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Deep Learning for Modulation Recognition: A Survey With a Demonstration

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ABSTRACT In this paper, we review a variety of deep learning algorithms and models for modulation recognition and classification of wireless communication signals. Specifically, deep learning (DL) has shown overwhelming advantages in computer vision, robotics, and voice recognition. Recently, DL has been proposed to apply to wireless communications for signal detection and classification in order to better learn the active users for electromagnetic spectrum sharing purposes. Therefore, we aim to provide a survey on the most recent techniques which use DL for recognizing and classifying a wireless signal. We focus on the most widely used DL models, emphasize the advantages and limitations, and discuss the challenges as well as future directions. In addition, we also apply a DL algorithm, convolutional neural network (CNN), to demonstrate the feasibility of using CNN to recognize and classify the over-the-air wireless signals using Mathworks DL toolbox with PlutoSDR and Universal Software Radio Peripheral (USRP), respectively.

INDEX TERMS Convolutional neural network, deep learning, deep belief network, modulation recognition, recurrent neural network, software defined radio.

I. INTRODUCTION

Modulation recognition and classification of wireless communication signals is vital when the electromagnetic spectrum is shared among civilian, government, and military to improve spectrum efficiency and resolve the shortage problem. Fast recognition and classification of a wireless signal is a significant process for accurately learning and reliably sharing the spectrum to improve spectrum utilization efficiency.

Machine learning (ML) and deep learning (DL) have shown overwhelming advantages in computer vision, robotics, and voice recognition. Recent research on the application of ML techniques in wireless communications is blooming. For example, National Institute of Standards and Technology (NIST) researchers have applied deep learning (DL) algorithms by training models with pre-existing offshore radar signals for accurate radar detection. Results confirmed that some deep learning algorithms outperform the traditional energy based radar detectors, which can enable successful sharing of 3.5GHz band between potential users and Navy, as well as other Department of Defense members without RF interference.

In this paper, we review the most recent techniques which use DL for recognizing and classifying a wireless signal in terms of modulation schemes. We focus on the most widely used DL models, emphasize the advantages and limitations, and discuss challenges as well as future directions. In addition, we also apply a DL algorithm, convolutional neural network (CNN), to demonstrate the feasibility of using CNN to recognize and classify the over-the-air wireless signals using Mathworks DL toolbox with Pluto Software Defined Radio (SDR) and Universal Software Radio Peripheral (USRP), respectively.

The paper is organized as follows: Section II briefly introduces ML and DL for recognizing and classifying signal modulations as well as the differences between DL and ML for modulation recognition; Section III reviews four major DL models and summarizes the advantages and limitations of such models in modulation recognition; Section IV demonstrates the feasibility of using CNN to recognize and classify the over-the-air wireless signals using Mathworks DL toolbox with Pluto SDR and USRP, respectively. Finally,

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challenges and open issues involved in modulation recognition are discussed in Section V.

II. ML AND DL FOR MODULATION RECOGNITION

ML algorithms for modulation recognition mainly include decision tree [1], [2], the k-nearest neighbor [3], support vector machine [4], [5], artificial neural network [6] and some hybrid algorithms [7]–[9].

DL, a branch of ML, originates from the study of artificial neural networks and aims at simulating the neural structure of the human brain. Currently, DL has made remarkable achievements in computer vision, speech recognition and natural language processing. In 2006, Hinton proposed an unsupervised greedy algorithm and used "complementary priors" to "eliminate the explaining away effects that made inference difficult in densely connected belief nets" [10], where the new net structure had many hidden layers. In 2007, Bengio validated the deep belief network (DBN) model [11]. Their research proved that multi-hidden layer neural network have excellent feature learning ability. The difficulty of deep neural network training could be effectively overcome by "layer-by-layer initialization". This discovery not only solves the computational complexity of the neural network, but illustrates the superiority of the deep neural network in learning. In recent years, DL algorithms are being applied into wireless communication system, such as non-orthogonal multiple access (NOMA) technology [12], [13], multiple input-multiple output (MIMO) technology [14], [15], resource allocation scheme [16], [17] and signal modulation recognition.

