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Machine learning assisted Optical-SAR Radar for Target Classification

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ABSTRACT

A new era of Synthetic Aperture Radar (SAR) has begun in recent years. Convolutional neural networks (CNNs) have garnered a lot of interest lately for their ability to analyze SAR data. This paper thoroughly studies the main subfields of SAR data analysis that CNNs have addressed, including segmentation, change detection, object identification, automatic target recognition, land use and land cover classification, and image denoising. Particular attention has been paid to useful methods like transfer learning and data augmentation. To overcome the issues of a high false alarm rate and the challenges of attaining high-performance detection using traditional approaches, a deep learning-based SAR target identification and classification method is proposed for target detection tasks in complex backdrops. An optical based approach is presented in this study for enhancing the security feature. A machine learning-based radar with better performance is suggested in light of the deep learning-based target models' problems with a high parameter count and memory usage. Even though there have been some significant advancements, deep learning research in radar is still mainly being tested in lab settings and is still in its theoretical stage. There are still a number of obstacles and potential restrictions in the application, including issues with dataset adequacy, robustness of the model, and electromagnetic modelling fidelity. Nonetheless, it is undeniable that deep learning technology will significantly advance radar. As a result, it is wise to recognize the field's current difficulties and potential future paths. Furthermore, it is hoped that this review will give readers fresh opportunities to investigate appropriate deep learning-based methods for radar applications. In this study, Long Short-Term Memory (LSTM) and SqueezeNet model are used for enhancing the accuracy of system designed.

Keywords: *Long Short-Term Memory, Machine Learning, Synthetic Aperture Radar, SqueezeNet*

INTRODUCTION

Machine learning (ML) approaches are becoming more and more significant in our data-intensive era. By retaining only useful and nonredundant portions, features are extracted to lower the input data's dimension to a more manageable size. The majority of machine learning issues involve two steps: feature extraction and feature classification. The traditional machine learning techniques extract handmade features. Currently, though, the focus is on automatically learning features. Without a question, the most well-liked trend in machine learning is deep learning (DL). It has demonstrated remarkable performance in computer vision and image processing over the last ten years, with applications including object detection, picture categorization, super-resolution restoration, and more. The field of Radar study is more crucial since military security applications involving visual surveillance are growing quickly. Area photography is necessary for military systems both at night and in inclement weather. Thus, SAR offers both high resolution and this capability. It has a great range for processing and disseminating complicated information.

In addition to intelligence operations, SAR has numerous additional uses in the most recent technological advancements, such as spotting ice risks, discovering oil spills to preserve biodiversity, and providing information about a region's topography profile for mineral extraction. Spaceborne SAR can operate day or night in any weather because it is an active microwave imaging system. There are currently a lot of spaceborne SAR sensors in use. Spaceborne SAR has been widely used in a number of sectors, including target recognition, resource discovery, disaster monitoring, and Earth system monitoring, because to its superior 2D high-resolution qualities and worldwide observation capabilities.

Depending on the orbit height, spaceborne SAR systems are classified as LEO- and MEO/GEO-SAR. They have submeter-level imaging resolution. The quality of the spaceborne SAR photographs determines the target information's correctness and dependability. High-quality ones provide as the foundation for several crucial applications, including as interferometry, target recognition, and stationary or moving target detection, among others. Several methods [1] of image categorization are also illustrated with the underlying hybrid model architecture, and researchers employ deep learning for the remote sensing application of SAR images. It would be easier to meet the requirement's theoretical bounds if the radar system's performance was assessed using variations in its primary parameters, such as bandwidth, operating frequency, and altitude. Therefore, the performance evaluation of the machine learning-based system is the main emphasis of the work reported in this study. Usually, CNNs are constructed from many fundamental feature extraction steps. Each stage's primary components are the pooling layer, activation function, and convolutional layer. A classification module and one or more completely connected layers come after these phases. The significance of each element is described as follows:

a) Convolutional Layer

The key component of every CNN stage is the convolutional layer. The coefficients of a filter bank, let's say M filters, must be learned by training. Assume that the convolutional layer receives a tensor (W1×H1×C1) as input, where W1, H1, and C1 stand for the input's width, height, and number of channels, respectively. The input tensor's width and height are slid over the first filter (K×K×C1), a tiny square kernel with a side length of K pixels and the same number of channels (C1) as the input tensor. A new tensor (W2×H2×C1) is created by element-wise multiplication and summing, with W2 and H2 standing for the new tensor's breadth and height, respectively.

