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Radar Target Classification Using Bi-Lstm Model Of Recurrent Neural Networks

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ABSTRACT: The classification of targets is one of the challenging tasks in the field of modern radar systems. Manual feature extraction with high level computer vision algorithms or neural networks needs knowledge of the subject domain. In this explore a pretrained Recurrent neural network (RNN) with a bidirectional LSTM model for radar target classification where a separate feature extraction is not required for this network. The canonical models for simple geometric shapes, namely sphere, cylinder, disc and frustum and complex geometric shapes, namely complex sphere, complex cylinder, complex frustum and complex disc are developed using dedicated phased backscatterd algorithms. In terms of performance metrics, Bi-LSTM network gives an accuracy of around 99.77% for simple targets and 99.63% for complex targets, far better than the machine learning models. The experimental study on target classification of radar sequence data using Bidirectional Long short-term memory (Bi-LSTM) of RNN is presented.

Keywords: Target Classification, Feature Extraction, RADAR, Bi-LSTM, RNN, Machine learning algorithms.

1. INTRODUCTION

The classification of Targets has created immense interest among the researchers using machine and deep learning. It plays the prominent role in the field of military and surveillance. Radars are used to detect the targets with highly accurate depth information using backscattered electromagnetic signals [1]. To attain high accuracy, returns from the radar are subjected to various feature engineering and classification algorithms by researchers [2].

Deep learning makes use of the pertained network, unlike machine learning, where manual feature extraction using advanced computer vision algorithms or neural networks are used and is extremely time consuming. Recurrent neural networks (RNN) process the sequence data and can be termed as DNN in a temporal sense as it is opposed to be spatially vertical. The feed-forward neural networks or DNNs make use of only present inputs and have no memory. Bidirectional Long Short-Term Memory (Bi-LSTM) Networks of RNN are feedback networks with two inputs that have memory and the ability to persist the important features over a long time [3]. RNN reduces the complexity of increasing parameters by converting the independent activations into dependent activations with the same weights and biases to all the layers and memorizes each previous output by giving each output as input to the next hidden layer. Bidirectional recurrent neural networks (RNN) are combining two independent RNNs together, which have both backward and forward information about the sequence at every time step.

Since it is cumbersome to obtain real-time data for experimental study, we developed target models for simple targets with geometrical shapes like sphere, cylinder, disc and frustum using dedicated algorithms. These developed models are subjected to classification using the Bi-LSTM, and accuracy is observed.

The paper is organized as follows. Section 2 presents the data set. Section 3 describes the overview of Bi-LSTM RNN followed by the experimental results in section 4. Finally, the experimental study is concluded in section 5.

2. DATA SET

Radar cross-section (RCS) is the crucial feature to classify the targets. RCS is the measurement of the targets ability to backscatter the radar signals in the direction of the radar receiver [4].

$$\sigma = \frac{Power\ reradiated\ towards\ source\ per\ unit\ solid\ angle}{incident\ power\ density/4\pi}\ m^2 \qquad (1)$$

For simple targets, RCS depends on the wavelength and its physical properties. For complex objects, RCS also depends on the aspect angle, polarization, frequency. For implementing the simple targets, four canonical models with geometric shapes sphere, cylinder, disc and frustum are considered, and their RCS representation in mathematical form is given in Table 1 & 2 as follows:

Table 1: RCS of sphere in different regions

Region	**RCS of sphere**
Optical	$\sigma = \pi r^2 \quad r \gg \lambda$
Rayleigh	$\sigma = 9\pi r^2 (kr)^4 \quad r \ll \lambda$
Mie	$\frac{\sigma}{\pi r^2} = (\frac{j}{kr}) \sum_{n=1}^{\infty} (-1)^n (2n+1)[\left(\frac{krJ_{n-1}(kr) - nJ_n(kr)}{krH_{n-1}^{(1)}(kr) - nH_n^{(1)}(kr)}\right) - (\frac{J_n(kr)}{H_n^{(1)}(kr)})]$

