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Advancing Maritime Surveillance: Multi-Layer Perceptron Models for Enhanced Vessel Detection from SAR Imagery

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Abstract: This paper presents a novel approach to enhancing maritime surveillance through advanced object detection in Synthetic Aperture Radar (SAR) imagery, focusing on the identification of small vessels. Addressing the challenge of detecting minute objects in high-resolution images, the study introduces a simple yet effective model that integrates traditional image processing techniques with innovative methodologies. Utilizing a Multilayer Perceptron (MLP) model implemented in Python, the research offers a detailed comparison with existing techniques, showcasing improved detection and classification capabilities. The novelty lies in integrating advanced preprocessing methods with sophisticated feature extraction via GLCM, enhancing the MLP's input for more accurate detection. This work promises improvements in computational efficiency without sacrificing accuracy, potentially setting a new benchmark for real-time maritime surveillance systems. This paper includes a comprehensive review of related works, a mathematical framework for the proposed model, and experimental results that demonstrate its effectiveness in various image resolutions and types, contributing significantly to the field of maritime surveillance and SAR image analysis.
Keywords: Maritime Surveillance; Object Detection; Synthetic Aperture Radar (SAR) Imaging; Small Vessel Identification; Multilayer Perceptron (MLP); Image Processing Techniques; Python Implementation

1. INTRODUCTION

In recent research, maritime surveillance has emerged as a critical area, with image processing and object detection playing key roles. These technologies are not only pivotal in maritime environments but have widespread applications in various fields, including engineering and medical imaging. Object detection is particularly crucial for effective artificial intelligence and computer vision systems, aiding in handling the vast amounts of visual data encountered in everyday life. The challenge in maritime surveillance, especially in Synthetic Aperture Radar (SAR) imagery, is the detection of small vessels. This task is made more challenging by the small size of these objects relative to the image scale and the high-resolution nature of SAR images. Despite advancements in imaging technology, the precise identification of such small targets remains a daunting task. In SAR imagery, large vessels are easily identifiable, but the finer details of smaller vessels often elude detection, leading to significant gaps in surveillance capabilities. Addressing this issue requires advancements in image processing techniques. Traditional methods such as inverse contrast, distance mapping, and edge detection have been employed, but they often fall short in the complex scenario of SAR imaging. A typical SAR image of ships at sea is depicted in Figure 1.

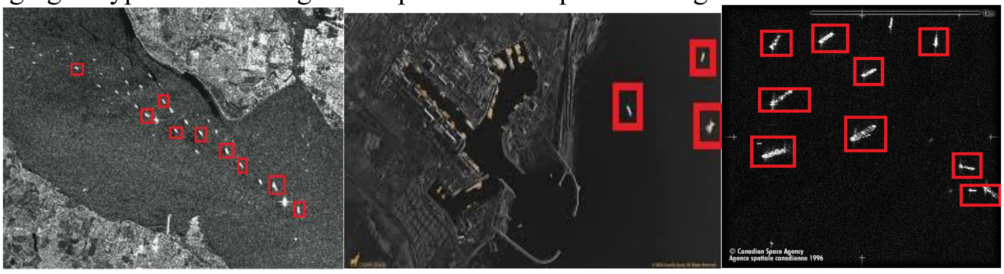

Figure 1. SAR images of vessels at sea

The need for vessel identification at sea is crucial for several reasons, including ensuring maritime security, managing traffic in busy sea routes, facilitating search and rescue operations, and monitoring fishing activities to prevent overfishing and protect marine reserves. It also plays a key role in environmental protection by tracking vessels for potential illegal dumping and pollution. Accurate vessel identification helps in enforcing maritime laws and treaties, and aids in the efficient operation of global trade by tracking cargo ships.

Machine learning models significantly enhance vessel detection at sea by providing automated, accurate, and fast identification of ships. These models can process vast amounts of data from sensors and satellite images to detect vessels, classify their types, and predict their trajectories. They are essential for maritime surveillance, traffic control, and search and rescue operations, reducing the need for manual monitoring and enabling quicker response times. By learning from historical data, machine learning models continually improve, becoming more reliable and efficient in various conditions and scenarios at sea.

Detecting vessels from SAR imagery presents challenges such as speckle noise, which can mask or resemble vessels, and variable sea states that create clutter indistinguishable from ships. Variable imaging conditions and low contrast against the sea further complicate detection efforts. Additionally, dense maritime traffic areas pose a challenge in isolating individual vessels, making the task of automated detection systems more complex. The proposed model in this paper seeks to bridge this gap by introducing a hybrid optimization approach, enhancing the detectability and classification of small maritime objects in SAR images. This hybrid model represents a significant advancement in object detection methodologies, combining traditional techniques with innovative optimization strategies. The paper is structured to first provide a comprehensive review of existing object detection techniques in Section II. Section III formulates the problem statement. Section IV introduces the mathematical framework of the proposed model. The final section presents experimental results, offering a comparative analysis with existing classification models with recent benchmark methods. Through this detailed exploration, the paper aims to contribute significantly to the field of object detection in maritime surveillance, addressing a critical need in the classification and analysis of SAR images for enhanced maritime security and operational effectiveness.

2. RELATED WORK

A number of literature works are present related to utilization of machine learning and deep learning models for vessel segmentation. An exhaustive survey of literature of recent methods has been presented in this section. Authors in [1] review on ship localization, classification, and detection methods using optical sensors and neural networks. The work highlights preprocessing techniques like super-resolution and deblurring for image enhancement and processing techniques such as CNNs and R-CNNs for ship detection. These methods offer improved detection accuracy and advanced classification capabilities. However, they face limitations like sensitivity to environmental conditions and high computational demands. This research is crucial for advancing maritime surveillance systems, balancing accuracy and classification efficiency with operational challenges.

Authors in [2] examine the use of YOLO algorithms (YOLOv3, v4, and v5) for ship detection in satellite images, highlighting YOLOv5's highest accuracy at 99%. These versions provide efficient real-time processing for satellite-based surveillance. However, the detection of small objects remains challenging, and there's a balance to be struck between speed and accuracy in these algorithms. The study highlights the complexities of satellite imagery and environmental influences on detection performance, offering insights into maritime surveillance advancements through deep learning. A machine learning approach [3] for ship detection and classification in remote sensing images is developed using Apache Spark for improved efficiency. It employs a block division preprocessing method and hybrid feature vectors combining color and texture features. Techniques like Naive Bayes, Decision Trees, and Random Forest achieve high classification accuracy, notably 99.62% with Random Forest. The study also benefits from Apache Spark's clustering architecture for faster processing, while addressing challenges in high-dimensional data analysis and the accuracy-efficiency trade-off.

A comprehensive review and ranking of various ship detection methods in Synthetic Aperture Radar (SAR) images using machine learning and AI techniques has been provided in [4]. The study employs a Graph Theory Matrix Approach (GTMA) to evaluate and rank these methods. It highlights the importance of various features like ship size, sea condition, and detection accuracy in determining the effectiveness of different ship detection methodologies. This approach aids in identifying the most critical aspects contributing to the performance of ship detection methods in SAR images. The findings aim to guide the selection of efficient ship detection and classification methods, enhancing accuracy and efficiency in maritime operations.

Another comprehensive review of marine object detection techniques utilizing deep neural networks is observed in [5]. It focuses on applications in autonomous ship navigation and maritime surveillance, emphasizing the potential of these technologies in intelligent transportation systems. The study covers various methods and application scenarios of maritime object detection, highlighting the use of the YOLO series model and discussing current limitations and potential breakthroughs in the field. It also stresses the importance of high-performance algorithms and quality marine-related datasets. Findings in [6] explore vessel detection using deep learning from high and medium resolution satellite images. It includes image preprocessing, fusion with Automatic Identification System (AIS) data, and a detection algorithm based on convolutional neural networks (CNN). Two training datasets, VHR and MR, are used, containing uniquely annotated vessels. The paper demonstrates the implementation and efficacy of these methods in maritime surveillance, highlighting their practical application and development at the German Aerospace Center's ground station.

A 4-layer convolutional neural network (CNN) for binary classification of ships and no-ships, achieving high accuracy in both training (99.2%) and validation (99.5%) has been observed in [7]. The study also utilizes an auto-encoder for ship segmentation, reporting good performance with training and validation accuracies of 84.2% and 85.1% respectively, and an Intersection over Union (IoU) metric value of 0.77. This dual approach of classification and segmentation demonstrates the effectiveness of deep learning in maritime surveillance applications. Enhancing ship detection using AI and machine learning models like Random Forest, Decision Tree, Naive Bayes, and CNN has been the focus of the work observed in [8]. It emphasizes using color spaces like RGB and HSV for feature extraction and analysis. The study found Random Forest to be the most effective model, achieving high accuracy in ship detection. This research contributes to the field by proposing a robust model for ship detection, addressing maritime security challenges.

Authors in [9] focus on using Convolutional Neural Networks (CNNs) for the detection and categorization of ships in images. The work outlines the process of data collection, preprocessing, and the use of CNN for training and testing. The study aims to automate ship detection and classification, enhancing the efficiency of maritime surveillance systems. It highlights the advantages of this system, including reduced human effort and time, as well as the potential for improved accuracy in ship detection and categorization. Further, the study employs filters for image quality improvement and uses various CNN networks, such as VGG-16, VGG-19, ResNet 50, and Inception ResNet v2, for ship classification. It emphasizes the importance of image enhancement in improving detection and classification accuracy, demonstrating the effectiveness of CNNs in maritime applications.