Many of them are semi-supervised learning algorithms. They are used to deal with large data sets with a small amount of unlabeled data.

DL usually consists of multiple layers, which combine simple models and transfer data from one layer to another to build more complex models. Compared to ML algorithms for modulation recognition, DL requires a hardware accelerator to expedite computation.

III. MAIN DL MODELS IN AMR

The basic models in DL can be divided into three categories: multi-layer perceptron, deep neural network, and recursive neural network. Its representatives include DBN [18]–[25], convolutional neural network (CNN) [26]–[38], recurrent neural network (RNN) [39]–[41] and some hybrid models [42]–[45], respectively. In recent years, researchers use these basic models or improved models to recognize and classify signal modulation types.

A. DBN MODEL

DBN has been introduced by Hinton and his collaborators in 2006 [10]. It consists of multiple layers of restricted Boltzmann machines (RBM). RBMs are energy-based models and have the modeling capacity to represent complex distributions. As shown in Fig. 1, DBN consists of three RBM units stacked together. Each RBM has two layers: an upper hidden layer and a lower visible layer. When stacked into the network, the RBM1 hidden layer h1 encodes features from the input layer v and then the data acts as the input layer of RBM2. If there is labeled data in the training set, the visible layer of the last RBM contains both the hidden layer unit of the previous RBM and the labeled layer unit.

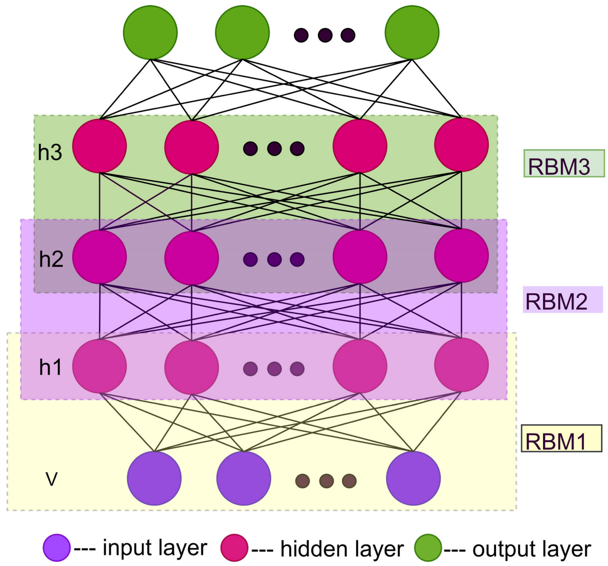

FIGURE 1. Structure of deep belief network.

DBN is a probabilistic generation model and can establish a joint distribution between observation data and labels. It has achieved unprecedented success in speech recognition [46]–[48], image recognition [49]–[52], automatic modulation recognition [18]–[25] and other fields [53]–[55]. Table 1 summarizes the recent DBN-based modulation recognition.

In [18], [19], the authors employ spectral correlation function (SCF) as pre-processed data to feed into DBN-based identification scheme. They transform the 3-D SCF patterns of received modulation signals into 2-D SCF patterns. Then, the grayscale images of the 2-D SCF patterns are used as the input data for the semi-supervised training of the DBN. They obtain a higher accuracy of classification in the presence of environment noise. Using the scheme, the authors of [20] could detect and identify micro unmanned aerial systems (UASs). The authors of [21] use amplitude information and spectrum of receiving signals as the training data of DBNs. The limitation of this scheme is that the recognition accuracy of noisy PSK is lower because phase information is more obscure in training data.

A common application of DBN is feature extraction. Its feature extraction function can be used in different concepts with different granularity. The authors of [22] propose a combination of DBN and SVM, where the stacked RBM networks are used to form a DBN structure to extract features of input data. SVM is used to classify extracted features.

Because the huge amount of floating-point multiplication operations and the nonlinear activation functions of artificial

TABLE 1. DBN-based MR.