Where r is the radius of the sphere,

$k = \frac{2\pi}{\lambda}$, λ is the wavelength

J_n is the spherical Bessel of the first kind of order n,

Y_n is the spherical Bessel of the second kind of order n,

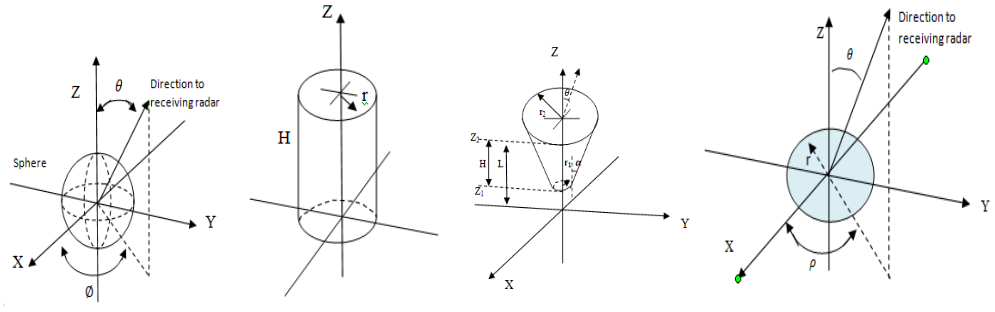
and $H_n^{(1)}$ is the Hankel function of order n, $H_n^{(1)} = J_n(kr) + jY_n(kr)$

RCS of circular cylinder, frustum and circular flat plate are mentioned in the Table 2 and their corresponding shapes in Fig 1.

Table 2: RCS for circular cylinder, Frustum and Disc

Shape	**RCS for normal backscattered incidence**	**RCS for non-normal backscattered incidence**
Circular cylinder	$\sigma_{\theta_n} = \frac{2\pi H^2 r}{\lambda}$	$\sigma = \frac{\lambda r sin\theta}{8\pi (cos\theta)^2}$
Frustum	$\sigma_{\theta_n} = \frac{8\pi\left(z_2^{\frac{3}{2}} - z_1^{\frac{3}{2}}\right)^2}{9\lambda} \frac{sin\alpha}{(cos\alpha)^4}$	$\sigma = \frac{\lambda z tan\alpha}{8\pi sin\theta} (\tan(\theta - \alpha))^2$
Disc	$\sigma_{\theta_n} = \frac{4\pi^3 r^4}{\lambda^2} \quad (\theta = 0°)$	$\sigma = \frac{\lambda r}{8\pi sin\theta (tan\theta)^2}$

Here the cone angle, $tan\alpha = \frac{r_2 - r_1}{H}$



(a) (b) (c) (d)

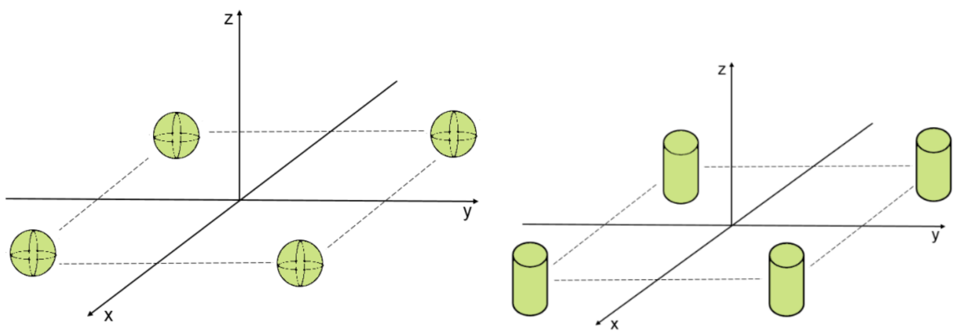
Fig 1: a) sphere b) circular cylinder c) frustum d) circular flat plate (disc)

The complex targets like aircrafts, ships can be modelled as a combination of these simple target models. As analytical methods like geometric optics are difficult to apply and also to avoid high computations for real time targets, Numerical methods like like Finite Element Analysis (FEM) or Method of Moments (MoM) are used.

