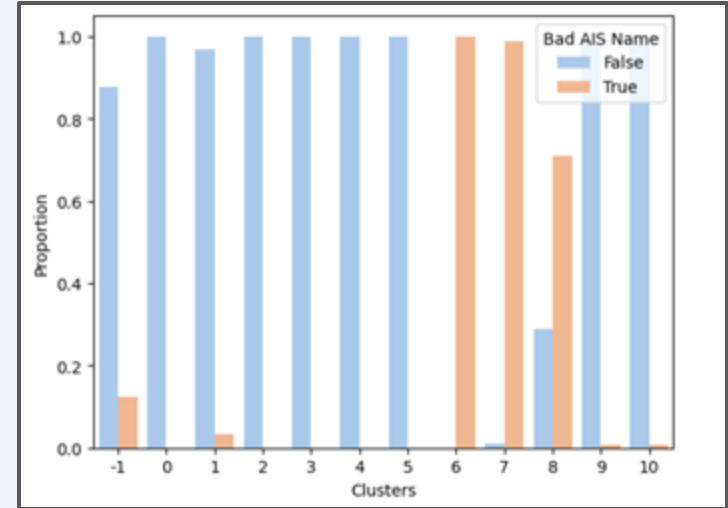
- Treats dataset as truly unlabelled
- Clustering with HDBSCAN
  - 2 clustering iterations
- After first round new score is built:
  - Aggregates mean red flag score of each cluster onto respective observations



# Unsupervised Clustering Results

- 3 primary clusters identified
  - Reflect 36.2% of total trips in dataset
  - Includes 1% of observations with valid *net\_name*
- The developed features may be valid indicators of IUU activity that cannot be detected with naming conventions alone

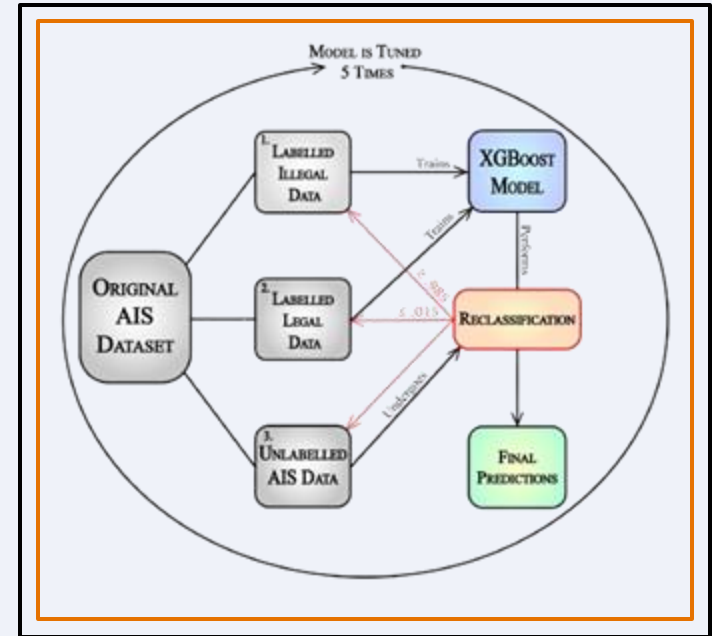
*Cluster Results Analyzed by net\_name*



# Semi-Supervised Classification

- Small set of confident pseudo-labelled points, other points are left unlabelled
- Model trained on sample of labelled AIS data
- Iteratively classifies unlabelled dataset if confident and retrains on updated labelled dataset

*Workflow for XGBoost & ANN*



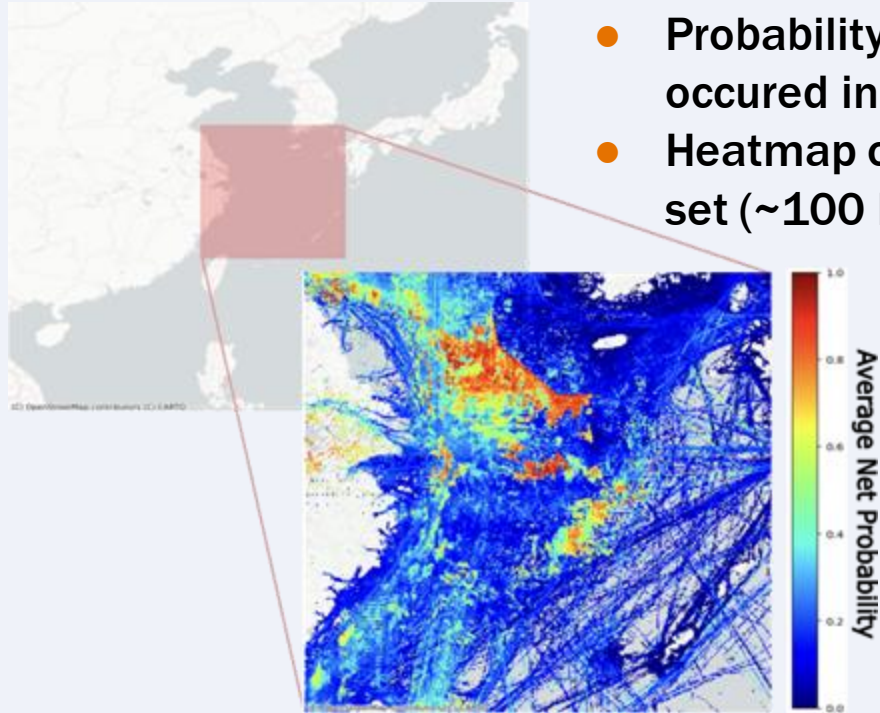
# Supervised Classification with ANN



- Uses pseudo-labelled training data once to build model
- Simple ANN predicts binary classification for each AIS trip
  - Same 4-layer ANN framework used for both semi and fully supervised models



