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Deep Learning Techniques in Radar Emitter Identification

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ABSTRACT

In the field of electronic warfare (EW), one of the crucial roles of electronic intelligence is the identification of radar signals. In an operational environment, it is very essential to identify radar emitters whether friend or foe so that appropriate radar countermeasures can be taken against them. With the electromagnetic environment becoming increasingly complex and the diversity of signal features, radar emitter identification with high recognition accuracy has become a significantly challenging task. Traditional radar identification methods have shown some limitations in this complex electromagnetic scenario. Several radar classification and identification methods based on artificial neural networks have emerged with the emergence of artificial neural networks, notably deep learning approaches. Machine learning and deep learning algorithms are now frequently utilized to extract various types of information from radar signals more accurately and robustly. This paper illustrates the use of Deep Neural Networks (DNN) in radar applications for emitter classification and identification. Since deep learning approaches are capable of accurately classifying complicated patterns in radar signals, they have demonstrated significant promise for identifying radar emitters. By offering a thorough literature analysis of deep learning-based methodologies, the study intends to assist researchers and practitioners in better understanding the application of deep learning techniques to challenges related to the classification and identification of radar emitters. The study demonstrates that DNN can be used successfully in applications for radar classification and identification.

Keywords: Deep neural network; Machine learning; Deep learning; Radar identification

1. INTRODUCTION

Identification of radar is of critical importance in the EW domain to invoke appropriate countermeasures against the threat radar. The most widely utilized radar identification technique is the Pulse Descriptor Word (PDW)-based method. Modern radar systems are becoming increasingly complicated, making it difficult to identify radars using conventional methods. Conventional techniques of radar emitter identification depend on prior information on the pulse parameters of the emitter such as Radio Frequency, Pulse Amplitude, Pulse Width (PW), type of pulse modulation, and Pulse Repetition Intervals (PRI). The radar threat scenario has evolved over time. The parameters of modern radars are becoming more agile and their operations are becoming more cognitive. Due to the parameter agility and adaptive capabilities of cognitive radars, the conventional radar identification approaches will fail to correctly identify them. As a result, to prevent cognitive radar threats, new radar identification techniques are required. The identification of this cognitive radar must be based on the intrinsic and distinctive features of the emitter. Machine learning and deep learning-based algorithms are presently the widest accepted method for radar signal classification and automatic target recognition (ATR)[1-4]. The traditional signal processing approaches like a short-time Fourier transform (STFT)[5], Fast Fourier transform[6], Wavelet transform[7-8], Fractional Fourier Transform[9], etc. are transformation techniques used for extracting the features of a radar signal. Inter-pulse and intra-pulse feature extraction for radar signals is also done using time and/ or frequency-domain techniques[10-11]. Nevertheless, the characterization of waveforms has become extremely difficult, with increasing overlap in the feature space of agile emitters, leading to severe problems such as low recognition rate and poor robustness[12]. The traditional signal processing approaches assist in determining the features but expertise is required in selecting the essential features. This method necessitates more time and resources, as well as is expensive too. Hence the research areas are more focused to replace manual feature extraction with intelligent systems like neural networks and machine learning/deep learning algorithms to classify and identify radar signals.

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1.1 Related Work in Traditional Machine Learning Models

A subfield of artificial intelligence called "machine learning" focuses on creating models and algorithms that enable computers to learn from data without having to be explicitly programmed to do so. K means clustering[13], Support vector machine (SVM)[14], principal component analysis (PCA)[15], k-nearest neighbors (KNN)[16], random forest[17], AdaBoost[18,] and

Table 1. Machine learning approaches for radar emitter identification & classification

Ref	Title	Techniques	Result
4	In Electronic Support Measures (ESM), NN-based identification and tracking are proposed.	A neural network classifier with an online clustering mechanism and an evidence accumulation module is part of this architecture.	On complex, partial, and overlapping radar data, simulation results demonstrate a high level of performance.
11	Classification and identification of communication emitter signals are discussed.	A hybrid classification model using KNN, random forest, and neural network is built According to simulations, the recognition rates are 94.23 percent at 4 dB and 99.82 percent at 6 dB SNR.	Identification accuracy is greater than 97%
20	Utilization of Feedforward Networks for Radar Emitter Signals Recognition and Classification is proposed.	The neural network structure investigated comprises a hidden layer with fully connected neurons in the successive layers supported with batch-mode training.	On the testing, data set very competitive results of around 82%, 84%, and 67% are demonstrated.
21	Radar applications for target classification using Neural networks (NN) are shown.	A Multilayer Perceptron network with backpropagation is used for target classification.	The suggested NN achieves correct classification at a greater percentage than the KNN classifier.
34	A Vector Neural Network (VNN) for identifying the radar emitter problem is proposed.	The Emitter Identification problem was solved using a VNN and a new vector-type backpropagation (NVTBP) learning technique.	The simulated results show high identification accuracy and insensitivity to additive error.

Hidden Markov Model[19] are some of the widely applied ML algorithms in radar emitter identification.

Table 1 briefly describes the machine learning algorithm and ANN used for radar emitter classification and identification.

1.2 Motivation

Although the traditional machine learning models are widely used and provide a reasonable extent of accuracy, this approach has some limitations. The effectiveness of the ML algorithm depends on how accurately the features are identified and extracted which requires domain knowledge to create a feature extractor. This procedure is time-consuming and difficult. Contrarily, deep learning algorithms can automate the feature extraction process eliminating some of the manual intervention required. Deep learning techniques have shown great potential for radar emitter identification, as they can learn complex patterns in the radar signals and classify them with high accuracy. Some of the well-known deep learning techniques applied for this task include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks.