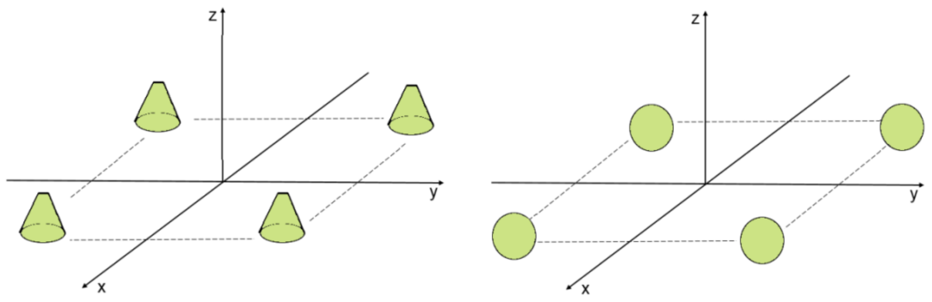
The RCS pattern of the complex targets is which a coherence of the simple scatters is given by

$$\sigma = \left| \sum_p \sqrt{\sigma_p e^{i\emptyset_p}} \right|^2$$

Where, σ_p is the RCs of the p^th scatter and $\emptyset_p$is the relative phase of the p^th scatter.



(a) (b)



(c) (d)

FIG 2: Complex target modeling using four simple scatters of a) complex sphere b) complex cylinder c) complex frustum and d) complex circular disc

The target models thus developed are subjected to feature engineering, and the obtained feature set is used for training and testing using the Bi-LSTM [5].

3. CLASSIFICATION USING Bi-LSTM RNN

Deep neural networks are widely used in classification problems due to their excellent performance. DNN consists of more than one hidden layer, and it is capable of solving the classification problem using pretrained networks without relying on the specific input data or algorithm. A DNN with a feed forward network consists of multiple fully connected (FC) hidden layers between the input and output layers, and each layer has several neurons. The main objective of the DNN during the training process is to minimize the cost function. The feed forward neural networks depend on present inputs and are not dependent or correlated to adjacent samples for an input sequence.

The Recurrent Neural Networks are feedback loop networks belonging to the neural networks and depend on the previous nodes to determine the output [6]. But these lack long term memory due to vanishing and exploding gradients. LSTM overcomes this problem by having information for an extended period and thus preserves the previous error by back-propagating through layers.

In LSTM, the data is processed through a gated memory cell. The decisions of a cell such as data storage, data deletion, and data read or data write can be controlled by gates [7]. Fig 2 below shows a series of three blocks of Bidirectional LSTM recurrent neural network with input x and output y at time instances t-1, t, t+1 and activation function σ. This set of layers are considered up to 100 layers for the work.

