A Game-Theoretic Federated Learning Approach for Ship Detection from Aerial Images

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***Abstract*—Detection and monitoring of ships in the images captured from satellites or aerial vehicles is a pivotal task in maritime security applications. Recent advancements in aerial communication and computer vision has enabled real-time collection of such images as well as development of robust and precise models for ship detection. However, conventional machine learning (ML) based models are prone to security and privacy issues as the real-time data captured through aerial imagery may be exposed during transfer or after storage in the cloud server. Furthermore, real-time decision making is a challenging task with conventional ML models due to the latency incurred while transmitting large amount of data from maritime aerial network to the cloud. To address the privacy and latency challenges, we propose a privacy-preserving *game-theory based federated learning approach* for ship detection in aerial images from maritime network. FL improves privacy by allowing raw data to reside at the edges/clients, and game theory helps in optimizing the parameter updates that are sent to the centralized server. Evaluation results prove the efficacy of the proposed model with a prediction accuracy of 96.01%, 92.96% reduction in time complexity and also 8.28% reduction in communication overhead.**

***Index Terms*—Aerial Communication, Federated Learning, Game Theory, Ship Detection.**

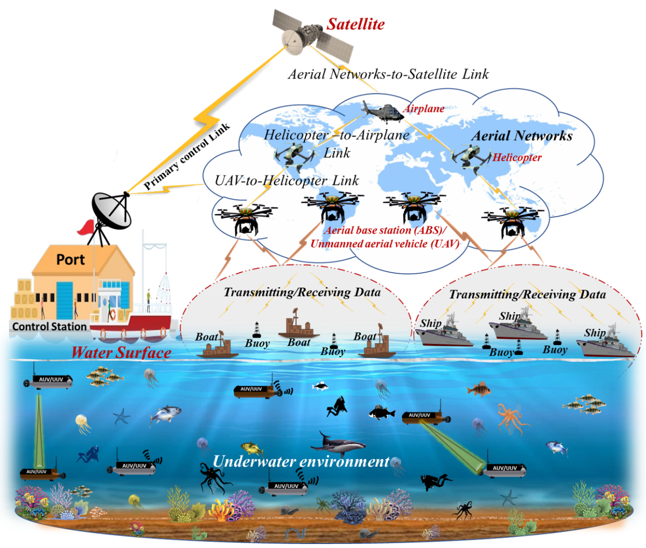

Fig. 1: Maritime monitoring communication network that uses images captured from satellites and aerial vehicles to detect ships.

I. Introduction

Detection and monitoring of ship's location and their movement is a critical task for maritime security applications. However, about 71% of the Earth's surface is covered with water, and oceans hold about 96.5% of all water[1]. It would be challenging to monitor such large areas using ground-based sensors and human analysis. *Automated Identification Systems* (AIS) can be employed to monitor marine traffic, aid in navigation, and promote safety and security by exchanging location and status messages between ships and shore stations [1]. However, AIS is often unavailable due to security and privacy concerns, malfunction, or even for malicious purposes. Then, detecting ships without AIS becomes a significant challenge.

Recent advancements in aerial platforms such as unmanned aerial vehicles (UAV) enable them to be installed with cameras, sensors, and long-range data communication capabilities so that they can be utilized for various real-time monitoring applications including disaster prevention, defense, and marine monitoring [2]–[4]. Aerial monitoring provides more coverage, both in terms of communication and sensing, when compared to their terrestrial counterparts. When an aerial platform is unavailable at the region of interest, satellites can be used for the same purpose. Nevertheless, as satellite communication has high latency and prone to signal interference, integration of satellites and aerial platforms have been investigated [5]. Hence, an automated ship detection system using the images captured from satellites or aerial vehicles can be used for maritime traffic surveillance.

Fig. 1 depicts the proposed maritime monitoring architecture. The marine network is linked with underwater networks, terrestrial networks, and aerial networks. The main task is

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[1] *'How Much Water is There on Earth?'*, https://www.usgs.gov/special-topics/water-science-school/science/how-much-water-there-earth

to monitor the ships on the water surface via the images captured by the aerial nodes. Aerial network components such as aerial base stations (ABS), UAVs, and helicopters establish line-of-sight (LoS) connections to capture the images of the ships. In addition, the aerial network components can act as the intermediate relay to transfer information to the satellites as well as to terrestrial networks. Furthermore, the control station can monitor and control all activities captured by aerial networks and satellite communication.