The need for this work arises from the increasing demand for accurate and efficient radar emitter identification systems, as well as the growing availability of large amounts of data for training deep learning models. Prior work in this field has focused on traditional signal processing techniques, such as feature extraction and pattern recognition, which have limitations in handling the complexity and variability of radar signals. Radar emitter identification systems could be made more accurate and resilient by utilizing deep learning techniques, which have the ability to overcome these constraints. Recent research in this area has shown promising results, with deep learning techniques achieving higher accuracy than traditional techniques in various benchmark datasets.

Deep Learning (DL) is a subclass of machine learning. Deep learning algorithms are built on the backbone of artificial neural networks (ANN). In almost every sector, ANNs are broadly used, for speech recognition, pattern identification, industrial procedures, medical prognosis, websites, and social networking applications[21]. These ANNs have also yielded promising results in radar signal processing and target recognition. Simple neural networks, multilayer perceptron (MLP), convolution neural network (CNN)[22], recurrent neural network (RNN), deep belief network[23], deep restricted Boltzmann machine[24], radial basis function neural network[25], deep feedforward network[26], etc. are areas where significant research has been done to identify radar emitters.

2. PROBLEM STATEMENT

Modern electromagnetic spectrum scenarios are characterized by a high density of emitters with agile and adaptive waveforms that often share similar or equal conventional parameters (e.g. RF, PRI, and PW). Distinguishing these radar emitters is not possible through standard identification techniques (ambiguities frequently occur). The current situation calls for Specific Emitter Identification (SEI) capabilities.

Identification of radar signals in real-time with reliability is important for early threat detection and its avoidance, for situation awareness, and for taking counter-measure actions. In this respect, the research explores the possible use of deep learning techniques for identifying radar emitters in a timely and reliable manner.

3. RADAR IDENTIFICATION

Radar Emitter Signal Identification is a crucial activity in the Electronic Warfare domain. It helps in making a decision for the countermeasures to be taken against the enemy radar. Electronic Warfare is defined as military action that makes use of the electromagnetic spectrum for carrying out military and intelligence missions. The objective of Electronic Warfare is gained through Electronic Attack (EA) actions, Electronic Protection (EP) actions, and Electronic Support (ES) actions. The Electronic Attack subdomain of Electronic Warfare focuses on the use of electromagnetic energy as a way to degrade, neutralize or destroy enemy combat capabilities by attacking personnel, structures, or equipment. The Electronic Protection (EP) subdomain of Electronic Warfare protects friendly sensors against enemy electronic attack actions. The Electronic Support (ES) subdomain of Electronic Warfare identifies the threat by intercepting, identifying, and locating the emitters of electromagnetic sources of the hostile military system.

The ESM/ES intercepts enemy signals to take quick action against the signals or the weapons linked with them. It's possible that the received signal will be jammed or that its information will be passed on to a lethal reaction capability. The received signals can also be utilised for situation awareness, i.e., determining the types and locations of the enemy's forces, weaponry, and electronic capability. In most cases, ESM/ES assesses which of the known emitter types is present and where it is located. Real-time recognition of the radar emitter linked to each intercepted pulse train is the main goal of the ESM system. Now, modern radar uses complex waveforms. Some of these waveforms are generated intentionally to make the intercept difficult. A received signal is processed in an emitter identification system to extract parameters that are needed to predict radar type. The ESM system recognizes emitters from the receiver's pulse measurement and indicates the presence of known radars as hostile or friendly. It also identifies platforms and assesses threats. In conventional ESM systems, key parameters of the intercepted radar pulses (Frequency, Amplitude, Bearing, Pulse Width, and Time of Arrival) are measured. The received pulse data are de-interleaved into groups deemed to be emanating from one emitter and exploited to estimate the time-dependent parameters (Pulse Repetition Frequency(PRF), Antenna Scan Period (ASP)[35-36]. Finally, the ESM system compares the signal signatures which are made up of average parameters from each fragmented group, to known emitter parameters available in the radar database. This operation enables the system to categorize intercepted radar signals that may contain inherent ambiguity as a result of the processing and data collection methods used.

This process can present a challenge because some radar modes may not have an entry in the radar database. Overlap of parameters of different radar types; complex electromagnetic scenarios with increased pulse density, the agility of radar parameters such as radio frequency, pulse repetition interval, sample time, etc., noise and propagation distortion are different scenarios that result in incomplete or erroneous signals and make emitter identification very difficult.

4. DEEP LEARNING MODELS

The deep learning technique uses artificial neural networks for learning representation. Multiple layers are used in deep learning architectures to extract high-level features from raw input.

Conventional machine learning methods have limitations in processing the raw input data. Considerable domain expertise is required in extracting features that convert the raw data into internal representations or feature vectors from which the system recognizes or classifies the patterns from the input data. Deep learning techniques allow for direct input of raw data without extracting the features and it learns the correct set of features automatically.

The appeal of deep learning techniques is due to the efficiency with which they can learn complicated problems. Convolutional Neural Network is the frequently employed supervised deep learning model. Researchers have proposed some of the CNN architectures which include LeNet-5, ResNet, DenseNet, AlexNet, ZFNet, VGGNet, GoogleNet, and CapsNet[27].

Unlike CNN, Recurrent Neural Networks (RNN) are being employed to address the issue of data prediction with time-series data. The present results are linked to previous data sequences. Although the RNN design can perform memory functions, the gradient vanishing problem becomes apparent as the length of the time series increases during training. As a solution to this issue, the long short-term memory (LSTM) structure, a kind of RNN is proposed[28].

