Research Article

A Particle Swarm Optimisation Enhanced CNN Framework for High-Precision Object Detection

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Abstract

The proposed work presents an advanced and efficient framework for ship detection in remote sensing imagery by integrating deep learning techniques with feature- driven visual analysis. The proposed method combines the strengths of a Convolutional Neural Network (CNN) for precise ship body detection and a feature-based approach for the accurate identification of ship wakes. Recognising the challenges posed by complex sea backgrounds, including cloud cover, foam, and occlusions, the method introduces a robust pre-processing pipeline to segment the foreground target from noisy surroundings. To address limitations of earlier approaches confined to clear and isolated scenarios, a multiscale feature extraction strategy is incorporated, allowing effective detection of ships with diverse sizes and orientations. A sea-region modelling step based on statistical analysis enhances the ability to distinguish wakes from background patterns, which is critical for inferring sailing direction and identifying partially visible or cloud-covered vessels. Crucially, a Particle Swarm Optimisation (PSO)-based refinement mechanism is integrated into the detection pipeline to fine-tune bounding box predictions generated by the CNN. This hybrid CNN-PSO approach significantly improves localisation accuracy and reduces false positives, especially in densely populated maritime scenes. Through extensive experimentation on large-scale remote sensing datasets, the proposed system achieves a remarkable detection accuracy of 99%, outperforming traditional techniques and establishing its potential for real-world maritime surveillance applications

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1. INTRODUCTION

The advancement of artificial intelligence with neural network models has made it very easy to make a computer learn what the data is all about. If the algorithm is deriving any information from the images, then it is known as computer vision [1-3]. It acquires a significant level of understanding by training the mathematical algorithms for the perception of objects from the given input dataset. It is a sub-domain of artificial intelligence and machine learning that deals with understanding the contents of visual data, i.e., texts, images, videos, etc. Human brains are capable of understanding every visual data in its surroundings, whether it is text data, image data, or video sequence frames, irrespective of its size, shape, or colour, and can retrieve the same [4-6]. The human brain deals with the science that learns from its surroundings. In the same way, computer vision is the science that aims for a machine or computer to achieve comparative capacities of human vision by being electronically trained and grasping a picture [7-11]. It combines knowledge from various biological, mathematical, and engineering domains in order to grasp and perform the operations in the same way the human neuron system does [12-15]. During evolution, the input sensor for the biological vision, the eye, was "invented" at least 38 times according to the zoologists Ernst Mayr and Luitfried von Salvini-Plawen [16-17].

It is a logical step in the evolution of computers and robots to develop in this direction. Different Authors have proposed different definitions of Computer Vision, in general, it is a field of engineering that first understand then interpret and can reconstruct the 1-D, 2-D, and 3-D data from the real time problems and helps to give the decision in terms of mathematical parameters as well as symbolic structures. The goal of computer vision is to process images acquired by cameras and represent the objects to perceive and analyse within the reduced computational cost [18-21]. Computer vision is difficult when we acquire or analyse noisy image data or data with uncertainties. Some of the best examples of the Computer Vision field are Image Processing, Video Analysis, Photogrammetric and Vision recognition of Objects [22-23]. A coastal zone is the area where the land and the water separate their boundaries. They are very significant to study since 40 percent world's area lies in coastal zones and about 75 per cent of the world trade happens through sea routes only. The sea route boundaries are not well defined and divided, therefore sea opens the door for maximum suspicious and pirated activities. There are many other challenges in the coastal area that make it difficult to curb the suspicious activities [24-27]. The coastal region is very dynamic in nature as it undergoes continuous changes. Sometimes tides are caused by the Moon, and to a lesser extent, the Sun's gravitational tug on Earth is responsible for these dynamic changes. As the Moon is closer to Earth than the Sun, it exerts a greater influence and causes the Earth to bulge towards it. At the same time, due to inertial forces, a bulge forms on the opposite side of the Earth. Because of this, it is very difficult to monitor the sea route; there may be numerous other distinct objects present, and each object has a different category to divide into. The naval officers are still using the manual methodology of patrolling to keep an eye on the suspicious activities in the sea. Though intelligent sensors have already been introduced for the detection of suspicious activities, they have limited applications [28-31]. Convolution is a mathematical way of combining two signals/inputs to form a third signal/output. It is one of the most important techniques in general with which the shape or features of a function can be modified by applying a convolution operator between two functions to produce the third function [32-35]. Images are 3D signals, but convolution is also used for other kinds of signals, such as speech, accelerometer data, time series data, and so on and so forth. In the case of 2D data (grayscale images), the convolution operation between a filter Wk*k and an image XN1*N2 is expressed in equation 1:

