Advanced Vessel Detection and Classification in SAR Imagery through Integrated Deep Learning Framework Utilizing Multi Architecture Neural Synthesis

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Abstract - Maritime surveillance remains a critical component of national security and environmental monitoring thereby necessitating the continuous advancement of vessel detection technologies. Traditional methods often struggle with the challenges posed by Synthetic Aperture Radar (SAR) imagery, particularly in detecting small or partially obscured vessels within complex marine environments. This paper introduces a novel approach that significantly enhances the accuracy and efficiency of maritime vessel detection by utilizing advanced deep learning techniques. Utilizing the High-Resolution SAR Images Dataset (HRSID), the proposed method incorporates a sophisticated preprocessing phase that combines Median Filtering for noise reduction and Adaptive Histogram Equalization for contrast enhancement. The novelty in proposed work methodology is a state-of-the-art segmentation process using Mask-RCNN which is well-known for its efficiency in distinguishing objects from cluttered backgrounds, which is quite crucial in marine settings. This is further complemented by the innovative use of DenseNet101 for robust feature extraction, capturing complex vessel characteristics often missed by conventional models. A Convolutional Recurrent Neural Network (CRNN) is then employed for the classification of vessels, integrating spatial and temporal data to enhance detection accuracy. The proposed approach not only fills the existing gap in real-time and reliable small vessel detection but also sets new benchmarks in computational efficiency which is a critical factor for real-time applications. Experimental results demonstrate significant improvements over existing methods in both accuracy and processing speed, promising a substantial impact on the operational capabilities of maritime surveillance systems.

Keywords - Synthetic Aperture Radar (SAR) Imagery, Deep Learning in Maritime Surveillance, Mask-RCNN for Object Segmentation, DenseNet101 Feature Extraction, Convolutional Recurrent Neural Network (CRNN), Adaptive Histogram Equalization.

I. INTRODUCTION

In the field of maritime surveillance, the ability to accurately detect and classify vessels from Synthetic Aperture Radar (SAR) imagery is a critical component for ensuring maritime safety, security, and efficient navigation [1, 2]. SAR systems provide high-resolution images that are essential for identifying vessels in various weather conditions, day or night. However, the complex nature of marine environments, coupled with the challenges posed by SAR imagery, such as speckle noise and variable imaging conditions, makes vessel detection a challenging task. A typical SAR imagery depicting vessels on-and-offshore is depicted in **Fig 1**. Recent advancements in image processing and machine learning have opened new avenues for enhancing vessel detection techniques. In spite of these technological advancements, the detection of small, partially obscured, or closely positioned vessels remains a significant challenge. Traditional methods often fall short in handling the high noise levels and the dynamic range of pixel intensities found in SAR images. Moreover, the increasing volume of data from modern SAR sensors demands algorithms that are not only accurate but also computationally efficient to enable real-time processing.

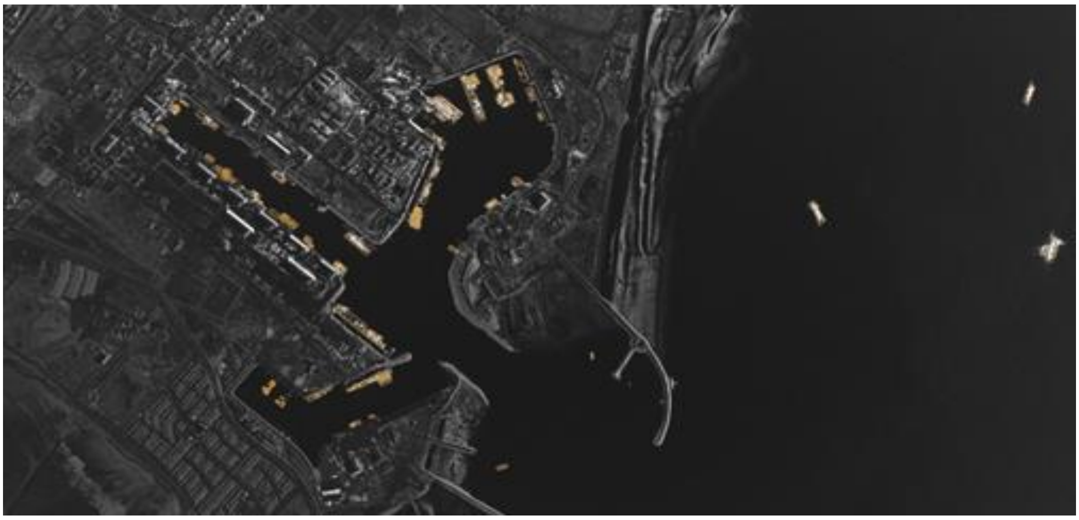


Fig 1. Illustration of SAR Imagery of Vessels Anchored at Port.

Several research works [3 - 7] have addressed these challenges by exploring various deep learning architectures, which have shown promise in many image recognition tasks due to their ability to learn complex patterns and features directly from the data. Among these, convolutional neural networks (CNNs) stand out for their effectiveness in spatial data analysis. However, the unique characteristics of SAR images require adaptations to these models or the development of hybrid models that can better capture the spatial and temporal features relevant to maritime scenarios. Neural networks are also used in a variety of applications [8]

This paper introduces a novel Integrated Deep Learning Framework Utilizing Multi-Architecture Neural Synthesis, which utilizes the strengths of multiple neural network architectures, including Mask-RCNN for segmentation, DenseNet101 for feature extraction, and Convolutional Recurrent Neural Networks (CRNN) for classification. This multi-architecture approach is designed to enhance both the accuracy and the computational efficiency of vessel detection systems. Mask-RCNN provides precise segmentation capabilities that are crucial for accurate vessel isolation from complex maritime backgrounds. DenseNet101 is utilized for its efficiency in feature extraction, capturing essential details from SAR images that are critical for classification. Lastly, CRNN combines convolutional and recurrent layers to effectively handle the sequential and spatial dependencies in image data, thus improving classification outcomes. This paper aims address the research gap by targeting the specific challenges of SAR image processing for vessel detection, particularly focusing on small and obscured vessel identification in cluttered maritime scenes. By integrating advanced preprocessing methods with sophisticated feature extraction and classification techniques, our approach sets a new benchmark for SAR-based maritime surveillance systems. Through detailed experimental analysis, this research work demonstrates the superior performance of the proposed framework over existing methods, contributing significantly to the fields of remote sensing and maritime surveillance.

II. LITERATURE REVIEW

A novel CNN is proposed by Zhao et al. [9] for vessel identification in synthetic aperture radar (SAR) images. To improve feature extraction, CVGG-Net combines phase and amplitude information from complex-valued SAR data with an entirely novel complex max-pooling technique called Complex Area Max-Pooling. The network's architecture is based on the VGG method, modified to handle complex-valued data through complex convolutional blocks, batch normalization, and activation functions tailored for the complex domain. Experimental evaluation on two SAR datasets showed that CVGG-Net outperforms traditional real-valued convolutional networks. The superior performance is depending on the effective use of complex data characteristics and the network's ability to maintain the integrity of complex information throughout the layers. Merits of the work include the innovative approach to complex data handling in neural networks and the demonstrated effectiveness of complex max-pooling. Demerits may include the potential complexity and computational demands of the network, given the need for specialized operations to process complex data. Moreover, while the network shows improved performance, the gains in accuracy may require validation in broader real-world applications to establish its practical benefits beyond the datasets used.

Mishra et al. [10] proposed deep CNN utilizingVGG16 architecture for classifying vessel images. It employs a transfer learning strategy by using CNN techniques that have already been trained and are subsequently modified for the classification of particular vessel types. To improve the method's capacity to generalize from the training set of data, this approach incorporates data augmentation. Merits of this work include the high accuracy achieved, which indicates the method's effectiveness in handling complex image classification tasks. The use of transfer learning also allows for more efficient training by adapting a pre-existing method trained on a large dataset. However, demerits include the potential for overfitting, as indicated by the initial high training accuracy versus lower validation accuracy. While methods like Dropout and Early Stopping were used to mitigate this, the risk remains, especially when adapting to new or more diverse datasets that were not represented in the training phase. Additionally, the dependency on pre-trained methods may limit the adaptability of the approach to drastically different types of images or classification tasks without gradual re-training or modification.