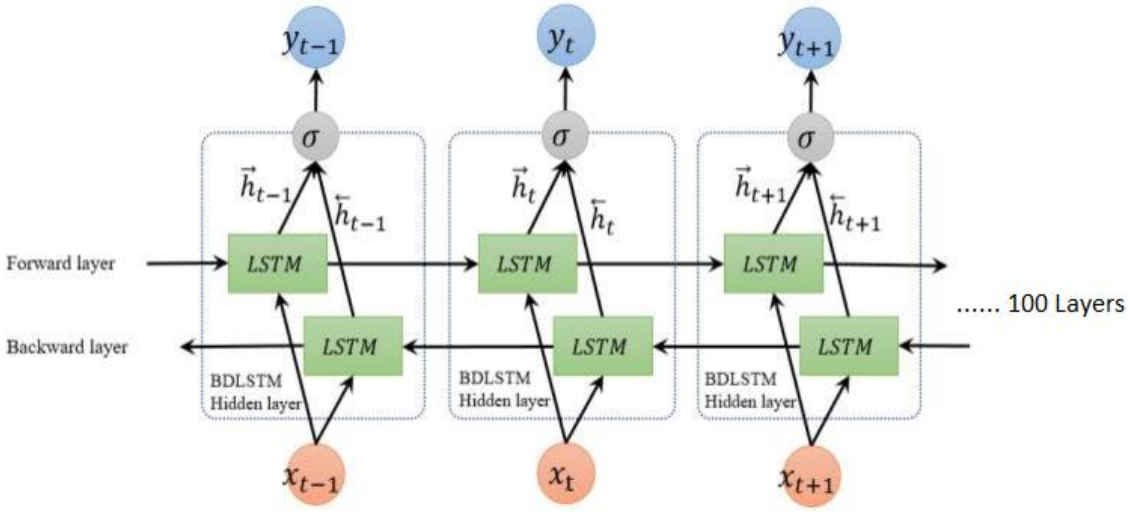


Fig 2: Bidirectional LSTM Network with hidden layers [8].

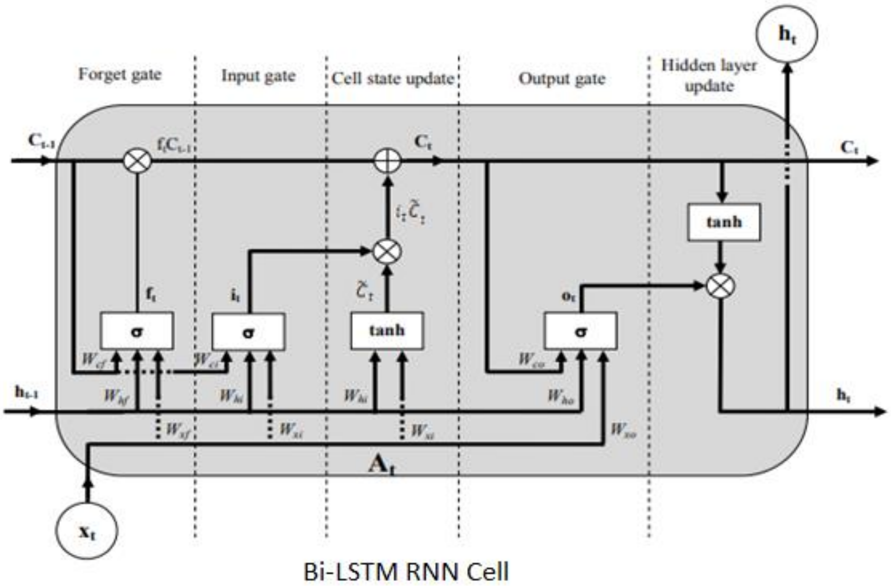


Fig 3: A Single Bidirectional LSTM Recurrent Neural Network.

Fig .3 illustrates an arbitrary t[th] memory unit cell layer of a Bi-LSTM RNN. For every time step t in Fig.3, x_t denotes input applied to the memory cell consisting of input gate (i_t), forget gate (f_t), output gate (o_t), cell layer(c_t), and hidden layer(h_t). The input layer is connected to i-gate, f-gate, o-gate and cell layer by the following weights $W_{xi}, W_{xf}, W_{xc}, and\ W_{xo}$ respectively. At t-1 time step, the hidden layer is connected to i-gate, f-gate, o-gate and cell layer by the following weights $W_{hi}, W_{hf}, W_{hc}, and\ W_{ho}$ respectively. At t-1 time step, the cell layer is connected to i-gate, f-gate and o-gate by the following weights $W_{ci}, W_{cf}, and\ W_{co}$ respectively. Bias values of i-gate, f-gate, cell & o-gate are given by b_i, b_f, b_c & b_o respectively.