# Semi-Supervised and Supervised Classification Results



- Probability of 1 indicates illegal likely to have occurred in region
- Heatmap of XGBoost prediction results on test set (~100 hours)

Model	Test Accuracy	TPR	TNR
** Semi-supervised XGBoost	0.891	0.915	0.848
Semi-supervised ANN	0.879	0.900	0.842
Supervised ANN	0.867	0.907	0.801

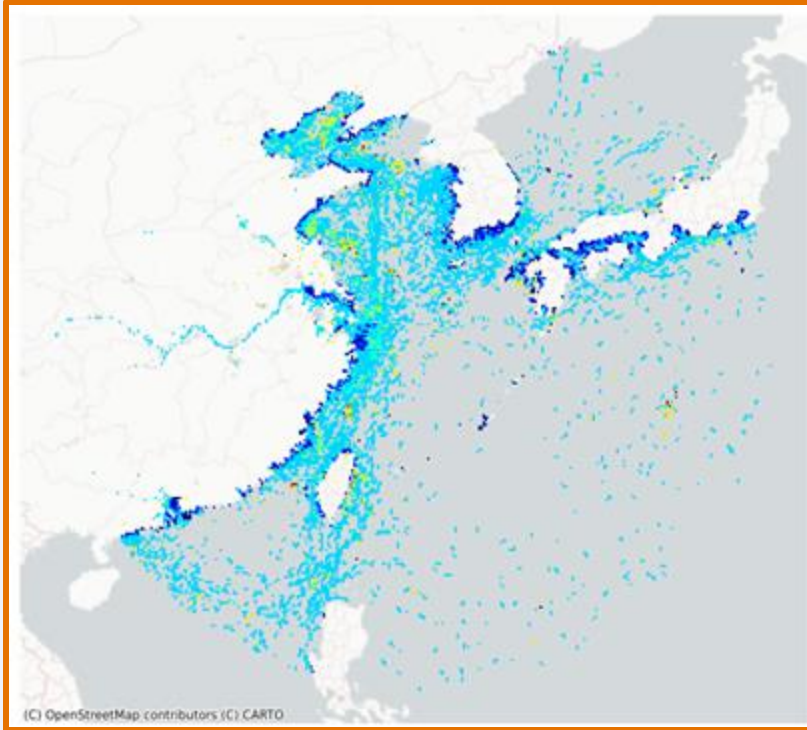
\*\*XGBoost model was the top performer with test set

# Regional Analysis

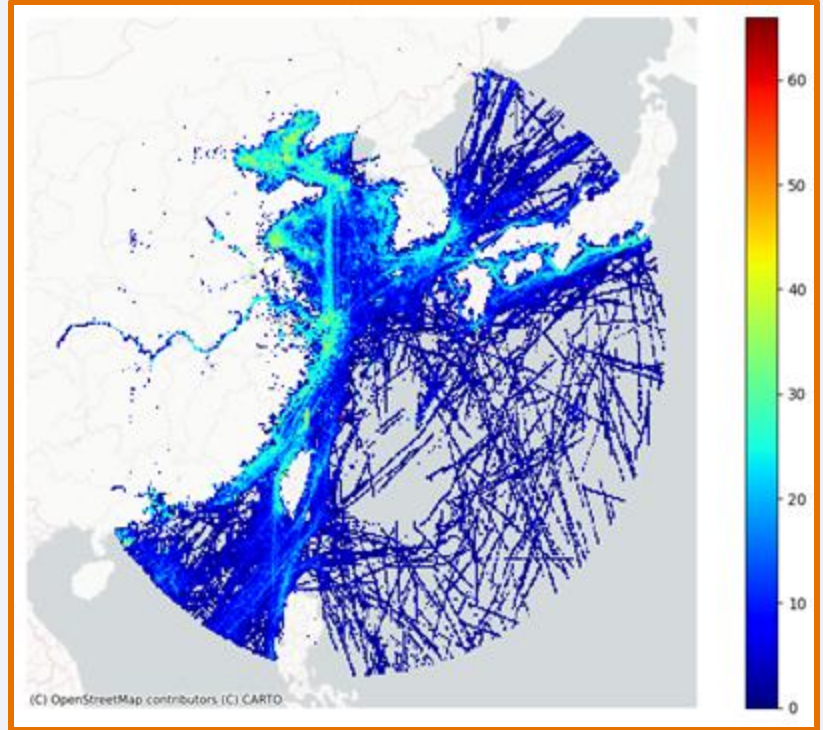
- Divided region into  $.1^{\circ} \times .1^{\circ}$  cells
  - 36 mi<sup>2</sup>
- ***hot\_score***: number of unique red flags divided by count of unique vessels
- Position each AIS signal within its corresponding grid cell
- Calculate total number of 'red flags' per unique vessel for each cell
  - Aggregate each hours' score per cell to see which areas showed most signs of illegal activity per day

# Regional Analysis Visual Results

*September 1st, 1 hour*



*September 1st, 24 hours*



# Acknowledgements

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# Capstone Team

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 Danielle Katz

 Dana Korotovskikh

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