In order to improve the classification of vessels in SAR images, Zhang et al. [11] develop HOG-ShipCLSNet, a new deep learning network that fuses Histogram of Oriented Gradients (HOG) features. The classification accuracy is greatly enhanced by this network through the use of four essential mechanisms: multiscale classification, global self-attention, completely connected balancing, and HOG feature fusion. Although the excerpt fails to specify exact numerical numbers for accuracy gains, it is demonstrated that the method outperforms both classic customized feature methods and current CNN-based methods when tested on two available SAR ship datasets. The primary merit of HOG-ShipCLSNet lies in its innovative integration of traditional HOG features with advanced neural network architectures, potentially offering a robust approach to feature representation and classification. This approach effectively captures and utilizes both local and abstract features, enhancing the method's ability to generalize across different SAR images. However, the complexity of the method and the integration of multiple mechanisms could potentially increase computational costs and training time, representing challenges for real-time applications. The effectiveness of the method in operational environments or across diverse datasets also remains to be validated, as the performance gains are primarily demonstrated in controlled experiments.

In order to overcome the drawbacks of current algorithms for SAR ship detection, which mostly depend on geographical feature information, Li et al. [12] introduces a new multidimensional domain deep learning network specifically designed for SAR ship recognition. Especially in difficult conditions with multiscale and rotational ship targets, this network improves detection efficiency by utilizing both spatial-domain and frequency-domain data. To improve detection accuracy, the network uses a fusion network to combine data obtained by a Feature Pyramid Network (FPN) for spatial feature extraction and a polar Fourier transform for features that are rotation-invariant. When examined on the SAR Ship Detection Dataset (SSDD), the approach outperformed more conventional methods based on convolutional neural networks (CNNs), particularly when faced with difficult situations such as multiscale and rotational objects. The merits of this approach include its innovative integration of multidimensional domain features and its effectiveness in complex scenarios. However, the increased computational complexity and potential overfitting due to the advanced method architecture could be considered as demerits, especially in real-time application scenarios where computational efficiency is complex.

In their research, Dechesne et al. [13] presents a deep learning method that can detect, classify, and estimate the length of ships using Sentinel-1 SAR data. In order to create training datasets gradually, the method decreases the synergy between Sentinel-1 data and the Automatic Identification System (AIS). The neural network architecture comprises a joint convolutional network that feeds into three separate networks for each specific task. This method not only detects ships but also classifies them into categories such as Cargo, Tanker, Fishing, and Passenger, and estimates their lengths. During the evaluation, the network achieved satisfactory results with precise classification and length estimation. The merits of the work include its innovative multi-task approach that effectively handles different aspects of ship analysis in SAR images, potentially improving both the efficiency and accuracy over traditional methods that depends on manual interpretation. However, the demerits might include the complexity of training such a multi-task network and the need for extensive labeled data to train the method effectively.

A deep learning method named FishNet is designed by Guan et al. [14], specifically designed for classifying fishing vessels in SAR images. To improve feature extraction and use, FishNet incorporates novel modules. In order to handle class imbalance effectively, the approach also uses an adaptive loss function. One of FishNet's main strengths is that it can handle the tough components of SAR image analysis (the small size and minor interclass differences among fishing vessels) quite well. For thorough feature extraction and strong classification performance, it is necessary to combine various deep learning methods. However, the method's complexity and the intensive computational resources required could be seen as demerits, potentially limiting its use in real-time applications or on platforms with limited processing power. The method's performance also heavily depends on the availability of high-quality, labelled training data, which can be challenging to obtain for SAR images of fishing vessels.

Using a combination of image processing techniques and acnn , Bereta et al. [15] discusses a vessel detection system that integrates satellite optical imagery with Automatic Identification System (AIS) data. The system is designed to identify vessels, particularly those that might have their AIS transponders switched off. It utilizes a multistage data-centric workflow involving the preprocessing of multispectral Sentinel-2 data and the application of CNN for the classification of extracted features. The experimental evaluation of this framework indicates an impressive accuracy exceeding 95%. The merits of this work include the integration of different data types and methodologies to improve maritime situational awareness, the high accuracy of vessel detection, and the automation of the data processing pipeline.

Addressing the loss of spatial information typical in deep convolutional neural networks, Xu et al. [16] introduces a novel Multi-Scale Convolutional Neural Network (MS-CNN) for classifying ships in SAR images. By integrating multi-scale features to enhance feature expression, the MS-CNN demonstrated an improvement in classification accuracy. Specifically, the experiments conducted on the OpenSARShip dataset showed that MS-CNN increased the classification accuracy by 4.81% compared to a benchmark network. The main merit of this approach is its ability to capture detailed spatial and semantic information simultaneously, making it highly effective for SAR ship classification. However, a potential demerit could be the complexity and computational demands of managing multi-scale data inputs, which might affect performance and scalability in real-time applications.

Using a Grid Convolutional Neural Network (G-CNN), Zhang et al. [17] presents a method for rapidly identifying ships in SAR images. This technique uses depthwise separable convolutions to improve detection performance while maintaining accuracy relatively constant. Validation was done on RadarSat-1 and Gaofen-3 SAR images, and the experimental evaluation was carried out on an open SAR Ship Detection Dataset (SSDD). Under identical hardware settings, G-CNN outperformed state-of-the-art approaches in terms of detection speed without reducing accuracy. When it comes to applications like real-time marine disaster response and military strategy, G-CNN really shines because of how fast it can detect ships.

Mukherjee et al. [18] utilized Faster R-CNN model to detect ships from satellite images, utilizing deep learning techniques. The model was enhanced through various data augmentation techniques such as Gaussian filtering, edge detection, horizontal flipping, random cropping, and color modifications, along with Affine transformations. These methods helped to train the method effectively, achieving high accuracy rates of 98.16% on validation data and 97.33% on test data. The model used Adam Optimizer and binary cross-entropy as the loss function across 50 training epochs. The merits of this study include the comprehensive approach to enhancing model accuracy through feature engineering and robust data augmentation. However, demerits may include the heavy computational demand due to the complex preprocessing and the need for extensive training data to achieve such high accuracy, which may not generalize well across different scenarios or datasets with less preprocessing.

To classify land and sea pixels, Tajima et al. [19] presented a shoreline detection method using satellite Synthetic Aperture Radar (SAR) imagery, which utilizes an artificial neural network (NN), thereby defining the shoreline as the boundary between these classes. The NN employs a feedforward architecture, using a novel input layer strategy that enhances pixel classification by considering both local and broader spatial variations in pixel intensity. This approach is particularly designed to be robust against typical challenges in SAR imagery, such as speckle noise and variable backscattering properties of sandy and gravel beaches. The study demonstrates high classification accuracies, generally exceeding 95%, and shoreline extraction with root mean square errors typically less than 15 meters. These results suggest significant potential for operational use, especially given the method's calibration-free approach and adaptability to shorelines of various configurations. Merits of this technique include its high accuracy, low computational cost, and robustness across different shoreline profiles and conditions. However, the method's performance can be affected by extreme environmental conditions such as very smooth or rough sea states, which can lead to misclassifications. Furthermore, while the method is designed to minimize dependency on specific shoreline orientations or conditions, its effectiveness in highly variable coastal environments may still be an area requiring further validation.

Using a combination of morphological processing and a deep learning neural network method, [20] present M-DLNN, a new vessel detection and classification algorithm that aims to enhance the detection and classification of vessels from optical satellite images. Incorporating morphological features for vessel segmentation and detection and using a deep learning neural network for vessel classification are all parts of the process. The evaluation of the algorithm's performance is presented with metrics such as accuracy, precision, and classification rates. Specifically, the algorithm achieved a notable accuracy of 94.89%, a precision rate that significantly reduces false positives, and an improved running time of 6.54 seconds compared to other traditional methods. Merits of this approach include its high accuracy and precision in vessel detection under various climatic conditions, and its efficiency in processing due to the integration of morphological processing with deep learning techniques. However, demerits might include potential challenges in handling very diverse or low-quality images where morphological traits are not distinctly observable, and the computational demand of deep learning methods, which might require significant computational resources for training and inference.