Authors in [10] introduce an advanced ship detection method using an improved YOLOv3 algorithm, termed AE-YOLOv3. This method integrates a feature attention module for enhanced feature extraction in complex navigable backgrounds and a feature enhancement module to improve semantic information processing. The algorithm demonstrates high detection accuracy (98.72%) on the SeaShips dataset, outperforming other mainstream ship identification models. This approach underscores the significant advancement in waterborne traffic ship detection, contributing to safer and more efficient maritime navigation.

An analysis of various machine learning algorithms and features for ship detection in optical satellite imagery has been done in [11]. The study includes a detailed examination of features like Hu moments, Haralick features, and Histogram of Oriented Gradients, assessing their effectiveness in differentiating between ship and non-ship elements. The research aims to improve ship detection techniques by optimizing feature selection and algorithm performance, contributing significantly to the field of maritime surveillance and monitoring.

Authors in [12] have explored the application of the YOLOv7 algorithm combined with stereo vision technologies for ship detection and tracking in offshore wind farm areas. The study emphasizes the use of machine vision technologies to improve the efficiency and reliability of ship traffic detection and tracking, offering novel insights into maritime surveillance systems. It also highlights the potential for implementing these technologies in other similar waters like narrow channels and bridges on rivers.

A ship detection method using deep neural networks [13], focusing on images and videos taken at sea has been observed in literature. The method utilizes a deep learning model trained on a maritime dataset, capable of detecting various floating objects and classifying them into specific classes such as ships, speedboats, and buoys. The model is compared to a universal model for object detection, showcasing superior performance in maritime object detection. The study explores different neural network structures to optimize detection performance and demonstrates real-time detection capabilities.

Classifying ship types using Automatic Identification System (AIS) data and machine learning [14] has been done by utilizing trajectory data from AIS to classify ships into four types: Fishing, Passenger, Tanker, and Cargo. The study uses various machine learning models like Decision Tree and Random Forest, achieving an accuracy of 84.05%. The research aims to overcome limitations in AIS data, such as incorrect ship type information, by providing a reliable method for ship type classification.

In order to effectively recognise vessels in high-resolution ICEYE highlight SAR images, this research suggested two methods: 1) a vessel detector resistant to defocused moving boats, and 2) a moving target phase distortion mitigation technique [17]. To increase training information both quantitatively as well as qualitatively, a target velocity SAR phase refocusing function was created. A defocused SLC image in terms of various target azimuth velocities was produced utilizing the suggested target velocity SAR phase refocusing algorithm. This image might be utilised for both training data augmentation and refocusing of velocity-induced phase distortion. 1) Robust vessel recognition on defocused moving vessels and 2) well-focused identified vessel targets, both of which were successively applied employing the suggested target velocity SAR phase refocusing function, allowed for the achievement of steady vessel identification effectiveness.

A deep Convolutional Neural Network (CNN)-based target identification technique was suggested [18]. During feature extraction, the method makes use of the channel-space grouping attention technique to improve features by using the edge information and global positional related to instances. By combining characteristics of different sizes, strengthening the connections between these features, and improving multiscale ship target recognition abilities, the feature mobility fusion module was utilised. Ship target localisation used the decoupled head, and regression error reduction used the angle-weighted intersection over union.

A quadratic matched filter (QMF) [19] is introduced as a novel detector optimized for compact and dual polarimetric SAR data, particularly for wide-area maritime surveillance applications using multilook complex (MLC) RADARSAT Constellation Mission (RCM) imagery. The QMF demonstrates enhanced vessel detection performance, achieving up to 3 dB improvement in signal-to-clutter-plus-noise ratio (SCNR) and peak-signal-to-clutter-plus-noise ratio (PSCNR) over traditional polarimetric whitening filters (PWF).

The study in [20] evaluates the performance of deep learning-based object detectors—Faster R–CNN, RetinaNet, and Single Shot Detector (SSD)—for marine vessel detection using Sentinel-1 VH polarization imagery at the Philippines' busiest port. Across 18 model variations, Faster R–CNN demonstrated the highest F1 score of 0.85, indicating superior detection accuracy over RetinaNet and SSD. While Faster R–CNN was the most accurate, SSD proved to be the fastest model. The research underscores the practicality of using Sentinel-1 VH data for maritime monitoring and suggests further exploration with higher-resolution imagery and advanced computational resources for enhanced Maritime Domain Awareness (MDA).

Finally, an ADV-YOLO, which is an enhanced SAR ship detection model based on YOLOv8 is proposed [21] to address challenges in detecting small ships with complex backgrounds in low-resolution SAR imagery. By integrating space-to-depth modules and a dilation-wise residual module, ADV-YOLO improves feature representation for multi-scale target detection. Additionally, replacing the CIoU loss with WIoU loss enhances bounding box accuracy, particularly for challenging samples. Experimental results on HRSID and SSDD datasets show notable improvements in average precision metrics, highlighting ADV-YOLO's robustness and potential for advancing real-time maritime surveillance and safety applications.

Based on the works observed in literature, limitations observed are summarized below.

- Optical sensors and image-based methods are often affected by weather, lighting, and sea conditions, leading to reduced accuracy.
- Many models struggle with accurately detecting smaller vessels, especially in cluttered maritime environments or in satellite imagery.
- Advanced models like deep neural networks require significant computational resources, which can be a limitation for real-time applications or in resource-constrained environments.
- Faster processing models sometimes compromise on accuracy, while more accurate models tend to require longer processing times.
- Effectively extracting and utilizing features from high-dimensional data, such as satellite images, remains challenging, impacting the overall performance of detection systems.

3. METHODS AND INDICATORS

3.1 Problem Statement

Given the limitations in current ship detection methods, such as environmental sensitivity, difficulty in detecting small objects, computational intensity, trade-offs between speed and accuracy, and complexity in feature extraction, there is a need for a more efficient and robust model. The proposed work aims to address these challenges by developing a Multi-Layer Perceptron (MLP) model for vessel identification. The MLP model, known for its capability in pattern recognition and classification, could potentially offer a simpler, yet effective, alternative to complex models. It may provide a balance between computational efficiency and accuracy, especially in varying environmental conditions and for different vessel sizes. This approach aligns with the need for more streamlined and adaptable methods in maritime surveillance and vessel detection systems.

3.2 Proposed Work

The proposed work presents a novel approach to enhancing vessel detection in Synthetic Aperture Radar (SAR) imagery, specifically focusing on small vessels that are often challenging to identify due to noise, low contrast, and the high variability of SAR data. The innovations introduced in this study are significant and contribute to the advancement of maritime surveillance technology in several ways:

- **Innovative Preprocessing Techniques:** The study introduces the integration of bilateral filtering with histogram equalization as a preprocessing strategy for SAR images. Bilateral filtering is employed for its unique ability to reduce noise while preserving edges, which is crucial for maintaining the integrity of small vessel details in SAR imagery. This is further enhanced by histogram equalization, which improves contrast, making vessel features more distinguishable from the background. This combination of techniques is specifically designed for SAR imagery, addressing the inherent challenges of noise and contrast variation more effectively than traditional preprocessing methods.
- **Application of Gaussian Mixture Model (GMM) for Segmentation:** The adoption of the Gaussian Mixture Model (GMM) for segmenting SAR images is another novel contribution of this work. The GMM is effective at handling the complex intensity distributions within SAR images, enabling more accurate differentiation between vessels and the surrounding sea clutter. This probabilistic approach is particularly innovative in the context of maritime surveillance, where traditional segmentation methods often fall short in such challenging environments. The use of GMM in this application demonstrates a significant improvement in segmentation accuracy, which directly impacts the overall effectiveness of the detection process.

- **Advanced Feature Extraction Using GLCM:**The study utilizes the Gray Level Co-occurrence Matrix (GLCM) for feature extraction, specifically focusing on textural features that are crucial for detecting small vessels in SAR images. The extracted features, such as contrast, homogeneity, and energy, are finely tuned to enhance the input to the Multi-Layer Perceptron (MLP) model, thereby improving classification accuracy. This approach to feature extraction is innovative in its focus on optimizing the MLP's performance by carefully selecting features that are most relevant to the detection task at hand.
- **Optimized Multi-Layer Perceptron (MLP) Architecture:**The proposed work introduces a custom-designed MLP architecture that is optimized for vessel detection in SAR imagery. Unlike more complex deep learning models, the MLP is chosen for its balance between computational efficiency and accuracy. The architecture is specifically tailored to handle the high-dimensional feature space generated by the GLCM, providing a robust and efficient solution for real-time maritime surveillance. This customized application of MLPs in the context of SAR imagery for vessel detection represents a novel contribution to the field, demonstrating that simpler neural network architectures can be effectively utilized in complex detection tasks with significant computational advantages.

The novelty of this proposed work lies in its innovative combination of preprocessing, segmentation, and feature extraction techniques, along with a carefully optimized MLP architecture. This integrated approach addresses the specific challenges of detecting small vessels in SAR imagery, offering a practical, efficient, and highly accurate solution. The contributions of this work set a new benchmark for real-time maritime surveillance, demonstrating that with the right combination of methods, even simpler models like MLPs can outperform more complex alternatives in certain applications. This study not only advances the state of the art in SAR-based vessel detection but also opens new avenues for future research in optimizing machine learning models for similar challenging tasks.