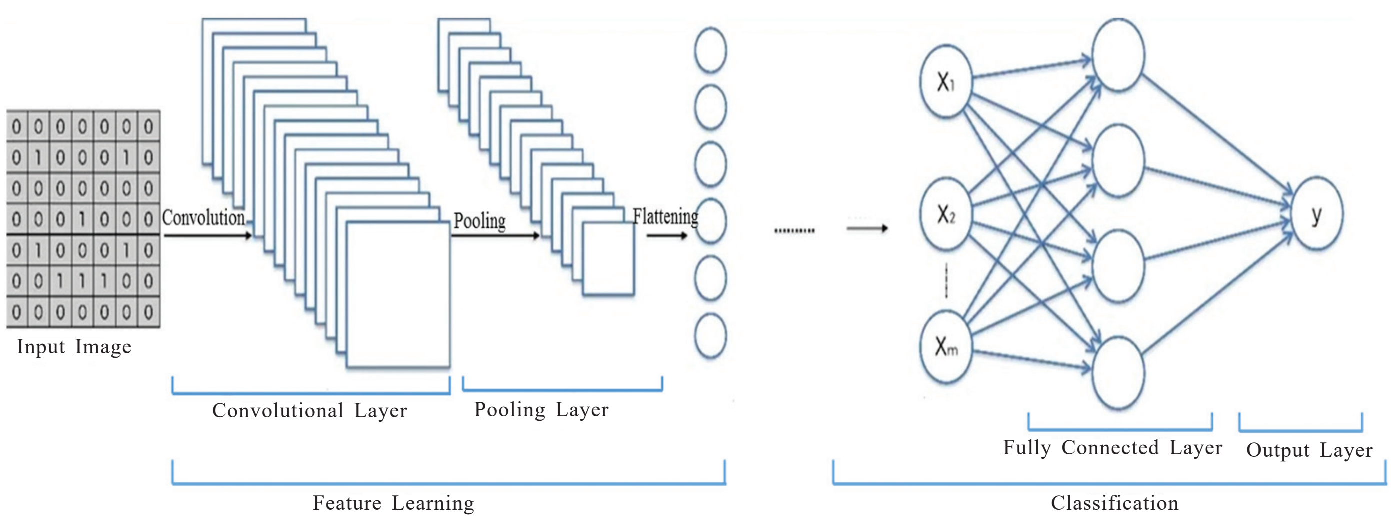

Figure 1. Architecture of CNN.

Many novel Deep-learning architectures using CNNs, RNNs, GAN, and other advanced deep-learning structures have been developed for Radar emitter signal classification and identification. The below section gives a brief overview of deep learning networks such as Deep Convolutional Neural Networks, LSTM, Generative Adversarial Networks (GAN), Restricted Boltzmann Machines (RBM), Deep Belief Networks (DBN), Auto Encoders (AE), Reinforcement Learning(RL).

4.1 Deep Convolutional Neural Network

Deep Convolutional Neural Network (DCNN) is widely used to identify patterns in images, audio, and video. DCNNs have evolved from the architecture of the brain. Deep convolutional neural networks accept image pixels as input and use them to train a classifier. The network employs multiple hidden layers which extract features from the image. The architecture of a typical convolutional neural network comprises four kinds of layers: convolution, pooling, activation, and fully connected. With each layer, the DCNN extracts more complex features for identifying the intended object. DCNN is widely used for the accurate classification of radar emitters. The typical architecture of CNN is shown in Fig. 1.

4.2 Long Short Term Memory

Long Short Term Memory (LSTM) network is a deep learning, sequential neural network that enables information to persist. It is a specific kind of Recurrent Neural Network (RNN) that has the capacity to address the vanishing gradient issue that RNNs are afflicted with. The LSTM network architecture comprises memory cells controlled by three gates. Forget gate is the first gate and it determines whether the information from the prior timestamp should be remembered or is irrelevant and should be ignored. The second gate is the input gate tries to learn information from the input provided to the cell. The output gate controls what information is output to the memory cell at the current time step. This gating mechanism helps the LSTM network to retain information for a longer period. The LSTM architecture is depicted in Fig. 2.

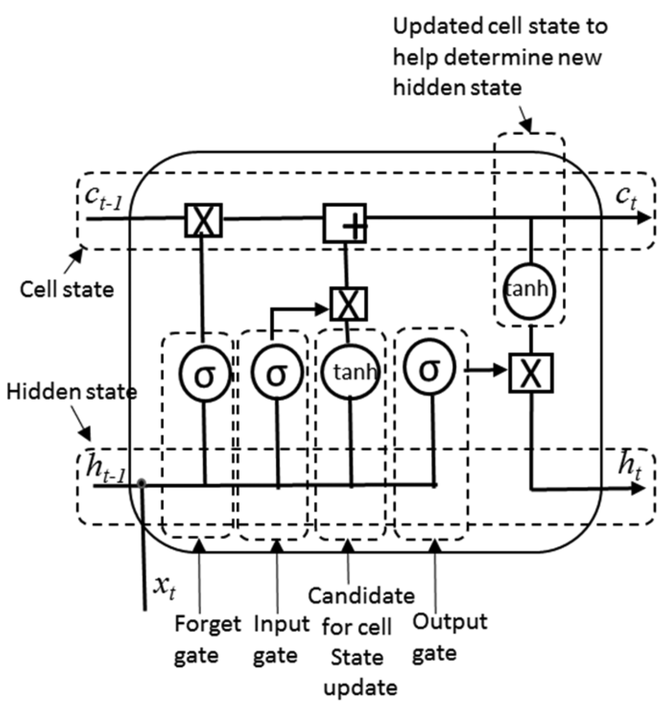

Figure 2. LSTM recurrent unit.

4.3 Generative Adversarial Networks

Generative Adversarial Networks (GANs) are a sort of generative model that uses deep learning methods. The objective of a generative model is to examine a set of training samples and understand the probability distribution that generated them. The estimated probability distribution is then used by Generative Adversarial Networks (GANs) to produce more examples. GANs are among the successful deep learning-based generative models, especially for generating realistic high-resolution images[29].

The GAN model architecture involves two primary components: Generator and Discriminative.