Sharifzadeh et al. [21] presents a hybrid deep learning approach for ship classification in SAR images, integrating a multi-layer perceptron and CNN to form a CNN-MLP classifier. This innovative method utilizes the strengths of both networks to enhance classification accuracy under varied conditions. The hybrid system uses CNN to process raw SAR data to exploit its ability to automatically extract and learn features directly from the images. Performance evaluation reveals significant improvements with this hybrid approach. For example, the CNN-MLP achieves a precision of 93.19% and an accuracy of 92%, outperforming CNN or MLP methods. Merits of this method include its high classification accuracy and the effective fusion of deep learning with traditional texture analysis, providing robustness against the complex demerits common in SAR images. However, a demerit could include the increased computational complexity and potential overfitting due to the complexity of the method, especially when training on very diverse datasets.

A deep learning approach for ship detection using satellite imagery is introduced by Stofa et al. [22], specifically focusing on the effectiveness of the DenseNet architecture. This approach was tested on the Kaggle Ships dataset, comprising 4,200 images, achieving a high accuracy rate of over 99.75% using the Adam optimizer with a learning rate of 0.0001. The technique involves fine-tuning three hyperparameters: optimizer selection, batch size, and learning rate to optimize performance. The merits are ability to accurately detect ships in harbour areas, which is complex for maritime security. Merits of this approach include the high accuracy rate and the adaptability of the DenseNet architecture to the specific task of ship detection, which benefits from DenseNet's capability for feature retention through its deep, densely connected layers. However, the demerits could include the potential need for large amounts of computational resources due to the complexity of the DenseNet architecture and the dependence on a large and varied dataset to maintain performance across different operational environments. Furthermore, while the system achieves high accuracy, the specifics of its performance under varying conditions like weather changes and different satellite imaging settings were not discussed, which could affect its practical deployment in real-world scenarios. DenseNet features are highly useful in various applications, including image segmentation and predictive modelling [23].

To enhance classification performance, Zhu et al. [24] introduces a novel ship classification architecture using SAR images, incorporating a sequence input method. The method employs a combination of CNN for feature extraction from individual frames and Long Short-Term Memory (LSTM) networks to process sequences of these frames, capturing temporal dependencies among consecutive images. This architecture is trained on the OpenSARShip dataset, achieving an impressive classification accuracy of 99.24% across six target classes, which indicates improvement over traditional methods that use single-image inputs. The principal merit of this approach is its high accuracy and innovative use of sequence data, which effectively utilizes the temporal information inherent in SAR image sequences, thus providing a more robust framework for ship classification under various conditions. However, the demerits include potentially increased computational requirements due to the complex nature of processing multiple image sequences and the need for large datasets to effectively train the LSTM component without overfitting. Additionally, the real-world applicability might be challenged by the variability in image quality and operational conditions not represented in the training dataset.

III. RESEARCH GAP

In spite of the considerable advancements in maritime surveillance technologies, existing methodologies for vessel detection in Synthetic Aperture Radar (SAR) imagery often struggle with several persistent challenges. These challenges include the detection of small vessels, particularly in high sea states or in the presence of close proximity maritime traffic, and the efficient processing of large volumes of data generated by modern SAR systems. Traditional algorithms typically rely on simpler image processing techniques, which may not adequately distinguish between vessels and sea clutter, especially under adverse conditions. Moreover, while recent applications of deep learning have shown improved results, there remains a significant gap in the integration of these technologies in a way that utilizes their complementary strengths. Most current systems use either convolutional neural networks (CNNs) for their strong spatial analysis capabilities or recurrent neural networks (RNNs) for their ability to process temporal sequence data. However, few systems effectively combine these approaches to handle the complexities of SAR images, which require both spatial and temporal data processing to accurately identify and classify dynamic maritime objects.

IV. PROBLEM FORMULATION

The main issue addressed in this research is directed on the development of an efficient and robust system for vessel detection in SAR imagery, which can overcome the limitations of existing methods in detecting small and partially obscured vessels under various environmental conditions. The complexities of SAR data, characterized by high levels of speckle noise and significant variation in backscatter from different surfaces, require a sophisticated approach that can adaptively distinguish vessels from complex backgrounds.

To address these challenges, this study proposes a hybrid deep learning framework that combines the spatial discrimination power of convolutional layers and the sequence processing capabilities of recurrent layers. The specific objectives are to:

1. Enhance the clarity and contrast of SAR images through advanced preprocessing techniques, making it easier to identify vessels.
2. Achieve precise segmentation of vessels from highly cluttered maritime backgrounds using an improved Mask-RCNN model.
3. Extract robust features from segmented images using DenseNet101, which is renowned for its efficiency in learning important features without overfitting.
4. Classify the features into vessel and non-vessel categories using a Convolutional Recurrent Neural Network, which integrates temporal and spatial data for improved accuracy.

V. RESEARCH CONTRIBUTION

Particularly in the area of SAR image processing and analysis for vessel recognition, this study provides a number of new features to marine surveillance. These are the contributions:

- Development of an Integrated Deep Learning Framework: By synthesizing the capabilities of Mask-RCNN, DenseNet101, and CRNN into a single cohesive framework, this research addresses the gap in existing maritime surveillance systems that do not fully exploit the synergies of these advanced neural architectures.
- The introduction of a combination of median filtering and adaptive histogram equalization specifically tailored for SAR images represents a significant enhancement over traditional preprocessing methods, which often fail to adequately suppress noise and enhance feature definition in such images.
- The application of Mask-RCNN for segmentation and DenseNet101 for feature extraction sets new standards for accuracy in distinguishing vessels from complex maritime backgrounds. This methodology ensures that essential features are captured more effectively, significantly improving the reliability of subsequent classification stages.

- Utilizing a CRNN for classifying vessels incorporates both the spatial features extracted by CNN layers and the sequence analysis provided by RNN layers. The accuracy of vessel recognition and classification is enhanced by this dual method, which allows for a more advanced understanding of the temporal dynamics in SAR imagery.
- The research includes a thorough evaluation of the proposed framework against established benchmarks, providing clear evidence of its superior performance in terms of metrics.

VI. MATERIALS AND METHODS

The proposed work utilized advanced deep learning models which are crucial for various stages for processing. The overall schematic of the proposed work is depicted din **Fig 2**. The illustration outlines an advanced image processing workflow designed for handling synthetic aperture radar (SAR) images through several stages of refinement and analysis. Initially, an input SAR image is preprocessed to mitigate common issues like noise and contrast variability; this involves the application of a median filter to reduce speckle noise, followed by adaptive histogram equalization to enhance image contrast, making features more distinct. Following preprocessing, the image enters a segmentation phase using a Mask R-CNN model, a sophisticated convolutional neural network adept at both object detection and instance segmentation, which processes the image to detect and delineate distinct objects, outputting a series of refined feature maps.

The next process involves extraction of detailed features using the DenseNet101 architecture, a densely connected convolutional network well-known for its efficient handling of features through fewer parameters and enhanced feature reuse across its 101 layers. This extracted information is crucial for the next phase.