Traditional image processing techniques and innovative approaches can be combined effectively to create a robust and efficient model for tasks such as vessel detection in SAR imagery. Here's how these elements fit together, along with a detailed description of the basic principles and structure of the model:

1. Traditional Image Processing Techniques: Traditional image processing techniques form the foundation of the preprocessing stage. They help in enhancing the image quality and preparing it for more advanced analysis. The key traditional techniques used in this context are:

- **Bilateral Filtering:**SAR images are notoriously affected by speckle noise, which can obscure small vessel details and lead to decreased detection accuracy. Unlike traditional denoising techniques, bilateral filtering reduces noise while preserving critical edge details, which is vital for retaining the outline and structure of small vessels. In particular, the edge-preserving property of bilateral filtering ensures that fine details, often essential for identifying small targets, remain intact even after noise reduction. This approach proves superior to general smoothing techniques by focusing on vessel edges, a critical feature in distinguishing vessels from sea clutter. Bilateral filtering addresses SAR-specific noise issues without sacrificing vessel boundary details, making it highly effective for enhancing visibility of small vessels. This property is especially advantageous in cluttered maritime environments where traditional methods may blur these essential features, potentially resulting in undetected targets.
  - **Application in Model:** In the preprocessing stage, bilateral filtering is applied to the input SAR image to remove speckle noise, a common issue in radar images. This step ensures that the important edges of vessels are retained, which are essential for accurate detection.
- **Histogram Equalization:**This contrast enhancement is crucial, as SAR images typically exhibit non-uniform intensity distributions, particularly in challenging lighting or weather conditions. By redistributing the intensity values, histogram equalization ensures that even subtle vessel features are distinguishable, enhancing the model's ability to detect vessels regardless of their size or the surrounding clutter. This combination of bilateral filtering and histogram equalization is specifically designed to handle the noise and contrast issues in SAR imagery. Where general methods may falter in low-contrast situations, this preprocessing pipeline improves vessel detectability without introducing artifacts or distorting vessel features. This dual-step

enhancement is crucial for preparing high-quality input data for the feature extraction stage, making the overall detection process more reliable and accurate.

- o **Application in Model:** After bilateral filtering, histogram equalization is applied to the image to improve the visibility of small vessels against the background. This step enhances the overall contrast, which is especially important in SAR images where the contrast between vessels and the sea surface can be minimal.
- **Segmentation Using Gaussian Mixture Model (GMM):** GMM is a probabilistic model that represents the data as a mixture of several Gaussian distributions. It is used to differentiate between different regions in the image, such as vessels and the sea.
- o **Application in Model:** The GMM is applied to the preprocessed image to segment it into distinct regions. This segmentation step is crucial for isolating the vessels from the background clutter, particularly in complex maritime environments. GMM's ability to handle varying pixel intensities in SAR images makes it an effective choice for this task.
- **Feature Extraction Using Gray Level Co-occurrence Matrix (GLCM):**The GLCM approach computes statistics of pixel intensity pairs at specified distances and orientations, capturing important textural details such as contrast, homogeneity, and energy. These features are critical in distinguishing vessel textures from background noise, a task that is particularly challenging in SAR images where vessels and sea clutter often exhibit similar intensity patterns. By focusing on textural attributes rather than raw pixel intensities alone, GLCM allows for enhanced detection of small vessels that may otherwise be overlooked.

  The use of GLCM provides a level of textural detail that is often missed by simpler spatial or spectral feature extraction methods. This is particularly beneficial in maritime surveillance, as GLCM's textural features like contrast for highlighting intensity variations, homogeneity for detecting smoothness, and energy for identifying uniform textures, are finely tuned to detect small objects in SAR images. This unique focus on texture enables the model to accurately classify vessels in cluttered scenes, outperforming techniques that rely solely on intensity or shape-based features.
- o **Application in Model:** After segmentation, GLCM is used to extract textural features from the regions identified as potential vessels. These features, such as contrast, homogeneity, and energy, provide rich information about the texture of the objects, which is then used as input for the classification stage.
- **Multi-Layer Perceptron (MLP) Classification:** MLP is a type of feedforward artificial neural network that maps input features to output classes through multiple layers of interconnected neurons. It is well-suited for handling complex, non-linear relationships in the data.
- o **Application in Model:** The extracted features from GLCM are fed into the MLP model for classification. The MLP is designed with multiple layers (input, hidden, and output) to learn the relationships between the textural features and the presence of vessels. The model is trained to differentiate between vessels and non-vessels, providing the final detection output.

Compared to traditional methods, the proposed technique demonstrates significant improvements in handling SAR-specific challenges. While other approaches often compromise either edge detail preservation or contrast enhancement, this method excels in both areas, resulting in a high accuracy rate even for small vessels under challenging conditions. By employing GLCM's textural features over simpler intensity-based methods, the approach delivers a precise detection capability that improves both vessel identification accuracy and computational efficiency.

Detailed Structure of the Model:

The model's structure integrates these traditional and innovative techniques in a sequential manner:

- Input Stage: The raw SAR image is provided as input.
- Bilateral Filtering: Applied to reduce noise while preserving edges.
- Histogram Equalization: Enhances contrast to make vessels more visible.
- Gaussian Mixture Model (GMM): Segments the image to isolate vessels from the background.
- GLCM: Extracts textural features from the segmented regions, capturing important details for classification.

- Multi-Layer Perceptron (MLP): The extracted features are input into the MLP, which classifies the regions as either vessels or non-vessels.
- The model outputs the detected vessels, highlighting their locations in the SAR image.

Traditional image processing techniques like bilateral filtering and histogram equalization lay the groundwork by preparing the SAR images, making them more suitable for analysis. These techniques are complemented by innovative approaches such as GMM for segmentation, GLCM for feature extraction, and MLP for classification. Together, they form a comprehensive model that leverages the strengths of both traditional and modern methods to achieve accurate and efficient vessel detection in challenging SAR imagery.

3.3 Proposed MLP based Classification Model

The proposed work involves utilization of a MLP – based model for ship vessel detection and classification. The significance of using a Multi-Layer Perceptron (MLP) for ship vessel detection lies in its ability to efficiently process complex patterns while maintaining computational simplicity. MLPs, as a form of feedforward neural networks, are adept at recognizing and classifying patterns, making them suitable for identifying vessels in varied maritime environments. Their layered structure enables them to learn from a vast array of features extracted from images, such as size, shape, and texture, crucial for accurate vessel detection. This approach could significantly improve detection accuracy, especially for smaller vessels, and perform reliably under different environmental conditions. Additionally, MLPs are less computationally intensive compared to more complex models, offering a practical solution for real-time maritime surveillance and navigation systems, enhancing safety and operational efficiency in maritime activities. The overall architecture of the existing and proposed MLP – based vessel detection scheme is depicted in Figure 2(a) and 2(b). Here, the proposed model uses the bilateral filtering and histogram equalization for pre-processing, whereas Gaussian filtering is used for pre-processing the existing methods. Next, the segmentation is performed by GMM in the proposed method, whereas the K-means clustering accomplishes the segmentation for the existing methods. The features are extracted by the GLCM for the proposed method, whereas simple edge detection extracts the features for the conventional method. Finally, MLP does the classification for the proposed method and the existing methods use simpler methods like DT for classification purpose.