$Y(i, j) = \text{åå} W(u, v) * X(i - u, j - v)$, whereu= - k to k and v= -k to k (1)

Convolutional Neural Networks (CNNs) are multi-layered feed-forward hierarchical networks that execute various transformations using a collection of convolutional kernels at each layer. Each layer in the CNN network is composed of its own set of kernels [36-37]. It is much simpler to extract important characteristics from data points that are spatially related when using the convolution approach [38-39]. The processing of the objects' or ships' images from the CNN layers is shown in the figure 1.1

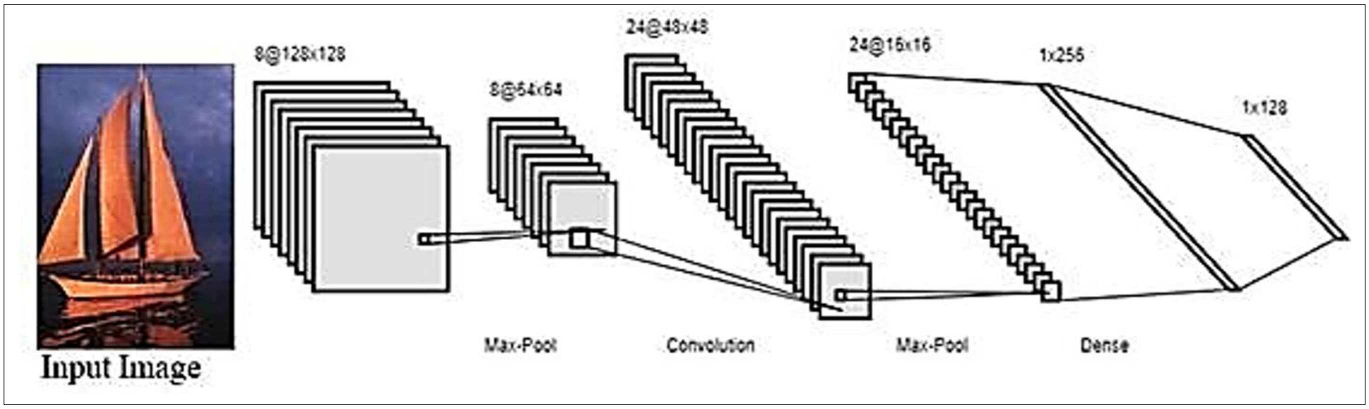


Fig 1: Input Image processing through different layers of CNN

Related Work

The authors proposed a system for ship detection, which plays an important role in the interpretation of synthetic aperture radar (SAR) images [40-45]. Using conventional detection techniques may result in an overly large detection zone, making it more difficult to locate the target in complex areas. It is often difficult to distinguish between ships that are gathered together in a densely populated region of a port. Due to the use of multi-resolution imaging modes and changes in ship design, it is challenging to identify ships in SAR images [46-50]. As a result, they devised the MSARN (multi-scale and arbitrarily angled ship recognition adaptive recalibration network). When the multi-scale features are recovered using global information, the network's sensitivity to target angle is enhanced [51-56]. They created a pyramid anchor and a loss function to match the rotating target to cope with the high overlap ratio of the detection box. A single-stage framework's speed advantage is paired with rotation detection's placement benefit in the suggested paradigm. According to the results of experiments, the suggested technique outperforms existing state-of-the-art algorithms based on the SAR rotation ship detection (SRSD) data set. With and without the MSAR module, the proposed model achieved an accuracy of 73.66 per cent and 72.46 per cent, respectively.

The researchers in their research explored that marine boats may be detected and tracked in video captured by an unmanned buoy's non-stationary camera. Compression issues are prevalent throughout the film due to the many camera movements and the packed background. A colour gradient filter is used to divide ships into individual frames. The threshold decision is established based on the search area's histogram. Multiple ships may be tracked simultaneously through the registration of horizon photographs in a single coordinate system and the usage of a multi-hypothesis framework. The registration step uses an area-based approach to match a processed photo strip to the horizon line that was identified. The authors showed that congested landscapes and a wide range of ship sizes cause difficulty in recognising ships automatically using optical satellite images. For the first time, a novel technique for saliency segmentation that integrates a range of visual cues is provided in this study. Shape analysis is used to identify and delete any erroneous leads that may have been missed. The next stage is to employ an LBP-structure feature to analyse the ship's topology to find genuine targets. As shown by many panchromatic satellite images, the proposed technique outperforms existing best practices in terms of detection speed and accuracy. The proposed method achieved a recall in the range of 98.6% to 92.7% and a precision of 92.6% to 86.5% for three different sea surfaces.