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \qquad (2)$$

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \qquad (3)$$

$$\check{C}_t = \tanh(W_{xi}x_t + W_{hi}h_{t-1} + b_c) \qquad (4)$$

$$C_t=f_tC_{t-1} + i_t \check{C}_t \quad (5)$$

$$O_t= \sigma(W_{xo}x_t+W_{ho}h_{t-1}+W_{co}c_{t-1}+b_o) \quad (6)$$

$$h_t=o_t \tanh (C_t) \quad (7)$$

The LSTM network is made up of different layers namely Sequence input layer with input as synthesized radar signal, Bi-LSTM layer, Fully Connected layer, Softmax layer and Classification output layer [9].

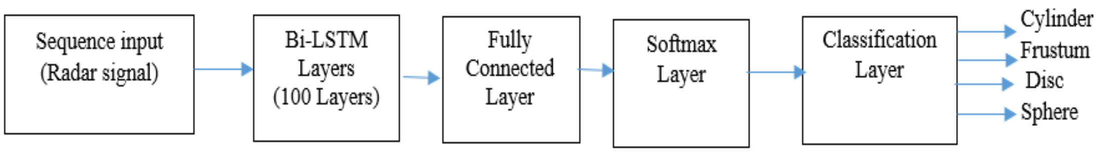


Fig 4: Proposed Architecture of Bi-LSTM Recurrent Neural Network model.

The sequence input layer and Bi-LSTM layers are the core components of a Bi-LSTM network. The sequence input layer inputs the data into the network, and the Bi-LSTM layer learns the long-term dependencies between time steps of the sequence input data in two ways. During the Training process, the Bi-LSTM layer improves the gradient flow by performing additive interactions. For state and gate activation functions in the Bi-LSTM layer, hyperbolic tan and sigmoid functions are used, respectively [10]. All the neurons in the FC layer are connected to the previous layer neurons. The size of the FC layer is equal to the number of Target classes. The Softmax layer applies the softmax function, an output unit activation function after the last fully connected layer. The classification layer is the last layer of the network, which assigns the class to each input using the cross-entropy function [11].

4. EXPERIMENTAL RESULTS

The experimental study is elaborately explained as follows:

1. Data generation
2. Classification using Bi-LSTM RNN model

These two phases are used to realise the classification of targets models. They are explained as follows:

I. Data generation

The data plays an important role in the field of machine learning and artificial intelligence to analyse and classify the targets. As it is wholesome difficult to obtain the data of real-time targets, by using dedicated algorithms, the target models are developed. For simple targets, four canonical models with geometric shapes sphere, cylinder, disc and frustum are developed. Similarly, the complex target models are also developed as a coherent combination of these simple scatters. Thus, the synthesised data is created using various mathematical forms replicating real-time scenarios. The Radar operational parameters like operating frequency, set of azimuth and elevating scan angles are chosen.

Then the geometric parameters of the target models like radius, height and the mathematical equation of the RCS pattern for the required shape are considered to develop the target models. The radar returns are stimulated by applying this obtained RCS pattern to a backscattered radar target model from different aspect angles, which changes from sample to sample.

The dimensions of each geometric shape are varied. For every four shapes, 10 such structures are developed, and their corresponding RCS patterns are synthesized. For each target model, 250 motion profiles (250 × 10) are generated. A total of 20 scans are performed at 50 different aspect angles per target, and their corresponding1000 (20 × 50) returns are collected. Thereby, a total of 10, 000 (2500 × 4) motion profiles are obtained for all 40 (4 × 10) targets corresponding to 4 geometrical shapes.

II. Classification using Bi-LSTM RNN model

The synthesized radar signal modelled as sequence data is given as input to the Bi-LSTM network. The data is split into 70% train data, and 30% test data and the network is trained with training options of 15 epochs and 0.01 initial learning rate and adaptive moment estimation optimizer for gradient descent. The training progress of the Bi-LSTM network is shown in Fig 5 for simple targets and is performed on a single CPU environment.

