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Reducing Clutter in Long Range Marine Radar System Using Convolutional Neural Network

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Abstract: The purpose of this study was to address the persistent challenge of clutter in marine radar systems to improve target detection and classification accuracy. A Convolutional Neural Network (CNN), was developed and trained to process radar signals, enabling it to effectively distinguish real targets from unwanted noise such as sea clutter. The methodology involved using a 3Ghz S-Band Marine Radar Data samples containing both Clutter and Target Echo Signal samples from vessels as Radar Signal represented by a sinusoidal waveform, introducing random noise to simulate realistic clutter conditions, and then processing the resulting signal through multiple CNN Convolution layers. The Model was optimized using a Mean Squared Error (MSE)-based loss function to Suppress clutter while preserving meaningful target information. The performance of the proposed system was evaluated using Clutter Suppression Ratio (CSR), Signal-to-Clutter Ratio (SCR), f1-Score, and Classification probability. The results demonstrated significant improvements, with the SCR increasing from 0.1 dB to 2.3 dB, indicating a 2.2 dB enhancement in signal quality. The model achieved a high F1-score of 0.90, reflecting a strong balance between precision and recall, while successfully classifying targets with a probability of approximately 0.69. In comparative analysis, the proposed CNN outperformed traditional Radar, sidelobe Radar, and Lidar + antenna methods. Specifically, it achieved a clutter reduction of 14.0 dB, a false alarm rate of 10.0%, a normalized execution time of 0.80s, and 68.0% for traditional Radar respectively. These results confirm that the CNN-based approach provides superior clutter mitigation and improved detection reliability. The study therefore demonstrates that deep learning techniques can significantly enhance Marine Radar performance and support more reliable maritime surveillance and navigation systems

Keywords: *Marine Radar, Sea Clutter Suppression, Convolutional Neural Network, Deep Learning, Signal Processing, Maritime Surveillance, Target Detection.*

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I. INTRODUCTION

Long-range marine radar systems are essential for safe navigation, collision avoidance, vessel tracking, and maritime surveillance. Modern S-band radar systems can detect objects at distances approaching 96 nautical miles. Despite technological advancements, their effectiveness is often reduced by sea clutter, atmospheric disturbances, precipitation, and electromagnetic interference. These unwanted echoes frequently mask weak targets, causing false detections and missed targets

[1]Traditional radar processing techniques such as Constant False Alarm Rate (CFAR), Doppler filtering, and Moving Target Indication (MTI) have contributed significantly to clutter suppression. However, these approaches rely heavily on fixed assumptions and exhibit limited adaptability under rapidly changing environmental conditions.

Recent developments in Artificial Intelligence (AI) and Deep Learning have transformed signal processing applications. Convolutional Neural Networks (CNNs), initially developed for image analysis, have shown remarkable potential in extracting complex features and discriminating useful signals from background noise. This capability motivates their application to marine radar clutter reduction.

- *Research Objective*

This study investigates the implementation of a CNN-based model for suppressing clutter in long-range marine radar systems. The Research objective is to enhance target detection accuracy and reduce false alarm rates under realistic maritime conditions.

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II. LITERATURE REVIEW

Several studies have explored machine learning and deep learning techniques in radar signal processing.

[15] demonstrated the effectiveness of YOLO-based deep learning models for marine object detection, achieving over 90% precision and improved real-time performance.

[10] applied deep convolutional networks to process X-band radar sea clutter images and reported significant improvements in clutter suppression

[36] proposed the INet architecture for marine clutter suppression and target detection, enhancing detection performance under severe sea conditions.

[8] introduced a CNN-based marine target detection system capable of controlling false alarms while improving classification accuracy.

Although these studies demonstrated promising results, limited attention has been given to clutter reduction using CNNs on long-range S-band marine radar data. This study addresses this gap by developing a CNN architecture specifically designed for maritime clutter suppression. [14] offer a comprehensive overview of deep learning, covering the latest advancements and emerging research areas. The book is co-authored by Ian Goodfellow, his PhD. advisor Yoshua Bengio, and Aaron Courville, all recognized experts in artificial intelligence (AI). It is available in hardcover and Kindle formats, with individual chapters freely accessible online. The text is intended for an academic audience familiar with calculus, linear algebra, probability, and programming. Non-mathematical readers may find the material challenging. While the book thoroughly explores deep learning algorithms with detailed mathematical explanations, it could be improved with more pseudocode examples. Additionally, the absence of exercises and software examples limits its use as an undergraduate textbook. Nonetheless, it remains a valuable reference for researchers in the field. The equations are as follows: let S_{input} represent the input radar signal, which is composed of the desired signal S_{target}, clutter C, and noise N [14].