Related Work	Topic	Concepts Covered	Recognized and Classified Modulation
Mendis et al. [18–20]	MR based on DBN	• Spectral correlation function feature • SCF-DBN • Noise-resilient	4-FSK, 16-QAM, BPSK, QPSK, OFDM-BPSK modulation types
Ma et al. [21]	MR of RFID signals	• Amplitude and spectrum • Ultra-low SNR signals	ASK, single subcarrier, dual subcarrier, PSK, carrier wave
Wang et al. [22]	Signals demodulation based on DBN-SVM	• Establishing real modulation dataset • DBN-SVM demodulator • Adaptive boosting-based demodulator	BPSK, 4-QAM, 8-QAM, 16-QAM, 32-QAM, 64-QAM, 128-QAM, 256-QAM
Wang et al. [23]	Graphic constellations and DBN	• GCP-DBNt • DBN-SVM demodulator • Image recognition processing	BPSK, QPSK, 8-PSK and 16-QAM
Mendis et al. [24]	DBN-based MR scheme and implication on FPGA	• SCF-DBN • Implemented on FPGA hardware • Identifying micro-UASs	ASK, BSPK, QPSK, 2-FSK, 4-FSK, and OFDM with BPSK sub-carrier modulated signals

neuron units are inevitable, DBN models in MR have a high computational complexity. In [23], the MR problem is converted into an image recognition problem by projecting the original data into a graphic constellation image. After that, they use DBN as the classifier and achieve a superior result compared to conventional ALRT in computational complexity. The authors of [24] use the average SCF of I- and Q- components as the input for the DBN-based pattern recognition and obtain a low-complexity DBN-based MR scheme. They represent the multiplication weight constants during the training procedure by using -1, 0, or 1 and employ approximation functions to achieve direct mapping to digital logic circuits. Such a scheme can realize the identification on FPGA hardware for real-time processing.

There are also problems with over-fitting in DBN. Because of the vanishing gradient, the training effect of lower and higher levels in network depth is different. In this case, the compulsory error monitoring training will make the model fit the input data directly, leading to the over-fitting phenomenon. Under different training data and network parameters, appropriate network depth should be selected to achieve better recognition results. In scheme of [21], the DBN with 3 hidden layers shows the best result.

B. CNN MODEL

CNN is a feedforward neural network which contains convolutional computation and deep structure. It is a popular DL model. The first convolutional neural network is Time Delay Neural Network (TDNN) [56]. It has two hidden layers and can discover acoustic-phonetic features as well as the temporal relationships between them. One of the advantages of CNN is translation-invariance. It is not blurred by temporal shifts in the input. After TDNN, LeCun constructed a convolutional neural network, LeNet [57], for image classification, and LeNet-5 for recognition of handwritten numbers [58]. LeNet-5 and its subsequent variants define the basic structure of modern convolutional neural networks. With the improvement of deep learning theory, the application of CNN models has developed rapidly and grown deeper in structure. Various learning and optimization theories are introduced and developed. The representative CNN algorithms include AlexNet [59], ZFNet [60], VGGNet [61], Google LeNet [62], and ResNet [63].

CNN has a number of merits such as local perception, weight sharing and shift invariance. It exploits spatially local correlation by enforcing a local connectivity pattern of adjacent layers, sharing weights across each layer [64]. An essential hypothesis of CNN is that input data is localized and shift invariant. The sampled data of communication signals are in accordance with the basic hypothesis. In the past few years, deep learning techniques have achieved state-of-the-art performance in pattern recognition tasks. In MR, the common architecture of CNN is shown in Fig. 2. The recent related work is summarized in Table 2.

For example, Wang *et al.* apply CNN to radar waveform recognition by transforming one-dimensional radar signals into time-frequency images (TFIs) using time-frequency analysis and design a convolutional neural network to recognize the frequency variation patterns exhibited in TFIs [26]. One-dimensional radio signals are transformed into spectrogram images using the short-time discrete Fourier transform (STFT) and fed into CNN [33]. The constellation diagrams are used to train CNN in [30] and [35]. In [30], the authors combine two convolutional neural networks (CNNs) trained on different datasets. Besides constellation diagrams, they also use phase and quadrature (IQ) samples and obtain a better result in classifying QAM signals with a low signal-to-noise ratio. CNN in signal modulation recognition is often hampered by insufficient data and overfitting. In [35], the authors use the auxiliary classifier generative adversarial networks (ACGANs) as the generator and improved training method to alleviate the overfitting and

