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Research Article

Sea clutter suppression using neural network

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Abstract

Sea clutter suppression is a critical task in radar systems to enhance target detection performance in complex naval environments and at coastlines. This paper discusses the use of neural networks for marine clutter suppression and coastal surveillance radar clutter suppression. Effective maritime clutter suppression is made possible by the Feed Forward Neural Network (FFNN) and Principal Component Analysis (PCA) based clutter reduction method, which uses neural network deep learning capabilities to automatically identify and extract features and patterns from raw radar data. Support Vector Machine (SVM) is utilized for clutter suppression along the shoreline. To train and test the network model, a sizable collection of radar measurements, including clutter and target echoes, is gathered. After pre-processing, the gathered data is used in a specially created model, which uses its underlying patterns to distinguish between target echoes and clutter. Then, clutter in real-time radar signals is suppressed using the learned neural network models, improving the detection of targets on the sea and at the coastline. Performance measures Structural Similarity (SSIM) and Signal to Noise Ratio (SNR) shows that the proposed method provides improved clutter reduction.

Nomenclature

FFNN - Feed Forward Neural Network
PCA - Principal Component Analysis
SVM - Support Vector Machine
SNR - Signal to Noise Ratio
SSIM - Structural Similarity
CFAR - Constant False Alarm Rate
CNN - Convolutional Neural Network
GAN - Generative Adversarial Network
GCN - Graph Convolutional
SOM - Self Organizing Map
OTHR - Over the Horizon RADAR
MLP - Multi-Layered Perceptron
RBF - Radial Basis Function
PPI - Plan Position Indicator
STAP - Space-Time Adaptive Processing
MTI - Moving Target Indication
MTD - Moving Target Detection
SVD - Singular Value Decomposition
SCSIF - Sea Clutter Suppression Improvement Factor

1. Introduction

Clutter refers to unwanted signals that interfere with the detection of the desired targets. This interference can be caused by various sources, such as precipitation, terrain, birds, or man-made objects. Radar clutter can degrade the performance of a radar system by making it difficult to distinguish between an actual target and an unwanted signal. It is crucial to assess the stability of a neural network when time delays are involved, as these delays can introduce instability, which is undesirable for the effective application of such networks. There are various techniques used to mitigate clutter in radar systems, such as signal processing algorithms, filtering, and the use of different radar frequencies. These methods help improve the radar system's ability to defeat and track targets in the presence of clutter.

Attaining exact synchronization of carrier frequency and pulse timing between a transmitter and scattered receivers is a major problem in the development of a multi-static radar system. The problem: radar often picks up unwanted echoes besides actual targets, called clutter. This can be from land, sea, weather, birds, or even chaff (deliberate radar countermeasures). There are different types of clutter, such as Surface Clutter- from ground or sea, which are usually stationary, though wind or waves can add movement. Volume Clutter- mainly weather, like rain or snow, which makes the target move and fluctuates. Point Clutter is from individual objects like birds or buildings that may be moving or stationary. Here we must consider fluctuations; Ground Clutter stays fairly consistent, and due to static features it is known as non-fluctuating, and Weather Clutter constantly moves and changes, making it harder to suppress it, and these are known as fluctuating.

This paper emphasizes Maritime Clutter, which bounces off wind-driven waves. Because the sea constantly moves, suppressing this clutter without losing target signals is quite tricky; MTI Radars only display moving targets, minimizing clutter issues. Here the main aspect is Doppler Shift. This is clutter with movement (waves, wind) that can show a slight shift in radar signal frequency, helping to isolate it from stationary targets. Maritime radar clutter in radar systems refers to unwanted radar echoes or reflections that arise from the sea surface, waves, rain, or other maritime-related sources. This type of clutter can interfere with the detection and tracking of maritime targets such as ships, boats, or buoys. Maritime radar clutter presents a significant challenge for radar systems operating over bodies of water, as it can obscure the presence of actual targets and degrade the overall performance of the radar system. Reducing clutter in maritime radar is essential for accurately and dependably detecting maritime targets in diverse weather and sea conditions. There are mainly three parameters used in maritime sea clutter, one is the standard deviation of the wave height, which is the vertical distance between a wave's crest and the other two parameters are wave slope and wind speed. Maritime clutter can pose significant challenges for navigation and surveillance in maritime environments. It can impact the detection and tracking of vessels, making it essential to employ effective clutter suppression techniques. Clutter in other environments may affect the performance of radar systems for different purposes, such as weather monitoring, air traffic control, or surveillance, each with its own set of challenges and requirements. Maritime clutter is distinct in its sources, nature, and challenges, compared to clutter encountered in other environments. Specialized techniques are often needed to effectively manage and mitigate clutter in maritime radar systems.

Clutter suppression in radar systems is essential for maintaining the system's ability to detect and track targets accurately in the presence of unwanted signals. Radar systems can enhance their ability to detect and track targets by reducing clutter, which leads to a better signal-to-noise ratio and fewer false alarms. Clutter suppression is especially important in maritime settings because of the prevalence of sea clutter, which originates from the sea surface, waves, and other maritime sources. By effectively suppressing sea clutter, maritime radar systems can improve their ability to detect and track ships, boats, and other maritime targets with greater accuracy and reliability. Overall, clutter suppression in radar systems is vital for optimizing target detection, reducing false alarms, and enhancing situational awareness in various operational environments, including maritime settings.

Radars for coastal surveillance are essential for traffic monitoring and maritime security. Nevertheless, clutter, unwanted radar signals reflecting off land and waves, hinders their efficacy. The weaker echoes from ships and other interesting targets are obscured by this congestion. For the purpose of separating these feeble target echoes from the overwhelming congestion, clutter reduction techniques are essential. Neural networks come into play here. Large radar data sets, including clutter and target signatures, can be used to train these intricate algorithms. Neural networks can learn to preserve the target echoes, while filtering away clutter, by examining the distinctive features of each. This makes it possible for coastal surveillance radars to obtain a better image of the maritime environment, resulting in more precise ship and other object detection and tracking.

2. State of art methods

The detection of maritime targets using radar is crucial for ocean monitoring. In practical applications, pulse-compression radar is extensively employed for civilian offshore surface target detection. The presence of sea clutter poses a significant challenge, causing interference in the detection capabilities of pulse-compression radar. Consequently, this interference results in diminished detection performance (Zhang, 2019).