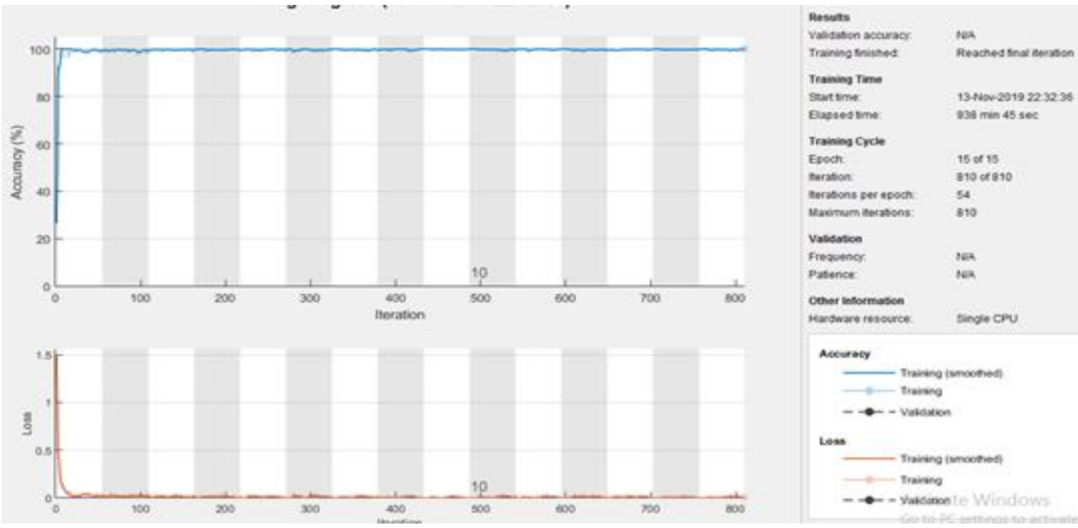


Fig 5: Training Progress of Bi-LSTM Recurrent neural networks for Simple radar targets.

The confusion plot of simple radar targets for multiclass classification is shown in Fig 6 which gives an overall accuracy of 99.77%.

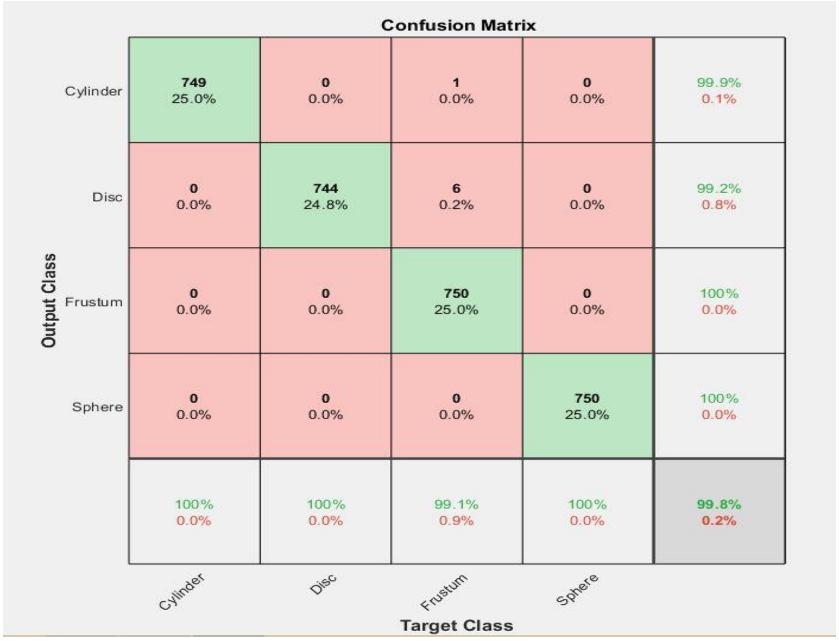


Fig 6: Confusion plot of Simple radar targets for Multiclass classification.

The various performance metrics using Bi-LSTM RNN model for simple radar target multiclass classification is shown in Table 3.

Table 3: Performance Metrics of simple radar targets for Multiclass classification using Bi-LSTM RNN model.