Despite the monitoring capability of maritime network, detecting ships from the aerial images is quite challenging due to the different sizes, orientation and aspect ratios of the images captured. To overcome this challenge, several machine learning (ML) models have been proposed for ship detection in aerial images [6]. However, sending raw image data over the network to a central server for training the model can lead to several challenges including data privacy, security, high latency, low response times and communication overheads.

Out of all these challenges, privacy is a significant concern that need to be addressed due to the sensitive nature of the data captured. Such data, if fallen into the hands of the malicious users, can lead to serious consequences. Anonymization techniques can be employed for preserving the privacy of the data. However, there is always a trade-off between privacy and accuracy. Federated Learning (FL) is an advancement in ML that helps in training a global model without requiring the raw data to be sent to a central location [7]–[10]. This helps in training the model without having to compromise neither the privacy nor the accuracy of the results. However, as all the local parameter updates are to be sent back to the server, communication overhead is still a burden on the FL-based systems. To overcome this challenge, *game theoretic* (GT) approach can be employed in such scenarios for identifying the optimal updates to be sent to the server [11].

To this end, we propose a *game-theory based FL* (GT-FL) approach for detecting ships from images captured through aerial nodes. Instead of sending all the parameter updates to the global model, this approach calculates the payoff of each client and sends the updates of only the clients with a good payoff. This system incentivizes clients to collaborate and share information, rather than working in isolation. This can lead to faster convergence and provide more accurate results when compared to standard FL algorithms.

The contributions of this work are highlighted as follows:

- Design a federated learning (FL) model that detects ships accurately from aerial images. Privacy is preserved through the inherent characteristics of FL that allows the global model to be trained without requiring the raw data to be sent to a central location.
- Propose a game-theoretic (GT) approach on FL to reduce the communication overhead of transmitting client updates to the central server.
- Evaluate the proposed GT-FL approach to show that the accuracy is improved significantly, while the communication cost and time complexity is decreased when compared to the state-of-the-art ML and FL models.

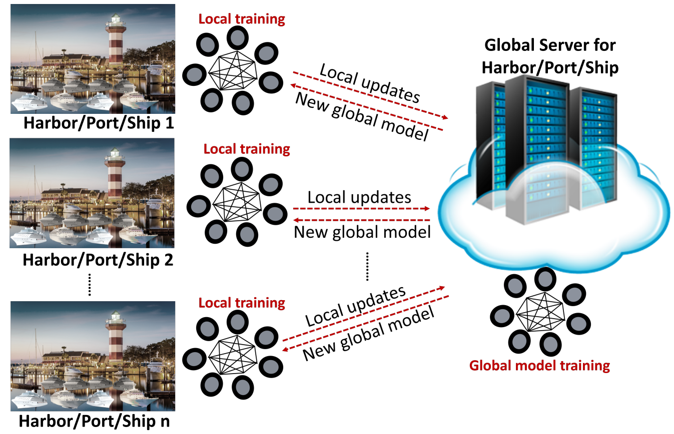


Fig. 2: Conventional federated learning approach for ship detection

The rest of the paper is organized as follows. We first discuss the recent works in FL and Game theory in §II, and describe our proposed methodology in §III. We present our evaluation results in §IV, and conclude the work in §V.

II. Background and Related Work

In marine networks, automated ship detection techniques are important for tracking illegal activities such as piracy attacks, illegal fishing, and logistical data monitoring. Machine-learning approaches are widely used for this purpose [12]. However, most of the prior work have risks of privacy attacks against ships in marine networks.