Due to the non-stationary nature and complexity of clutter statistics in marine radar, obtaining satisfactory constant false-alarm rate (CFAR) performance using conventional processors based on clutter statistical characteristics is challenging (Zhang, 2019). The primary focus of study (Zhang, 2019; Greet & Harris, 2011) is to enhance the robustness of CFAR, leading to the proposal of the new CFAR method based on the central limit theorem and the logarithmic compression principle of the signal. This method involves clutter two-parameter logarithmic compression processing and the accumulation of magnitudes average comprehensive CFAR processing. Experimental validation of CFAR characteristics and target detection performance in four typical clutter environments demonstrates that this method exhibits superior detection capabilities compared to the Non CFAR method (Greet & Harris, 2011). But clutter suppression is challenging, particularly for conventional algorithms like the constant false alarm rate (CFAR) (Liu et al., 2019). Hence, methods based on deep learning are employed for the detection of targets. Deep learning techniques encompass CNNs, GCNs, GANs, and SOMs. Dynamic convolution neural network (CNN) mechanism for maritime radar target detection adapts to different maritime targets' varied sizes by employing a dynamic convolution structure with multiple filters and adaptive weights. This method outperforms traditional CFAR methods and recent deep learning-based approaches (Wang & Li, 2023). Traditional deep learning approaches, specifically CNNs, faces challenges in achieving optimal performance for maritime target detection, due to the intricate sea clutter environment and target characteristics. It emphasizes the tendency of CNNs to process signal samples independently, neglecting the full utilization of temporal-spatial domain correlation information. To overcome this limitation, this study introduces a novel method for maritime target detection using graph convolution networks (GCNs). In this proposed method, graph structure data defines detection units and captures temporal and spatial information. The target detection process employs GCN on the signal associated with the nodes (Xu et al., 2023). For target detection, a novel approach using a machine learning method is used. This method incorporates a cyclic structure network with a pair of generative adversarial networks (GAN) to comprehensively learn the characteristics of sea clutter. This transforms the challenge of sea clutter suppression into a process of converting clutter radar data into clutter-free radar data. Additionally, target-consistency loss is introduced in the network's cost function to adeptly preserve target information while suppressing sea clutter. Consequently, this method not only efficiently eliminates sea clutter from radar data, but also safeguards target information from potential damage during the clutter suppression process (Ni et al., 2022). In intricate clutter environments, traditional approaches often yield numerous clutter residual diagrams. To address this, we introduce a novel clutter mitigation technique, SOM (Self Organizing Map), which focuses on target and clutter classification. This method focus on radar echo range profile to form a comprehensive feature set. SOM is used to tackle the problem of imbalanced datasets (Zhang et al., 2019). Sky wave over-the-horizon radar (OTHR) is vital for surveillance beyond direct line-of-sight. However, its operational efficiency often diminishes due to transient interferences. Most existing techniques for removing these interferences require data interpolation, which can be computationally intensive. Principal Component Analysis (PCA) estimates the principal components of clutter and potential targets using interference-free slow time samples. These components are then used to directly extract clutter and targets from the contaminated segment without the need for data interpolation (Liu et al., 2019). FFNN introduces novel nonlinear surface basis functions for the network's functional expansion and outlines a network optimization method employing an iterative function selection approach. The study presents comparative simulation outcomes for surface mappings generated by the FFNN, alongside those produced by Multi-Layered Perceptron (MLP) and Radial Basis Function (RBF) architectures. The primary objective is to develop a system capable of generating surface data mappings, with a specific emphasis on its potential application in sea surface modeling and target detection through sea clutter suppression (Panagopoulos & Soraghan, 2002).

3. Clutter suppression using neural networks

At first, we consider various Plan Position Indicator (PPI) images as sea clutter datasets which are fed as input to the network model. When we train a model, it extracts various features and patterns from the dataset. Based on the feature identification, the network model suppresses clutter and identifies the target easily. 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 (**Figure 1**).

3.1 Types of neural networks

In the realm of deep learning, various neural networks can be employed to suppress clutter, each offering distinct advantages and applications. Radar clutter suppression uses a kind of artificial intelligence called Feed Forward Neural Networks, or FFNNs. Labelled data with distinct objectives and clutter identification is used to train FFNNs. This enables the network to identify their distinctions from one another. After being taught, FFNNs can evaluate radar data and discriminate between possible targets (ships) and clutter (wind, waves).

FFNNs pick up on minute differences in the data that conventional filters can overlook. FFNNs are flexible. They can constantly get better at what they do, as they come across more data and various patterns of clutter, unlike set filters. FFNN functions essentially as a smart filter, having been trained to identify clutter by analyzing prior instances. This enables radars to concentrate on the real targets at sea, which are what are really important.

Principal Component Analysis, or PCA, is a method frequently used for data simplification and dimensionality reduction. When it comes to reducing clutter, PCA is useful because finding significant differences allows the visualization of clutter data as a point cloud. The primary components, or main directions, where the points spread out the most are identified by PCA analysis of this data. In reducing data complexity, PCA efficiently compresses the clutter data by concentrating only on these key components. This preserves the core structure of the clutter, while reducing the amount of information that needs to be processed. In clutter separation from targets, the data analysis is made simpler with PCA. Because clutter is more likely to be concentrated along certain primary components, it can be distinguished from target signatures, which may be distributed throughout the reduced data space. This makes it simpler to recognize and sort through clutter, which eventually makes it easier to spot intended objectives.

Another machine learning method that can be used for tasks involving clutter suppression is Support Vector Machines (SVMs). SVMs, as opposed to FFNNs, concentrate on locating a hyper plane in a high-dimensional feature space that optimally divides data points indicating targets from those representing clutter. In feature extraction pre-processing of the data is important, just as with FFNNs. The radar signal is processed to extract characteristics that allow for the successful separation of targets from clutter. These traits could include combinations of polarization characteristics, signal strength, and the doppler shift.

For training, labelled data is used to train the SVM, with each data point being categorized as either a target or clutter. In the high-dimensional feature space, the training procedure determines the ideal hyperplane that maximizes the margin between the two classes (clutter and target). Here, the clutter suppression is based on their location in relation to the defined hyperplane, and newly discovered data points can be classified as either clutter or targets by the SVM once it has been trained. Data points that land on the hyperplane's clutter side are categorized as clutter, and are suppressible.