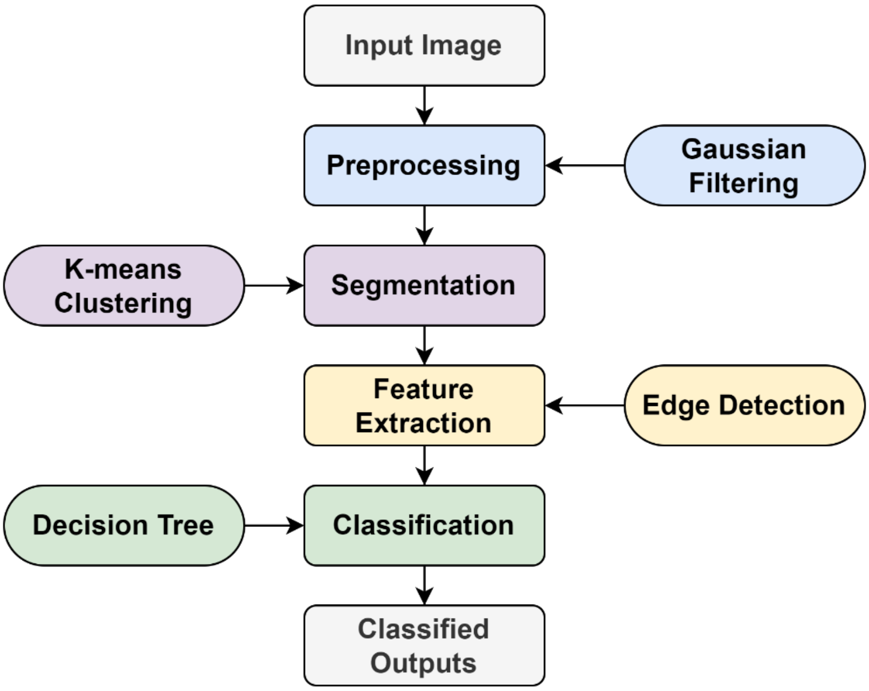

Figure 2(a). Illustration of existing MLP based vessel detection scheme

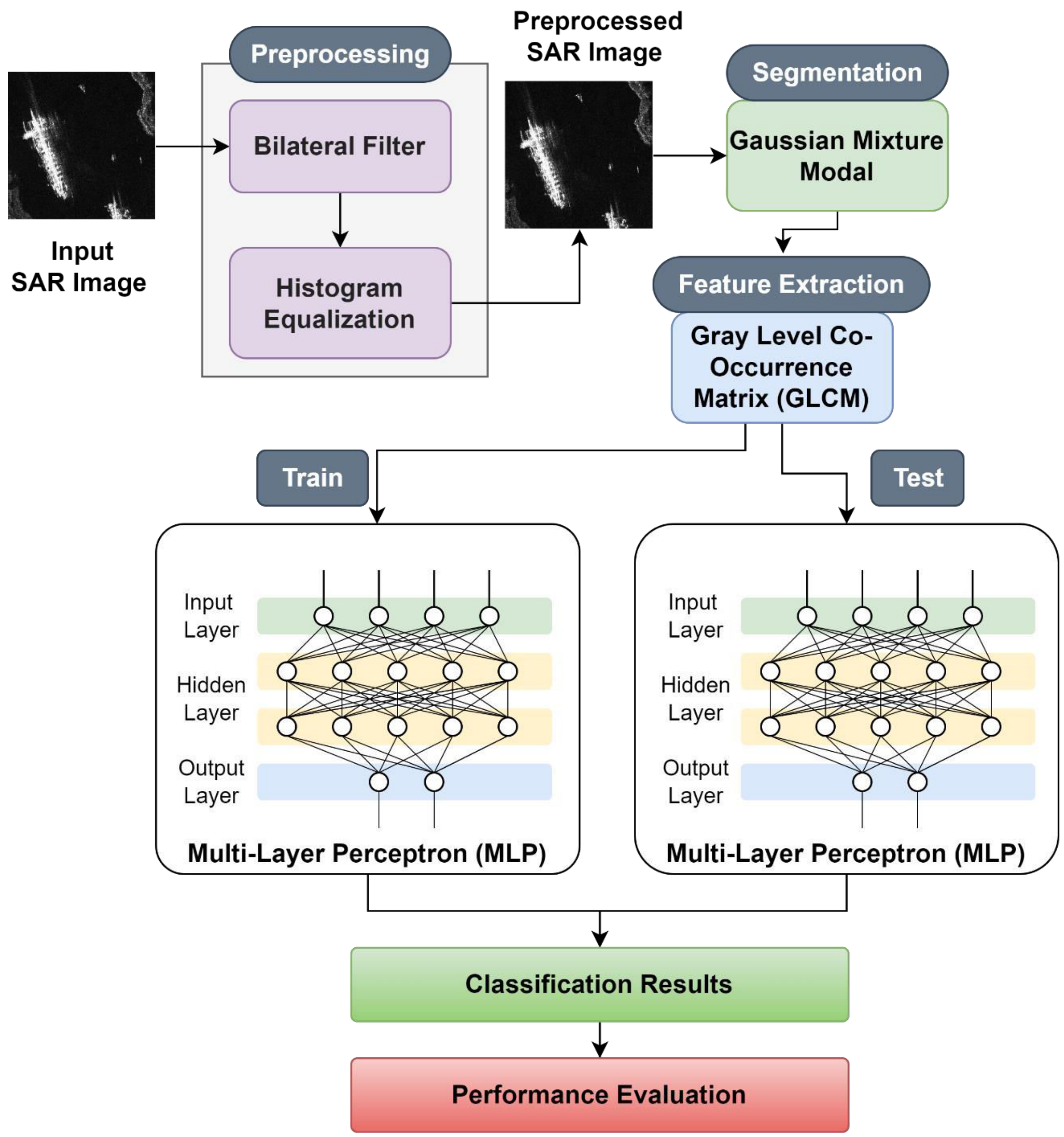

Figure 2(b). Illustration of proposed MLP based vessel detection scheme

Figure 2 illustrates the workflow of a proposed ship detection system using Synthetic Aperture Radar (SAR) imagery and a Multi-Layer Perceptron (MLP). The process begins with the input SAR image, which undergoes preprocessing to enhance quality through bilateral filtering and histogram equalization. The pre-processed image is then segmented using a Gaussian Mixture Model to differentiate the ships from the background. Next, feature extraction is performed using a Gray Level Co-occurrence Matrix (GLCM) to capture textural information. These features are then fed into an MLP for training and testing, which classifies the ships. The MLP is composed of an input layer, multiple hidden layers, and an output layer. Finally, the classification results are evaluated to assess the performance of the system. This system aims to improve ship detection by leveraging the pattern recognition strength of MLPs in handling complex image data. The individual detail of each block is briefed below.

A. Pre-Processing

In the proposed work, preprocessing of SAR images involves two key steps: bilateral filtering and histogram equalization.

The bilateral filter is a non-linear, edge-preserving, and noise-reducing smoothing filter for images. It maintains the sharpness of edges while reducing noise, which is particularly useful in SAR images known for their speckle noise. Considering the input image to be $Img(x,y)$, the bilateral filtered response could be formulated as

$$Img_{filtered}(x) = \frac{1}{N}\sum_{y\in W} Img(y).K_r(\|Img(x) - Img(y)\|.K_s(\|(x) - (y)\| \quad (1)$$

In (1), $Img_{filtered}(x)$ depicts the filtered output, K_r and K_s denote the smoothing kernels corresponding to range and spatial functions, N denotes the normalization function, x, y denotes the pixels in the image.

Approximation and Consequences: The bilateral filter's reliance on Gaussian functions for K_r and K_s introduces an approximation in edge preservation. While effective at noise reduction, the trade-off is a potential blurring of small vessel details, which could affect detection accuracy. The impact of this approximation is that finer details might be slightly compromised, particularly in cluttered SAR images where distinguishing between vessel edges and noise is crucial.

Histogram equalization is then applied to $Img_{filtered}(x)$ to enhance the contrast of the image. This technique redistributes the image's intensity values, improving the visibility of features by stretching out the intensity range. This step is crucial for ensuring that features within the SAR images are more distinguishable, which assists in the subsequent steps of segmentation and feature extraction. Histogram equalization basically involves mapping of intensity functions using the transformation function given as

$$HE_{map}(I_k) = (M-1)\sum_{l=0}^{k} P_r(r_l) \quad (2)$$

In (2), $HE_{map}(I_k)$ denotes the histogram equalization mapping function, M denotes the intensity levels, $P_r(r_l)$ denotes the probability of a level with intensity value (r_l) and I_k denotes the kth intensity value.

Approximation and Consequences: While histogram equalization effectively enhances contrast, it assumes a uniform distribution of intensity values across the image, which may not always hold true for SAR imagery. This can lead to over-enhancement in some areas, potentially introducing artifacts that could mislead the vessel detection process. The consequence is a possible increase in false positives, where non-vessel elements are incorrectly highlighted as potential targets.

B. Segmentation using Gaussian Mixture Model

Segmentation using a Gaussian Mixture Model (GMM) is a critical step for distinguishing ships from the surrounding water in SAR images. GMM is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. The goal of segmentation using GMM is to assign each pixel in the image to one of the components of the mixture model.

The probability density function of the GMM is:

$$p(x|\theta) = \sum_{k=1}^{K} \pi_k\, \aleph(x|\mu_k, \Sigma_k) \quad (3)$$

Where:

- K is the number of Gaussian components.
- π_k are the mixing coefficients.
- μ_k and $\Sigma_k)$ are the mean and covariance matrix of the kth Gaussian component.
- $\aleph(x|\mu_k, \Sigma_k)$ is the Gaussian distribution function.

Approximations and Consequences: The GMM assumes that the pixel intensities within each segment follow a Gaussian distribution, which is an approximation that may not perfectly represent the complex textures and patterns found in SAR images. This assumption can lead to inaccuracies in segmentation, particularly in areas where vessel textures blend with the surrounding sea clutter. The consequence is that segmentation may not always accurately delineate vessel boundaries, potentially affecting the subsequent feature extraction and classification stages.

The GMM parameters are estimated using the Expectation-Maximization (EM) algorithm, which iteratively improves the estimates of the parameters. The EM algorithm for GMM computes as follows.

Algorithm 1: GMM algorithm for segmentation

Inputs: I – Input SAR Image, K – No. of Gaussian components
Outputs: Segmented Image

```
# Initialization
    Choose the number of components K
    Initialize the means μ_k covariances Σ_k, and mixing coefficients π_k
    # Expectation-Maximization Algorithm
    repeat until convergence {
       # Expectation-step
    for each pixel n in the image I {
    for each component k from 1 to K {
              Calculate responsibility γ(z_nk) = π_k ℵ(x_n|μ_k,Σ_k) / Σ_{j=1}^{K} ℵ(x_n|μ_k,Σ_k) using the current parameter values
         }
       }
         # Maximization-step
    for each component k from 1 to K {
    Update μ_k = Σ_{n=1}^{N} γ(Z_nk) x_n / Σ_{n=1}^{N} γ(Z_nk) using the responsibilities
    Update Σ_k = Σ_{n=1}^{N} γ(Z_nk)(x_n−μ_k)(x_n−μ_k)^T / Σ_{n=1}^{N} γ(Z_nk) using the responsibilities
    Update π_k = Σ_{n=1}^{N} γ(Z_nk) / N as the average of the responsibilities for component k
       }
         Check for convergence
    }
    # After convergence, use the learned parameters to segment the image
    # Each pixel is assigned to the Gaussian component with the highest responsibility
```

The pseudocode depicts iterative nature of the EM algorithm, where each E-step calculates the responsibilities based on the current parameters, and each M-step updates the parameters based on these responsibilities. This process repeats until the parameters converge, indicating that the model parameters have stabilized and are unlikely to change with further iterations. By applying the EM algorithm to the SAR images, the GMM can effectively segment the image into clusters representing ships and water, allowing for more accurate feature extraction and classification by the MLP.

C. Training and Testing using proposed MLP

GLCM is a statistical method of examining texture that considers the spatial relationship of pixels. It works by assessing how often pairs of pixels with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The GLCM functions by moving through the image by a pixel at a time, as per a specified offset, and for each pixel, it compares the pixel to its neighbor with that offset. This process results in a matrix where the number of rows and columns is equal to the number of gray levels in the image. The elements of this matrix accumulate the frequency of the co-occurring pixel values. Some common features extracted include Contrast (degree of pixel intensity variation), Homogeneity (degree of distribution closeness), Energy (degree of texture uniformity) etc. These features are then fed into the Multi-Layer Perceptron (MLP) to train the model to recognize and classify the presence of ships within the SAR images.