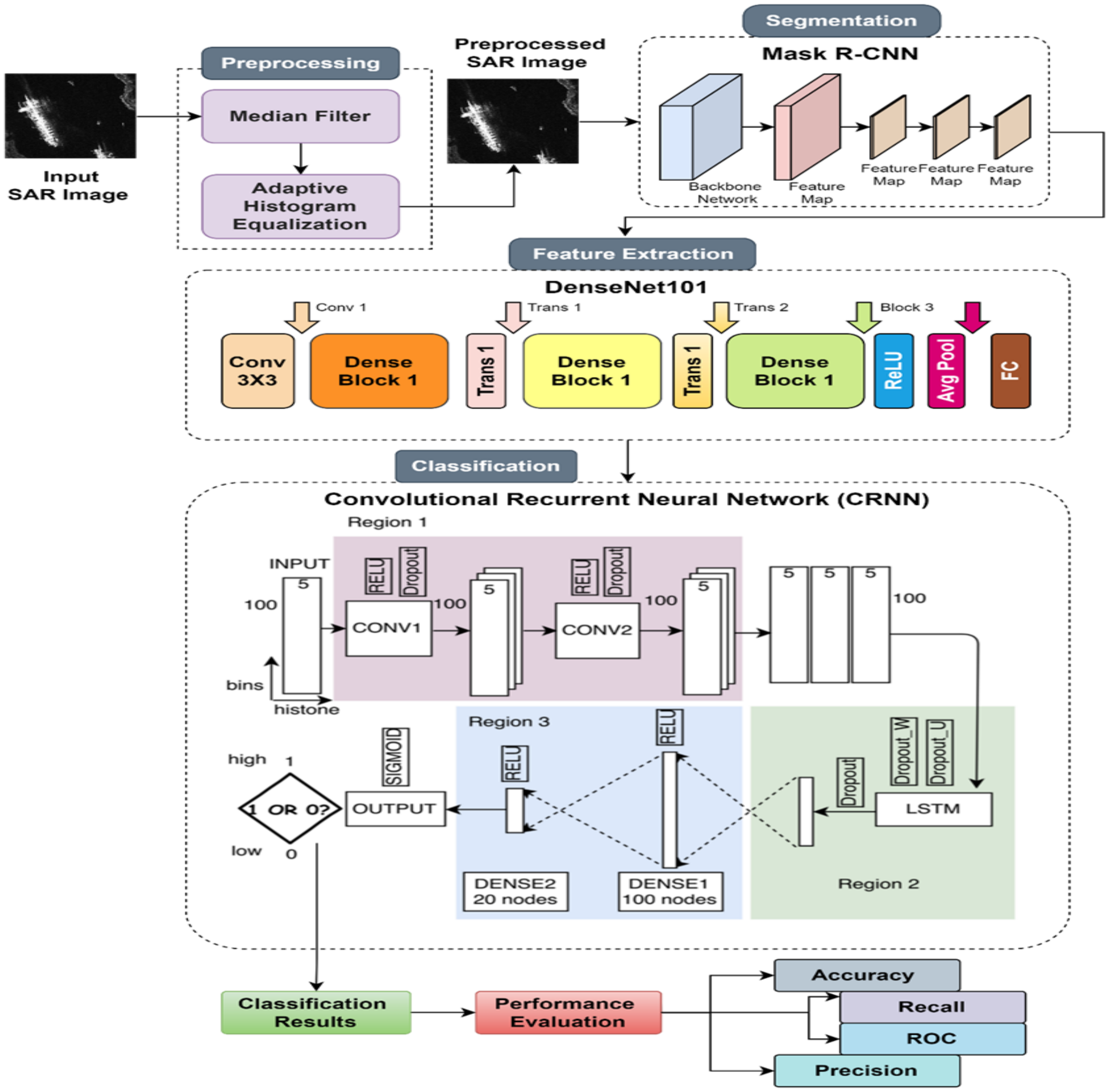


Fig 2. Illustration of The Flow Process of The Proposed Classification Model.

The classification stage employs a convolutional recurrent neural network (CRNN) that incorporates both convolutional layers for processing spatial features and LSTM (long short-term memory) units for handling sequential data, allowing it to effectively classify regions within the image.

Finally, the results of this classification are systematically evaluated through a series of performance metrics, including accuracy, recall, ROC (receiver operating characteristic) curve analysis, and precision.

Dataset

The proposed work utilizes the High-Resolution SAR Images Dataset (HRSID), which is specifically designed for advancing the technology of vessel detection and segmentation in SAR imagery. This dataset is publicly available and can be accessed via its repository on GitHub. HRSID comprises a collection of 5,604 high-resolution SAR images, involving a total of 16,951 ship instances. These images are characterized by their diversity in terms of resolution, polarization, and varied maritime conditions, which include different sea areas and coastal ports. The dataset images are captured with resolutions ranging from 0.5m to 3m, providing a detailed view that is crucial for identifying small and complex objects such as vessels in complex maritime scenarios. Sample images from the dataset are depicted in **Fig 3** shown below.

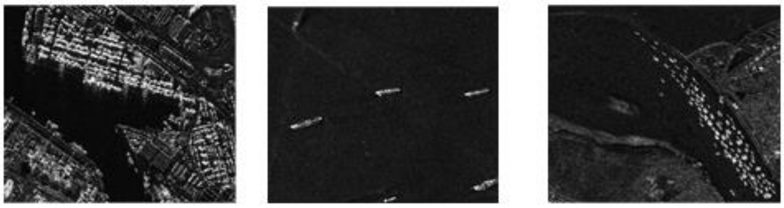


Fig 3. Illustration of Sample Images from HRSID Dataset.

Preprocessing

Preprocessing SAR imagery for vessel detection involves critical enhancements to improve image quality by reducing noise and enhancing contrast. These steps are essential to prepare images for accurate feature extraction and classification by deep learning models. Median filtering is employed to reduce speckle noise, which is prevalent in SAR images. Speckle noise can obscure important features and make segmentation and classification tasks more challenging. Mathematically, the filter could be formulated as

$$I_{(x,y)}'=median(I_{(x-r:x+r,y-r:y+r)}) \tag{1}$$

In Equation (1)

$(I_{(x-r:x+r,y-r:y+r)})$ – Neighborhood of pixels

$I_{(x,y)}'$ - new pixel value at position (x,y)

The median filter is particularly useful for preserving edges while removing noise, as it does not blur the edges like average filtering might, making it ideal for detailed and texture-rich images like SAR.

After noise reduction, Adaptive Histogram Equalization (AHE) is used to enhance the contrast of the images. This step is critical for improving the visibility of features, especially in images where the contrast between the vessels and the sea may be low. Mathematically it is formulated

$$I_{(x,y)}'=CDF_{(x,y)}(I_{(x,y)})X(L-1) \tag{2}$$

In Equation (2),

$I_{(x,y)}'$ - Enhanced pixel value

$I_{(x,y)}$ – Original pixel

L – Intensity levels

$CDF_{(x,y)}$ – Cumulative Distribution Function of intensities centered around (x,y)

AHE divides the image into several tiles. Histograms are computed for each tile and used to redistribute the lightness values. This method is better suited for local contrast enhancement and reduces the noise amplification typical with global histogram equalization. AHE is especially effective for images with local shadowing or variable brightness, which are common in maritime scenarios captured in SAR imagery. It enhances the local contrast without affecting the global contrast, making it easier to detect vessels against varying backgrounds. The above-mentioned preprocessing steps prepare the SAR imagery effectively, ensuring that subsequent deep learning models can perform optimally. These steps are foundational for achieving high accuracy in vessel detection and classification from SAR images.

Segmentation

Segmentation is a crucial step in the vessel detection process, where the goal is to accurately distinguish between vessel and non-vessel areas within the SAR imagery. For this purpose, the Mask R-CNN framework has been employed due to its proficiency in generating high-quality instance segmentation maps. This section details the implementation of Mask R-CNN for vessel segmentation, adhering closely to the methods described in the "implementation" document. Mask R-CNN enhances Faster R-CNN's functionality. The R-CNN model is notably effective at object detection because it incorporates a branch that predicts segmentation masks for each ROI separately from the class labels. Accurate pixel-level segmentation and exact object localization (in this case, vessels) are both made possible by this dual method. Mask R-CNN integrates both convolutional neural networks (CNNs) for feature extraction and a Region Proposal Network (RPN) for generating object proposals. The architecture is depicted din **Fig 4**. It processes the input image in two stages: the first stage scans the image and proposes areas where objects might exist, and the second stage classifies the objects and refines their boundaries while simultaneously generating a mask at the pixel level for each instance.

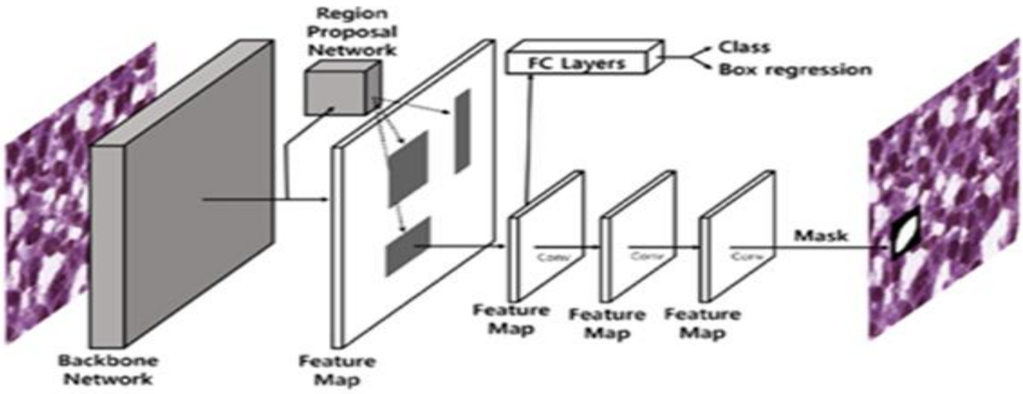


Fig 4. Illustration of Mask R-CNN Model for Segmentation.