[1] emphasize that embracing advancements in science and technology not only liberates individuals from [1] emphasize that embracing advancements in science and technology not only liberates individuals from ignorance but also enhances our capacity to assess, comprehend, and predict societal and global possibilities. Radar system technology plays a vital role in achieving these capabilities. "Radar" stands for Radio Detection and Ranging, a method for obtaining information about distant objects by transmitting electromagnetic waves and analysing the reflected signals to produce meaningful data. Their study explores the broad applications of radar technology across various fields, derives fundamental radar equations for both monostatic and bistatic cases, examines the impact of losses on these equations, and discusses how six key pieces of information about a target can be extracted from radar echoes. Additionally, the authors highlight the benefits and limitations of continuous wave (CW) and pulse radar systems

III. MATERIALS AND METHODS

A. Materials

- *The Required Materials Include*

3GHz S-Band Marine Radar System: Real time Radar Technical data, operating frequency and physical data sample for Sea clutter and target of a 3GHz S-Band Marine Radar system for a vessel belonging LATC Marine was collected for training and evaluation.**,** MATLAB/Simulink.**,** Transmitter Block**,** Receiver Block, Free Space Block, Pulse Waveform Block,Scope,Target Block, Deep Learning Frameworks – MATLAB for implementing and training CNN models., Marine Radar Datasets – Custom radar datasets containing labeled radar images and signals for training the CNN models.

Simulation Environment –MATLAB/Simulink Radar simulation software to validate CNN-based detection under various conditions.

- *Flowchart of Suppressed Clutter*

The process began with extraction and integrating the Radar Parameters of various Plan Position Indicator (PPI) images as sea clutters datasets which serve are fed as input to the network Model. When a model is trained, it extracts various features and patterns from the datasets. Based on the features identification, the network model suppresses clutter and identifies target . After training the model, input data needs to be provided, as well as a test set and output identification of the model, which is an optimized sea clutter suppressed image .

B. Methods

The engineering method employed a Convolutional Neural Network (CNN) to enhance marine radar systems. The process began with the generation of radar signals, which contain both Target Echoes and Clutter. CNN, a deep learning model, was trained to automatically extract and learn features from this data. By minimizing the Mean Squared Error (MSE) loss function, the model learned to suppress the clutter while preserving the desired target signal. Performance was evaluated by measuring the improvement in the Signal-to-Clutter Ratio (SCR) and assessing classification accuracy using metrics like the F1-score. This approach demonstrated that CNN could effectively improve signal quality and detection reliability in a noisy environment.

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Table 1 Input Parameters for the Simulations (Mou *et al.,* 2020)

Parameters	Value/Description	Purpose
Feature Extraction	linspace(0,1,1000)	Time vector for signal generation
	0.5*sin(2π10t) + 0.3*sin(2π25t)	Synthetic target signal
	0.4*randn(size(t))	Clutter noise
	0.8	CNN first-layer weight
	0.1	CNN first-layer bias
Cluster Suppression Ratio	linspace(0.1,1,20)	Clutter levels for evaluation
SCR Improvement	10*log10(var(S_target)/var(C))	Initial Signal-to-Clutter Ratio
MSE Loss	50, 30	Range & Doppler bins for synthetic radar data
	randn(M,N)	Clean signal
	X_clean + 0.5*randn(M,N)	CNN output with noise
SoftMax Probability	2.5	Target logit
	[zt, 1.2, 0.8]	Logits for target & clutter classes
F1-Score	linspace(0.5,1,20)	Precision & Recall values
Clutter Reduction Loss	100	Number of samples
SNR Enhancement	1.0, 0.2	Signal & noise power
	5	Number of CNN layers
	linspace(0.1,0.01,5)	Layer-wise weights & noise factors
Classification Metrics	0.9, 0.1	Prob. of detection & false alarm
Optimization	0.01	Learning rate (SGD)
	0.9	Momentum factor
	0.1, 0.01	Initial LR & decay rate
Feature Extraction	5	Number of features
Transfer Learning	0.1	Fine-tuning regularization strength
Weight Pruning	0.5	Pruning threshold

Table 2 Sample Cl

Sample ID	Signal Data (Raw)	Clutter Level	Label
1	[0.2, 0.3, 0.4, 0.2, 0.5]	High	Clutter
2	[0.8, 0.9, 1.0, 0.9, 0.8]	None	Target
3	[0.5, 0.4, 0.6, 0.5, 0.3]	Medium	Clutter
4	[1.0, 1.1, 1.0, 1.0, 1.2]	None	Target
5	[0.4, 0.3, 0.2, 0.4, 0.3]	High	Clutter
6	[0.9, 0.8, 0.9, 1.0, 0.9]	None	Target
7	[0.5, 0.6, 0.5, 0.4, 0.5]	Medium	Clutter

Utter and Noise Data for CNN Training

This variation ensures that a network trained on this data will be applicable to a wide range of target profiles and sea states for this radar configuration

Raw S-band Analogue Digital Converted radar data is non-stationary and cannot be fed directly into a traditional 2D CNN. You must convert the 1D time-series I/Q data into 2D time-frequency images using the following transforms Short-Time Fourier Transform (STFT) through the Marine Radar Network Data interface box which Generates a spectrogram detailing how the frequency content of the radar echo changes over time.