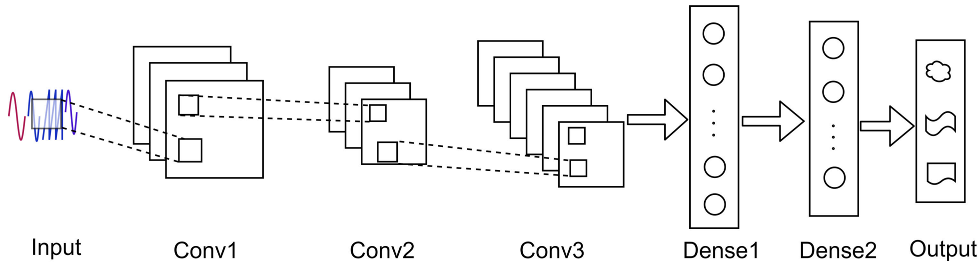

FIGURE 2. Structure of convolutional neural network.

TABLE 2. CNN-based MR.

Related Work	Topic	Concepts Covered	Involved Modulation Pattern
Wang et al. [26]	Radar waveform recognition	• Time-frequency images • CNN for frequency variation patterns	LFM, SCR, PCR3, NLFM
Xu et al. [27]	Improved CNN	• Stacked denoising sparse autoencoder • Transfer learning improvement method	2-ASK, BPSK, QPSK, 8PSK, and 16QAM
Yashashwi et al. [28]	Distortion correction module	• Signal distortion correction module(CM) • CM+CNN model	8-PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, 16-QAM, 64-QAM, PSK, WBFM [29]
Wang et al. [30]	Data-driven DL for MR	• Combined with two CNNs • Constellation diagrams • In-phase and quadrature (IQ) samples	BPSK, QPSK, 8-PSK, GFSK, CPFSK, PAM4, 16-QAM, and 64-QAM
Kulin et al. [31]	DL approach for Spectrum Monitoring	• Radio signal modulation recognition • Wireless interference detection	8-PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, 16-QAM, 64-QAM, PSK, WBFM
Li et al. [32]	VHF modulation Recognition	• Anti-noise processing • CNN with sparse-filtering pretraining	BPSK, QPSK, 2-FSK, 4-FSK, MSK, AM, FM
Zeng et al. [33]	Spectrum analysis and CNN	• Spectrogram images • short-time discrete Fourier transform	8-PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4,16-QAM, 64-QAM, PSK, WBFM
Li et al. [34]	Pulse repetition interval MR	• CNN-based recognition for seven PRI modulation types	Fixed PRI, Jittered PRI, Staggered PRI, Sliding PRI, Agile PRI, Dwell and Switch PRI and Wobulated PRI
Tang et al. [35]	Digital signal MR	• Auxiliary classifier generative adversarial networks • Contour Stellar image data	4-ASK, BPSK, QPSK, OQPSK, 8-PSK, 16-QAM, 32-QAM, 64-QAM

model collapse. It could improve CNN classification and obtained 0.1%-6% increase in the accuracy.

C. RNN MODEL

Fully connected DNNs have a significant limitation. The signals of each neuron layer can only be transmitted to the upper layer, and the processing of samples is independent at each time. It cannot model changes in time sequences and can only be used in the condition that inputs and targets can be encoded with vectors of fixed dimensionality [65]. However, in many cases, such as natural language processing, speech recognition, handwriting recognition and other applications, the time sequence of sample occurrence is very important [66], [67]. As shown in Fig. 3, there are weights between the neurons in the hidden layer. The output of neurons can directly act on itself in the next time stamp. As the sequence progresses, the previous layer will affect the next hidden layer. The biggest difference between RNN and basic neural network is that the latter only establishes weighted connections between layers, while the former establishes weighted connections between neurons in the same layer. The recent related work is summarized in Table 3. The special memory function of RNN can be applied to some forecasting problems which are not independent of the data at the previous and later moments. The authors of [39] propose an improved structure based on RNN models which has two gated recurrent unit (GRU) layers and two dense fully-connected layers. In this scheme, temporal sequence characteristics of the communication signals are used as input directly and obtain a higher performance compared to the CNN model in [36].