The pre-processed SAR images that were used to train the Mask R-CNN model contain annotations for vessels of different sizes and types. In addition to the class label and bounding box, the training dataset contains annotated instances that have a segmentation mask that specifies the exact vessels. Mask R-CNN generates a segmentation mask that defines the vessel's outlines for every object it detects. Similar in size to the RoI, this mask is a binary image where ones denote the item and zeros the background. The segmentation task in Mask R-CNN can be described by the loss function specified in Equation (3). It is used during training to improve the accuracy of both the mask predictions and the bounding box identifications. Considering L_cls to be the classification loss, L_box to be the loss associated with the bounding box, L_mask the mask loss, the overall loss function could be formulated as

$$L=L\_cls+L\_mask+L\_box+L\_mask \quad (3)$$

The use of Mask R-CNN for vessel segmentation allows for the precise segmentation of vessels in complex maritime environments, handling overlapping vessels and various vessel orientations effectively. Additionally, the pixel-level segmentation capability of Mask R-CNN ensures that the features extracted in subsequent steps are highly accurate, which is crucial for the effective classification of vessels. This implementation of Mask R-CNN for vessel detection in SAR imagery marks a significant step forward in the use of advanced deep learning techniques for maritime surveillance. The model's ability to provide detailed segmentation results helps in improving the overall accuracy of the vessel detection system, ensuring robust performance across different maritime conditions.

Pseudocode for Vessel Segmentation using Mask R-CNN
Input: Preprocess Images
Output: Segmented Images

```
I[x, y]  : Input preprocessed image matrix at pixel coordinates (x, y)
W        : Pre-trained weights for Mask R-CNN
R[x, y] : Region Proposals from RPN
M[k, a, b] :Mask for k-th proposal at pixel coordinates (a, b)
C[k]     : Class scores for k-th proposal
B[k, (x1, y1, x2, y2)] : Bounding box for k-th proposal
D: List for storing final detections
    I = load_image(image)
    R = generate_region_proposals(I)
for k from 1 to length(R):
region = I[R[k, (x1, y1, x2, y2)]]
        C[k], B[k] = classify_and_adjust_bbox(region)
M[k] = generate_mask(region)
```

```
        if C[k] > detection_threshold:
            refine_bbox(B[k])
            refine_mask(M[k], B[k])
            D.append((C[k], B[k], M[k]))
for each detection in D:
    class_score, bbox, mask = detection
    print("Detected class score:", class_score)
print("Bounding box coordinates:", bbox)
display(mask)
```

Feature Extraction

After the segmentation process where vessels are precisely isolated from the maritime background, the next critical step is the feature extraction. DenseNet101 architecture is particularly well-suited for capturing a rich set of features from complex images like SAR imagery used for vessel detection and hence used in proposed approach. DenseNet101 is depicted in **Fig 5**. It is part of the Dense Convolutional Network (DenseNet) family that connects each layer to every other layer in a feed-forward fashion. For SAR images, where the detection and classification of objects depend heavily on the clarity and detail of the features, DenseNet101 provides several advantages.

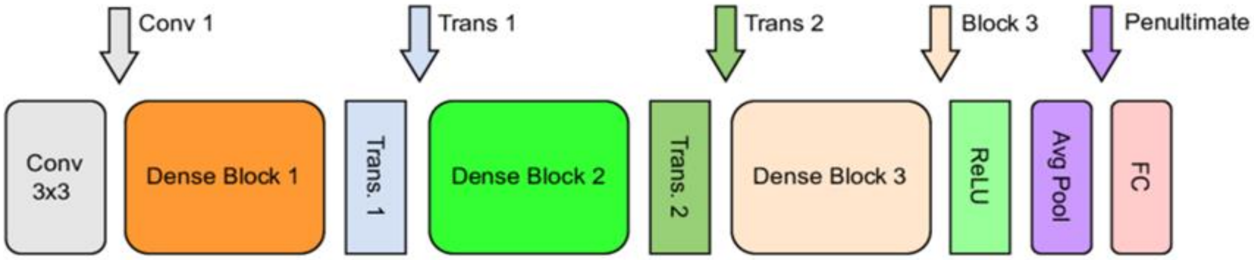


Fig 5. Illustration of DenseNet101 Model for Segmentation.

In DenseNet101, each layer receives additional inputs from all preceding layers and passes its own feature-maps to all subsequent layers. This dense connectivity pattern promotes feature reuse throughout the network, which is critical for learning detailed features from SAR images with minimal loss of information through the layers. Unlike traditional architectures that sum the outputs of previous layers, DenseNet101 concatenates outputs. This method preserves features from earlier in the network, enhancing the network's ability to learn varied and complex features essential for recognizing different types of vessels. Due to its dense connectivity, DenseNet101 requires fewer parameters than traditional CNNs with similar depth, making it more efficient to train. This efficiency is crucial when dealing with large datasets of SAR images.

The segmented images (masks) from the Mask R-CNN are resized and normalized to match the input size requirements of DenseNet101. Each masked region corresponding to a vessel is input into DenseNet101 to extract feature vectors. DenseNet101 processes each input image through its layers, culminating in a feature vector for each image. This vector captures the essential characteristics of the vessel, such as shape, texture, and other relevant maritime features. The extracted feature vectors are crucial inputs for the subsequent classification stage, where each vector is used to determine the type of vessel present in the image. By utilizing DenseNet101 for feature extraction, we ensure that our vessel detection system captures the most detailed and significant features from SAR images, which significantly enhances the accuracy and reliability of the classification results. This step is instrumental in building a robust model that can effectively differentiate between various vessel types and sizes under different conditions typical of maritime environments.

Pseudocode for Feature Extraction using DenseNet101
Input: Segmented Images
Output: Feature Extracted List

```
M[k, a, b]  :Mask for k-th detected vessel at pixel coordinates (a, b)
V[k]        : Extracted vessel images ready for feature extraction
F[k]        : Feature vectors for k-th vessel
for k from 1 to length(M):
    V[k] = crop_image(I, M[k])
    V_preprocessed[k] = preprocess_for_denseNet(V[k])
    F[k] = DenseNet101(V_preprocessed[k])
for k from 1 to length(F):
    store_features(F[k])
print("Feature extraction complete for all vessels.")
```

Classification

Following the feature extraction stage, the next critical step in the proposed vessel detection process is the classification of vessels using the extracted features. In this study, we utilize a Convolutional Recurrent Neural Network (CRNN) to classify the vessels based on the features provided by DenseNet101. As shown in **Fig 6**, CRNN combines the capabilities of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to utilize both spatial and temporal feature dependencies, which is particularly beneficial for images where context and sequence matter. In the proposed work, while the temporal component is less emphasized, the recurrent layer's ability to handle sequences helps in classifying images that have been segmented and feature-encoded sequentially in the pipeline.