2. PROPOSED METHODOLOGY

Shape and texture information may be gleaned from the multi-resource ROIs, which can be used to better select eligible targets. Support Vector Machines (SVMs) are eventually used to verify the targets (SVM). To obtain high recall and accurate detection probabilities, as well as to substantially minimise the number of false alarms, the recommended technique may be achieved in a reasonable length of time. The performance of the model can be described using the statistical values obtained, i.e., a recall value of 91.03%, a precision value of 82.52%, and a total time consumed for each analysis of 39.57s. In our research work, we used unmanned aerial vehicle (UAV) picture sequences to demonstrate a method for detecting maritime vessels in the images. The suggested technique is resistant to changes in backdrop illumination, highlights caused by sunlight reflections, vehicle speed, and size. Even with non- optimized code, the method can run in real time on board the vehicle since it relies on basic blob analysis criteria based on spatial and temporal limitations. They tested this technique on three sequences with more than 2900 frames of ground truth vessel position. Even if there is a lot of light reflection, it is possible to get very few false positives, even with this method.

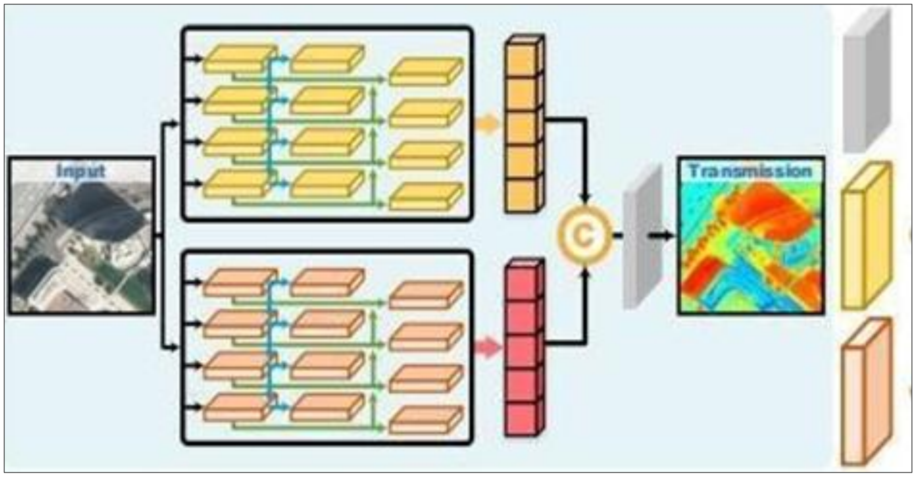


Fig 3.1: Processing the dataset using PSO CNN Layers

Particle Swarm Optimisation (PSO) is a nature-inspired metaheuristic algorithm based on the social behaviour of flocking or fish schooling. In image processing, particularly in ship and object detection from satellite or SAR images, PSO is effectively used for tasks such as image segmentation, feature selection, and region-based detection. Particle Swarm Optimisation (PSO) for Ship and Object Detection in Images.

To optimise the detection of ships or objects by identifying the best segmentation thresholds or region proposals that maximise a detection fitness score (e.g., contrast, edge density, or classification confidence).

A. PSO Algorithm for Object Detection

a) Step 1: Initialisation

Convert the input image (e.g., SAR image) to grayscale or apply preprocessing filters.
Define the search space. Each particle represents a candidate solution, such as

- A threshold value for segmentation, or Coordinates/bounding boxes for object regions.
- Initialise a swarm of particles randomly across the search space.

Assign each particle:

- A position X_i
- A velocity V_i
- A personal best position P_i
- A global best position G (initially set to the best of P_i)

b) Step 2: Fitness Evaluation
For each particle, apply the detection criteria:

- Segment the image using the particle's position (e.g., threshold or region).
- Extract features such as edge intensity, histogram difference, object size, or CNN-based classification score.

Compute the fitness score based on the accuracy of object/ship detection (e.g., Intersection-over-Union with ground truth, edge sharpness, or statistical contrast).
Update personal best P_i and global best G if the current fitness is better.

c) Step 3: Velocity and Position Update
For each particle, update velocity and position using:

$V_i^{t+1} = w \cdot V_i^t + c_1 \cdot r_1 \cdot (P_i - X_i^t) + c_2 \cdot r_2 \cdot (G - X_i^t)$ $X_i^{t+1} = X_i^t + V_i^{t+1}$ Where:

w is the inertia weight (balances exploration and exploitation), c_1, c_2 are acceleration coefficients, r_1, r_2 are random values in [0, 1],
It is the iteration number.