Benefits of SVMs for clutter reduction are Effective Separation: SVMs are well-suited for applications where strong clutter separation is essential, because they are excellent at identifying distinct boundaries between classes. High-Dimensional Data Handling: SVMs are useful when numerous features are utilized to distinguish targets from clutter, since they can handle data in high-dimensional feature spaces. Memory Efficiency: SVMs operate with little memory consumption, because they define the hyperplane using only a subset of data points, known as the support vectors.

3.2 Different methods for maritime clutter suppression

Space-Time Adaptive Processing (STAP) is a radar signal processing technique designed to reduce clutter interference and improve target detection in challenging and dynamic radar environments. Unlike conventional methods, STAP considers both the time and frequency aspects of clutter, acknowledging its non-stationary characteristics. By utilizing multiple radar pulses and antennas (Ren et al., 2020), STAP analyzes the spatiotemporal characteristics of received signals. This enables the differentiation between clutter and potential targets, especially in scenarios with challenging interference, such as sea clutter or terrain reflections. STAP's adaptability lies in its ability to dynamically adjust filter weights and parameters in response to the changing radar environment. This adaptiveness optimizes clutter rejection, while maintaining sensitivity to legitimate target returns. In maritime applications, where clutter sources exhibit spatial and temporal variability, STAP proves particularly effective, contributing to heightened radar performance and precise target detection.

Support Vector Machines: the Support Vector Machine (SVM) emerges as a machine learning algorithm that has found utility in mitigating maritime clutter within radar systems. Operating by determining an optimal hyperplane to segregate distinct classes in the data space, SVM, in the realm of clutter suppression, can undergo training on annotated data to discern between clutter and genuine targets (Tang et al., 2004). Its proficiency in managing non-linear relationships and processing high-dimensional data renders it well-suited for navigating the intricate and dynamic characteristics inherent in maritime environments. The approach to clutter suppression employing SVMs entails the model's training on historical radar returns, enabling it to internalize patterns associated with clutter. Following training, SVMs can effectively categorize new radar returns, facilitating the discrimination between clutter and potential targets. The efficacy of SVMs in clutter suppression hinges on the quality and relevance of the training dataset, and it may be supplemented with other signal processing techniques to furnish a holistic solution in maritime surveillance applications.

3.3 Different steps used in proposed neural network approach

Training is a complex process of iterative optimization to enable the model to learn patterns and representations from unlabeled data. Initially, a carefully organized dataset is created, usually divided into training, validation, and test sets. The architecture of the neural network is then established, detailing the layer count, the size of each layer, and the activation functions employed. Training itself unfolds through multiple epochs, where each epoch entails a complete pass through the training dataset.

Testing refers to the evaluation and assessment of a trained model using previously unseen held out data, commonly known as test set. The purpose of testing is to gauge how well the neural network generalizes to new and unseen examples, providing insights into its ability to make accurate predictions on real world data. A separate dataset is reserved for testing. The trained neural network model, obtained after the training phase, is loaded for testing, and the test data is fed forward through the neural network using the learn parameters. The performance measures obtained from the testing process provide insights into the model's strengths and weaknesses. Testing is a crucial phase in the development of Neural Network models, as it provides a realistic evaluation for their real-world applicability.

Weights in a neural network are the parameters linked to the connections between neurons across various layers of the network. They are pivotal in determining the strength of these connections, and are instrumental in shaping the model's predictive capability. Each connection between neurons is assigned a weight, and these weights are fine-tuned during the training phase. Initially, when a neural network is initialized, the weights are typically assigned small random values. The learning process, steered by a training algorithm and guided by a loss function, entails iteratively adjusting these weights to minimize the disparity between the predicted output and the actual labels in the training data.

4. Coastal surveillance radar clutter suppression

Coastal surveillance radar clutter suppression involves the utilization of diverse methods and technologies to alleviate unwanted radar returns or echoes in areas proximate to coastlines. The primary goal is to augment the radar system's ability to identify and monitor relevant targets, such as ships or aircraft, amidst the backdrop of ambient noise and disruptions caused by both natural elements and artificial structures. The strategies encompass signal processing techniques, adaptive radar systems, sophisticated algorithms, polarization diversity, frequency adaptability, and compensation for weather effects. Through the efficient reduction of clutter, these methodologies contribute to enhancing the precision of target detection and tracking in maritime settings along coastal regions (Fickenscher et al., 2012).

4.1 Different methods for Coastal Surveillance Clutter Suppression

Time Domain Cancellation: Time Domain Cancellation stands as a crucial technique within radar systems to alleviate clutter and interference in temporal domains. This approach involves the continual processing of radar signals over time, to differentiate between signals originating from mobile targets and those arising from stationary clutter. In coastal surveillance radar suppression, the application of time domain cancellation is pivotal for enhancing the radar's efficiency in identifying and monitoring pertinent targets. There are some key aspects of time domain cancellation: Moving Target Indication (MTI), Range Gating, and Moving Target Detection (MTD) (He et al., 2023). The presence of moving targets induces a Doppler shift in the radar return signal, facilitating discrimination against stationary clutter. Through the incorporation of MTI filters or methodologies, radar systems can suppress or eliminate returns associated with slow-moving or stationary entities. Range gating entails the selection of specific ranges of interest while excluding others. By isolating particular ranges associated with clutter, the radar system can concentrate on the detection and tracking of targets within the desired range. MTD algorithms are deployed to recognize and isolate moving targets within radar returns. These algorithms scrutinize the temporal evolution of radar echoes, discerning against clutter and spotlighting potential moving targets (Chen et al., 2011).

Subspace Projection Class Method: Subspace Projection methods represent sophisticated signal processing techniques utilized in radar systems to mitigate clutter, especially in coastal surveillance scenarios where the distinction between pertinent targets and unwanted clutter is paramount (Li et al., 2020). A prevalent subspace projection technique is Principal Component Analysis (PCA). PCA is a widely utilized statistical approach for mitigating clutter in coastal surveillance radar systems. PCA serves as a subspace projection technique, with the objective of reducing data dimensionality while preserving critical information. In the radar system, PCA proves beneficial for differentiating clutter from genuine targets, thereby enhancing overall radar performance in coastal surveillance scenarios (Lin & Jiang, 2015). In Subspace Projection Class method, particularly leveraging PCA proves to be a robust tool for mitigating clutter in coastal surveillance radar systems. By exploiting the inherent correlation structure in clutter returns, PCA facilitates the creation of a clutter subspace instrumental in suppressing undesired signals, thereby advancing target detection and tracking capabilities in intricate maritime environments. The most popularly used algorithm for clutter suppression is Singular Value Decomposition (SVD). Singular Value Decomposition constitutes a mathematical technique applicable in radar signal processing for the purpose of clutter suppression. This decomposition is integral to clutter suppression methodologies, facilitating the identification and separation of predominant clutter components within received radar signals. The adaptability of SVD enables it to accommodate variations in clutter characteristics over time. SVD proves particularly effective in scenarios where clutter occupies a subspace featuring a few dominant modes. By applying SVD for clutter suppression, radar systems can elevate their capability to detect and track relevant targets amid clutter. This method capitalizes on the mathematical properties of SVD to discern and suppress undesired clutter components, thereby enhancing the overall performance of radar systems (Wang et al., 2019).