Performance Metrics	Simple cylinder	Simple disc	simple frustum	simple sphere
Sensitivity	1	1	0.9908	1
Specificity	0.9996	0.9973	1	1
Precision	0.9987	0.9920	1	1

The overall performance metrics using Bi-LSTM RNN model for simple radar target multiclass classification is shown in Table 4.

Table 4: Overall Performance Metrics of simple radar targets for Multiclass classification using Bi-LSTM RNN model.

Overall Metrics	Bi-LSTM
Accuracy	99.77%
Classification Error	0.0023
Overall F1 score	0.9977

The training progress of the Bi-LSTM network is shown in Fig 5 for complex targets and is performed on a single CPU environment.

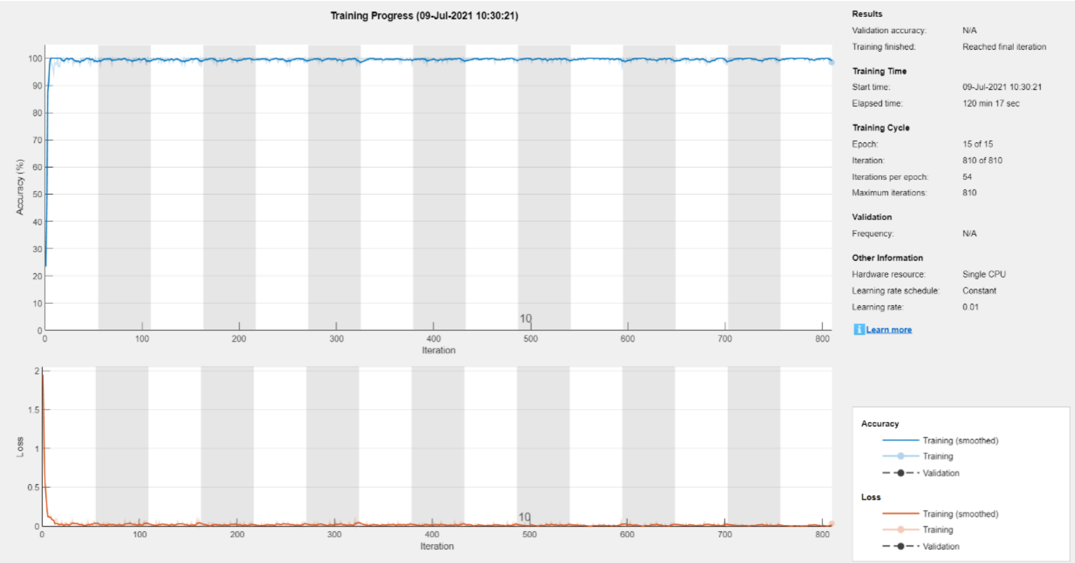


Fig 7: Training Progress of Bi-LSTM Recurrent neural networks for complex radar targets.

The confusion plot of complex radar targets for multiclass classification is shown in Fig 8 which gives an overall accuracy of 99.63%.

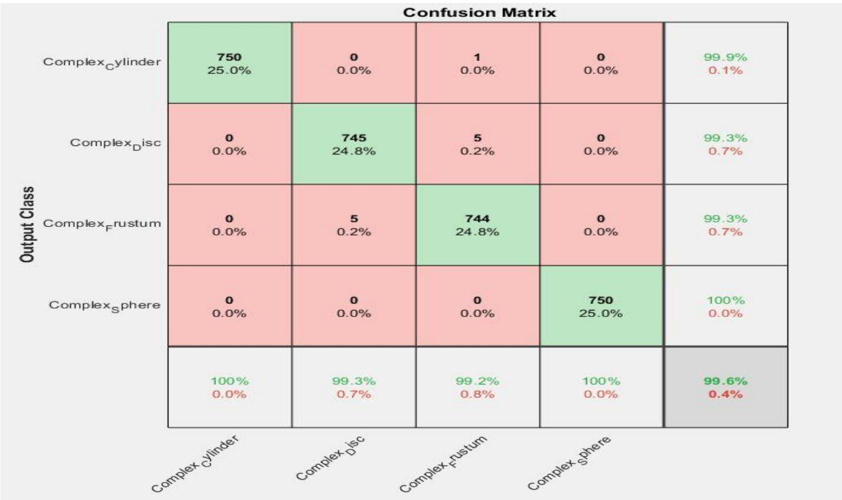


Fig 8: Confusion plot of complex radar targets for Multiclass classification.