b) Activation function

To add nonlinearity to the network, the activation function—a straightforward mathematical function—is applied element-by-element to the output of a convolutional layer. Without this nonlinearity, the network's depth would be equivalent to that of a single layer, regardless of how complex the architecture is. CNNs frequently use Rectified Linear Units (ReLU), $y = \max(0, x)$, since they are computationally economical, speed up convergence, and prevent the vanishing gradient issue. It does, however, have certain drawbacks. The occurrence of neuronal necrosis is likely to occur because the derivative of the ReLU function is always zero when the input value is negative.

c) Pooling Layer

The dimension of each feature map is reduced by a pooling layer, which is usually applied after convolutional and nonlinear layers. Sliding a window—usually a square window—over each feature map and extracting just one value from each window is how pooling is done. After pooling, the number of channels won't change because down sampling is only applied to the width and height dimensions. The two most popular pooling techniques in CNNs are max-pooling and average-pooling. Additionally, pooling makes the representation roughly invariant to slight changes in the input.

d) Fully connected Layer

A fully connected layer receives the flattened vector output from the last pooling/convolutional layer. Nonlinear combinations of prior high-level features are to be learned by a fully connected layer. Like a conventional MLP neural network, all of this layer's input elements are connected to its output elements. It is possible to employ one or more fully connected layers in succession.

e) Classification Layer

The output of the final fully connected layer is mapped to the probability domain by the classification layer, the final CNN module. For multiclass classification, the Softmax classifier with cross-entropy loss is frequently utilized. The classification module is eliminated for CNN applications of the regression type, and the output of the final fully connected layer is compared to the ground truth using the MSE loss function or other regression-appropriate loss functions.

The structure of the paper is as follows. Section II presents the literature review. The radar network's workflow is displayed in section III. Results are presented in section IV, together with a discussion of RADAR parameter modifications. The paper is finally concluded in section V.

LITERATURE REVIEW

Carl Wiley was the first to synthesize a huge aperture utilizing the echo signal's doppler spread feature. Synthetic Aperture Radar was created after it was discovered that radar's resolution has increased [1]. Chen et al. compared various feature extraction methods [2] in various operating settings and offered recommendations for choosing the best classifiers in various scenarios. They used classification techniques like Naive Bayes, Nearest Neighbor, and SVM (Support Vector Machine) with feature extraction techniques like LDA (Linear Discriminant Analysis) and PCA (Principal component Analysis) kernel in their experimental setting. In addition to observing the variation of feature dimensions, input data quality, and target detection classes, they examined the classification accuracy of several combined models. Wang et al. examined various input target sizes and suggested enhanced models [3]. Chan and Koo presented the usage of LFM (linear frequency waveform) [4] and the response of the matching filter in radar signal processing, as well as their discussion of the various SAR systems.

A framework [5] for compressed remote sensing was provided by Potter et al.'s study of the various techniques utilized for sparse reconstruction in radar processing. Using Generative Adversarial Nets (GAN) [6] as an augmentation technique, Ding et al. examined target recognition as a sample recognition problem with limited availability.