In theory, there is no limit on the length of the sequence data processed by RNN. However, the long sequence data cannot be processed in practice due to the problem of gradient vanishing or explosion. In 1997, Hochreiter

TABLE 3. AMR using RNN, LSTM and hybrid model.

Related Work	Training Data	Concepts Covered	Involved Modulation Pattern
Hong et al. [39]	In-phase and quadrature (I/Q) samples	• RNN model	WB-FM, AM-SSB, AMDSB, BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, BFSK, CPFSK, and PAM4
Rajendram et al. [40]	Amplitude and phase of the input I/Q sample	• Two-layer LSTM model • Variable symbol rate scenario	WB-FM, AM-SSB, AMDSB, BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, BFSK, CPFSK, and PAM4
Nathan E et al. [41]	128-sample complex (baseband I/Q) time-domain vector	• LSTM network • Residual networks • CLDNN	WB-FM, AM-SSB, AMDSB, BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, BFSK, CPFSK, and PAM4
Liu et al. [42]	128-sample complex time-domain vector	• CLDNN • Residual Networks • Densely Connected Networks	WB-FM, AMDSB, BPSK, QPSK, 8-PSK,16-QAM, 64-QAM, BFSK, CPFSK, and PAM4
Zhang et al. [43]	Time-domain signals with AWGN and channel fading	• HDMF • CNN+LSTM model	2-ASK, 2-FSK, 2-PSK, 4-ASK, 4-FSK, 4-PSK, 8-ASK, 8-FSK, 8-PSK,16-QAM, and 64-QAM
Sang et al. [44]	128-sample complex (baseband I/Q) time-domain vector	• CNN+LSTM model	WB-FM, AM-SSB, AMDSB, BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, BFSK, CPFSK, and PAM4
Zhang et al. [45]	Sequence data consisting of IQ data and Fourth order Cumulants of signals	• CNN+LSTM model	WB-FM, AM-SSB, AMDSB, BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, BFSK, CPFSK, and PAM4

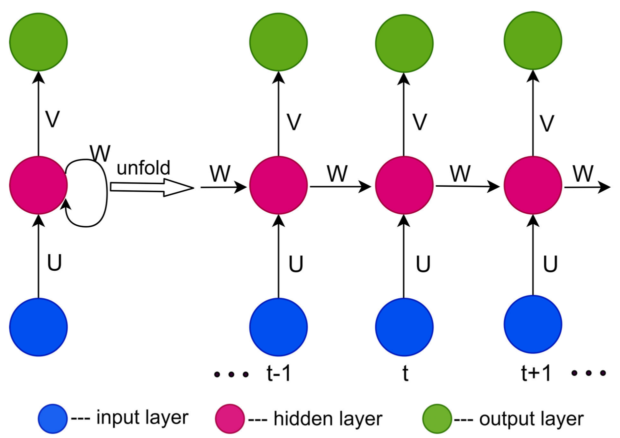

FIGURE 3. Structure of recurrent neural network.

and Schmidhuber [65] designed a Long Short-Term Memory (LSTM) architecture to address the vanishing and exploding gradient problems of conventional RNNs. Subsequently, researchers such as Graves and Hasim have improved the algorithm [68]–[71] and LSTM has achieved considerable success and been widely used. In recent years, some LSTM-based RNN architectures can obtain state-of-the-art performance in MR. As shown in Table 3, researchers use the same dataset (RML2016.10a [29]) as the initial communication signals and different LSTM structures for MR [40], [41].

D. HYBRID MODEL

As shown in Table 3, a combination of CNN and LSTM called CLDNN is proposed in [41]. In the scheme, two or three convolution layers are followed by recurrent layers. It can be seen as a hybrid model. CNNs and LSTMs are complementary in their modeling capabilities, as CNNs are good at reducing frequency variations and LSTMs are good at temporal modeling [71], [72].