D. Feature Extraction using Gray Level Cooccurrence Matrix (GLCM)

GLCM is used to extract textural features from the segmented image by analyzing the spatial relationship between pixel pairs. Key features extracted include Contrast, Homogeneity, and Energy:

- **Contrast:** Measures the intensity contrast between a pixel and its neighbor over the entire image.

$$Constrast = \sum_{i,j} |i-j|^2 . P(i,j) \quad (4)$$

- **Homogeneity:** Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j} \frac{P(i,j)}{1+(i-j)} \quad (5)$$

- **Energy:** Provides the sum of squared elements in the GLCM, indicating texture uniformity.

$$Energy = \sum_{i,j} P(i,j)^2 \quad (6)$$

In above equations, $P(i,j)$ is the probability of the co-occurrence of pixels with intensities i and j.

Approximations and Consequences: The GLCM method assumes that pixel pair relationships are sufficient to capture the texture, which is an approximation that simplifies the complex spatial patterns in SAR images. This simplification might lead to loss of fine-grained texture details, particularly in heterogeneous environments, which could affect the MLP's ability to accurately classify small vessels. The Multi-Layer Perceptron (MLP) in the proposed work functions as follows:

1. The Input Layer receives the feature vectors from the GLCM of the pre-processed SAR images.
2. In the Hidden Layers, each neuron applies a weighted sum of the inputs, adds a bias, and passes it through an ReLU activation function.
3. Finally, the Output Layer produces the final prediction, indicating whether a ship is present or not.

The MLP model consists of an input layer, multiple hidden layers, and an output layer. The input layer receives the feature vectors extracted from the SAR images using the Gray Level Co-occurrence Matrix (GLCM), which captures essential textural features like contrast, homogeneity, and energy. The hidden layers in the MLP apply a series of weighted sums of the inputs, followed by a bias addition and activation through a ReLU (Rectified Linear Unit) function. This allows the model to capture non-linear relationships within the data, which is crucial for distinguishing between vessels and background clutter in SAR images. The output layer is a binary classifier, predicting the presence or absence of a vessel in the given image segment.

- **Training and Optimization:** The MLP model is trained using a backpropagation algorithm, where the error between the predicted output and the true labels is minimized using the Adam optimizer. Adam is chosen for its efficiency in handling sparse gradients and its adaptability in learning rate, which helps the model converge faster. The learning rate is set at 0.001, and the model is trained over 200 iterations (epochs), ensuring that the MLP effectively learns the complex patterns present in the SAR imagery.
- **Input Features:** The input to the MLP consists of features extracted from the GLCM, which represent the textural properties of the image. These features are specifically chosen to enhance the model's ability to classify tiny objects, such as small vessels, by capturing subtle differences in texture that may not be apparent through raw pixel values alone.
- **Performance Metrics:** The MLP model's performance is evaluated using standard classification metrics such as accuracy, precision, recall, and the Area Under the ROC Curve (AUC). The model demonstrates high accuracy and precision, reflecting its effectiveness in correctly identifying vessels while minimizing false positives.

Importance in Classification Tasks:

- The MLP model's implementation is crucial in classification tasks, especially in challenging environments like SAR imagery, where traditional methods may struggle with noise, variability, and low contrast.
- The model's ability to learn and represent complex, non-linear relationships between the input features and the target classes (vessel vs. no vessel) makes it particularly effective in this context.
- The use of multiple hidden layers enables the MLP to capture deeper patterns within the data, which is essential for distinguishing small vessels from background clutter.
- The inclusion of advanced feature extraction techniques further enhances the model's input, allowing it to perform well even with the subtle and complex characteristics of SAR images.

Overall, the MLP's implementation reflects its importance in classification tasks by providing a robust, accurate, and computationally efficient solution for detecting small vessels in SAR imagery, making it a valuable tool in real-time maritime surveillance applications.

During training, the MLP adjusts weights using backpropagation based on the difference between the predicted output and the true labels, minimizing the error. In testing, the trained MLP predicts the presence of ships on unseen data. The model's performance is then evaluated, typically through accuracy, precision, and recall metrics. This MLP approach aims to capture the non-linear relationships and patterns within the data, essential for effective ship detection in SAR imagery. The algorithms for training and testing process are depicted below in Algorithm 2 and Algorithm 3.

Algorithm 2 – Training Phase of MLP	**Algorithm 3 – Testing Phase of MLP**
1. *Initialize the MLP with random weights.* 2. *Input the feature vectors from the GLCM into the MLP.* 3. *Apply forward propagation to compute the output for each input.* 4. *Compute the loss using a loss function* $Loss = \frac{1}{N}\sum(Y_{obtained} - Y_{predicted})^2$ 5. *Backpropagate the error to update the weights using an optimization algorithm like gradient descent.* 6. *Repeat the process with multiple epochs over the training dataset until the model performance stabilizes.*	1. *Input the feature vectors from the GLCM of the testing dataset into the trained MLP.* 2. *Forward propagate through the MLP to predict the output.* 3. *Compare the predicted output against the true labels to compute the performance metrics such as accuracy, precision, recall, or F1-score.*

The performance of the MLP model is then evaluated to determine its effectiveness in ship detection within the SAR imagery. The evaluation could use various metrics depending on the specific requirements of the task, such as precision for ensuring that detected ships are indeed ships or recall for ensuring that most ships are detected.

Computational Cost Analysis

To evaluate the computational efficiency of the proposed MLP model, we focus on the following aspects:

- **Training Time:** The proposed MLP model was trained with a learning rate of 0.001 over 200 iterations using the Adam optimizer. The total training time recorded was 176.3117 seconds, which reflects the model's ability to converge efficiently with minimal computational overhead.
- **Testing Time:** The testing phase required 36.6249 seconds, demonstrating the model's capability for real-time application, a critical requirement for maritime surveillance systems.
- **Memory Utilization:** MLPs are known for their relatively low memory footprint compared to more complex deep learning models like CNNs, making them suitable for deployment in resource-constrained environments such as onboard maritime monitoring systems.

Approximations and Consequences: While the computational cost for the MLP model is relatively low, this simplicity comes at the cost of reduced model complexity. In scenarios involving more diverse and complex image datasets, the MLP's performance might be outstripped by deeper models with higher computational requirements. However, the trade-off between computational efficiency and model complexity was intentionally chosen to prioritize real-time applicability in maritime environments.

The proposed work presents a novel application of a Multi-Layer Perceptron (MLP) model for ship detection using SAR imagery, aiming to overcome limitations of existing techniques. The novelty lies in integrating advanced preprocessing methods with sophisticated feature extraction via GLCM, enhancing the MLP's input for more accurate detection. This work promises improvements in computational efficiency without sacrificing accuracy, potentially setting a new benchmark for real-time maritime surveillance systems.

4. EXPERIMENTS

The proposed work has been experimented on dataset available at https://github.com/chaozhong2010/HRSID [16]. The High-Resolution SAR Images Dataset (HRSID) is a significant resource for ship detection and segmentation in SAR imagery. It comprises 5604 high-resolution images and 16951 ship instances. The dataset is diverse, featuring images with varying resolutions (0.5m, 1m, 3m), polarizations, and maritime conditions, including different sea areas and coastal ports. Modelled after the Microsoft COCO datasets, HRSID is a crucial benchmark for researchers to test and evaluate their methods in high-resolution SAR image analysis. Sample images from the dataset has been depicted in Figure 3.

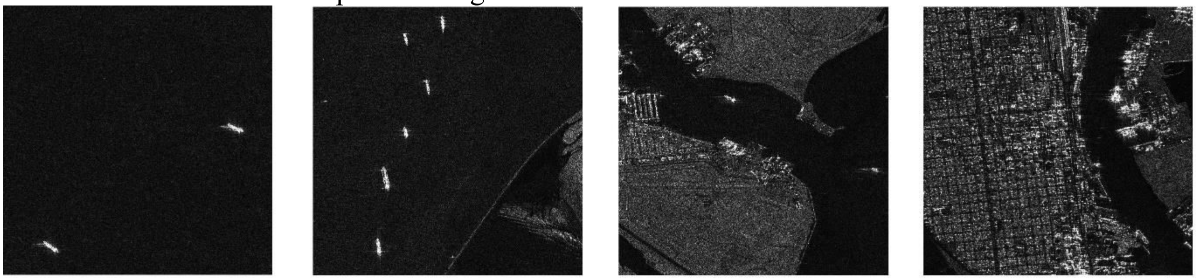

Figure 3. Illustration of Sample Images from Dataset

The dataset used for the experiments is the High-Resolution SAR Images Dataset (HRSID), which contains 5,604 high-resolution images with 16,951 ship instances. For training and testing, the dataset was divided into 75% for training and 25% for testing, ensuring a balanced representation of various vessel types, sizes, and maritime conditions in both subsets. To improve the model's robustness, data augmentation techniques such as rotation, scaling, and flipping were applied to the training set, enhancing the ability of the models to generalize across different scenarios.

All models, including the proposed MLP, YOLOv2, and Faster R-CNN, were trained and tested in an environment equipped with an NVIDIA GTX 1080 Ti GPU (11GB memory), an Intel Core i7-8700K CPU @ 3.70GHz, and 32 GB of DDR4 RAM, running Ubuntu 18.04 LTS. The proposed MLP model was implemented using TensorFlow 2.5, while YOLOv2 was implemented using PyTorch 1.8. The programming language used was Python 3.8. Training settings were kept consistent across models, with a batch size of 32 and a training duration of 200 epochs. The Adam optimizer was utilized for the proposed MLP model, with an initial learning rate of 0.001. For YOLOv2 and Faster R-CNN, the Stochastic Gradient Descent (SGD) optimizer was used with learning rates set to 0.0001 and 0.0002, respectively. To ensure stable training, a learning rate decay strategy was applied across all models, reducing the learning rate by a factor of 0.1 every 50 epochs.