TABLE 1. Key ideas from Literature Review

References	Remarks
[16]	Interferometric synthetic aperture radar (InSAR)
[17]	Geosciences application of SAR
[18]	Stereo wave observation projection
[19]	Review of projection algorithms
[20]	MANets for SAR target recognition

Using the SAR approach, D. Grom et al. introduced Passive Bistatic Radar (PBR) [7] by assessing the rate of change in Doppler frequency and range migration parameters for imaging objects. Assessing the change of radar characteristics like frequency and bandwidth could make it easier to realize the performance of the SAR Network, as the majority of study focuses on diverse area imaging settings and comparing the performance using different algorithms. SAR systems are employed in a variety of operational and weather scenarios. The ENVISAT satellite, which the European Space Agency (ESA) launched in 2001 to monitor the globe, is considered state of the art. Transmit and Receive (T/R) modules provide for a significantly more flexible selection of incidence angle ranges in the SAR system. The several waveforms [8] utilized in contemporary SAR systems, including as frequency-modulated continuous wave (FMCW) and linear frequency modulation (LFM) (chirp), were covered by Jakowatz et al. in 2012. By approximating the scattering matrix for inverse mapping, DeGuchy et al. introduced a learning approach to tackle the forward and inverse scattering problems [9] of SAR images. A method to combat the overfitting of SAR images caused by a lack of data was proposed by Shang et al. in 2018 [10]. A deep learning approach to the Synthetic and Measured Paired Labelled Experiment was created by Scarnati and Lewis in 2019 [11]. Using the SAR/PolSAR data set and the polarimetric decomposition technique, Praikh H. et al. demonstrated the progress in remote sensing applications [12-15]. The key points of literature survey after analysis of research gap are illustrated in Table 1.

WORK FLOW

T,his section covers the methodology for carrying out the study using simulation tool- MATLAB (R2024b).As it is known that Radar target recognition technology integrates sensor, target, environment, signal processing, and other technologies in a basic yet complex system engineering process

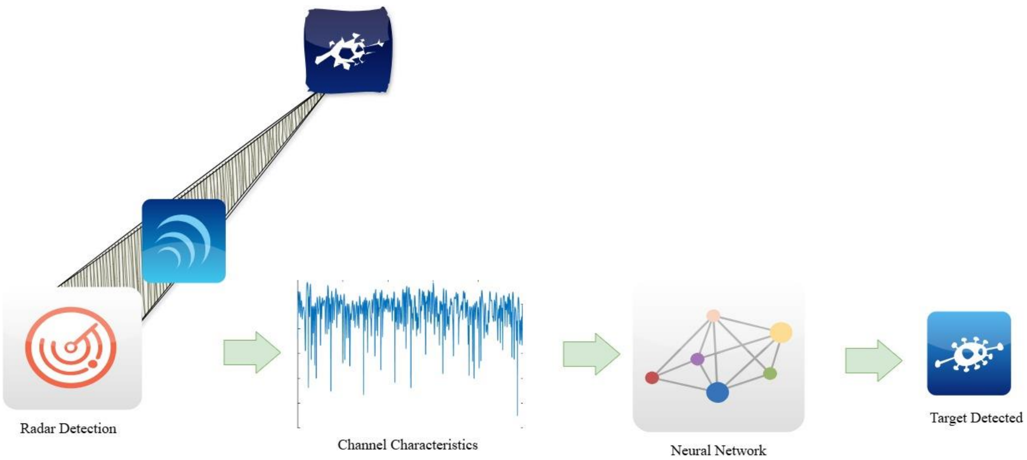

Fig.1 Steps followed in System designing

It significantly contributes to raising the degree and potential of automation in both the military and the civilian sector. Despite its effective use in certain areas, the full theoretical system is yet unestablished. Deep learning algorithms have drawn a lot of attention lately and have shown promise as workable solutions. It is envisaged that this paper can offer possible guidance for future research and use of deep learning in sectors connected to radar target classification, given the increasing focus and research findings published in recent years. The state of art work is described in Fig.1.