Researchers often combine CNN with LSTM algorithm as in [42]–[45] for recognizing modulation schemes. The hybrid model of CNN and LSTM are shown in Fig. 4. In the hybrid model, a LSTM layer is added into the CNN architecture. The input data is imported into CNN layer and the outcome of CNN is fed into LSTM layer. CNN layer extracts the implicit information in time dimension and transmits higher quality and high concentration features to LSTM layer. The authors of [42] apply the CLDNN architecture and obtain the best performance among all tested network architectures.

Due to its long-term memory ability, the hybrid method is suitable for the causality characteristic of time domain radio signals. Experimental results in [43] and [44] demonstrate that the fusion model achieves much better performance than the independent network. The lower computational complexity is also mentioned in both papers. In addition to the common combination of CNN and LSTM, there are other combinations, such as DNN&LSTM, CNN&LSTM&DNN, and so on. The related structural analysis is detailed in the literature [71].

E. DISCUSSION

The representative DL algorithms have been applied for MRC due to their ability to learn and extract features automatically from sampled data, make decision, and complete classification. Most of the literature only focuses on the advantages of the algorithms they have adopted, and seldom mention the shortcomings of the designed models. Less literature

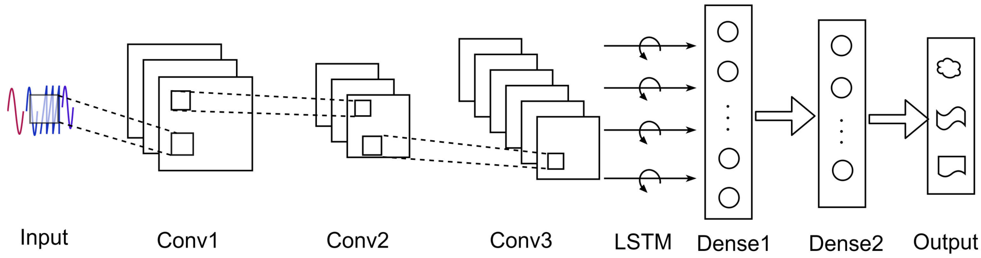

FIGURE 4. Structure of CNN & LSTM network.

TABLE 4. Advantages and limitations of the main DL models.

DL Method	Advantage	Limitations
DBN	• Establish a joint distribution between observation data and labels • Restore the conditional probability distribution	• Lower accuracy than conventional discriminant model • Higher complexity • Translation invariant of input data
CCN	• Weight sharing strategy • Reducing the spatial resolution of network • Low translation invariance requirement of input data	• Vanishing gradient is prone to occur • Preset the length of input vector
RNN (LSTM)	• Depth model in time dimension • No need to preset the length of input vector • Solving time series problems and extracting time series information	• No characteristic learning ability

systematically analyzes the advantages and limitations of various model structures. We summarize the advantages and limitations of the such models in the Table 4.

DBN is a probabilistic generation model and can establish a joint distribution between observation data and labels. In the existing literature, using SFC-based features of modulated signals can process the probability of the observation given the label as well as the probability of the label given the observation, and reflect the similarity of the same kind of data itself, while the conventional discriminant model can only evaluate the latter. However, the generated model does not care where the optimal classification surface is between different classes (SFC pattern in MR), so the classification accuracy may not be as high as that of the discriminant model when used in classification problems. The complexity of learning process is higher to some extent as the generative model learns from the joint distribution of data. CNN convolution is good at approaching global features from local features. Its weight sharing strategy reduces the parameters that need to be trained, and the same weight can make the filter detect the characteristics of the signal without the influence of the position of the signal. In MR using CNN, the pooling operation can reduce the spatial resolution of the network and eliminate the small offset and distortion of the signals. In the scheme, the translation invariance of the input data is not required. In depth model of CNN, the vanishing gradient problem is a distinct shortcoming. It has been partly solved by introducing ReLu function. Compared with CNN, RNN is a deep model in time dimension and is specially designed to solve time series problems. Supplemented by LSTM, it has a certain memory effect and may overcome the vanishing gradient problem.