5. Challenges and opportunities

Sea clutter suppression in radar systems for maritime and coastal applications presents numerous challenges owing to the dynamic and intricate nature of the sea environment. The variability of sea clutter is pronounced, influenced by shifting sea states, wind conditions, and surface roughness. Effectively adapting clutter suppression techniques to accommodate these fluctuations constitutes a substantial challenge. Sea clutter often displays a wide Doppler spread due to the movement of ocean waves. Successfully suppressing clutter requires the ability to differentiate between clutter and moving targets, considering the dynamic spectrum of clutter.

Utilizing neural networks for the suppression of sea clutter in radar systems brings forth a unique set of challenges, notwithstanding the potent capabilities these networks possess in learning intricate patterns from data. Acquiring a satisfactory amount of labeled data specifically tailored for training neural networks in sea clutter suppression proves to be a demanding task. The availability of sea clutter data featuring accurate clutter and target annotations is pivotal for the effective training of models. Neural networks must exhibit adaptability to alterations in sea clutter characteristics, influenced by factors such as varying sea states, wind conditions, and diverse clutter environments. Developing models that can seamlessly adapt to these changes is imperative. Sea clutter datasets may exhibit an imbalance in the distribution of clutter and target data, with clutter instances outnumbering target instances.

Sea clutter suppression offers exciting prospects for advancing radar technology and signal processing. By leveraging state-of-the-art signal processing methodologies, which include the integration of machine learning and neural networks, there is an opening for the development of sophisticated clutter suppression algorithms. Utilizing sophisticated neural network structures, such as FFNN and PCA, offers a mean to capture complex patterns present in sea clutter data. This, in turn, enhances the system’s ability to differentiate between clutter and genuine targets. Deep learning techniques, which enable the generalization of knowledge acquired from one radar system to enhance performance in diverse environments with limited labeled data, present additional opportunities. The exploration of hybrid models that amalgamate neural networks with traditional signal processing methods allows for the synergistic utilization of their strengths, leading to more effective clutter mitigation. Moreover, the development of adaptive learning algorithms enables neural networks to dynamically adjust parameters, contributing to real-time adaptability in response to changing sea clutter conditions. As technology evolves, these opportunities pave the way for improved radar performance, minimized false alarms, and enhanced target detection capabilities in maritime applications.

6. Maritime clutter suppression using proposed method

The primary goal of clutter suppression is to discern genuine target signals from undesired clutter, thereby optimizing the accuracy and reliability of radar performance. These clutter suppression techniques encompass a range of strategies. Sea clutter filtering involves algorithms and filters that distinguish radar returns from the sea surface, reducing false alarms. From the literature, the neural network based clutter reduction approaches provide improved performance. The proposed method flow of neural network approach is shown in **Figure 1**.

As a pre-processing method for clutter suppression, PCA is used. This is a dimensionality reduction technique that finds the primary components which capture the most important fluctuations in the data after analyzing the clutter data. By concentrating on these primary components, PCA successfully lowers the dimensionality of the clutter while preserving the crucial data needed for target identification. As a result, it is simpler to handle and discern the clutter data from the real targets.

The proposed neural network model consists of total 4 layers, in which there are 2 hidden layers. 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, Leaky ReLU, and Sigmod are used in proposed work.

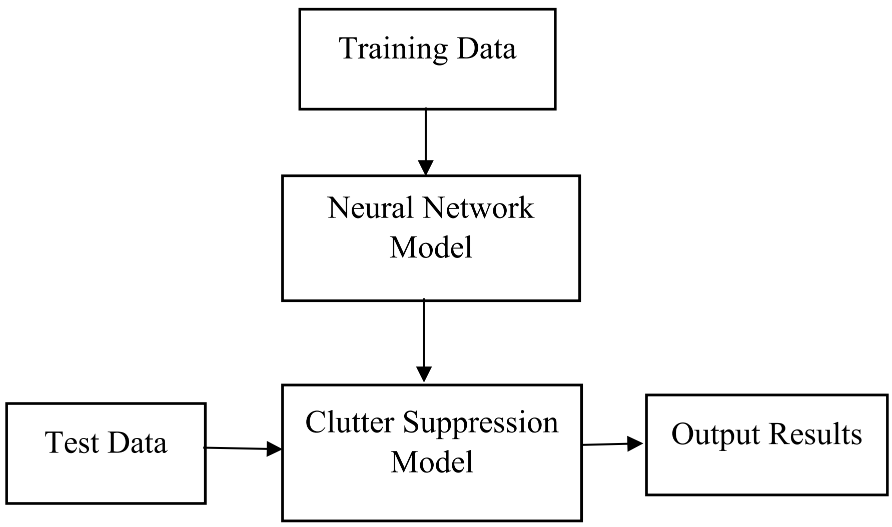


Figure 1 Proposed flow for clutter processing.