- Generator network: A generator is used to create new credible examples from the problem area. A generator uses random noise as input and produces a sample of data in the problem domain. Figure 3 shows generator G(z) taking inputs with probability distribution p(z) and generating data. This generated data is given as input to a discriminator network.
- Discriminator network: Discriminator is used to discriminate the examples as real or fake. The discriminator network receives input either in the form of real data from the problem domain or generated data from the network. The network tries to identify whether the given input is genuine or not. It solves a binary classification problem by taking as input x from the real data distribution $p_{data}(x)$ and yielding values ranging from 0 to 1 as output.

As the training goes on, the generator network learns to create new samples that are increasingly indistinguishable from the genuine ones, making it harder for the discriminator to discriminate between real and false data. The training is provided to the discriminator network to enhance its ability to detect phony data over time by increasing the realism of the generated data.

The generator tries to minimize the following objective function of GAN[30] and the discriminator tries to maximize it, in Eqn. (1).

$$\min_{G}\max_{D} V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{x\sim p_z(x)}[\log(1-D(G(z)))] \tag{1}$$

Because the amount of available unlabelled data is significantly bigger than the amount of labeled data, GANs have become prominent for their capacity to tackle the challenges imposed by unsupervised learning. Another reason that GANs have become the popular choice among other generative models, is their ability to generate realistic images. Fig. 3 depicts the basic structure of GAN[30].

For semi-supervised learning, generative models are a popular choice. The transfer learning methods are integrated with a semi-supervised learning approach for the identification of unknown radar emitters[31].

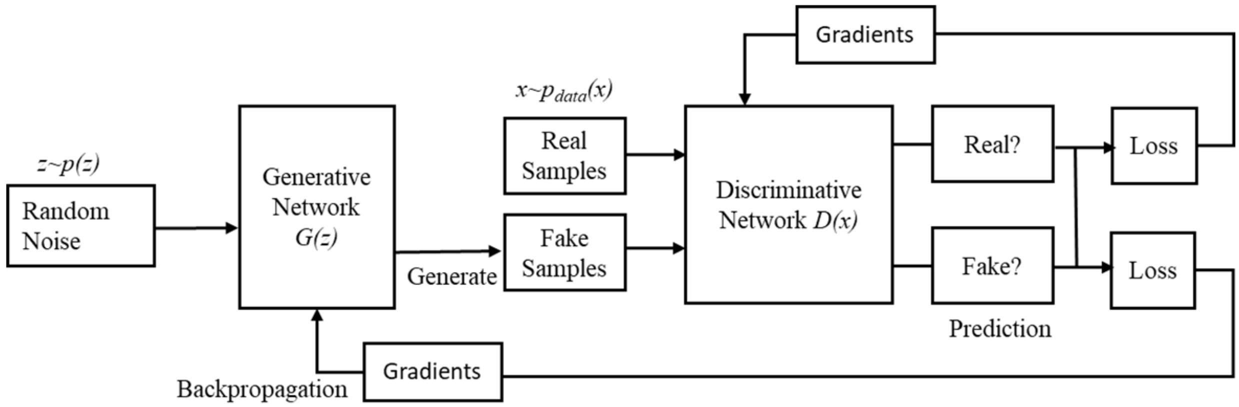

Figure 3. Architecture of GAN.

4.4 Restricted Boltzmann Machines

Restricted Boltzmann Machine (RBM) are common components of some of the deep probabilistic models. The word "restricted" means that there are no intra-layer connections i.e. nodes of the same layer are not connected. RBMs are generally utilized for dimensionality reduction, regression, feature learning, collaborative filtering, classification, and topic modeling.

RBM are generative models comprising two layers of neurons, one of which is visible and the other one is hidden. The visible layer is represented by the input vector *v* and the hidden layer is represented by vector *h*. Without intra-layer connections, all the neurons from the hidden layer are linked to the neurons from the visible layer.

As seen in Fig.4, In the visible layer of RBM, it contains *m* neurons and in the hidden layer, it contains *n* neurons. Weight matrix *W* represents the weight between visible and hidden neurons. The weight factor between i^{th} visible and j^{th} hidden neuron is represented by w_{ij}.

The energy function[30] in Eqn. (2) defines the RBM, which is an undirected graphical model built on energy with joint probability distributions across visible and hidden units (v, h):

$$p(v,h) = \frac{e^{-E(v,h)}}{\sum_{v,h} e^{-E(v,h)}} \tag{2}$$

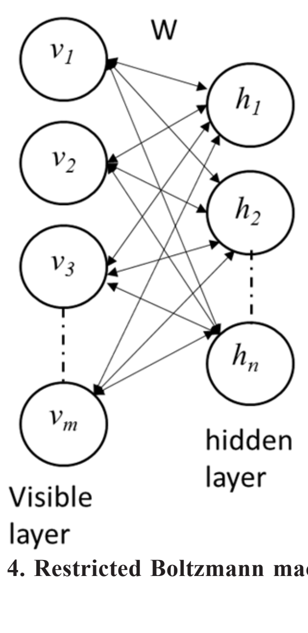

Figure 4. Restricted Boltzmann machine.

where, its denominator is referred to as the partition function. It denotes the sum of $e^{-E(v,h)}$ overall possible RBM configurations. *E(v,h)* denotes the energy function of the RBM with configuration *(v,h)* and is given in Eqn. (3):

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_i \sum_j v_i w_{ij} h_j \tag{3}$$

or in matrix notation as in Eqn. (4):

$$E(v,h;W,a,b) = -a^T v - b^T h - v^T W h \tag{4}$$

W stands for weights, *and* ***b*** and ***a*** are the bias for hidden units and visible units respectively. Visible vector *v* represents the state of the input data and the states of the hidden neurons are represented by vector *h*. The conditional probability distribution that the hidden layer neurons will be activated for a given data vector *v* is given in Eqn (5).

$$p(h_j = 1 \mid v) = \sigma(b_j + \sum_{i=1}^{m} w_{ij} h_j) \tag{5}$$

where, the sigmoid activation function is defined as $\sigma = \frac{1}{1+e^{-x}}$. Using the conditional probability distribution provided in Eqn. (6) to activate the units in the visible layer, the hidden states can be used to reconstruct the data[30].

$$p(v_i = 1 \mid h) = \sigma(a_i + \sum_{j=1}^{n} w_{ij} h_j) \tag{6}$$

In the radar signal recognition domain, a novel model which is modelled on a deep restricted Boltzmann machine is presented to resolve the radar signal recognition problem. The model which is based on the deep learning method comprises multiple restricted Boltzmann machines. The model can extract differentiating features from radar signals for classification and recognition[24].