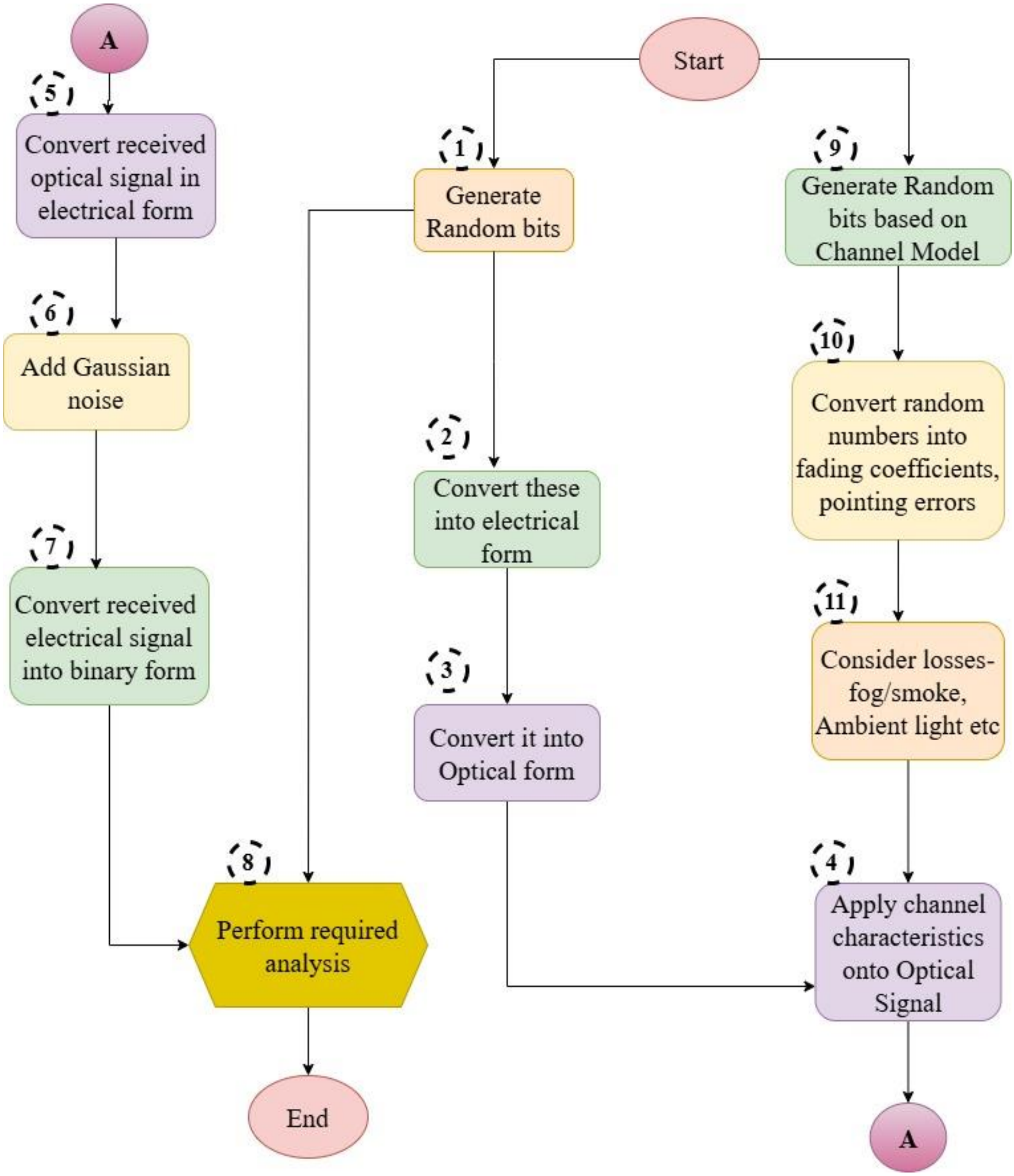

Fig. 2 Sequence of steps followed in analysis

The steps performed in serial manner are described as follows and same is illustrated in Fig.2. First, pseudo random bit sequence is generated and converted into electrical form. After this conversion, signal needs to be in optical form for error free transmission. On the receiver side, reverse process is performed and the data interpreted is analysed using Machine learning algorithms. On the basis of channel model, random numbers are generated considering the miscellaneous losses (like pointing errors, turbulence and environmental factors).