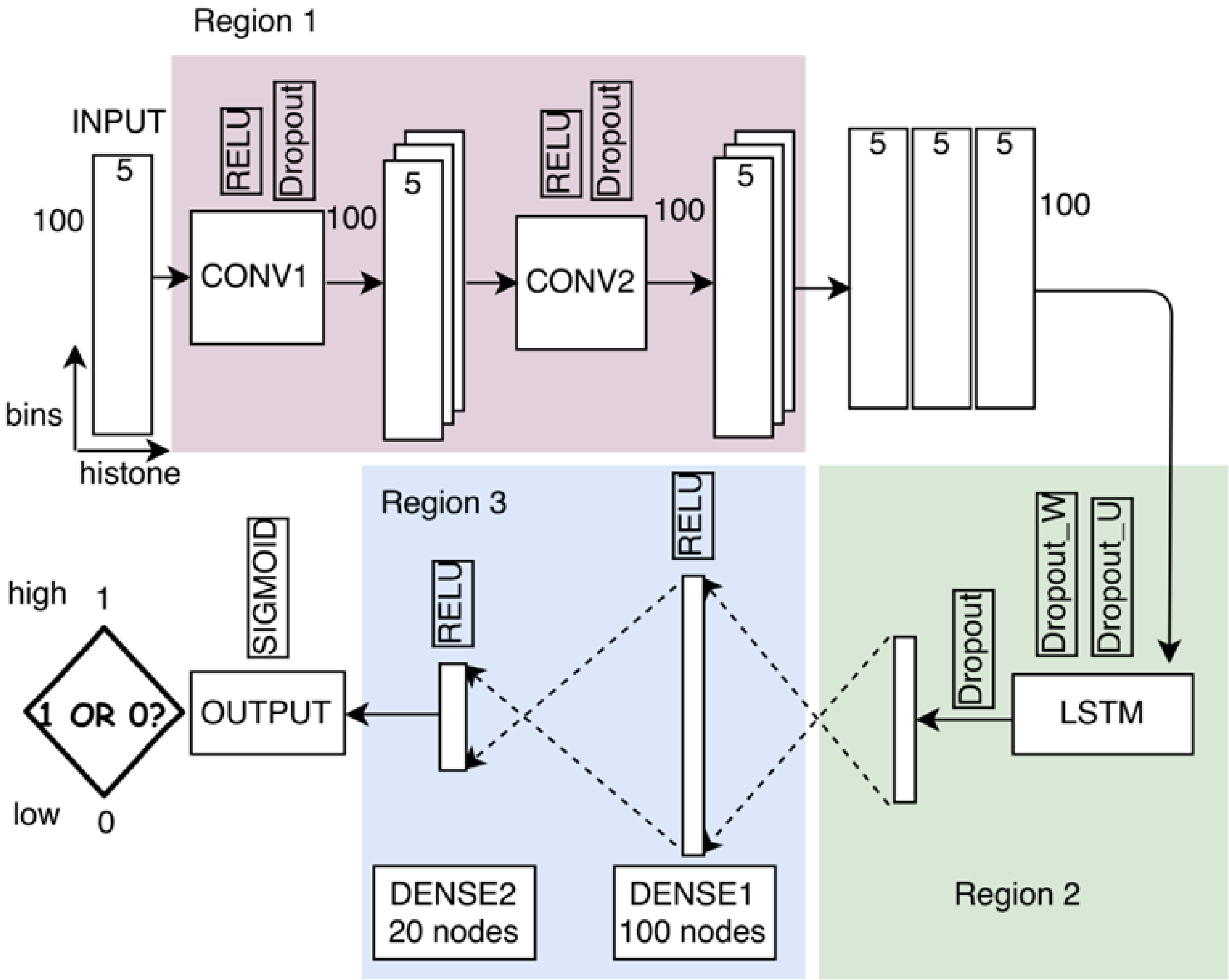


Fig 6. Illustration of CRNN Model for Classification.

Initially, the feature vectors extracted by DenseNet101 are passed through additional convolutional layers if needed to refine the features further before classification. This step ensures that the spatial hierarchy of features is well-represented. Following the convolutional layers, the features are fed into recurrent layers, typically LSTM (Long Short-Term Memory) units, which are adept at managing sequences. In this context, the sequence refers to the series of feature vectors from consecutive frames or image segments that are analysed for classification. The final layer in the CRNN is a fully connected layer that outputs the classification results. It categorizes each input feature vector into vessel classes based on the learned features, which may include vessel types such as cargo ships, fishing boats, or naval vessels. The feature vectors F[k] generated by DenseNet101 are the inputs to the CRNN. Each vector is treated as an independent input to the network, assuming no temporal dependencies unless the imagery sequence dictates otherwise. The CRNN is trained using a dataset of labelled vessel images processed through the same pipeline. The network is optimized for classification accuracy using a cross-entropy loss function, which is standard for multi-class classification tasks. Accuracy, precision, and recall are calculated to evaluate the performance of the vessel classification, ensuring that the CRNN correctly identifies and categorizes the vessels from the SAR images. This classification stage is crucial for the practical application of the vessel detection system, as it determines the type and possibly the activity of vessels within a monitored maritime area, contributing to surveillance, traffic management, and regulatory enforcement.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed research work utilizes the High-Resolution SAR Images Dataset (HRSID), accessible at https://github.com/chaozhong2010/HRSID. This comprehensive dataset is essential for advancing the analysis of ship detection and segmentation within SAR imagery. It contains a total of 5,604 high-resolution images that includes 16,951 instances of ships. The images are characterized by a variety of resolutions, including 0.5m, 1m, and 3m, and exhibit range of polarizations and diverse maritime environments from different oceanic and coastal regions. Inspired by the structure of the Microsoft COCO datasets, the HRSID serves as an essential benchmark, allowing researchers to rigorously test and refine their analytical methods in the context of detailed SAR image evaluation.

Pseudocode for Feature Extraction using DenseNet101
Input: Feature Vectors
Output: Classified Output

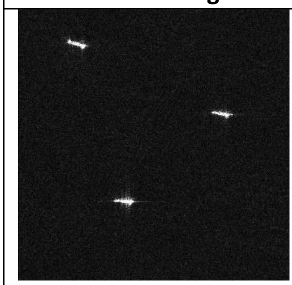
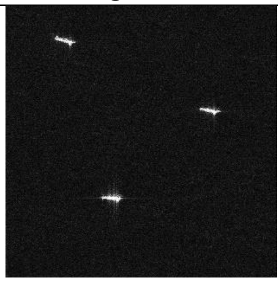
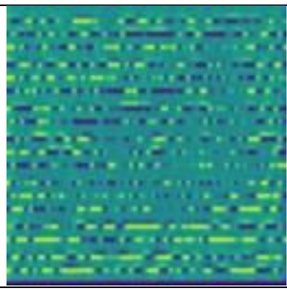
```
F[k]        : Feature vectors for k-th vessel from DenseNet101
C[k]        : Classification results for k-th vessel
CRNN        : CRNN model initialized with pre-trained parameters
L           : Loss function for training the CRNN
for k from 1 to length(F):
    input_vector = preprocess_for_CRNN(F[k])
    C[k] = CRNN(input_vector)
for epoch in range(total_epochs):
    for k in random.shuffle(range(length(F))):
        prediction = CRNN(F[k])
        true_label = get_true_label(F[k])
        # Calculate loss and backpropagate
        loss = L(prediction, true_label)
    if epoch % validation_interval == 0:
        accuracy, precision, recall = evaluate_performance(CRNN, validation_data)
        print(f'Epoch {epoch}: Accuracy={accuracy}, Precision={precision}, Recall={recall}')
for k from 1 to length(C):
    print(f'Vessel {k} classified as {C[k]}')
```

The proposed work has been implemented using Python programming by utilizing a suite of libraries like scikit-learn, numpy, pandas, scipy, prettytable, seaborn, and scikit-image to effectively process and analyze data. As outlined in section 6, the preprocessing phase involves the application of a Median filter to reduce noise, followed by Adaptive Histogram Equalization to enhance image contrast. Subsequent stages involve segmentation of the images using Mask R-CNN, which provides a robust framework for identifying and delineating individual vessels within the SAR imagery. Following segmentation, DenseNet101 is utilized for its deep feature extraction capabilities, capturing complex details essential for accurate vessel classification. Classification tasks are handled by a Convolutional Recurrent Neural Network (CRNN), which integrates the spatial hierarchies learned by CNNs with the sequence processing strength of RNNs, making it exceptionally suited for this application where both image details and sequence patterns are crucial.

Performance evaluation metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN), Accuracy, Precision, Recall, and Computation Time are systematically calculated to assess the efficacy and reliability of the vessel detection system. These metrics are critical for validating the accuracy of the CRNN model and ensuring its applicability in real-world maritime surveillance scenarios.

Table 1 is presented with the outcomes of intermediate stages for 3 sample images from the entire dataset.