4.5 Deep Belief Networks

Deep Belief Networks (DBNs) are generative graphical models constructed by the superposition of multiple layers of the Restricted Boltzmann Machine. The result of the output of the Boltzmann machine is then provided as input to the next Boltzmann machine in the sequence, which is then trained until convergence and so on until the complete network has been trained as shown in Fig. 5.

Like RBMs, DBNs show the capability to reconstruct the probability distribution of inputs without being supervised. Because it is often the case that real-world data are often organized into hierarchical patterns, which is beneficial for DBN, making them significantly better than shallow neural networks.

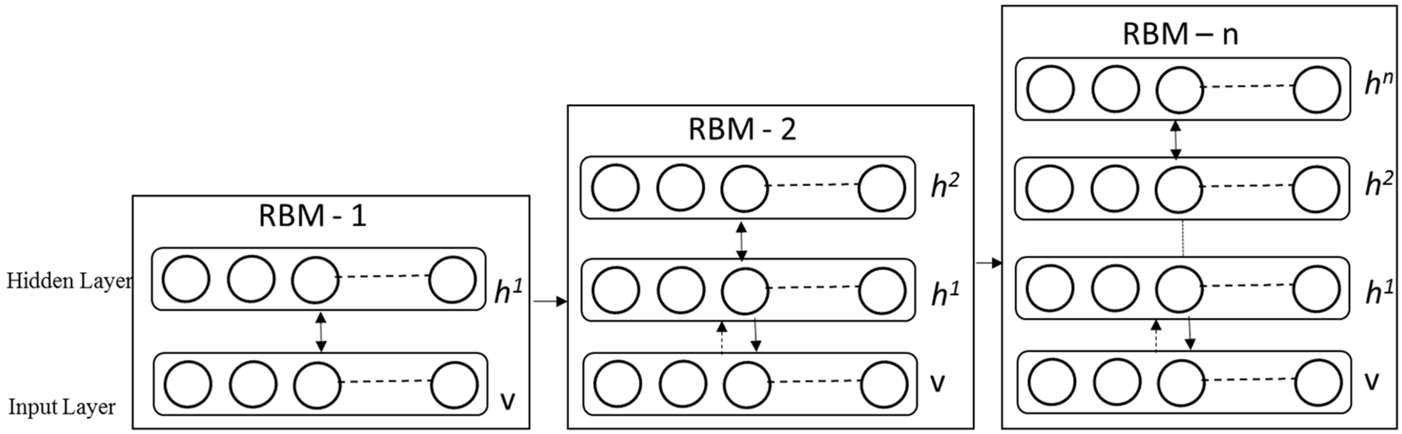

Figure 5. A deep belief network.

4.6 Auto Encoders

Auto-Encoders (AEs) leverage the use of the neural network for representation learning of input data using an unsupervised way. The auto-encoder learns the lower-dimensional representation (encoding) of input data which is of higher dimension, making it useful for dimensionality reduction by extracting the important features from the input data. This makes auto-encoders a powerful feature detector. Auto-encoders can also serve as a generative model by generating new data resembling the training data.

The fundamental architecture of an AEs is depicted in Fig. 6. An auto-encoder structure comprises three components: encoder, activation function, and decoder, as given in Fig. 7.

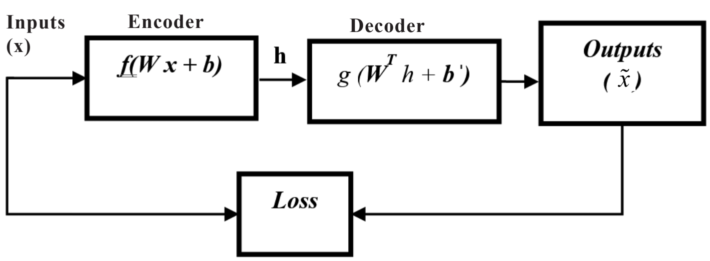

Figure 6. The general process of an auto-encoder.

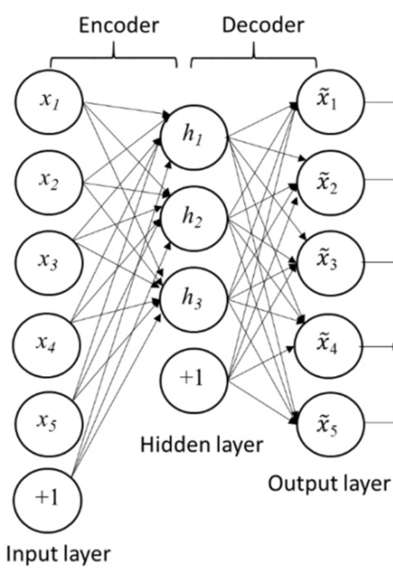

Figure 7. Structure of a basic AE.

The first component of the auto-encoder known as the Encoder converts the input vector into a compressed form that takes less space.

Encoder corresponds to a basic neural network with weight matrix W and bias b, and f is defined as the activation function. h is the latent representation of the input x, i.e. $h=f(Wx+b)$. The decoder decompresses the intermediate version to recover the original version, Here the decoder g is represented similarly but with different weights, bias and activation functions. It reconstructs $\tilde{x}$ of the input x, i.e. $\tilde{x} = g(W^T h + b')$

A loss function L measures the closeness of the recovered output $\tilde{x}$ with the input x. The training process minimises the loss between $\tilde{x}$ and x, i.e., $\min(L(\tilde{x}, x))$;

An auto-encoder is similar to a multilayer perceptron in terms of architecture, except that the output layer neurons must be identical to input layer neurons. The flavors of auto-encoders are briefly described as follows:

4.6.1 Sparse Auto-Encoder

Sparse Auto-Encoder (SAE) adds sparsity constraints to the hidden layers and activates only those neurons whose outputs are close to 1. It greatly reduced training time as the number of parameters need to learn is less.