For example, convolutional neural networks (CNNs) have been successful in detecting ships in marine networks [13]–[16]. In [13], the authors propose a rotational Libra R-CNN method that tracks the exact location with rotational angle data to remove the unwanted background and detect densely distributed ships in marine networks. In [14], the author amended the R-CNN approach to faster R-CNN based on constant false-alarm rate (CFAR) algorithm to enhance the recognition of small ships in marine networks. In [17], the authors utilize synthetic aperture radar (SAR) imagery for detecting ships. In [18], the authors propose a one-stage ship detector to solve the noisy and high interference issues in the existing SAR imagery approach. In [19], the authors propose a ship detection technique among the massive SAR imagery utilizing CenterNet. In this approach, the center point of the object is targeted, which is more effective and has high accuracy in detecting the ships in marine networks. Even though machine-learning techniques have produced promising results in ship tracking and detection, privacy and security issues are still a concern, especially in the case of leakage of sensitive data about the ships such as location, cargo information, and schedules.

Another problem of traditional machine-learning approach is that it requires a large communication overhead for transmitting raw data from an edge device to a central server. Federated learning (FL) is the technique that emanated to support privacy in terrestrial wireless communication [20]. Fig. 2 depicts the basic FL approach for detecting ships. The system works as follows. Initially, the central system builds a global model and broadcasts it to every participating edge node or client. The clients train the model using the data at their end. Once the training is complete, the local parameter updates are sent back to the central system. The parameters are then aggregated and the global model is updated at the centralized server. The updated global model will be then sent to all the clients. Using this mechanism, the model can be trained with the actual data, even without sharing any data with third parties. Such a system can ensure privacy that is required in mission-critical systems designed for the naval authorities.

As an example, in [21], the general idea behind FL in terrestrial wireless communication is expounded. The study in [22] discussed the FL techniques for aerial access networks (AAN); its challenges, applications, and future direction connected with the areal communication networks. In [23], the authors proposed a FL adapted model for multi-unmanned aerial vehicle (M-UAV). In this approach, the UAVs collect the images and train the model locally before sending them to the ground fusion center (GFC) via wireless communication. The study in [24] presented the taxonomy and future directions to blockchain-based aerial networks linked to Beyond 5G network (B5G). This work shows a gap analysis and provides a solution to B5G network connection in aerial communication. Another work in [25] proposed UAV-based air quality sensing using the FL approach. In this work, a lightweight dense-MobileNet model and the hazel images captured by UAVs are utilized to form energy-efficient end-to-end learning in aerial networks.

The previously mentioned works have proved to be effective in classification of ships from aerial images. However, they use ML and DL algorithms where the data needs to be sent to the central server. This is a time consuming process, and there is a chance of privacy breach. To address these issues, we proposed a FL-based method for real-time detection of the ships without compromising the privacy. Furthermore, game theory provides a method to analyze the behavior of the participants in the FL process and helps to identify strategies that can lead to better outcomes for all parties involved. In a FL setting, participants may have different incentives and objectives, and game theory can help to identify the optimal strategy for each participant to achieve their objectives while still contributing to the collective goal of training a high-quality model. To this end, this work is an implementation of FL using game theory. The objective is to train a model using multiple clients and calculate each client's payoff based on their accuracy on the test set.

III. Proposed Design

This section provides the design of the proposed game-theoretic approach-based on federated learning methodology for detecting ships in aerial images. We also describe the dataset used for training our model.

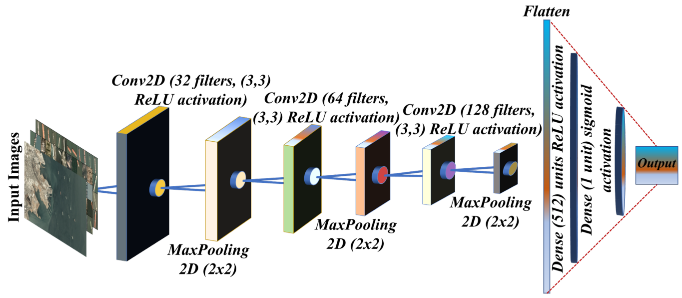


Fig. 3: Our CNN model architecture for GT-FL based ship detection.