Dimensionality reduction in data is handled by PCA. When an image is applied to PCA, it searches for and finds the set of orthogonal vectors that best represent the variance in pixel values. The *m*x*n* image can be flattened and made as a single vector. All the images are represented as columns and represent the whole dataset in a matrix. Let the matrix be M. The centered mean value is obtained by subtracting the mean vector μ of the columns of M and the mean vector from each column vector in M as;

$$M_{centered} = M - \mu \tag{1}$$

Later stage Singular Value Decomposition (SVD) is performed using;

$$M_{centered} = UPV^T \tag{2}$$

U, V are orthogonal matrices, and *P* is a diagonal matrix. Here, *P* matrix contains the singular values. The principal components are identified by selecting the largest singular values. Dimensionality reduction is obtained by projecting mean centered data onto the subspace spanned by U_k. The reduced representation Y is obtained as;

$$Y = U_k^T M_{centered} \tag{3}$$

The final images are reconstructed using;

$$M_{Reconstructed} = U_k Y + \mu \tag{4}$$

Fully connected Feed Forward Neural Networks consist of three important layers: input layer, hidden layer, and output layer. Each layer contains different neurons and produces output based on activation function. Neuron produces output based on weighted sum of input features and small bias b as follows;

$$k = \sum_{i=1}^{n} w_i x_i + b \tag{5}$$

$$a = f(k) \tag{6}$$

Here, x_i are the input features, w_i are the weights of corresponding input, *b* is the bias, *f* is the activation function, *k* is the weighted sum, and *a* is the output of the neuron. Sigmoid and ReLU activation functions are used in neural network. The sigmoid function is given as;

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{7}$$

And the ReLU is used as;

$$\text{ReLU}(z) = \max(0,z) \tag{8}$$

During forward propagation, the activations of neurons at each layer is performed using;

$$z_{(l)} = w_{(l)} a_{(l-1)} + b_l \tag{9}$$

Here, *f* is type of activation function. The output of layer is obtained by;

$$a_{(l)} = f_{(l)}\left(z^{(l)}\right) \tag{10}$$

After the dimensionality reduction of PCA, FFNNs become the main tool for fine-tuned clutter suppression. Artificial intelligence models known as FFNNs are modelled after the architecture and operations of the biological brain. Here, labelled data that distinguishes between target signatures and clutter echoes is used to train the FFNN, as given in **Figure 2**. The FFNN is now equipped to recognize intricate correlations and patterns in the data thanks to this training. After being trained, the FFNN may distinguish between possible targets and clutter by analyzing the preprocessed clutter data (from PCA). Target identification is improved by the FFNN's capacity to learn complex patterns, which enables it to discriminate between minute differences in clutter and target signals.

PCA uses the features from the input dataset. Here, the number of components is selected for dimensionality reduction using n_component parameter in the simulation model. In this paper, this is set to 20, meaning the algorithm will retain 20 principal components. The input images are flattened, such that they are reshaped where each row represents one image. On the flattened image, PCA is applied to analyze the 20 prominent principal components that fit the model for dimensionality reduction. After processing, the images are reconstructed by applying inverse transform of PCA to the reduced image dataset.

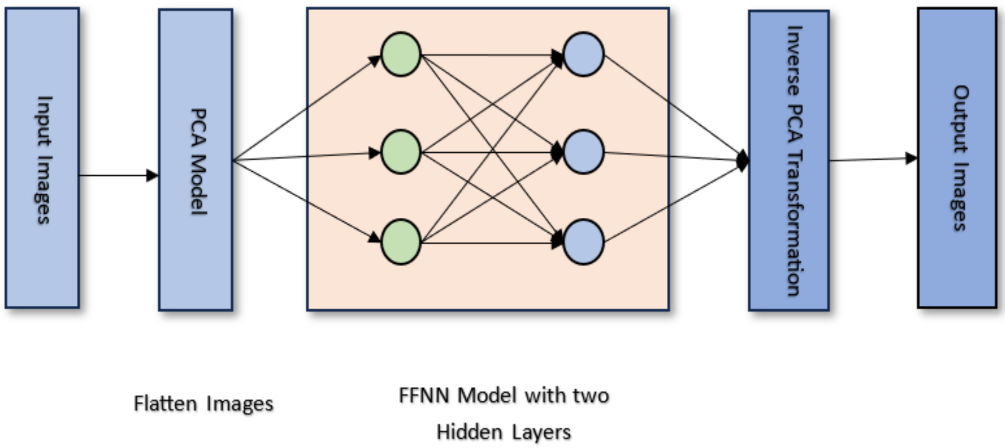


Figure 2 Proposed methodology using PCA and FFNN.

Combining PCA and FFNN has several benefits for reducing maritime clutter. The FFNN has reduced computational strain, thanks to PCA's initial data compression, which enables quicker processing. Additionally, PCA makes sure the FFNN is trained on the most informative parts of the clutter, improving its target identification capabilities, by concentrating on the most pertinent data components. In contrast, FFNNs offer greater versatility than conventional filtering methods. As they are exposed to more data, they might learn more and more over time, increasing their ability to suppress clutter. In real-world marine circumstances, where clutter characteristics might change based on weather patterns and sea conditions, this flexibility is essential.

To put it simply, PCA and FFNN combine to provide a stable and flexible method for suppressing marine clutter. PCA extracts the most important information from the input while maintaining essential details, while FFNN uses its learning capacity to accurately discern between targets and clutter. By combining these two strategies, radar systems in maritime situations become much more effective, leading to safer navigation and more successful surveillance activities.

Comparing the clutter suppression method proposed in the article with existing methods based on deep learning can provide valuable insights into its effectiveness and novelty. Deep learning methods have gained significant popularity in various fields, due to their ability to automatically learn features from data, and generalize well to different scenarios. In this work, deep neural networks, based on CNN and SAGAN, are considered for comparison.

7. Results

The proposed method utilizes PCA and FFNN for maritime clutter reduction. The simulation is performed by considering a PPI dataset from MATLAB. The data set is taken from mathworks, which consists of 84 pairs of images, along with their responses. 70 images are used for trainings set, 10 images are taken for validation set, and for the test set, 4 images are considered while performing simulations. The parameter considered in the simulation is 55 m radar height, which operates at a frequency of 10 GHz. Small targets and large targets of size 120×18×22 and 200×32×58 m^3 are assumed in clutter PPI images. The simulated data set uses random parameters of wind speed apf 7 to 17 m/s, and wind direction of 0 to 180 degrees is considered, with target speed of 4 to 19 m/sec around 0 to 360 degrees.

Table 1 Training parameters.

Parameter	Value
Learning Rate	0.1
Total epochs	80
Optimizer	RMS Prop
Loss function	Mean squared error

The data is splitted for testing and training. Simulations are performed up to 80 epochs. The results of training process are shown in **Figure 3**. Performance of proposed method is analyzed using performance measures like SSIM and SNR.