4.6.2 De-noising Auto-Encoder

In De-noising Auto-Encoder (DAE), the partially corrupted input data is fed into the network which is being trained to reconstruct the original input.

4.6.3 Contractive Auto-Encoder

Contractive Auto-Encoder (CAE) provides a robust representation of the input vector by adding a contractive penalty on the encoder portion to the standard cost function during the reconstruction of the raw input. It corrects the sensitivity of the input features.

4.6.4 Variational Auto-Encoder

Variational Auto-encoders (VAE) model[56] has significantly increased the ability of auto-encoders to represent data. VAE are generative models that make an effort to describe the generation of data using a probabilistic distribution.

Table 2. Variants of auto-encoders

Autoencoder	Characteristics	Advantages
Sparse auto-encoders	Sparsity constraint is added to hidden layers to make the representation sparse.	The categories are more distinct and significant, which enhances network performance.
De-noising auto-encoders	The partially corrupted input data is fed into the network which is brained to reconstruct the original input.	Robustness to noise.
Contractive auto-encoder	A contractive penalty is imposed on the standard cost function to achieve robustness.	It reduces the representation's sensitivity toward the training input data.
Variational auto-encoder	Describe data generation through a probabilistic distribution.	Smooth latent state representations of the input data can be learned.
Convolutional auto-encoder	Reduces the image reconstruction error by learning the optimal filters.	Improves image compression and image de-noising.
Zero bias auto-encoder	Auto-encoder is trained without explicit regularization penalty through shrinkage function.	It provides improved performance on data with greater intrinsic dimensionality.

4.6.5 Convolutional Auto-Encoder

The fully connected layers of the basic auto-encoder are changed to convolution layers in Convolutional Auto-Encoder (ConvAE). Convolution auto-encoder performs better than AE for image compression and image de-noising[32].

4.6.6 Zero Bias Auto-Encoder

Regularised auto-encoder training usually leads to hidden unit biases with substantial negative values. Negative biases are a natural byproduct of utilizing a hidden layer that is responsible for both representing the input data and acting as a selection process to guarantee that the representation is sparse. Negative biases make it difficult to learn data distributions with high intrinsic dimensionality. By merely minimising reconstruction error, Zero-bias Auto-encoders (ZAE) are trained without any explicit regularisation penalty such as sparsification, contraction, or de-noising[33].

Table 2, lists a summary of various auto-encoders and their advantages and characteristics.

A Convolutional De-noising Auto-encoder (CDAE) and deep convolutional neural network (DCNN)-based technique to detect intra-pulse modulation of radar signals is suggested[34]. The CDAE significantly eliminates noise interference in TFI classification and enhances classification performance even in a lower signal-to-noise ratio.

4.6.7 Deep Reinforcement Learning

Deep Reinforcement Learning (DRL) is a branch of machine learning that blends reinforcement learning algorithms with deep neural networks to enable computers to learn and make decisions in complex and dynamic environments. Deep reinforcement learning integrates artificial neural networks with a framework of reinforcement learning that enables software agents to learn how to accomplish their goals.

The Markov Decision Process (MDP) mathematical framework is used in Reinforcement Learning (RL) to model sequential decision-making problems. In Reinforcement Learning (RL), the sequential decision-making problems are modeled using the mathematical framework of the MDP. The MDP framework provides the representations of the environment in terms of states, actions, state transitions, and a reward function which is quite significant. It is predicated on the idea that the previous state and action determine the current state. Reinforcement learning algorithms can determine the best course of action to maximize the predicted cumulative reward using the Markov Decision Process. In order to solve these MDPs, deep reinforcement learning algorithms generally represent the learned functions as neural networks and create specialized algorithms that work well in this environment. The relationship between the agent and the environment is shown in Fig. 8.

Deep reinforcement learning-based specific emitter identification is proposed[55] with a high recognition rate of 98.42 % as compared to a recognition rate of 80 % with a conventional machine learning algorithm.

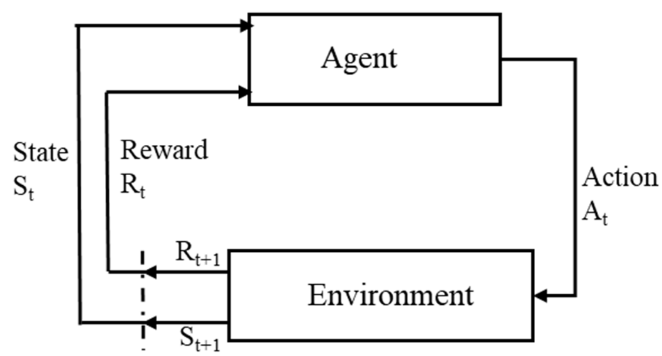

Figure 8. An agent and an environment relating to RL.

5. DEEP LEARNING IN RADAR EMITTER IDENTIFICATION

Due to their massively parallel designs, fault tolerance, and capacity to automatically infer features from the raw input data, Deep Neural Networks (DNNs) are utilized in a substantial percentage of research on the recognition and identification of radar emitters Unlike traditional methods of feature extraction, deep learning-based algorithms extract significant features directly from the raw data set. Radar experts take advantage of this automatic feature extraction of deep learning methods in radar emitter identification to improve radar identification performance. The deep learning of CNN is beneficial in extracting the feature representation of the radar signal spectrogram.