TABLE I: Constants used in FL implementation

Variable	Constant
Number of Clients	10
Number of epochs	10
Batch size	32
Learning rate	0.1

A. Proposed GT-FL methodology

As per our knowledge, the GT-FL approach using a convolutional neural network (CNN) to detect ships is the first of its kind. Fig. 3 is the pictorial representation of our proposed CNN architecture:

1) The first three layers are convolutional layers with 32, 64, and 128 filters respectively, where each filter has a size of 3x3. The activation function used is ReLU. The input shape is (150,150,3) which means the input images are 150x150 pixels with 3 color channels.
2) The next three layers are max pooling layers with a pool size of 2x2. This is used to downsample the feature maps produced by the convolutional layers and reduce the dimension of the data.
3) The next layer is a flatten layer which flattens the output of the previous layer into a 1D array.
4) The next layer is a fully connected layer with 512 neurons and ReLU activation function.
5) The final layer is a fully connected layer with 2 neurons and sigmoid activation function. This is the output layer of the network and is used for binary classification tasks.

Our model takes in training and test data, the number of clients, the number of epochs, batch size, and learning rate as inputs [26]. Table I gives the details of the constants that are used in our implementation.

It then creates a list of client models, with each model being a CNN with three convolutional layers, followed by two fully connected layers. The models are then trained on their respective local ship datasets for the given number of epochs. The function then calculates the accuracy and payoff for each client, updates their model based on their payoff, and aggregates the updated models to form the new global model. Finally, the global model is evaluated on the testing data. The Eq. (1) shows how the payoff is calculated.

$$payoff = client\_accuracy - mean(client\_accuracies) \quad (1)$$

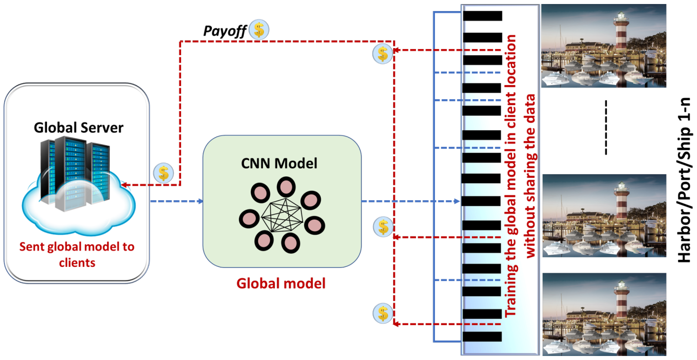


Fig. 4: Illustration of the proposed GT-FL approach

Here, *client_accuracy* is the accuracy of a particular client model on the test set, and *mean(client_accuracies)* is the mean accuracy of all client models on the test set. The equation calculates the difference between the accuracy of a particular client model and the mean accuracy of all the client models. The resulting value is the payoff of the client model, which can be positive, negative, or zero. If a client's model has higher accuracy than the average accuracy of all client models, then its payoff will be positive, which indicates that the client has made a positive contribution to the global model. Conversely, if a client's model has lower accuracy than the average accuracy, then its payoff will be negative, indicating that the client has made a negative contribution to the global model. Fig. 4 illustrates the overall architecture of the proposed GT-FL algorithm.

In addition, the time complexity and communication cost of the GT-FL model are calculated, and the results are compared with the existing FL mechanism. Time complexity measures the computational effort required by the GT-FL algorithm. In our model, the time complexity is calculated by measuring the elapsed time between the start and end of each client training process. The total time complexity is measured by calculating the sum of the time taken by each client to complete their training. In GT-FL, communication cost represents the amount of data transferred during the GT-FL learning process. In our approach, the communication cost is estimated by calculating the size of the weights of each layer in the client's model. The communication cost is measured in terms of the number of bits transmitted in each round; i.e., the size of the weights of each layer in the client's model.

Alg. 1 gives the step-by-step procedure of the proposed system. By incorporating game-theoretic principles, the FL algorithm incentivizes clients to collaborate and share information rather than working in isolation. This can lead to faster convergence and higher accuracy compared to standard FL algorithms. Finally, our implementation of the proposed GT-FL model for ship detection is publicly available online as open source[2] for interested researchers.