IV. DEMONSTRATION OF CNN-BASED SIGNAL CLASSIFICATION USING SDR

As an example of a current deep learning model used to automatically classify signal modulation types, Mathworks has created a demonstration [73] which uses the CNN along with PLUTO SDR peripherals as a proof-of-concept of the MR. We expand upon the example by introducing USRP's to be used as the RF front-end in place of the PLUTO SDR peripherals in order to demonstrate the efficacy of the CNN model used in [73] across different hardware environments. The comparison of two different RF front-end is summarized in Table 5.

TABLE 5. Comparison of PLUTO and USRP.

	PLUTO SDR	USRP N210 + SBX
Frequency	325 - 3800 MHz	400 - 4400 MHz
Max Instantaneous BW	20 MHz	56 MHz
Interface	USB 2.0	1Gbps Ethernet
ADC Rate	Flexible Rate	100 MS/s
DAC Rate	Flexible Rate	400 MS/s
ADC Resolution	12-bit	14-bit
DAC Resolution	12-bit	16-bit

A. TRAINING AND VALIDATION

The initial investigation into the behavior of the CNN begins by removing a section of 4 hidden layers from the architecture of the model, shown in [73]. No adjustment to the hyperparameters of the CNN is made. The four removed hidden layers are all unique, namely: a convolution layer, a batch normalization layer, a ReLU (rectified linear unit) layer, and a max pooling layer. All of the hidden layers follow this pattern, respectively. As they are dependent on one another, all 4 layers are removed as a unit. The network is then trained using the generated waveforms. An example of a training accuracy and loss graph is shown in Fig. 5. Notice that the greatest leap in learning takes place over the course of the first epoch, with much smaller increases in classification accuracy occurring over the remaining 11 epochs.

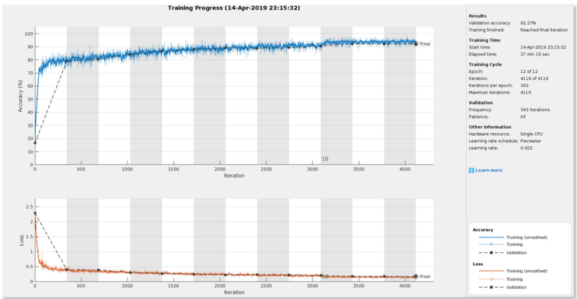

FIGURE 5. Training accuracy and loss curves - remove a section of layers.

Training the CNN with 4 layers removed achieved a validation accuracy of 92.37% after an elapsed time of 37 minutes 18 seconds operating on a single 12-core cpu. These values do not differ significantly from the baseline validation accuracy of 95.69% in [73], and the training time increases by about 12 minutes.

Then, the removed hidden layers are returned, and 4 more hidden layers are added in the same manner that they are removed (a convolution layer, a batch normalization layer, a ReLU layer, and a max pooling layer). Adding layers requires the stride length for the first two hidden layers be adjusted in order to allow for the input to the final fully connected layer to be of the proper dimensions. No other hyperparameters are changed.

Training the CNN with an additional layer took a total elapsed time of 80 minutes 16 seconds. The accuracy increased relative to both the baseline network and the network with 4 layers removed, ending with a validation accuracy of 96.15%, shown in Fig. 6. Table 6 summarizes the training statistics.

B. DEMO

Eight digital modulation types are recognized and classified in this demonstration: 64-QAM, 16-QAM, 8-PSK, BPSK, CPFSK, GFSK, PAM4, and QPSK. The transmitting radio repeatedly and without interruption sends out the modulated signal until 100 frames are captured by the receiving radio. These frames are passed to the trained CNN model to be classified as one of the eight digital modulation types. This process is repeated for each modulation type. Upon completion of the demonstration a confusion matrix is displayed

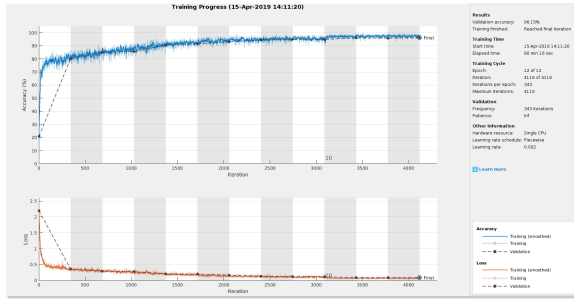

FIGURE 6. Training accuracy and loss curves - add a section of layers.