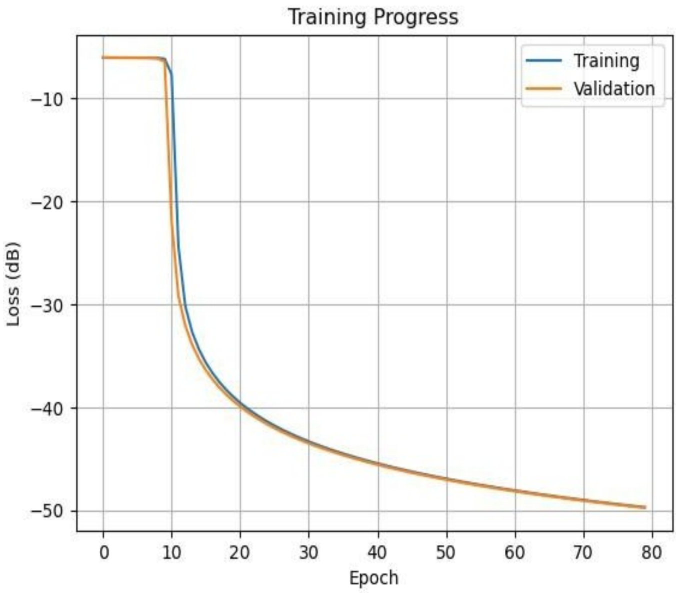


Figure 3 Training and validation loss of 80 epochs.

The above graph illustrates the training process. Training loss refers to the error or discrepancy between the predicted outputs of the model and the actual target outputs on the training dataset. During the training process, the model's parameters are adjusted iteratively to minimize this loss. Lower training loss indicates that the model is better at fitting the training data. The image shows less loss at and after 80 epochs. Hence, 80 epochs is chosen as the suitable number for training.

Validation loss is similar to training loss, but is calculated on a separate dataset called the validation set. The validation set is typically used to evaluate the performance of the model during training and to prevent over fitting. Over fitting occurs when the model performs well on the training data, but fails to generalize to new, unseen data. By monitoring the validation loss over fitting can be detected: if the training loss continues to decrease while the validation loss starts to increase or remains stagnant, it suggests that the model is over fitting to the training data. Reduced training loss and validation loss gives accurate results for the specific model.

7.1 Performance measures for clutter suppression

It is very important to learn about performance measures because the model is very effective in predicting the output results. Some of the performance measures for clutter suppression are now discussed.

7.1.1 Signal-to-Noise Ratio (SNR)

Signal-to-noise ratio performance measure is important in digital and analog communications. The strength of the desirable signal in relation to background noise, or the undesired signal, is measured by SNR. A predefined formula analyses the two levels and yields the ratio- which indicates if the noise level is affecting the desired signal- can be used to calculate S/N. SNR is used as a supplementary statistic to comprehend noise constraints, and maybe assess the efficacy of clutter reduction strategies. In radar systems, unwanted signals resulting from reflections off non-target objects or ambient elements are referred to as clutter, whereas the signal is the echoes from targets of interest.

$$SNR = \frac{P_{Signal}}{P_{Clutter} + P_{Noise}} \tag{11}$$

P_{Signal} is the power of the Signal
$P_{Clutter}$ is the power of the Clutter
P_{Noise} is the power of the Noise

7.1.2 Structural Similarity Index (SSIM)

A perceptual metric called the Structural Similarity Index (SSIM) measures the reduction in image quality brought on by processing operations like data compression or transmission losses. For instance, it can apply standard picture degradations followed by standard image enhancement signal processing techniques. SSIM can be applied in a training or assessment procedure to determine how well the target signals are recreated following clutter reduction. When converting radar data into a visual format, SSIM may be used to evaluate the picture quality of these visualizations.

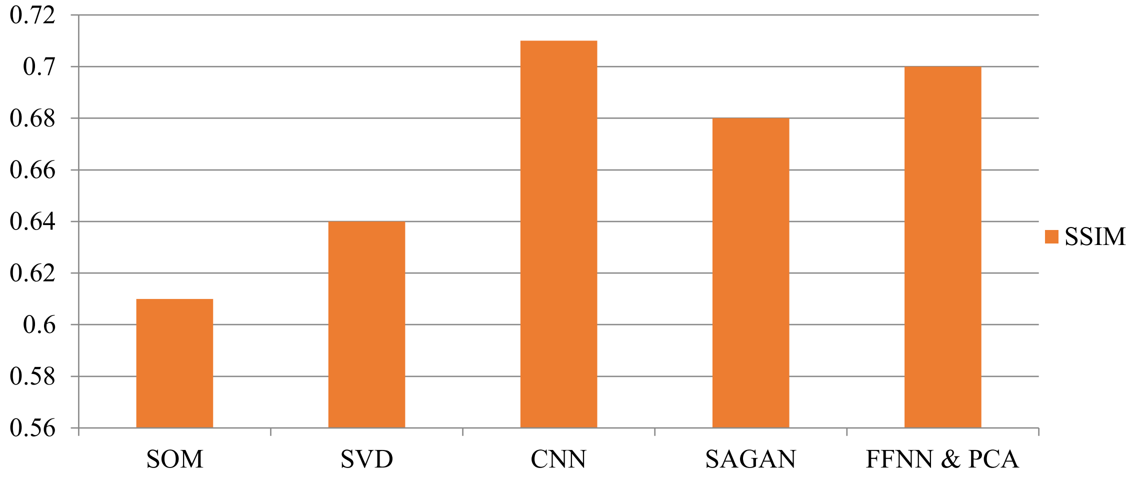
$$SSIM\ (x, y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{(\mu_x^2 + \mu_y^2 + C_1)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{12}$$

x and y are the images being compared
μ_x and μ_y are the means of x and y, respectively
σ_x^2 and σ_y^2 are the variances of x and y, respectively
σ_{xy} is the covariance of x and y
C_1 and $C_2$are small constants to stabilise the division with weak denominator