RESULTS AND DISCUSSION

The findings of the simulation demonstrate radar categorization using both machine learning and deep learning techniques. The machine learning method combines a support vector machine with wavelet scattering feature extraction. Two deep learning techniques are also demonstrated: a Long Short-Term Memory (LSTM) recurrent neural network and transfer learning with SqueezeNet. Classifying targets is a crucial feature of contemporary radar systems.
It classifies radar echoes from a cone and a cylinder using deep learning and machine learning. The RCS pattern of a cylinder with a radius of 0.5 meters and a height of 20 meters is replicated by the system.
The radar operates at a frequency of 750 MHz.

The pattern (as shown in Fig.3) can then be used to replicate returns from various aspect angles on a backscatter radar target. The cone's return can be produced in a similar manner. The aforementioned procedure is performed for five randomly chosen cylinder radii to produce the training set. Furthermore, ten motion profiles are simulated for every radius by altering the incident angle while observing ten randomly produced sinusoids around the boresight. Each motion profile contains 700 samples, which means that there are 700-by-50 samples. A 700-by-100 matrix of training data with 50 cylinder and 50 cone profiles is produced by repeating the procedure for the cylinder target. In the test set, we generate a 700-by-50 training set using 25 cylinder and 25 cone profiles.

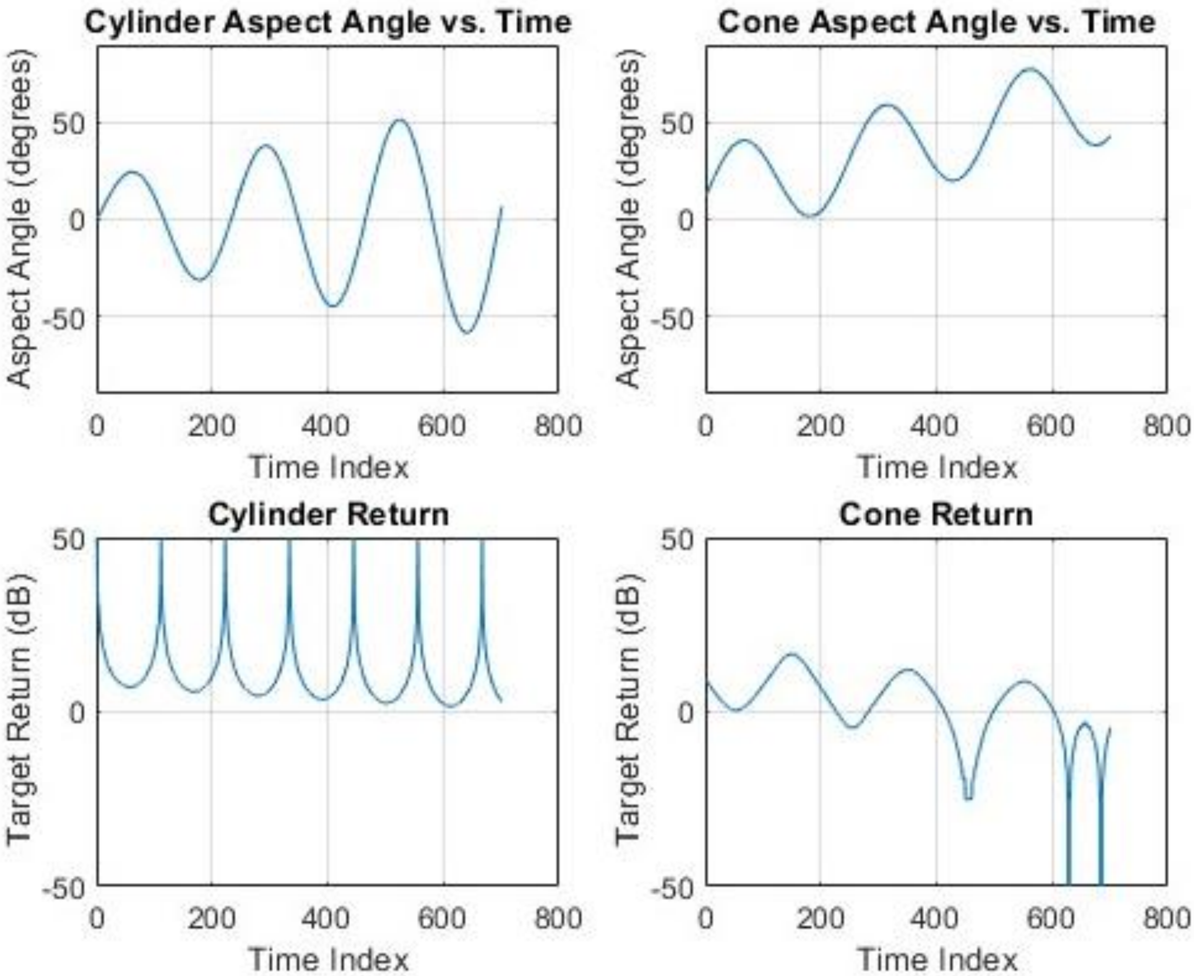

Fig.3 Incident azimuth angles and the target returns of Radar

TABLE II. Output parameters for ML based SAR Model

Parameters	**Real Antenna**	**Ideal SAR**	**Effective SAR**	**Units**
Synthetic Aperture length	NaN	4.58	5.8	Km
Range Resolution	0.375	0.389	0.386	m
Cross Range Resolution	7388	2.35	2.1	m
Integration Time	NaN	764	850	ms

The wavelet scattering feature extractor propagates data through a series of wavelet transforms, nonlinearities, and averaging to generate low-variance representations of time series. Wavelet time scattering produces signal representations that are insensitive to changes in the input signal without compromising class discriminability. The crucial parameters (as shown in Table II) to specify in a wavelet time scattering network are the number of wavelets transforms, the number of wavelets per octave in each of the wavelet filter banks, and the scale of the time invariant. In many applications, a cascade of two filter banks is enough to achieve good performance and confusion matrix is shown in Fig.4.