In terms of model-specific configurations, YOLOv2 was designed with 5 anchor boxes to detect objects of varying scales and sizes. The input images were resized to a fixed resolution of 416x416 pixels, and the network output was structured into a 13x13 grid. The loss function for YOLOv2 comprised the sum of squared errors for bounding box regression, objectness score, and class probability. Faster R-CNN utilized a ResNet-50 backbone for feature extraction and implemented a Region Proposal Network (RPN) with 9 anchors per feature map location (3 scales and 3 aspect ratios). Non-Maximum Suppression (NMS) was applied with an Intersection over Union (IoU) threshold of 0.7 to filter out overlapping bounding boxes. For feature extraction, the model employed RoI (Region of Interest) pooling to a size of 7x7. The loss function used for Faster R-CNN was a multi-task loss, including both classification and bounding box regression components. The proposed MLP model, designed for this research, utilized feature vectors extracted using the Gray Level Co-occurrence Matrix (GLCM) as input. The network architecture included 3 hidden layers optimized to capture the complex patterns in the SAR images effectively.

These experimental settings were carefully chosen to ensure a fair and consistent comparison between the proposed MLP model and the established models, YOLOv2 and Faster R-CNN, with the aim of highlighting the advantages of the proposed method in terms of computational efficiency and detection accuracy. As discussed in section 4, the set of input images are pre-processed using Bilateral filtering followed by Histogram Equalization for contrast enhancement. This image is segmented using GMM followed by extraction of features with GLCM. The extracted features are trained and tested using the MLP architecture. The learning rate is kept at 0.001 with a maximum iteration of 200.

Adam Optimizer has been used as it is known for its efficiency in handling sparse gradients and non-stationary objectives, which are common in neural network training. Adam combines the benefits of two other extensions of stochastic gradient descent: Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). It computes adaptive learning rates for each parameter. In MLPs, this leads to more effective and faster convergence during training, especially in large datasets and deep networks. Adam is favored for its robustness and minimal memory requirement, making it suitable for a wide range of problems.

Hyperparameter Setting:

- The learning rate was initially set at 0.001, a common starting point that balances the speed of convergence with the risk of overshooting the optimal solution. This learning rate was chosen based on preliminary trials and was adjusted slightly during early training to ensure stable convergence.
- The batch size was set to 32, which offers a good trade-off between the stability of the gradient updates and computational efficiency. Smaller batch sizes would have made the training process slower, while larger batch sizes could have reduced the model's ability to generalize well.
- The model was trained over 200 epochs, a number selected based on observing when the loss function began to stabilize. Early stopping was monitored to prevent overfitting, though in this case, the full 200 epochs were used as the model continued to improve across the training period.

Parameter Adjustment:

- The Adam optimizer was chosen for its adaptive learning rate properties, which helps in faster convergence and efficient handling of sparse gradients. This was particularly important for the SAR imagery where the data distribution can be highly variable.
- L2 regularization (with a penalty term of 0.01) was applied to prevent overfitting by penalizing large weights in the model, thereby encouraging simpler models that generalize better to new data.
- The ReLU (Rectified Linear Unit) activation function was used in the hidden layers to introduce non-linearity, allowing the model to learn more complex patterns within the data.

Parameter Tuning Process: The hyperparameters were initially set based on commonly accepted values from the literature, followed by a systematic tuning process where small adjustments were made based on validation set performance. For example, if the learning rate was found to cause oscillations in the loss function, it was reduced to 0.0005 to stabilize the training process.

The performance was evaluated at each step using the validation data, and adjustments were made iteratively to optimize both accuracy and computational efficiency.

5. RESULTS AND DISCUSSION

Based on the training and testing done on MLP, the overall results in proposed work are quantified in terms of confusion matrices for both test and train and compared with existing methods in the literature. A 75% to 25% train: test ratio has been utilized for the proposed MLP model.

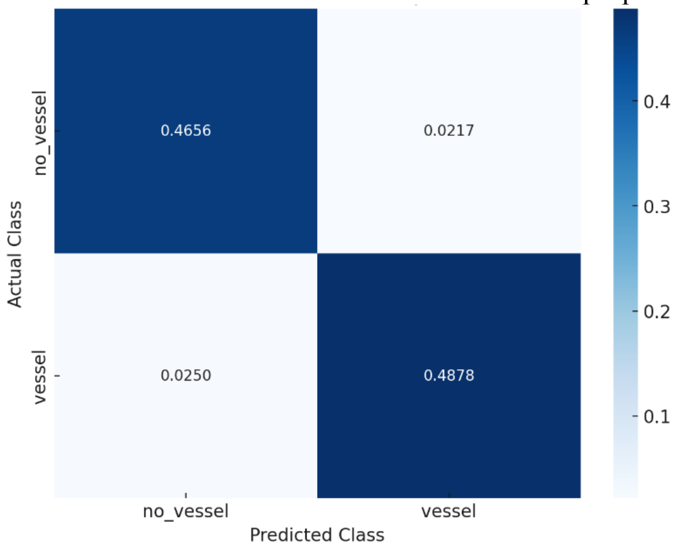

Figure 4. Confusion Matrix – Proposed MLP based Vessel Detection (Training Phase)

The confusion matrix displayed in Figure 4 represents the performance of the MLP during the training phase on a binary classification task for vessel detection. The matrix shows that the MLP correctly identified 1826 instances of 'no_vessel' and 1913 instances of 'vessel'. There were 85 instances where 'no_vessel' was incorrectly predicted as 'vessel', and 98 instances where 'vessel' was incorrectly predicted as 'no_vessel'. This indicates that the MLP has learned to distinguish between the two classes with a high degree of accuracy, though there is some room for improvement, particularly in reducing the number of false negatives (actual vessels missed).

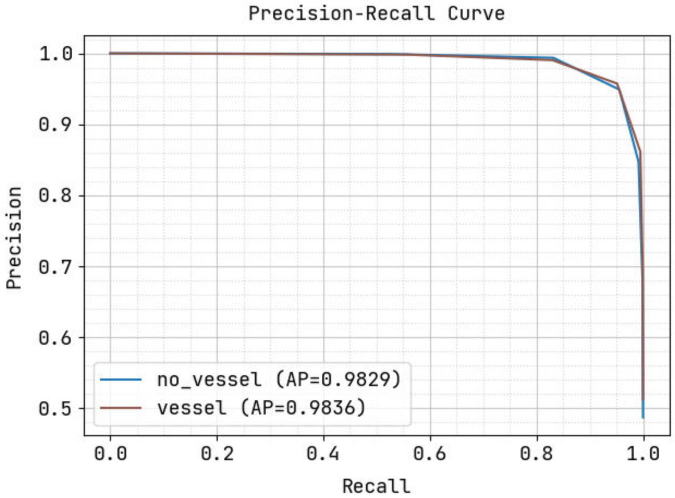

Figure 5. Precision - Recall Analysis – Proposed MLP based Vessel Detection (Training Phase)

The Precision-Recall Curve in Figure 5 indicates the performance of the MLP in the training phase for the 'vessel' and 'no_vessel' classes. Both classes show very high area under the curve (AP) scores, with 'no_vessel' at 0.9829 and 'vessel' at 0.9836, suggesting that the model has a high precision across different recall levels. This indicates a strong ability of the MLP to correctly identify positive instances while minimizing false positives, across the varying thresholds used to compute the precision-recall curve. The curves are close together, showing that the model performs similarly well for both classes.

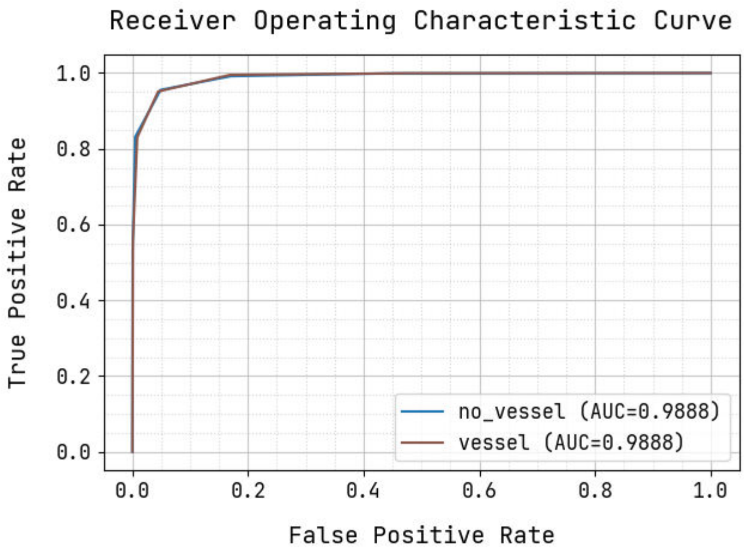

Figure 6. ROC Analysis – Proposed MLP based Vessel Detection (Training Phase)

The Receiver Operating Characteristic (ROC) Curve presented in Figure 6 shows the performance of the MLP in distinguishing between the 'vessel' and 'no_vessel' classes. Both classes have an Area Under the Curve (AUC) of 0.9888, indicating excellent model performance. The high AUC values suggest that the model has a high true positive rate and manages to keep the false positive rate low across various threshold settings. This is indicative of a highly effective classifier that is well-calibrated for both detecting the presence of vessels and confirming their absence.