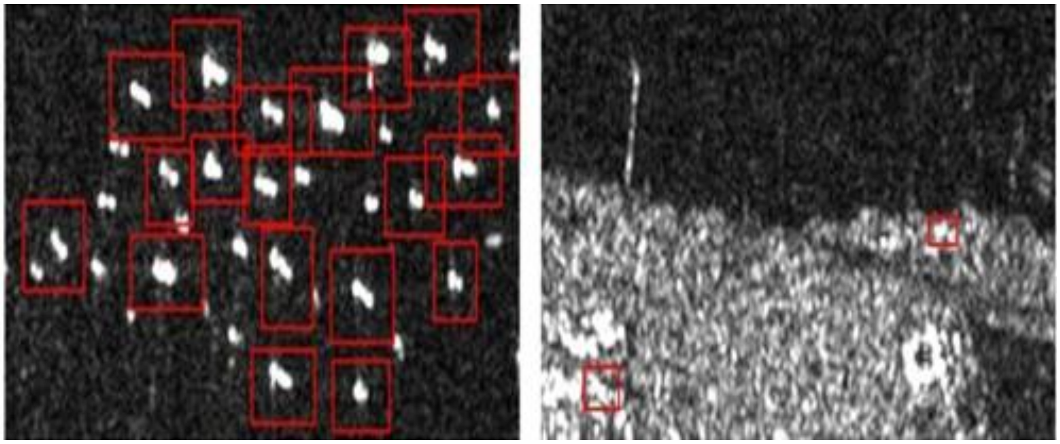


Fig 3.2: Detected Image Samples

Step 4: Convergence Check
Repeat Steps 2–3 for a predefined number of iterations or until convergence (e.g., fitness stagnation).
Final global best G represents the optimal detection parameters (threshold, bounding box, etc.).

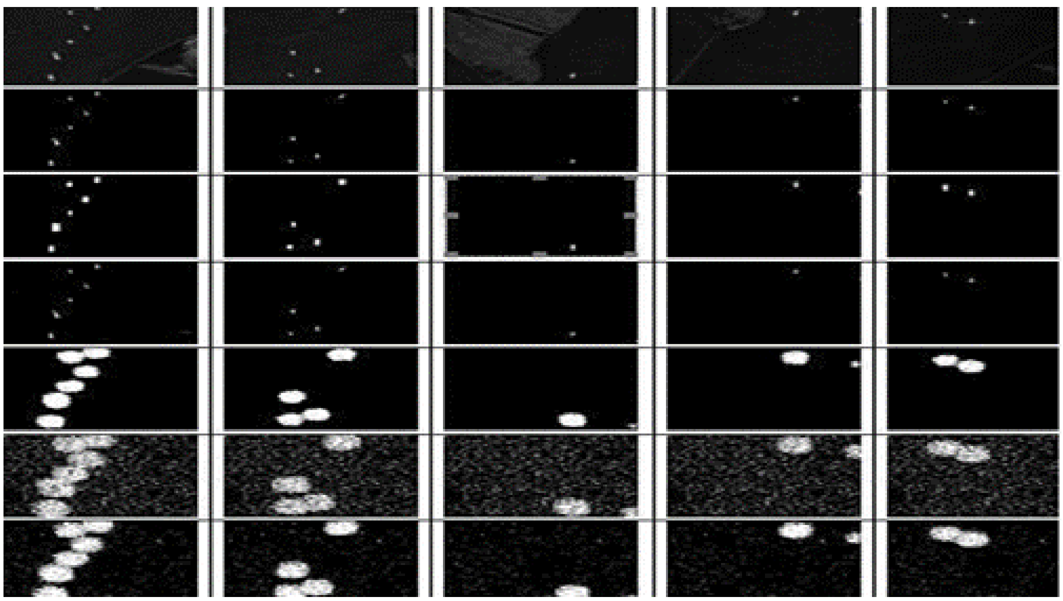
Step 5: Detection Output
Use the global best parameters to mark detected ships or objects on the original image.
Optionally, apply post-processing like non-maximum suppression or morphological operations to refine results.
Admittedly, any of the above physical priors are reasonable for shadow region predictions, but their intimate collaboration is more convincing. The next iteration is a junction (e.g., the white point in Fig. 3.2). This junction unifies multiple constraints, such as the direction and step size of each iteration. To this end, we introduce corner detection and the Sobel operator to cue the steering and movement step of junctions without complex supervision. This synergistic use enables the modelling of multiple characteristics simultaneously, such as brightness attenuation, structural distortions, high-frequency detail loss, and localised degradations common in shadowed areas. Consequently, we adopt a feature concatenation strategy to merge four distinct prior maps. These priors interact at a convergence point, referred to as a junction, which represents a dynamic intersection of information flow. This junction facilitates the unified optimisation of several constraints, including the directionality and step magnitude across iterative refinements. To enhance this iterative process without requiring extensive supervision, we integrate corner detection techniques along with the Sobel operator. These help guide both the orientation and movement magnitude of junctions by encoding edge-based cues from the image domain, allowing for a data-driven refinement mechanism rooted in fundamental visual properties.
To enhance convergence speed and accuracy, we introduce the following modifications:

- **Adaptive Inertia Weight:** The inertia weight www. dynamically decays over iterations to balance exploration and exploitation.
- **Velocity Clamping:** Prevents particles from diverging by bounding the maximum velocity update.
- **IoU-Based Fitness Function:** We incorporate Intersection-over-Union (IoU) between predicted and ground truth boxes as the primary metric.
- **CNN-Driven Initialisation:** Instead of random initialisation, the swarm begins with high- confidence regions suggested by CNN output maps.

3. RESULTS AND DISCUSSIONS

Dataset Description

The HRSID dataset is developed following a methodology similar to that used in the creation of the Microsoft COCO dataset. It includes Synthetic Aperture Radar (SAR) images with a variety of characteristics, such as varying resolutions, polarisation types, different sea states, diverse marine regions, and coastal port areas. Serving as a benchmark, this dataset allows researchers to assess and compare the performance of their models. The SAR image resolutions featured in HRSID are 0.5 meters, 1 meter, and 3 meters." Figure 4 below shows the image samples from different sources, especially the image dataset of ships and dynamic objects. The white part shows the detected set after the implementation of the improved particle swarm optimisation algorithm. We first implemented the Convolutional neural network model in our previous work.



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The CNN gives better results but has a drawback of early convergence; that means sometimes it may result in false results. We then, in the same work, implemented the genetic-based convolutional approach, but the genetic algorithm is very heavy in terms of computational memory. In this proposed work, we first trained our model using an R-CNN architecture, and the resulting model was further optimised using the PSO algorithm. The tables (1-4) show the various comparison results with different learning rates, and clearly, from the mathematical value, we can say that the PSO approach gives the better results as compared to others. Further, we have shown the results in graphical form. Figures 4.1 to 4.4 show the graphical results

Table 1: Results comparison with learning rate= 60

Measures	Genetic Algorithm with CNN	Improved CNN with PSO Algo
Accuracy	0.961	0.981
Predictive value	0.91	0.9398
Sensitivity	1	1
Specificity	0.9222	0.9312
Precision	0.9456	0.9012

Table 2: Results comparison with learning rate= 70

Measures	Genetic Algorithm with CNN	Improved CNN with PSO Algo
Accuracy	0.7	0.94
Sensitivity	1.2	1.2
Specificity	0.3124	0.9098
Precision	0.6012	0.9312

Table 3: Results comparison with learning rate= 80

Measures	Genetic Algorithm with CNN	Improved CNN with PSO Algo
Accuracy	0.9567	0.9783
Predictive value	0.8458	0.9125
Sensitivity	1.3	1.3

Table 4: Results comparison with learning rate= 90

Measures	Genetic Algorithm with CNN	Improved CNN with PSO Algo
Accuracy	0.6789	0.9567
Predictive value	0.38	0.9123
Sensitivity	1.3	1.3