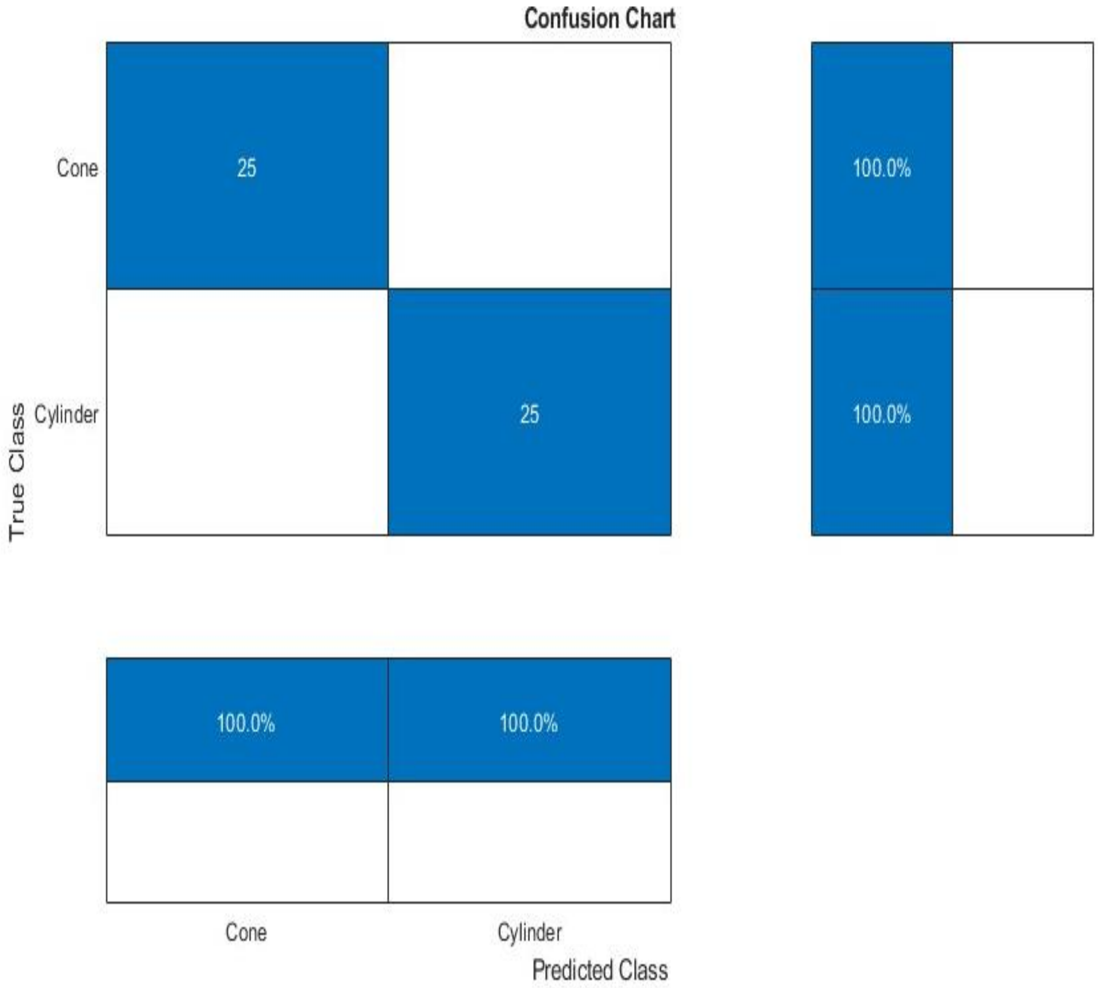

Fig.4 Confusion Matrix for SAR radar

SqueezeNet is made to recognize variations in pictures and categorize the outcomes. Consequently, we need to convert the 1-D radar return time series into an image in order to apply SqueezeNet to classify radar returns. Using a time-frequency representation (TFR) is a popular method. The best time-frequency representation of a signal can be chosen from a variety of options, depending on the signal's properties. Plot a few radar signals from each class at random to find out which TFR would be suitable for this issue (as shown in Fig.5)

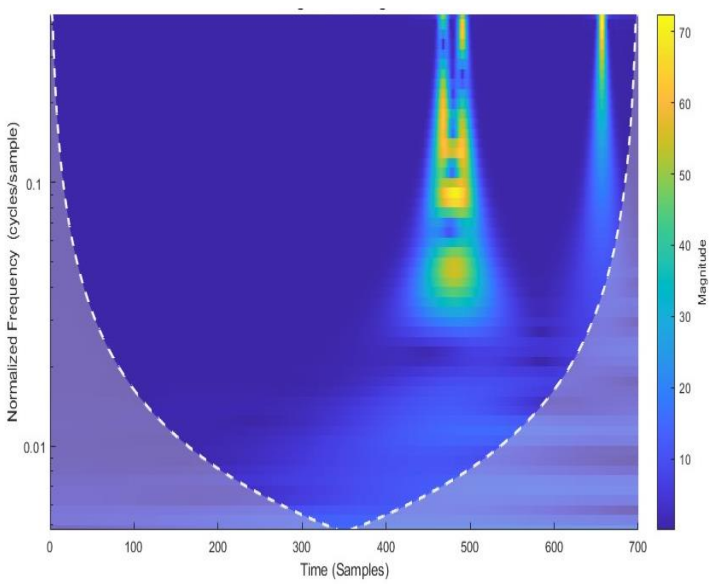

Fig.5 Magnitude Scalogram

In terms of communication systems, especially in free-space, unfavorable weather conditions such as heavy rain, fog, or snow cause BER to increase significantly when compared to clear weather. This means that the error rate in data transmission is significantly higher during bad weather; in other words, the worse the weather, the higher the BER.