Table 1. Illustration of Intermediate Outcomes in Proposed Work

Source Image	Segmented	Feature Extracted
		

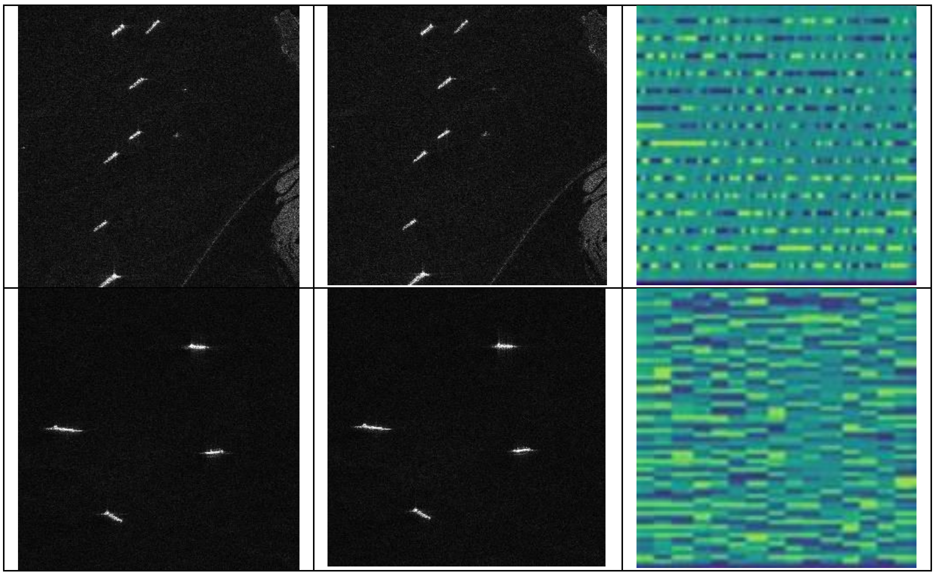


Fig 7 illustrates the confusion matrix for the classification of vessels into three categories such as Small, Medium, and Large by using the advanced deep learning technique involving a Convolutional Recurrent Neural Network (CRNN).

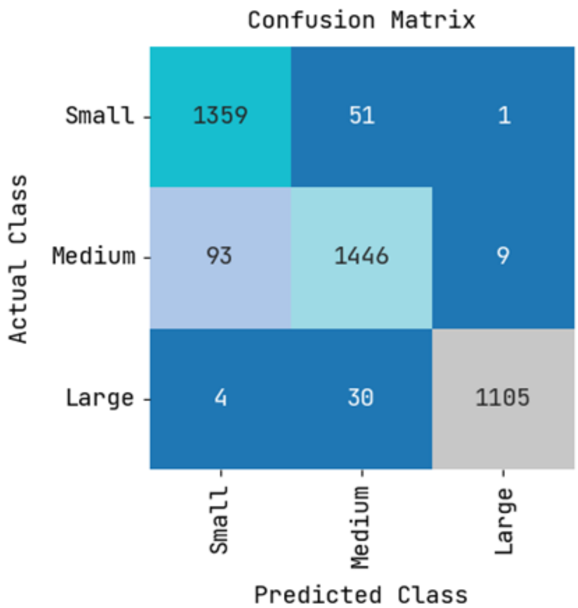


Fig 7. Illustration of Confusion Matrix Output (Training Phase).

The matrix shows the performance of the CRNN in predicting the correct vessel sizes based on the feature vectors extracted using DenseNet101. The model correctly identified 1359 small vessels, with 51 instances where small vessels were misclassified as medium and 1 instance as large. This indicates a high level of accuracy in detecting small vessels, suggesting that the feature extraction and sequential processing capabilities of the CRNN are particularly effective at capturing and classifying the nuanced features typical of smaller objects. For medium vessels, the model successfully classified 1446 correctly, with 93 instances misclassified as small and 9 as large. The relatively lower misclassification rates compared to the accurate predictions demonstrate the model's effectiveness in distinguishing medium-sized vessels from others, which can often be challenging due to their intermediate feature scale. The classification of large vessels shows an accuracy with 1105 correct predictions. Misclassifications included 4 instances predicted as small and 30 as medium. This indicates that while the model is highly capable of identifying large vessels, there is a slight challenge in differentiating between large and medium vessels, possibly due to overlapping features or similar scaling in the feature vectors processed by the DenseNet101.

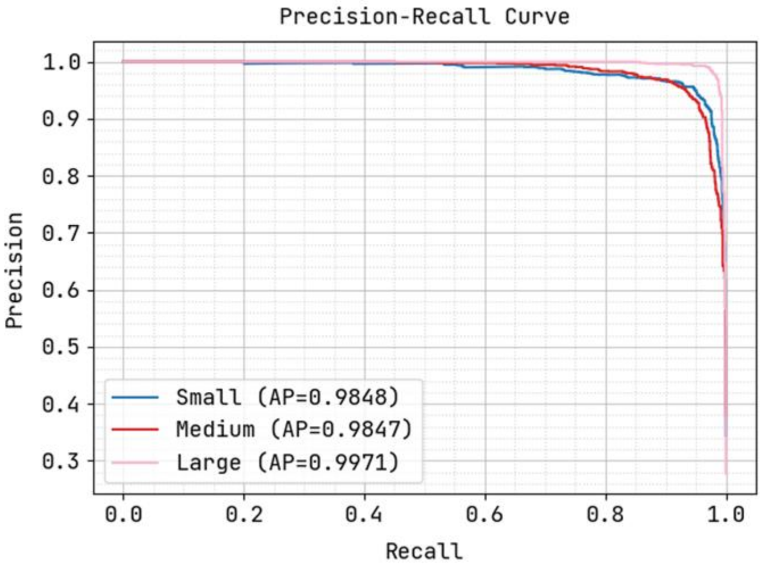


Fig 8. Illustration of Precision Recall Curve (Training Phase).

Fig 8 illustrates the Precision-Recall curve for the classification of vessels utilizing the advanced deep learning technique The curves depict the trade-off between precision and recall for each class at various threshold levels, with the area under the curve (AP) providing a measure of the overall performance across all thresholds.

The precision for small vessels remains high across almost all levels of recall until it sharply drops near the recall of 1.0. This high precision indicates that the CRNN model, combined with DenseNet101's robust feature extraction, is particularly effective in accurately identifying small vessels with minimal false positives. The high AP value close to 1.0 underscores the model's effectiveness in this category. Similar to the small vessels, medium vessels also show a high level of precision across most recall values, with a slight decrease as recall approaches 1.0. The near-identical AP value to that of the small vessels demonstrates the model's consistent performance in distinguishing medium vessels accurately, highlighting the efficacy of the CRNN in handling feature vectors that characterize medium-sized objects. The precision-recall curve for large vessels shows an exceptional level of precision across all recall levels, maintaining close to perfect precision throughout. The AP score is notably higher than the other two categories, reflecting the model's superior capability in identifying large vessels. This suggests that the distinguishing features of large vessels are captured exceptionally well by the DenseNet101 architecture and effectively utilized by the CRNN for classification. The high precision across all vessel categories with excellent recall performance illustrates the strength of combining DenseNet101 and CRNN in the classification system.

Fig 9 illustrates the Receiver Operating Characteristic (ROC). The curves demonstrate the model's performance in discriminating between the positive class and the negative class at various threshold settings.

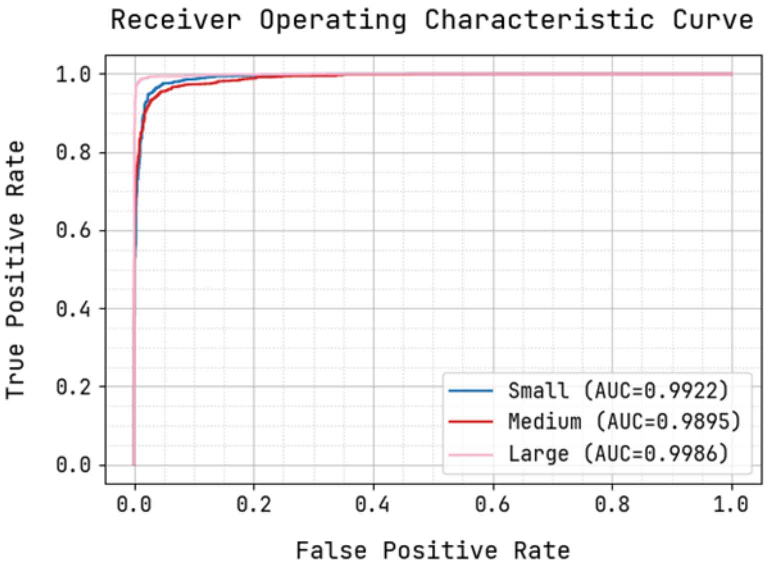


Fig 9. Illustration of ROC (Training Phase).