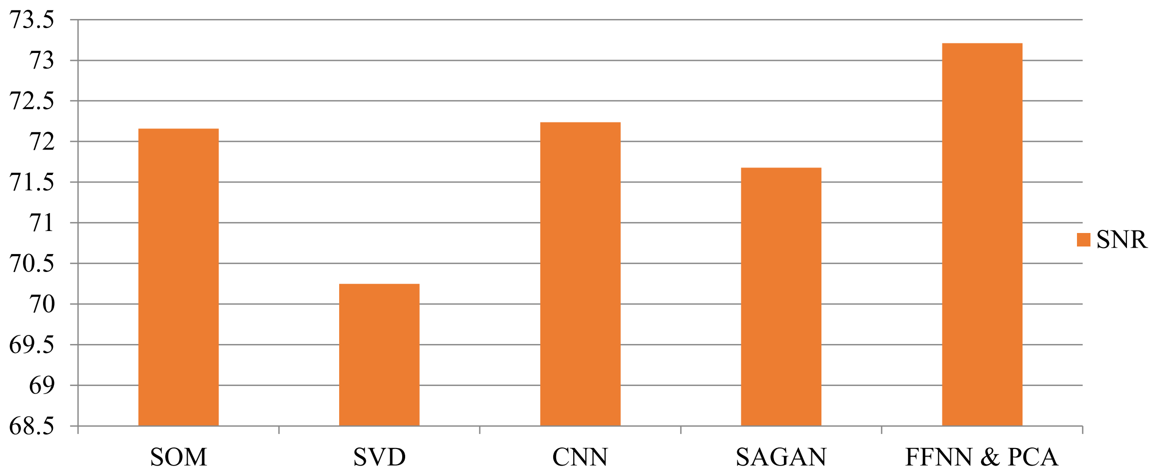
The Structural Similarity Index (SSIM) is commonly applied to compare images in terms of their structural information; it can also be adapted and utilized in other domains, including radar signal processing and clutter suppression. In the context of clutter suppression, SSIM can be justified and deemed appropriate for several reasons. Firstly, clutter in radar signals often introduces noise and distortions that can degrade the quality of the signal. SSIM, by measuring the similarity of structural information between two signals, can effectively quantify the extent of distortion or degradation caused by clutter. Secondly, clutter in radar signals can exhibit structural patterns or characteristics that differ from the desired signal. SSIM’s ability to capture structural similarities or differences makes it suitable for identifying and distinguishing clutter from the desired signal. Furthermore, SSIM is sensitive to both luminance and contrast changes, which are common effects of clutter in radar signals. By considering both luminance and contrast information, SSIM can provide a comprehensive assessment of signal quality, and effectively distinguish clutter from useful signal components. SSIM index has values between −1 to 1, where 1 indicates perfect similarity, 0 indicates no similarity, and -1 indicates perfect anti-correlation. In this work, when comparing the input image to the output image, a lower SSIM value indicates a significant difference between the two, which indicates the output image is clutter free.

Table 2 Performance comparison of different methods on measured data.

Parameter	SOM	SVD	CNN	SAGAN	FFNN & PCA
SCSIF	10.68	11.14	13.99	14.25	14.32
SSIM	0.91	0.74	0.70	0.68	0.69
SNR	75.16	70.25	72.24	71.68	79.82
SCR	9.21	9.19	12.24	12.11	12.11

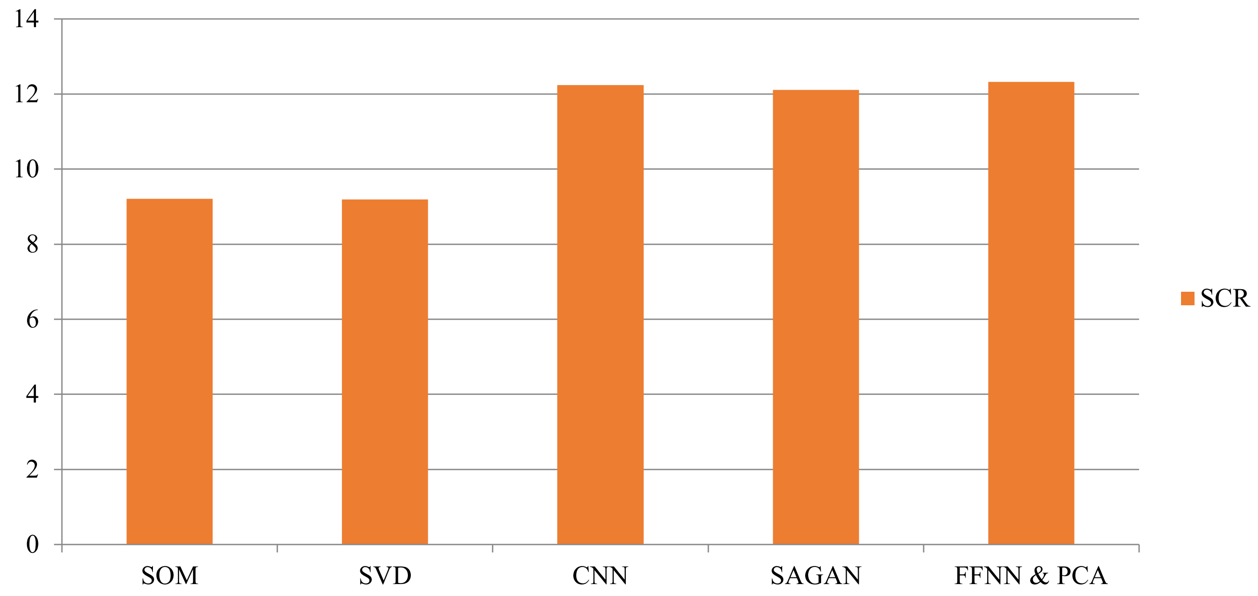


(a)