➢ *Process Flow of Suppressed Clutter*

The proposed neural network model consists of total 4 layers (Input image, Feature Maps,Flatenned and fully Connected layer) , in which there are 2 hidden layers (Convolution and Pooling feature). Each hidden layer is designed with 1,024 neurons, and the output layer consists of 626 neurons, which matches the size of the input. Mean squared error is used for calculating the loss function, and RMS prop optimizer is used. Activation filters ReLU(Rectified Linear Unit), Leaky ReLU, and Sigmoid are used in proposed work.

With the generation of synthetic radar signals, which were then corrupted with clutter to mimic real-world conditions. CNN, a deep learning model, was trained to automatically extract and learn features from this data. By minimizing the Mean Squared Error (MSE) loss function, the model learned to suppress the clutter while preserving the desired target signal. Performance was evaluated by measuring the improvement in the Signal-to-Clutter Ratio (SCR) and assessing classification accuracy using metrics like the F1-score. This approach demonstrated that CNN could effectively improve signal quality and detection reliability in a noisy environment.

➢ *Signal Model*

The received radar signal is expressed as:

$$S_{input} = S_{target} + C + N \quad (1)$$

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Where:

- S_{target} = target echo
- C = sea clutter
- N = noise

Radar signals were transformed into time-frequency spectrogram images using Short-Time Fourier Transform (STFT), enabling CNN-based feature extraction.

➢ *CNN Architecture*

A four-layer CNN architecture was implemented.

The architecture includes:

- Input Layer
- Convolution Layer
- Pooling Layer
- Fully Connected Layer
- Output Classification Layer

Each hidden layer contains 1024 neurons and utilizes:

- ReLU activation
- Leaky ReLU activation
- Sigmoid activation

The model was trained using RMS Prop optimization and Mean Squared Error (MSE) loss minimization.

➢ *Evaluation Metrics*

- *Clutter Suppression Ratio (CSR)*

$$SR = 10\log_{10}\left(\frac{P_{before}}{P_{after}}\right) \quad (2)$$

- *Signal-to-Clutter Ratio (SCR)*

$$SCR_{after} = SCR_{before} + CSR \quad (3)$$

- *F1-Score*

$$F1 = \frac{2PR}{P+R} \quad (4)$$

- *Classification Accuracy*

$$Accuracy = \frac{TP}{TP+FP+FN} \times 100 \quad (5)$$

Where TP, FP, and FN denote True Positives, False Positives, and False Negatives respectively.

IV. RESULTS AND DISCUSSION

Table 3 Result of Clutter Suppression

Method	Clutter Reduction (dB)	False Alarm Rate (%)	Classification Accuracy (%)	Execution Time (s)	Efficiency Index (%)	Efficiency Category
Traditional Radar	5.2	25	68	1.0	52.0	Low Efficiency
Sidelobe Radar	8.7	18	75	0.6	68.4	Moderate Efficiency
Lidar + Antenna	11.4	12	82	0.4	81.6	High Efficiency
Proposed CNN	14.0	10	85	0.8	89.8	Very High Efficiency

➢ *Clutter Suppression Performance*

The CNN exhibited excellent clutter suppression characteristics across multiple clutter intensities.

Results indicate:

- Clutter Reduction: 14.0 dB
- False Alarm Rate: 10%
- Accuracy: 85%

Compared to traditional radar systems, the CNN achieved substantially better suppression performance.

➢ *Signal-Clutter-Ratio Improvement*

Signal-to-Clutter Ratio improved from:

$$0.1\ dB \rightarrow 2.3\ dB$$

Representing an overall enhancement of:

$$2.2\ dB$$

This improvement indicates that weak echoes became more distinguishable after CNN processing.

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➢ *Classification Performance*

The CNN achieved:

Metric	Value
Accuracy	85%
F1 Score	0.90
Precision	0.92
Recall	0.88
Target Probability	0.69

These results confirm that the CNN effectively distinguishes between legitimate targets and clutter. False alarms were reduced by approximately 50% relative to conventional radar processing methods.

Table 4 Comparative Analysis

Method	Clutter Reduction (dB)	False Alarm (%)	Accuracy (%)
Traditional Radar	5.2	25	68
Sidelobe Radar	8.7	18	75
Lidar + Antenna	11.4	12	82
Proposed CNN	14.0	10	85

The proposed CNN clearly outperformed all benchmark approaches across all performance indicators.

V. CONCLUSION

This study presented a CNN-based clutter reduction framework for long-range marine radar systems. Using deep convolutional feature extraction techniques, the system successfully distinguished target echoes from sea clutter and environmental noise. Results demonstrated significant improvements in clutter suppression, target classification accuracy, and false alarm reduction.

The proposed CNN achieved:

- 14 dB clutter reduction,
- 2.2 dB SCR improvement,
- 85% classification accuracy,
- 0.90 F1-score,
- 10% false alarm rate.

These findings demonstrate the effectiveness of deep learning methodologies for intelligent marine radar processing and future autonomous navigation systems.

FUTURE WORK

➢ *Future research should explore:*

- Real-time FPGA/GPU implementation.
- Transformer-CNN hybrid architectures.
- Multi-sensor fusion with AIS, LiDAR, and EO/IR systems.
- Transfer learning on larger maritime datasets.
- Explainable AI techniques for radar decision transparency.

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