The ROC curve for small vessels shows excellent performance with an AUC close to 1, indicating a high true positive rate (TPR) and a low false positive rate (FPR) across most threshold levels. The curve quickly rises to a high TPR at a very low FPR, suggesting that the model is highly effective at identifying small vessels with minimal misclassifications. The curve for medium vessels shows an outstanding discriminative performance with the highest AUC among the three categories. This implies that the model is exceptionally effective at distinguishing medium vessels from non-vessels, maintaining high sensitivity and specificity across various threshold levels. The steep ascent of the curve near the origin highlights its effectiveness in achieving a high TPR while maintaining a very low FPR. Similar to the medium vessels, the ROC curve for large vessels indicates superior performance with an AUC nearly perfect. The integration of DenseNet101 and CRNN enables the model not only to extract rich and discriminative features from SAR images but also to effectively utilize these features to classify different sizes of vessels with high accuracy. **Table 2** illustrates the comparative performance of various deep learning models including the proposed advanced deep learning (DL) model, highlighting its superiority in vessel classification tasks.

Table 2. Comparative Analysis of Performance Metrics

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%
MLP	91.08%	94.91%	95.55%
Proposed Advanced DL	**95.34%**	**94.55%**	**98.35**

The proposed advanced DL model achieves an accuracy of 95.34%, a precision of 94.55%, and a recall of 98.35%, outperforming other noted techniques such as Yolov2, Faster R-CNN, and an Ensemble Transfer Learning model. This exemplary performance underscores the effectiveness of the integration of DenseNet101 and CRNN in the proposed model, demonstrating its ability to achieve higher reliability and efficiency in detecting and classifying vessels from SAR imagery. The high recall rate particularly emphasizes the model's capability to identify true positive cases, making it a robust choice for practical applications in maritime surveillance. **Fig 10** illustrates the confusion matrix from the classification in the testing phase. The model correctly identified 593 small vessels, with 24 misclassified as medium; 620 medium vessels, with 53 misclassified as small and 7 as large; and 436 large vessels, with 21 misclassified as medium and 3 as small. Overall, the matrix shows strong performance in correctly identifying vessel sizes, particularly for large vessels, though some misclassifications indicate areas for refinement in distinguishing overlapping features. The high accuracy across all categories underscores the effectiveness of the chosen deep learning techniques for maritime vessel classification.

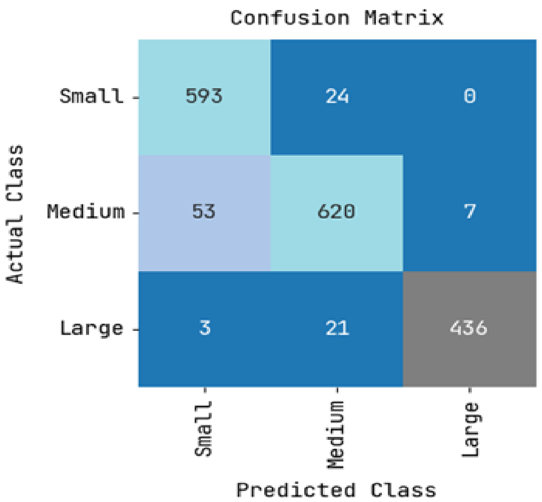


Fig 10. Illustration of Confusion Matrix Output (Testing Phase).

Fig 11 illustrates the Precision-Recall curves for the classification of vessel sizes during the testing phase using an advanced deep learning technique that integrates DenseNet101 and a Convolutional Recurrent Neural Network (CRNN). The curves show high precision across almost all recall levels with Area Under the Curve (AP) values of 0.9794 for Small, 0.974 for Medium, and 0.9905 for Large. These results indicate that the model performs with high accuracy and reliability in classifying different vessel sizes under test conditions, effectively distinguishing between small, medium, and large vessels with minimal false positives.

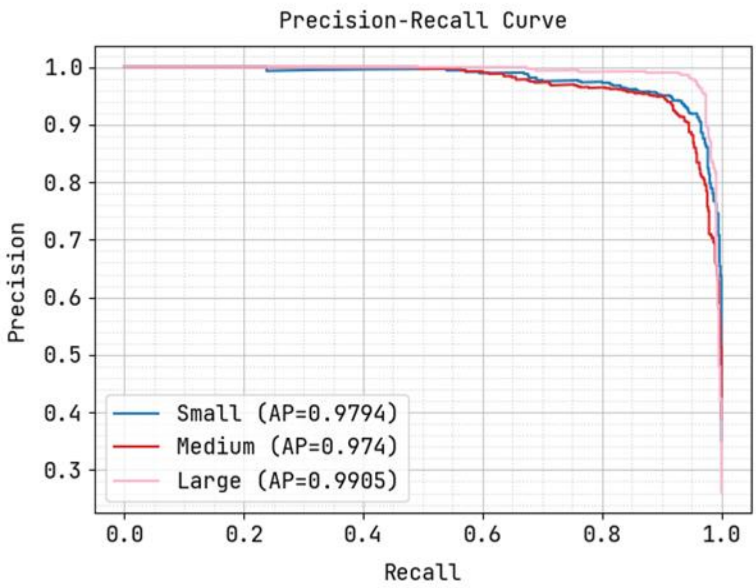


Fig 11. Illustration of Precision – Recall Analysis (Testing Phase).

Fig 12 illustrates the Receiver Operating Characteristic (ROC) curves for the classification of vessel sizes during the testing phase using an advanced deep learning approach that integrates DenseNet101 with a Convolutional Recurrent Neural Network (CRNN).

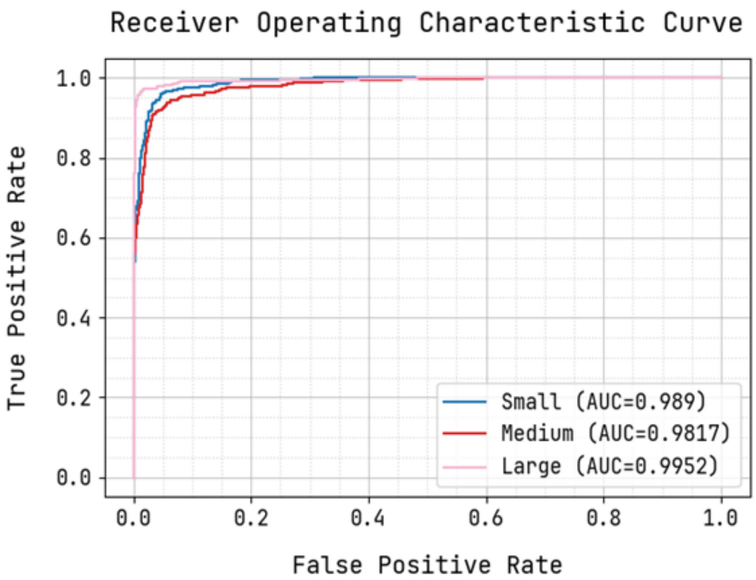


Fig 12. Illustration of ROC Analysis (Testing Phase).

The ROC curves demonstrate excellent discriminatory ability with AUC values of 0.989 for Small, 0.9817 for Medium, and 0.9952 for Large. These results reflect the model's high accuracy and reliability in distinguishing between different vessel sizes under test conditions, highlighting its effectiveness in minimizing false positives while maintaining high true positive rates across all categories.

VIII. CONCLUSION

This research paper projects the effectiveness of the proposed advanced deep learning model, which integrates DenseNet101 and a Convolutional Recurrent Neural Network (CRNN), in the detection and classification of vessels from Synthetic Aperture Radar (SAR) imagery. The performance metrics, as demonstrated in **Table 2**, reveal that the proposed model not only achieves superior accuracy (95.34%) but also performs well in precision (94.55%) and recall (98.35%), significantly outperforming established models like Yolov2, Faster R-CNN, and Ensemble Transfer Learning models. These results highlight the model's robustness in correctly identifying and classifying various vessel sizes under diverse and challenging conditions, with minimal false positives and high sensitivity to true positives. The integration of

DenseNet101 enables the extraction of detailed and comprehensive features from the SAR images, while the CRNN effectively utilizes these features to classify the vessels accurately, capitalizing on both spatial and sequential data inherent in SAR imagery. This advanced methodological approach not only enhances the detection capabilities but also contributes significantly to the reliability and efficiency of maritime surveillance systems. The high recall rate further indicates the model's potential in operational environments, where high detection rates are critical for security and navigational safety.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Devika Priyadharshini S and Vadivazhagan K; **Methodology:** Devika Priyadharshini S; **Writing-Original Draft Preparation:** Devika Priyadharshini S and Vadivazhagan K; **Investigation:** Vadivazhagan K; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

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Competing Interests

There are no competing interests

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