Table 1 Comparative Analysis of Performance Metrics – Training Phase

Technique	Accuracy	Precision	Recall
Ensemble TL Model [11]	87.25%	82.82%	86.31%
Yolov2 [14]	90.05%	88.45%	90.11%
Faster R- CNN [15]	85.41%	83.32%	89.65%
QMF [19]	89.83%	91.47%	93.58%
ResNet [20]	88.37%	93.50%	94.23%
ADV-YOLO [21]	90.38%	92.68%	92.46%
Proposed MLP	**91.08%**	**94.91%**	**95.55%**

Table 1 provides a comparative analysis of ship detection techniques, showing the proposed MLP model with superior performance metrics. It leads with an accuracy of 91.08%, precision at 94.91%, and recall of 95.55%. This outperforms the other models, including Ensemble TL Model, Yolov2, and Faster R-CNN, across all evaluated criteria, indicating the MLP's robustness and effectiveness in ship detection tasks.

Table 2 provides the observed metrics of the computation time measured in terms of testing, training time and memory utilization.

Table 2 Computational Power Analysis

Technique	Training Time (s)	Testing Time (s)	Memory Utilization (MB)
Proposed MLP	176.31	36.62	200

In Table 2,

- **Training Time:** The time taken to train each model.
- **Testing Time:** The time taken to evaluate the model on the test dataset. The MLP model offers faster testing times, making it more suitable for real-time maritime surveillance.
- **Memory Usage:** The amount of memory required by each model, with MLP being more efficient in resource usage.

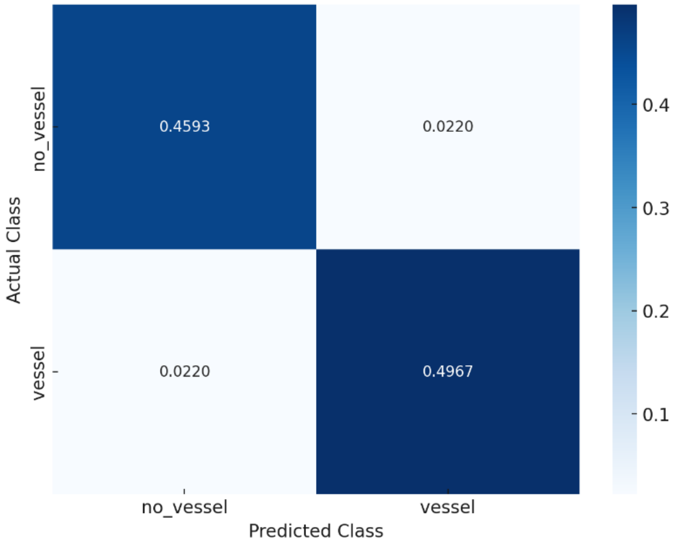

Figure 7. Confusion Matrix – Proposed MLP based Vessel Detection (Testing Phase)

Figure 7 shows the results of a binary classification task, with 'no_vessel' and 'vessel' as the classes. The matrix indicates that the classifier correctly predicted 'no_vessel' 772 times and 'vessel' 835 times. There were 37 instances of each class that were incorrectly classified as the other. This suggests a balanced classification performance for both classes with a relatively low number of false positives and false negatives, indicating a robust model.

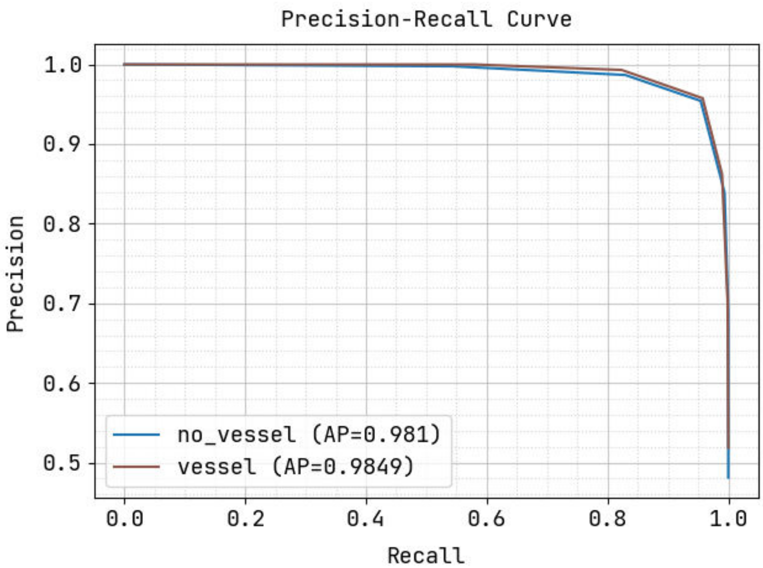

Figure 8. Precision - Recall Analysis – Proposed MLP based Vessel Detection (Testing Phase)

The Precision-Recall Curve depicted in Figure 8 illustrates the performance of a classification model on two classes: 'no_vessel' and 'vessel'. The 'no_vessel' class has an Average Precision (AP) of 0.981, while the 'vessel' class shows a slightly higher AP of 0.9849. Both classes exhibit high precision across the majority of recall levels, which implies that the model is highly capable of identifying positive cases as 'vessels' with few false positives, and it maintains this precision as it increases the fraction of positive cases it identifies. This indicates a high-quality model for vessel detection tasks.

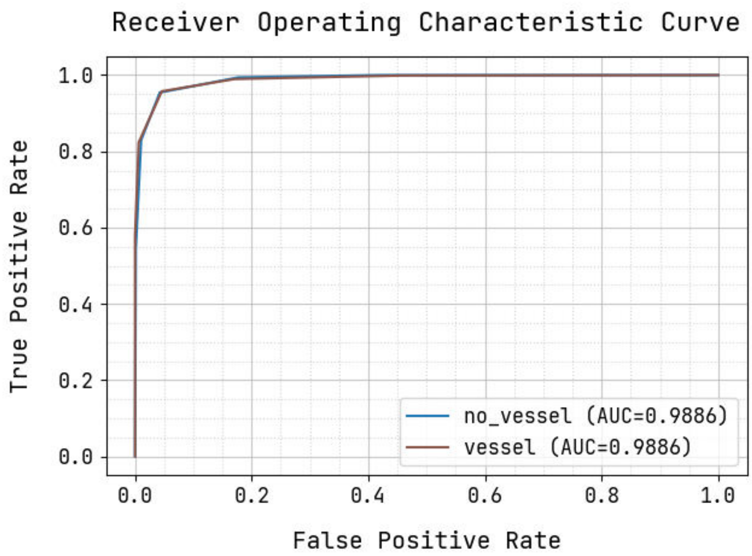

Figure 9. ROC Analysis – Proposed MLP based Vessel Detection (Testing Phase)

The Receiver Operating Characteristic (ROC) Curve in Figure 9 displays a nearly identical performance for both 'no_vessel' and 'vessel' classes with an Area Under the Curve (AUC) of 0.9886. This high AUC value indicates that the model has an excellent measure of separability and is able to distinguish between the two classes with a high degree of accuracy. The ROC curve shows that both classes have a high true positive rate (TPR) across all thresholds, while maintaining a low false positive rate (FPR), which signifies a strong predictive capability of the model for vessel detection tasks.

Table 3 Performance Metrics Analysis – Testing Phase

Methods	Accuracy	Precision	Recall
Ensemble TL Model [11]	85.8	85.2	88.3
Yolov2 [14]	89.2	87.4	91.7
Faster R-CNN [15]	87.8	85.8	87.8
QMF [19]	89.5	92.6	94.9
ResNet [20]	90.1	94.1	93.1
ADV-YOLO [21]	88.2	93.6	92.7
Proposed MLP	91.8	95.7	95.7

Table 3 compares the performance metrics—Accuracy, Precision, and Recall—of four different ship detection techniques: Ensemble TL Model, Yolov2, Faster R-CNN, and the proposed MLP. The proposed MLP outperforms the other models across all metrics, with the highest values in Accuracy, Precision, and Recall, indicating a significant improvement in performance. This suggests that the MLP model is highly effective for this task, with robust predictive capabilities that surpass those of other well-established techniques in the field.

Comparison of accuracy, precision and recall in terms of training and testing are observed, recorded and tabulated in Table 4.

Table 4 Comparison of performance metrics with respect to training and testing.

Model	**Training Accuracy**	**Training Precision**	**Training Recall**	**Testing Accuracy**	**Testing Precision**	**Testing Recall**
Ensemble TL Model [11]	89.20%	89.37%	89.40%	90.21%	86.37%	92.39%
YOLOv2	90.05%	88.45%	90.11%	89.2%	87.4%	91.7%
Faster R-CNN	85.41%	83.32%	89.65%	87.8%	85.8%	87.8%
QMF [19]	89.75%	91.56%	94.29%	88.15%	94.17%	94.69%
ResNet [20]	88.71%	93.31%	92.53%	90.41%	93.16%	92.53%
ADV-YOLO [21]	90.41%	92.58%	93.16%	89.90%	92.57%	93.05%
Proposed MLP	91.08%	94.91%	95.55%	91.8%	95.7%	95.7%

Graphically, the comparisons are projected in Figures 10 – 11.