[2]https://github.com/supriyayj/Federated-Learning-game-theory/blob/main/ship-aerial-game-theory-federated-learning

Algorithm 1: Proposed FL-based Ship Detection Alg.

```
Input: Training data D, number of clients N, number of rounds T
Output: Global model M
Initialize global model M_0;
for t = 1 to T do
    for i = 1 to N do
        Initialize client model M_i with M_{t-1};
        Select subset of data D_i ⊂ D;
        Train client model M_i on D_i;
        Evaluate client model M_i on holdout set H_i;
        Compute payoff π_i;
        Update client model M_i based on π_i;
    end
    Aggregate client models to form new global model M_t;
    Evaluate new global model M_t on holdout set H;
end
```

Fig. 5: Samples of aerial imagery from the *Ship-detection dataset*

B. Dataset

Ship-detection dataset[3] is an open collection of images that have been labeled to identify the presence or absence of ships. There are a total of 621 images in the dataset that are of different sizes, aspect ratios, and orientations. Fig. 5 displays a collection of sample images extracted from the dataset. The dataset is primarily intended for use in object detection tasks, where the goal is to detect the presence of ships and localize them by drawing bounding boxes around them. It can be used for training and evaluating machine learning models, particularly deep learning models [27], for ship detection.

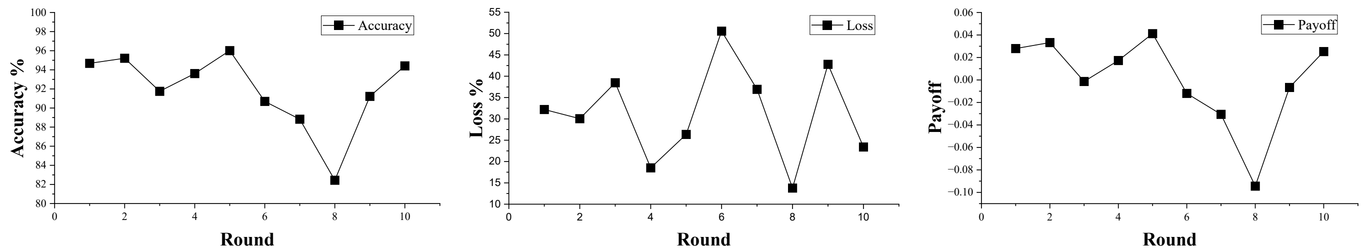
Note that the images are collected from different sources, including satellites, drones, and aircrafts, but all from an elevated position, whereas terrestrial images of ships are captured from a horizontal perspective, usually from the ground or a lower vantage point. Aerial images of ships often capture a larger area. Terrestrial images of ships, on the other hand, typically focus on individual ships or smaller groups of ships within a closer proximity. These characteristics of images pose distinct challenges and require different learning models for detecting ships, which we propose in this work.

IV. Evaluation Results and Analysis

The proposed system implements a game-theoretic FL approach using CNN to improve the performance of the FL model. The experiment was conducted based on the *aerial images of ships dataset* that is fed into the GT-FL model.

By tracking the loss and accuracy within the model, we can assess how well our model is learning and improving over time. The prediction correctness of our model is about

[3]https://www.kaggle.com/datasets/andrewmvd/ship-detection



(a) Accuracy of ship detection **(b)** Loss within the learning model **(c)** Best client payoff value for each round