The various performance metrics using Bi-LSTM RNN model for complex radar target multiclass classification is shown in Table 5.

Table 5: Performance Metrics of complex radar targets for Multiclass classification using Bi-LSTM RNN model.

Performance Metrics	Simple cylinder	Simple disc	simple frustum	simple sphere
Sensitivity	0.9987	0.9933	0.9933	1
Specificity	1	0.9978	0.9973	1
Precision	1	0.9933	0.9920	1

The overall performance metrics using Bi-LSTM RNN model for complex radar target multiclass classification is shown in Table 6.

Table 6: Overall Performance Metrics of complex radar targets for Multiclass classification using Bi-LSTM RNN model.

Overall Metrics	Bi-LSTM
Accuracy	99.63%
Classification Error	0.0037
Overall F1 score	0.9963

5. CONCLUSION

The canonical models for simple geometric shapes, namely sphere, cylinder, disc and frustum and complex geometric shapes, namely complex sphere, complex cylinder, complex frustum and complex disc are developed using dedicated phased backscatter algorithms and their RCS patterns are synthesised. Deep learning using the Bi-LSTM is used for the training process. The Bi-LSTM layer is used to learn the dependencies between the adjacent input samples. Based on the cross-entropy function, the class is assigned at the output of the classification layer. The overall performance of the classification is observed over some iterations. It is found that classification using Bi-LSTM RNN resulted in 99.77% accuracy for simple targets and 99.63% accuracy for complex targets. .

REFERENCES

1. "Recognition of Spoken Languages from Acoustic Speech Signals Using Fourier Parameters",N. S. Sai Srinivas, N. Sugan; Circuits, Systems, and Signal Processing (2019)
2. "Introduction to Radar Systems", Merrill.I.Skolnik, Third Edition, McGraw-Hill, 2001
3. Mahmoud Khodjet-Kesba, "Automatic target classification based on radar backscattered ultrawide-band signals", Université Blaise Pascal - Clermont-Ferrand II, 2014.
4. 4. E. F. Knott, "Radar Cross Section", In aspects of Modern Radar, E. Brooker (ed.), Norwood.MA: Artech House, 1988.
5. Bassem R. Mahafza, " Radar systems analysis and design using Matlab", secondedition.
6. "A DNN-LSTM based Target Tracking Approach using mmWave Radar and Camera Sensor Fusion", Arindam Sengupta, Feng Jin, IEEE 2019
7. "LSTM Recurrent Neural Networks for High Resolution Range Profile Based Radar Target Classification", V Jithesh, Justin Sagayaraj M, IEEE, 2017.
8. Zhiyong Cui, Ruimin Ke, and Yinhai Wang. (2018). "Deep Bidirectional and Unidirectional LSTM Recurrent Neural Network for Network-wide Traffic Speed Prediction." arXiv preprint arXiv:1801.02143
9. Hochreiter, S., and J. Schmidhuber. "Long short-term memory." *Neural computation*. Vol. 9, Number 8, 1997, pp.1735–1780.
10. B. Widrow and M. A. Lehr, "30 years of adaptive neural networks: perceptron, madaline, and backpropagation," Proceedings of the IEEE, vol. 78, no. 9, pp. 1415–1442, 1990.
11. "Exploiting LSTM structure in deep neural networks for speech recognition", Tianxing He;Jasha Droppo, IEEE, 2016.