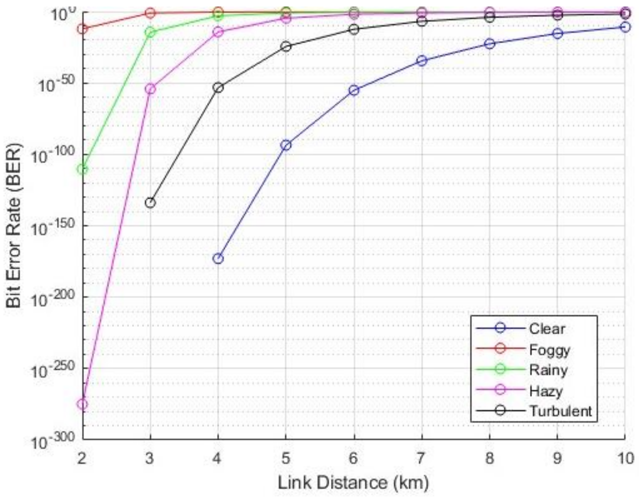

Fig.6 Comparison of BER in Different Weather conditions

For this, Monte-Carlo simulations are run to assess the effectiveness of the optical communication link utilizing the modulation techniques under study in the presence of the previously indicated weather conditions. The BER of the system in each scenario is then compared to demonstrate a performance comparison (Fig.6).

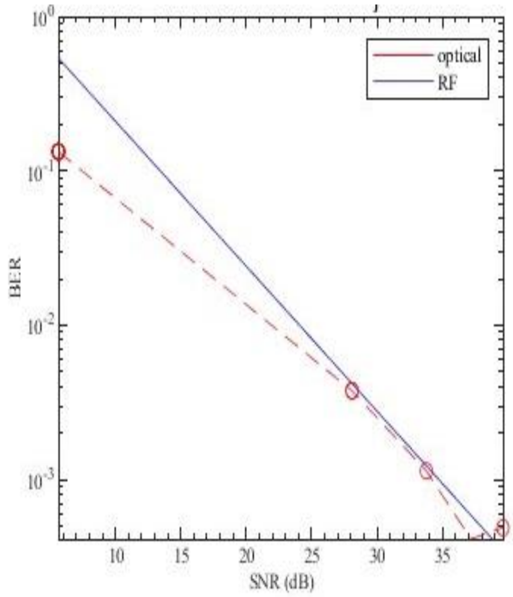

Fig.7 Comparison of BER Vs SNR for Optical and RF based RADAR

Fig.7 shows the performance comparison between optical and RF RADAR system. The BER reaches value of 10^{-3} at approximately SNR 37 dB in case of optical based RADAR system. The model of gamma-gamma channels works well with weak to strong turbulence. The modified Rytov theory was explained by Andrew.The probability density function, or gamma-gamma pdf, is a controllable mathematical model that works well under particular turbulence conditions according to this theory. According to doubly stochastic theory, there are two distributional factors. This hypothesis assumes that large-scale irradiance variations of the transmitted wave are used to influence small irradiance changes. The direction of all fluctuations is independent of gamma distributions.

CONCLUSION

In light of the need for future secure radars, the paper applies the widely used deep learning models to radar data in this study and suggest a radar target detection network based on LSTM and squeezeNet machine learning models. The study utilizes optical signal communication rather than RF for enhancing security. The experimental findings (MATLAB R2024b) demonstrate that the method used in this work produces better outcomes in terms of confusion matrix, model size, and detection accuracy (96%). Future studies can expand the radar model described in this paper to include additional application scenarios. Long Short-Term Memory (LSTM) and the SqueezeNet model are employed in this study to improve the system's design correctness. Given the issues with a high number of parameters and memory utilization of the deep learning-based target models, a machine learning-based radar with improved performance is proposed.

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