Fig. 6: Accuracy, loss, and payoff of the proposed GT-FL model

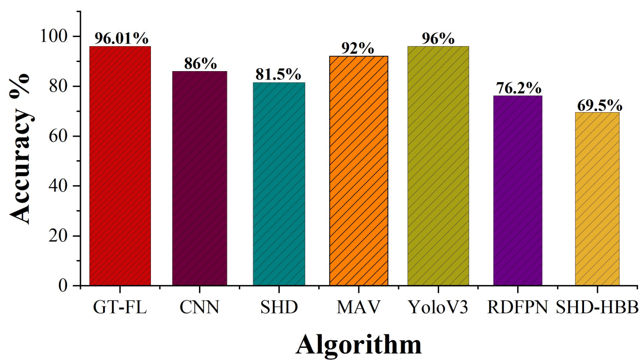


Fig. 7: Performance comparison of GT-FL with other models

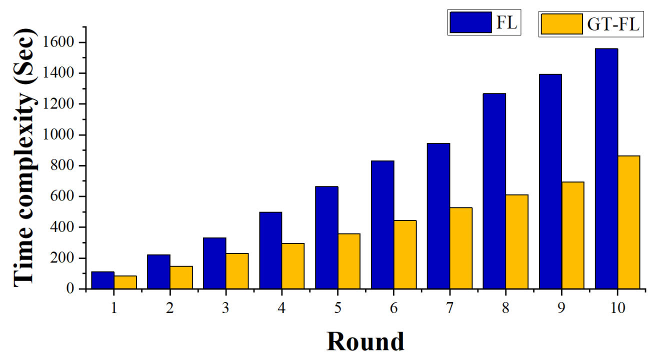


Fig. 8: Time complexity comparison of FL vs GT-FL

96.01% (Fig. 6a), which indicate that the model has achieved a high level of accuracy in detecting the ships. The loss value of 26% (Fig. 6b) represents the average discrepancy between the predicted and true values, indicating that the model's predictions have some level of error.

The client's accuracy is calculated on the test set and their payoff based on their accuracy. The payoff for each client is plotted in Fig. 6c. The client payoff provides a measure of how well a client is performing relative to other clients. Positive payoff indicates that the client's model is performing better than the average, while negative payoff suggests that the client's model is underperforming compared to the average. In the game-theoretic federated learning, clients with positive payoff receive more weight during the aggregation of model updates, thereby influencing the global model more. On the other hand, clients with negative payoff may have less impact on the global model. Specifically, clients with higher payoffs are given a higher probability of being selected to participate in future rounds of training. The GT-FL approach goes a step further that encourage participants to contribute more effectively thereby enhancing the overall performance of the model when compared to the regular FL approach. According to Fig. 6c which plots the payoff of the clients, when the client payoff is good and positive (at around 0.26), the GT-FL model accuracy is 96.01%.

To evaluate the accuracy of the proposed model, we compare it with the recent state-of-the-art algorithms in prior works. These include the work in [28] which proposes a CNN model to classify ships and achieve an accuracy of 86%. YOLOv3 model has been suggested in [29] for effective ship detection from satellite images. The authors in [30] propose automated ship detection and category recognition from high-resolution aerial images. The SLC-HRoI Detection (SHD) model showed an accuracy of 81.5 % while the Rotation Dense Feature Pyramid Network (RDFPN) and Sequence Local Context-HRol Detection (SHD-HBB) had an accuracy of 76.2% and 69.5% respectively. The work in [31] used micro aerial vehicle (MAV) for the same purpose. Fig. 7 plots the comparison result. It can be observed that the proposed model has highest performance.

The time complexity and communication cost of our proposed GT-FL model are compared with the time complexity and communication cost of FL mechanism, and the results are displayed in Fig. 8 and Table II. The comparison result shows that the computational effort required for the GT-FL model is less compared to the FL mechanism. Finally, the total time complexity requires for the GT-FL approach is 4,051.87 seconds when compare to FL approach which is 7818.873 seconds. And, the communication cost of GT-FL is 4,254,364,760 bits which is less when compared to the communication cost of the FL mechanism which is 4,606,777,840 bits. The proposed model proves that the GT-FL approach is effective with a detection accuracy of 96.01% when compared to other models such as CNN, SHD, YoloV3, etc. Furthermore, the proposed GT-FL proves that its communication cost and time complexity is much more lesser than the regular FL approach.

TABLE II: Communication cost of GT-FL and FL in each round

Round	GT-FL (in bits)	FL (in bits)
1	76,136,708	76,138,760
2	152,273,416	152,277,520
3	228,410,124	228,416,280
4	304,546,832	304,555,040
5	380,683,540	380,693,800
6	456,820,248	456,832,560
7	532,956,956	532,971,320
8	609,093,664	609,110,080
9	685,230,372	685,248,840
10	761,367,080	761,387,600
Total cost	**4,254,364,760**	**4,606,777,840**

V. Conclusion

This work proposed a model for real-time detection of ships in aerial images without exposing sensitive information of the ships. A federated learning approach is used to preserve the privacy of the data collected as well as to reduce latency of data transfer. Furthermore, game theory is integrated with federated learning to reduce the number of clients considered for aggregating the weights in the federated learning process. Evaluation results show that the proposed approach outperforms the state-of-the-art approaches in terms of detection accuracy with reduced overhead and complexity. In our future work, we aim to further enhance the privacy of the proposed approach by utilizing differential privacy mechanisms, and also improve the ship detection accuracy beyond 96.01%.

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