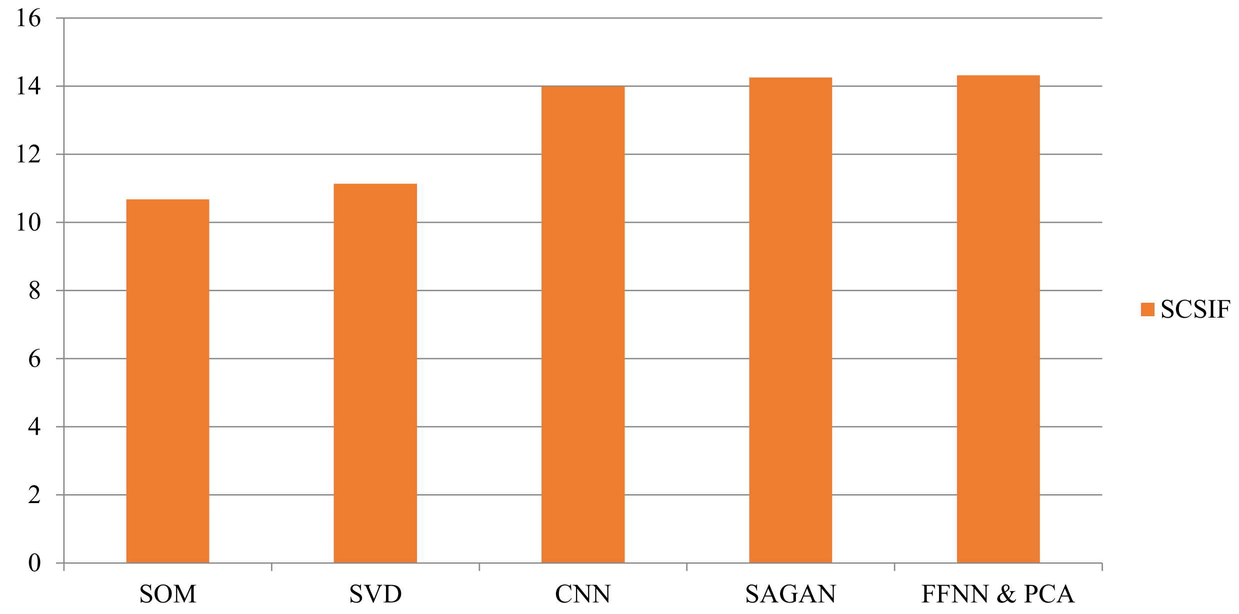


(b)

Figure 4 Comparison of proposed method with existing methods.



(c)



(d)

Figure 4 (continued) Comparison of proposed method with existing methods.

Here, SSIM values were calculated for various methods such as SOM, SVD, and FFNN & PCA. When the above table is observed, FFNN & PCA has a low SSIM and high SNR value compared to the remaining methods. So, the proposed method is very effective compared to the remaining methods (**Table 2**). Graphical representations of the results are given in **Figures 4a** and **4b**. More analysis of the proposed method is performed using SCSIF and SCR performance measures. The results are given in **Figures 4c** and **4d**.

PPI images are processed for maritime clutter. Here, different cluttered PPI images are used for analyzing the proposed method, as shown in **Figure 5**. PPI images in the figure clearly show that the maritime clutter is removed for better target detection.

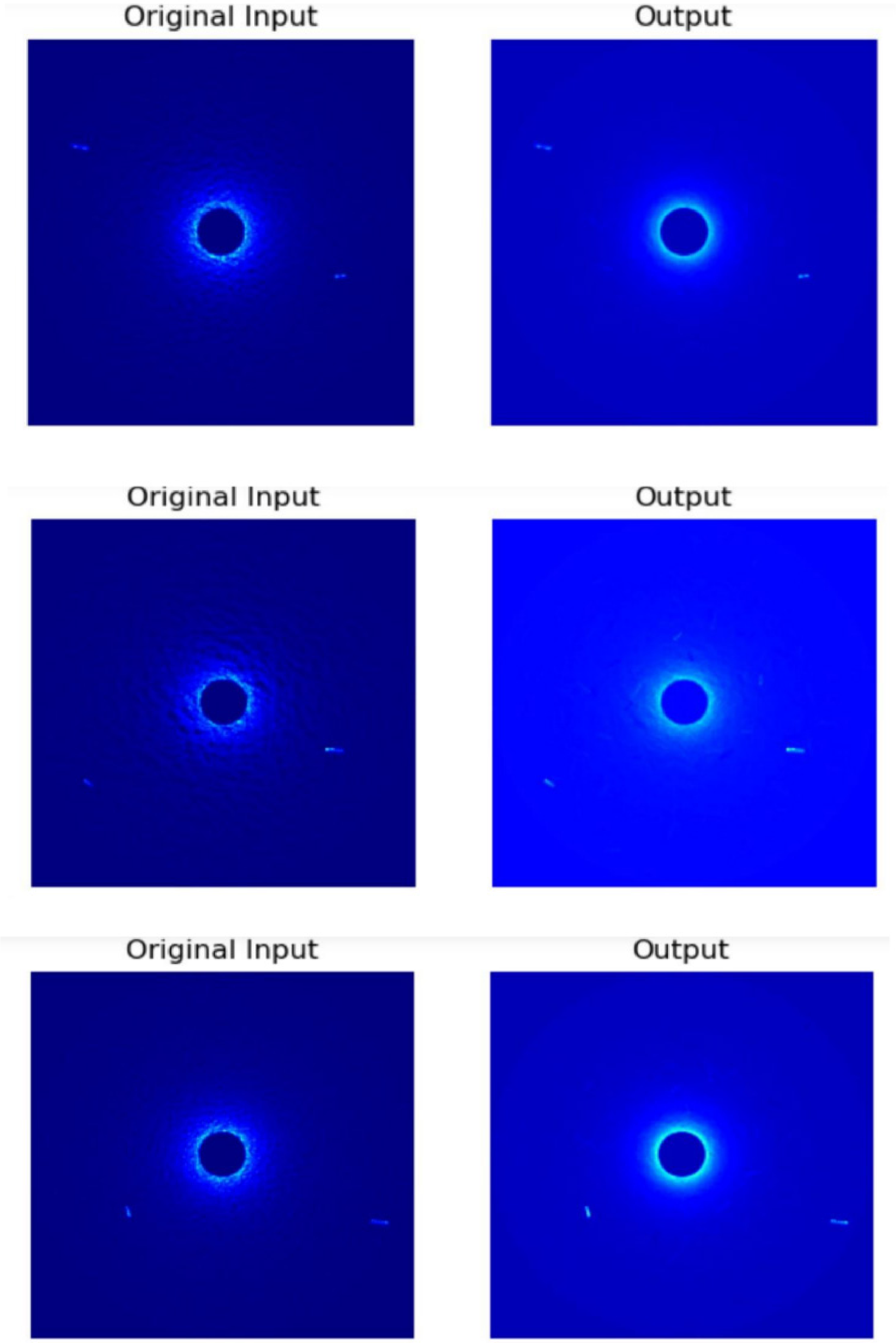


Figure 5 Clutter removed images using proposed method.

8. Conclusion and future scope

Employing a combination of Feed-Forward Neural Networks (FFNN) and Principal Component Analysis (PCA) has yielded promising results in suppressing sea clutter. This methodology has effectively minimized interference from sea clutter, leading to improved precision and efficiency in processing radar signals in maritime and coastal environments. The utilization of FFNN and PCA has resulted in significant enhancements in the capabilities of radar systems to detect and identify targets, underscoring the effectiveness of this approach in addressing the challenges posed by sea clutter. Exploring advanced neural network designs, possibly incorporating reinforcement learning, could enhance the ability to analyze complex patterns in sea clutter data.

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