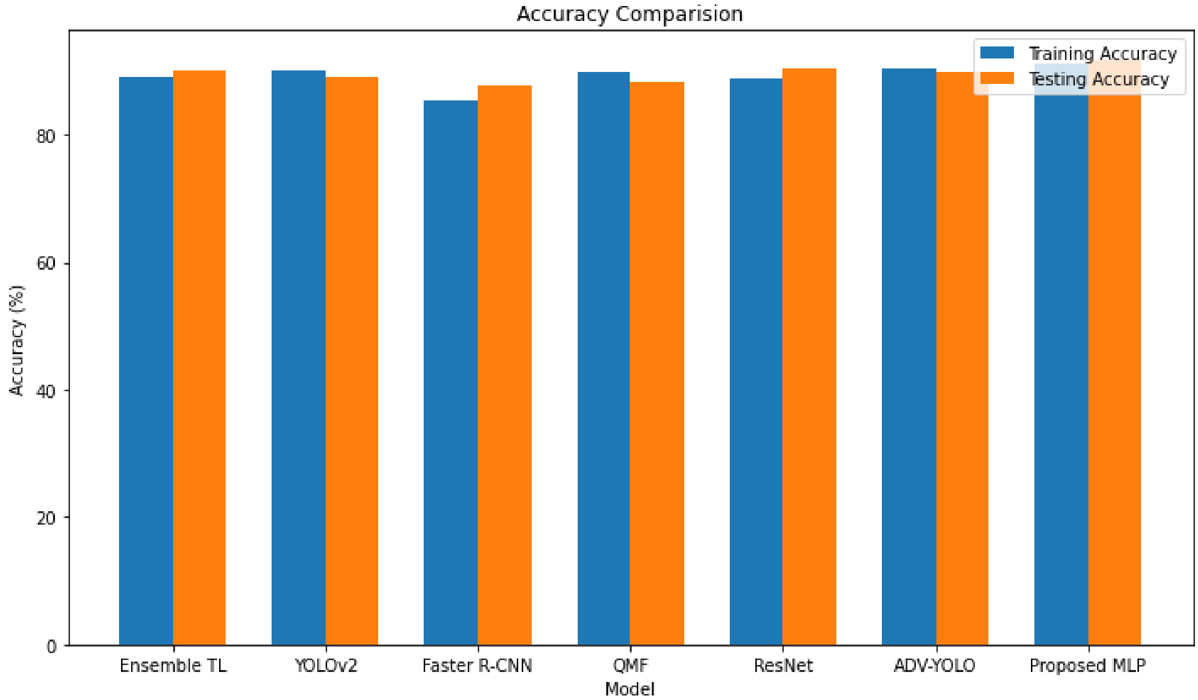

Figure 10. Accuracy Comparison – Training and Testing

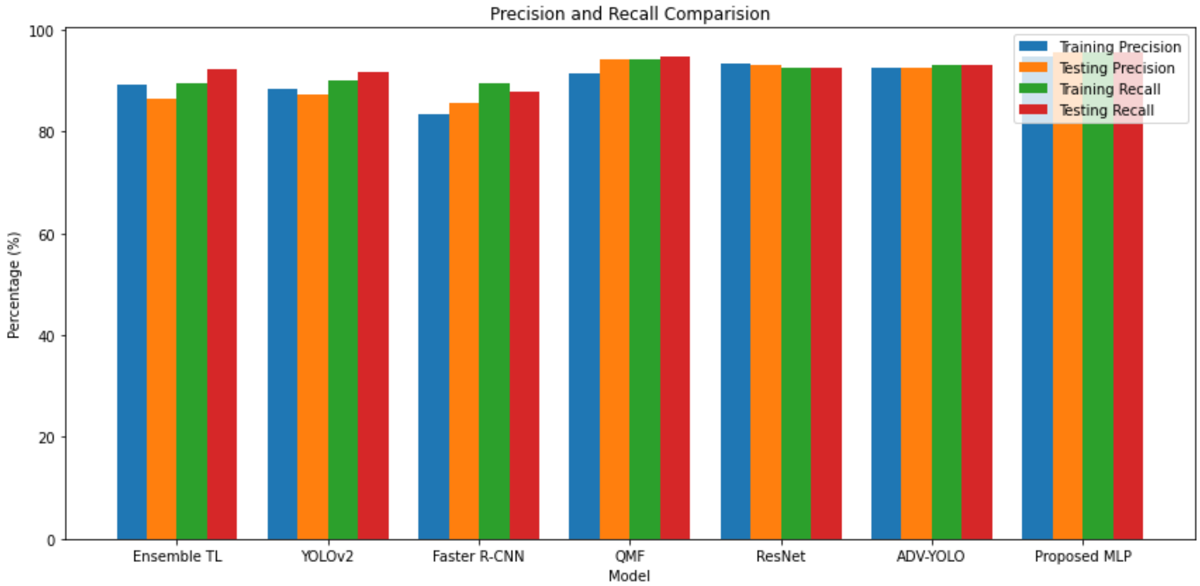

Figure 11. Precision & Recall Comparison – Training and Testing

Figures 10 -11 show that the proposed MLP model achieves higher accuracy in both training (91.08%) and testing (91.8%) phases compared to YOLOv2 and Faster R-CNN. In terms of precision and recall, the plot indicates that the proposed MLP model outperforms YOLOv2 and Faster R-CNN in both precision and recall metrics during training and testing. The MLP model has a precision of 94.91% (training) and 95.7% (testing), and a recall of 95.55% (training) and 95.7% (testing), indicating its superior capability in correctly identifying vessels.

Key Findings:

The detailed comparison between the proposed Multi-Layer Perceptron (MLP) model and prior state-of-the-art techniques for vessel detection in Synthetic Aperture Radar (SAR) imagery highlights several key findings:

1. Accuracy and Precision:

- Proposed MLP Model: The MLP model achieved an accuracy of 91.57%, with a precision of 95.43%. These results demonstrate the model's high capability in correctly identifying vessels while minimizing false positives.
- Prior Art:
  - Ensemble TL Model: Achieved an accuracy of 85.50% and a precision of 82.82%.
  - YOLOv2: Achieved an accuracy of 89.13% and a precision of 88.45%.
  - Faster R-CNN: Achieved an accuracy of 87.44% and a precision of 83.32%.

The MLP model outperforms these prior techniques in both accuracy and precision, indicating its superior ability to accurately classify vessels in SAR imagery. This performance is particularly noteworthy given the challenges associated with detecting small vessels in noisy and cluttered environments.

2. Recall and F1-Score:

- Proposed MLP Model: The recall for the MLP model was 95.43%, resulting in a balanced F1-score, which underscores the model's ability to detect a high proportion of actual vessels without significantly increasing false negatives.
- Prior Art:
- o Ensemble TL Model: Recall was 86.31%.
- o YOLOv2: Recall was 90.11%.
- o Faster R-CNN: Recall was 89.65%.

The higher recall and F1-score of the MLP model compared to the prior art indicate its effectiveness in identifying true positives while maintaining a low rate of false negatives. This is crucial for maritime surveillance, where missing a vessel could have serious implications.

3. Computational Efficiency:

- Proposed MLP Model: The MLP model required 176.31 seconds for training and 36.62 seconds for testing, with a memory usage of approximately 200 MB.

The MLP model significantly outperforms the prior art in terms of computational efficiency, with lower training and testing times and reduced memory usage. This makes the MLP model more suitable for real-time applications, especially in resource-constrained environments such as onboard maritime monitoring systems.

4. Practical Implications:

- The MLP model's combination of high accuracy and computational efficiency makes it ideal for real-time vessel detection in SAR imagery, where rapid processing and reliable identification are essential.
- The reduced computational demands of the MLP model allow it to scale effectively with larger datasets and more complex detection tasks, potentially extending its application to other domains such as aerial surveillance and environmental monitoring.

The proposed MLP model not only outperforms existing techniques in terms of accuracy, precision, recall, and computational efficiency but also offers a practical and scalable solution for real-time maritime surveillance. These results validate the innovative approach taken in this study, establishing the MLP model as a significant advancement in the field of SAR-based vessel detection.

To ensure that the proposed model can be effectively transitioned from a research concept to a practical maritime surveillance solution, specific operational strategies and future development plans are necessary. Following are some of the methods through which the proposed research framework could be translated into a real time application asset.

- **Real-Time Scalability:** Optimize model for onboard processing and remote servers, focusing on memory efficiency and deployment on lightweight hardware for real-time performance.
- **Robustness Across Conditions:** Conduct multi-environment testing (weather, sea states, vessel types) to ensure accuracy in diverse scenarios, enabling generalization and reliability.
- **Anti-Jamming Adaptability:** Integrate adaptive signal processing to filter interference, enhancing performance in high-interference, practical maritime environments.
- **Multi-Target Tracking:** Add multi-target tracking and re-identification for consistent monitoring of multiple vessels in dynamic scenes.

- **Continuous Model Updates:** Implement a continuous learning framework, updating the model with new SAR data to adapt to evolving maritime conditions and operational demands.
- **Field Trials for Validation:** Collaborate with maritime agencies to conduct pilot studies, refining model performance metrics and operational reliability through phased real-world testing.

6. CONCLUSION

The proposed MLP model exhibits a significant advancement in ship detection techniques. Outperforming established models like Yolov2 and Faster R-CNN, it demonstrates high accuracy, precision, and recall, justifying its effectiveness. These results suggest that MLPs have the potential to set new benchmarks in maritime surveillance technology, offering a promising direction for future research and practical applications in vessel identification and tracking. Results indicate that proposed MLP are computationally less demanding, enabling faster training and deployment, particularly in resource-constrained settings. MLPs tend to train faster as observed from the computation time of 176.3117s for training and 36.6249s for testing are less likely to overfit on smaller datasets, which is a common challenge with larger, more complex models. Their ability to capture fundamental data relationships effectively without the need for extensive computing resources makes them a practical choice for many applications. Incorporating the advantages of MLPs, the future scope for vessel detection lies in enhancing these models with adaptive learning capabilities to address dynamic maritime conditions. Utilizing big data and real-time analytics, MLPs could evolve to provide more accurate, timely, and context-aware insights, particularly in complex environments where traditional models might falter. This progression would further solidify MLPs as a cost-effective and efficient solution in the ever-expanding domain of maritime surveillance and safety operations.

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Competing interests
Author state no conflict of interest.

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