Feature extraction in radar classification and recognition is employed to extract radar signal parameters from the pre-processed signal for categorization, model training, and identification[37]. The extracted features encompass pulse description words (PDWs) of radar signals containing the measured signal parameters of the pulses such as RF, PW, DOA, amplitude, and TOA[38-39]. Signal parameters, on the other hand, change over time, which can contribute to signal ambiguity. The authors proposed a 1D-CNN-based target recognition method to surmount the poor identification accuracy of conventional methods[40].

A 1D-CNN with an Attention mechanism is proposed[5] for extracting distinctive features and identifying the radar signals. The 1 D convolutional layer is integrated with the attention unit to automatically weigh the feature maps according to the importance of their features and improve the recognition accuracy.

The author has proposed a method[41] to adaptively classify radar signals into corresponding optimal jamming techniques without a library. The method uses machine learning by using the parameters of the threat radar signal as inputs. The CNN is used for the classifier and learned using the existing library.

Similarly, a CNN model based on multiple denoised TFD images with zero-mean scaling of intra pulse-modulated signals from radar transmitters was presented[42].

A multiplatform fusion recognition structure based on ensemble learning is proposed[43]. High-level signal characteristics are extracted from time-frequency images of radar signals using a CNN model. The ensemble learning-based architecture addresses the problem of performance deterioration of a single platform and boosts the performance of recognition by the multi-platform fusion method.

An approach with an updated CNN model is provided[44] to improve the identification of radar signal modulation. The dense connection blocks and global pooling is used to improve the CNN model. The AdaGrad, an adaptive learning rate algorithm, is chosen to expedite network training. The experimental findings reveal that the suggested technique outperforms the standard CNNS with a higher recognition rate, shorter training time, and stronger generalization performance.

A convolution neural network model based on feature fusion is proposed[45] that automatically extracts and classifies features of frequency and phase-modulated pulses. The resulting data is fed into a deep network architecture consisting of two CNNs and a feature fusion layer for fusing the output of CNN networks.

A key characteristic feature of radar emitter signals is the pulse repetition interval (PRI). A CNN model to identify the PRI modulation of the radar pulses is suggested[3]. During the simulation, there were 50 % lost pulses and 20 % false pulses, giving in recognition accuracy of 96.1 %.

The generation of an effective threat library based on the DBN model is presented for the classification of radar signals[23]. The DBN model is made up of independent Restricted Boltzmann Machines (RBMs) for radar frequency, pulse width, and pulse repetition interval, as well as an RBM that fuses the results from the preceding RBMs. The experiments revealed a performance boost of more than 6 % over the existing systems.

The authors have proposed[46], a radar-specific emitter recognition technique based on the DBN feature extraction method. The deep features extracted by the DBN model are providing better results when compared to the ambiguity function slice feature and dimension reduction algorithm.

For classification, de-noising, and de-interleaving of pulse streams, an end-to-end structure was presented[47]. This proposed structure leverage RNNs for extracting long-term patterns from previously gathered streams using supervised learning and understanding the current features to predict features of incoming pulses, which is beneficial in identifying the pulse agility in radars.

A method for identifying various multi-function radar emitter types is provided[48]. It is centered on Long Short Term Memory based recurrent neural networks and a hierarchical modeling technique. The sequential information presented in the PDW stream must be taken into account while recognizing an agile radar. The identification method is demonstrated to be robust in the presence of missing and redundant data in the input stream.

A new architecture of CNN-LSTM is analyzed for automatic recognition of radar signals[2]. To emphasize the information on the type of modulation of the radar signal, first, it is converted into a time-frequency image. Finally, the CNN-LSTM network is developed which exploits the spatial and temporal properties simultaneously and extracts the features from the time-frequency image of the signal. According to simulation results, the suggested method can efficiently identify eight different types of low signal-to-noise ratio radar signals (SNR).

The authors have proposed deep learning techniques for recognizing radar signals using the deep CNN model[49]. Since variation in frequency over time is one of the crucial parameters for distinguishing between radar signals with various types of modulation, time-frequency analysis for converting 1D radar emitter waveforms into time-frequency images (TFIs). The suggested recognition approach has a high generalization capability and excellent recognition rate at low SNR, as evidenced by simulation results.

To address the issue of complexity in radar parameters and the agility in multi-function radars for the recognition of radar signals, a new structure for feature extraction and recognition of radar emitters is proposed[12].

The model is shown to have a strong recognition ability and a high level of robustness.

Table 3 briefly describes the deep learning algorithm used for radar emitter classification and identification.

In brief, the subsection has offered a thorough investigation into the identification of radar emitters using deep learning methodologies including the recognition of radar waveforms and classification of radar signal modulation.