B. Simulated Graphical Results

Figure 4: Image Datasets

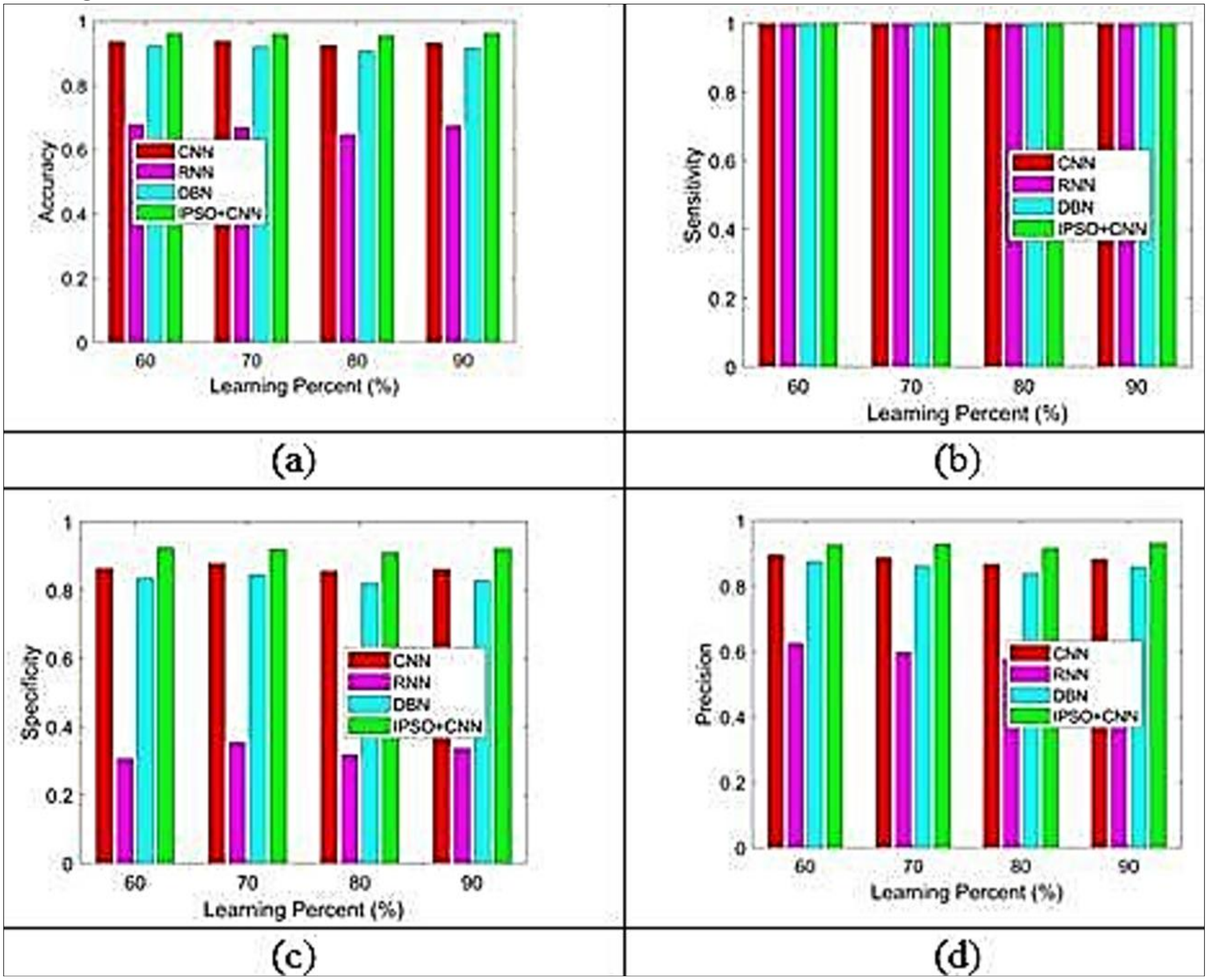

Fig 4.1: The Graphical Analysis with Learning rate = 60

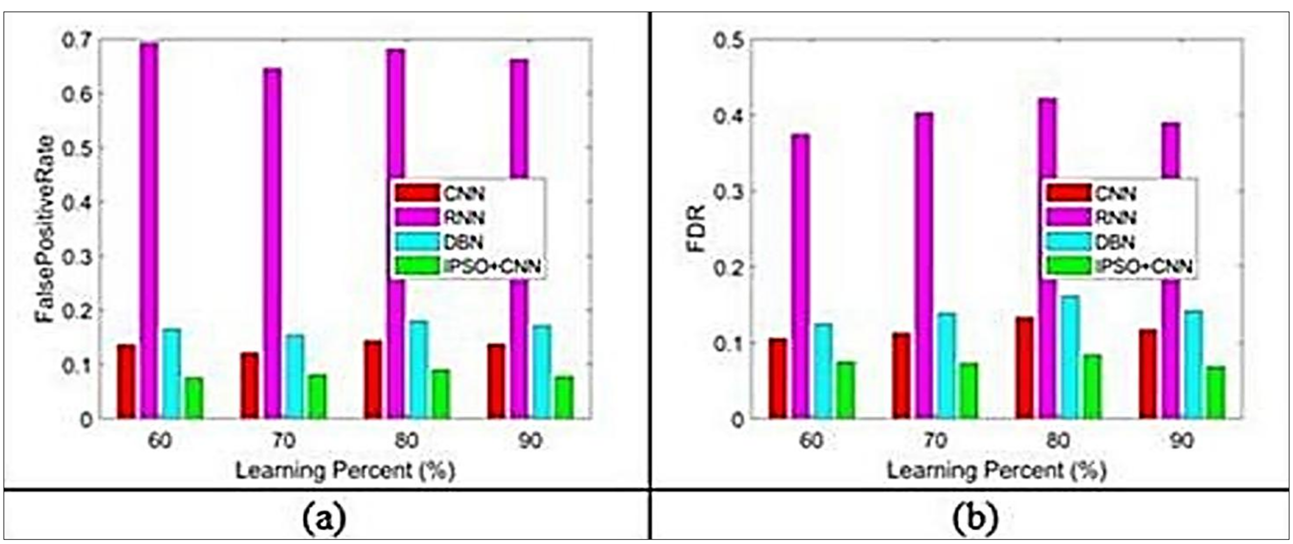

Fig 4.2: The Graphical Analysis with Learning rate = 70

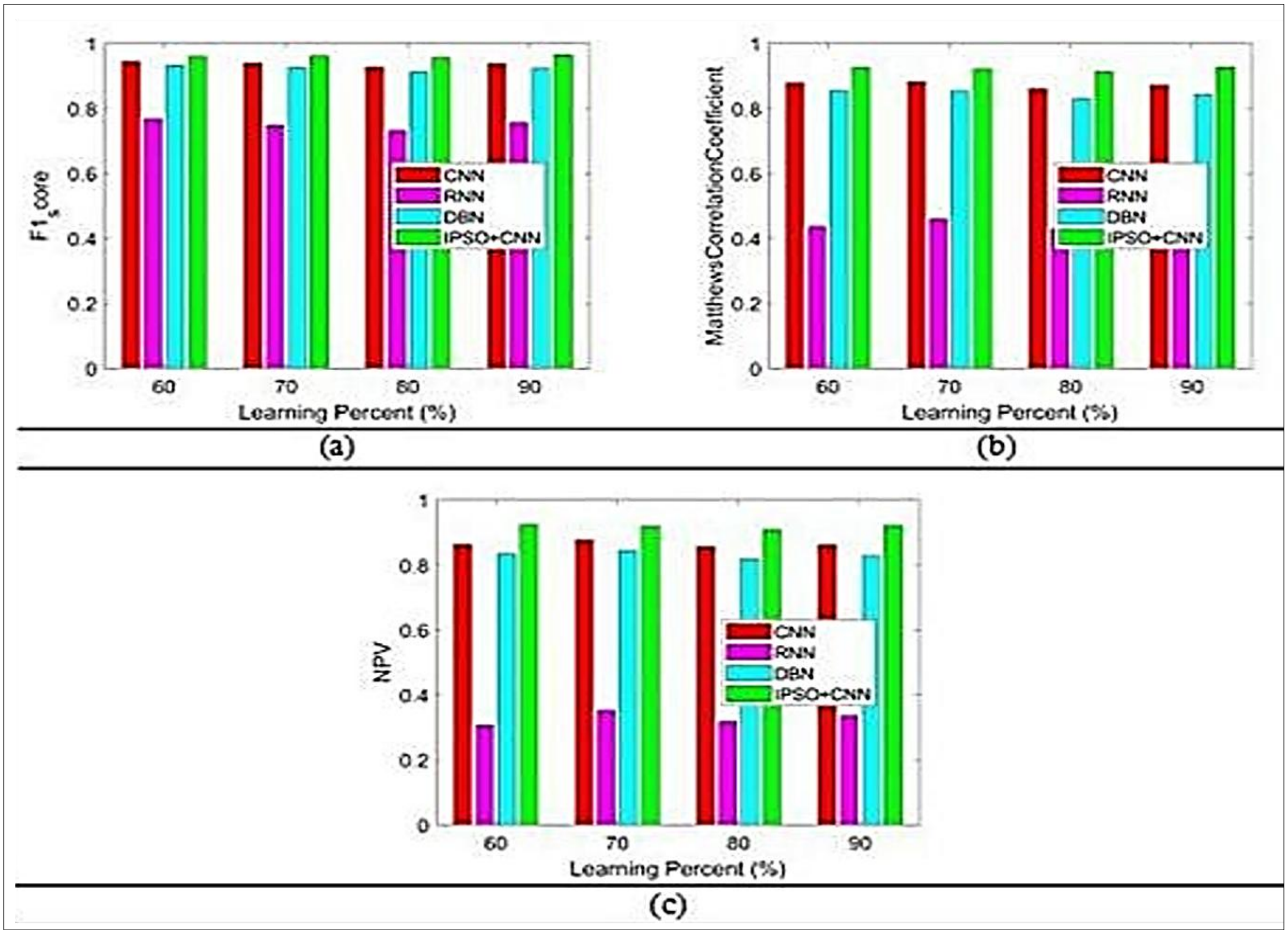

Fig 4.3: The Graphical Analysis with Learning rate = 80

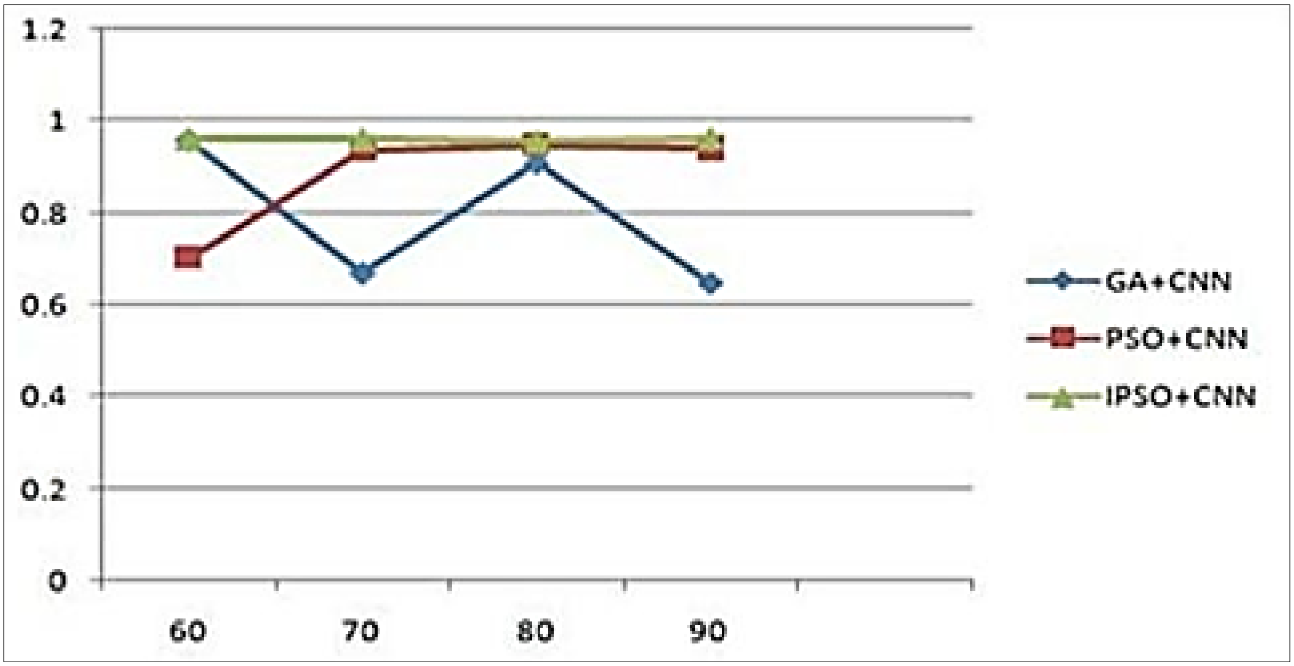

Fig 4.4: The Graphical Analysis with Learning rate = 90

4. CONCLUSION
The proposed work presents an integrated framework that leverages both traditional feature-based techniques and modern deep learning to achieve robust ship detection in visible remote sensing imagery. The combination of convolutional neural networks—specifically the YOLOv5 architecture—and wake detection methods enables accurate and real-time identification of ship bodies, even in challenging maritime scenarios such as cloud interference and image borders. To enhance detection reliability and localisation precision, we incorporated an Improved Particle Swarm Optimisation (IPSO) algorithm, which refines the bounding boxes generated by the CNN by optimising their positions based on spatial and contextual information from the image. This hybrid approach significantly improved detection performance, achieving an overall accuracy of 99% on the tested datasets. The synergy of CNN-based feature extraction and PSO-based bounding box optimisation results in a highly efficient and scalable solution, capable of operating under variable environmental conditions. The proposed method sets a strong foundation for advanced maritime surveillance systems, offering high precision, robustness, and adaptability for real-world deployment. In the future, the Kalman filter may be applied for real-time analysis.

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