Table 3. Summary of DL techniques employed for radar emitter identification

Ref	Title	DL techniques	Result	Future scope
2	The study of autonomous recognition of the type of radar signals is done using the CNN-LSTM .	A CNN-LSTM algorithm is presented for utilizing temporal and spatial signal characteristics.	Based on simulations, the recognition accuracy for eight varieties of complex reconnaissance signals is ~90% at an SNR of 0 dB.	The future scope may involve improving the recognition rate greater than 90.2% with other kinds of radar signal
12	Identification of Agile Waveform of radar is done using DNN.	Both DNN and RNN using GRUs structures are designed to fuse agile RF pulses for identification.	The simulation result shows that the identification is 72.3% with DNN and 84.8% with RNN solution.	Reconsideration of the pulse sorting problem can be future scope.
22	A deep CNN model for radar emitter identification is presented	Two different CNN model is designed for the identification of spectrogram	CNN's deep learning o provides a better edge in feature extraction from the spectrogram.	Future work may involve improving network structure for identification.
24	The deep restricted Boltzmann machine structure is proposed for radar signal recognition.	Multiple restricted Boltzmann machines are used for the constitution of the network.	Experiments show that the proposed method recognizes the radar emitters with a highly correct recognition rate.	Future work involves a reduction in complexity and analysis of the number of hidden layers.
25	The deep network model is studied for radar emitter identification.	The estimated parameters sample diagram is utilized as the parameters data input and for identification, Deep Feedforward Network is built.	The simulation results suggest that using a deep network model enhances the rate of identification significantly.	Future work may involve improving network structure for identification with greater accuracy.
34	A recognition method based on radar signals intra-pulse modulation is proposed.	Convolutional Denoising Auto Encoder for denoising the TFI images and deep CNN is used for identification.	With SNR -9 dB, it is capable of identifying 12 categories of signals with a recognition probability of more than 90 %.	Future work may involve the identification of signals.
40	The use of one-dimensional (1D) CNN to recognize radar emitter targets is proposed.	The frequency-domain features of Automatic- Dependent-Surveillance-Broadcast signal is given as input to 1D-CNN.	The accurate recognition rate reaches 97 % with target category 10, and with target category 50, the accuracy is more than 85 %.	An improved CNN model can be worked for increasing the classification accuracy.
41	Classification of radar signals with CNN is proposed.	An adaptive jamming selection method using CNN is proposed for parameter classification.	Simulation findings indicate that the classifier works well for new radar types which have not been learned previously.	Future work may involve designing the network structure to work with the limited data set.
42	Recognition of radar emitters using energy cumulant of STFT with Reinforced Deep Belief Network (RDBN) is suggested.	When combined with RDBN, the time-frequency domain feature that is transformed gets a greater identification rate with lower SNR.	The methods based on EC STFT outperform other approaches to recognition.	In the future, several features may be combined in a deep learning model for recognition.
43	An investigation of recognizing multi-platform radar emitters automatically is done.	CNN's deep features are incorporated into an ensemble learning framework in order to create a multi-platform fusion architecture.	Experiments show that the suggested algorithms outperform traditional fusion strategies.	The structure of CNNs and ensemble methods can be improved in future work.
44	For identifying radar signal modulation, a proposed technique based on an enhanced CNN model is presented.	Performance is increased by pairing a global pooling layer with a dense connection block layer.	Experiments reveal that the suggested technique has a higher recognition rate than traditional CNNs while requiring less training time.	Future work may involve the design of a network for the recognition of other radar feature parameters.
45	A Feature fusion-based CNN is presented for classifying intrapulse modulation of radar signals.	Types of frequency and phase modulation in radar are classified using the proposed structure.	According to simulation data, the suggested method outperforms the best alternatives and is scalable across a wide range of classes.	NN architecture for calculating parameter values and finding class probabilities need to be investigated.

Table 3. Summary of DL techniques employed for radar emitter identification

Ref	Title	DL techniques	Result	Future scope
46	The radar-specific emitter recognition algorithm is proposed using the Deep Belief Network.	The deep features of the radar signal are extracted with DBN directly in the time domain.	The recognition rate outperforms the recognition from the traditional method.	Future work involves increasing the recognition accuracy with low SNR.
48	Radar emitter type identification using RNN is proposed.	Long Short-Term Memory structures along with a hierarchical modeling method of radar language are used.	It is demonstrated that LSTMs are extremely resistant to corrupted data.	Design of network structure for syllables and longer sequences
49	Recognition of radar waveforms with different types of modulation using DL is proposed.	TFIs of radar signals are exploited by utilizing a CNN model and a noise-reduction methodology is presented.	The TFI-CNN approach has remarkable performance in simulations.	Future work involves proving the capability with more types of radar signals.
50	A PCA+ CNN-based emitter signal recognition technique is suggested.	PCA reduces the dimension of TFI of radar signals which is input to CNN for identification.	According to the simulation, the proposed algorithm performs better at recognizing than the conventional technique.	Future work may involve improving network structure for recognition.
51	Radar Waveform Recognition using Neural networks is proposed	A hybrid classifier consisting of CNN and Elman neural network is proposed for recognition.	The system can classify 12 kinds of signals with an RSR of 94.5 % with SNR -2 dB.	Identification of radar signals can be explored in the future.
52	CNN classifier for automatic cognitive radio waveform recognition is explored.	TFI images from the Choi-Williams distribution are given as input to the CNN network.	The findings indicate that the system can categorize 8 different types of cognitive radio waveforms with a Ratio of Successful Recognition > 93.7 % when SNR>=-2dB.	Classification of complex multiple samples is to be realised in the future.
53	Recognition of radar signal intrapulse modulation is proposed.	CNN for feature extraction from TFI of signal and Deep Q Learning network for recognition is researched.	According to simulation data, the overall PSR of dual-component and single-component radar signals can reach 94 % when the signal-to-noise ratio (SNR) is -6 dB.	Designing the network structure for recognizing a wide variety of signals with a limited dataset can be future scope.
54	The Non-Negative Matrix Factorisation Network (NMFN) and Improved Artificial Bee Colony (IABC) algorithms are used to create a radar signal recognition system.	A novel radar signal recognition system using NMFN for extracting essential features and the IABC algorithm as an ensemble learning strategy is proposed.	According to simulations, the recognition rates are 94.23 % at 4 dB & 99.82 % at 6 dB SNR.	Recognition of multiple unknown signals can be realised in the future.

6. CONCLUSIONS

A review of the literature undertaken found that deep learning-based radar emitter identification and classification algorithms have been employed in a variety of radar-related domains. Numerous researchers have thoroughly investigated Deep learning for radar signal classification and identification. The survey shows that the different flavors of CNN have been widely used for radar recognition. This study offers a comprehensive analysis of the research on the application of deep learning techniques for identifying radar emitters. It should be noted that although numerous research works on radar target recognition using Deep Learning networks have claimed classification accuracies up to 99%, there is still a long way to go before the DL techniques become reliable replacements for the traditional radar classification and Identification methods. The literature review provides us with valuable new insights into the subject which will assist in exploring new methodologies using a deep learning framework for radar emitter identification.

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