TABLE 6. Summary of training statistics.

	Baseline [73]	Removed	Added
Validation Accuracy (%)	95.69	92.37	96.15
Training Time (Min:Sec)	25:58	37:18	80:16
Epochs	12	12	12
Total Iterations	4116	4116	4116
Iterations / Epoch	343	343	343
Validation Frequency (iterations)	343	343	343
Learning Rate	0.002	0.002	0.002
Hardware Resource	single GPU	single CPU	single CPU

which details the accuracy of the CNN by comparing the true signal type to the predicted signal type. An overall accuracy is also calculated and displayed based on this result. The physical system for the PLUTO SDR setup is shown in Fig. 7. Notice that the PLUTO SDRs are about two feet apart without any obstructions between them in a low-noise environment. The given parameters are preserved for this portion of the demonstration. Important parameters are center frequency set to 900MHz, sample rate set to 200KHz, and a gain value which is automatically set using the matlab parameters related to the PLUTO SDR system object.

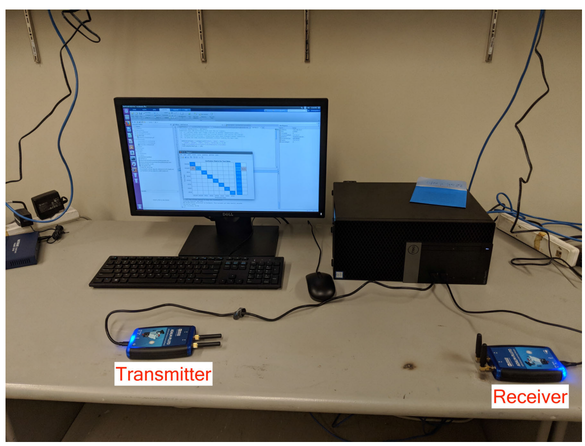

FIGURE 7. Physical system using PLUTO SDR peripherals.

A classification accuracy of 95.5% is achieved using PLUTO SDR. The resultant confusion matrix is shown

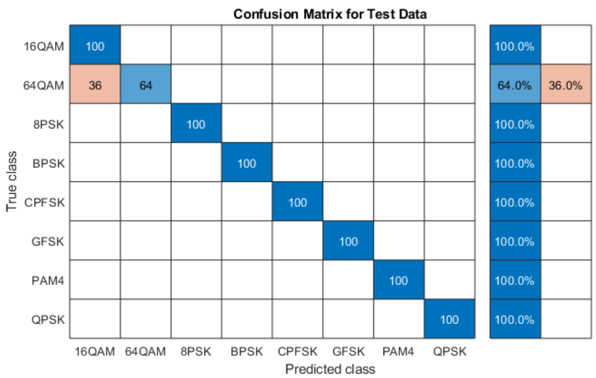

FIGURE 8. Confusion matrix for PLUTO CNN classification demonstration.

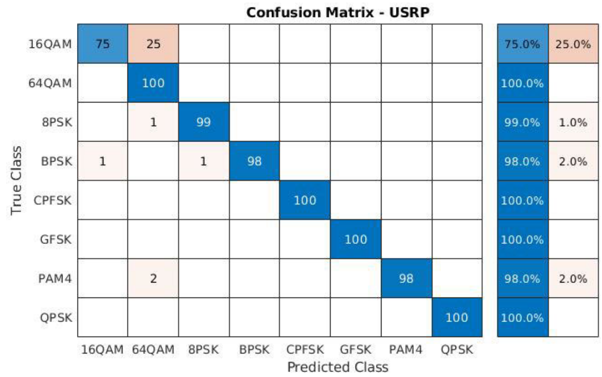

FIGURE 10. Confusion matrix for USRP CNN classification demonstration.

in Fig. 8. As may be gathered by the overall classification accuracy, as well as the confusion matrix, the CNN model successfully classifies a very high percentage of signals properly indicating it can be useful for practical implementations.

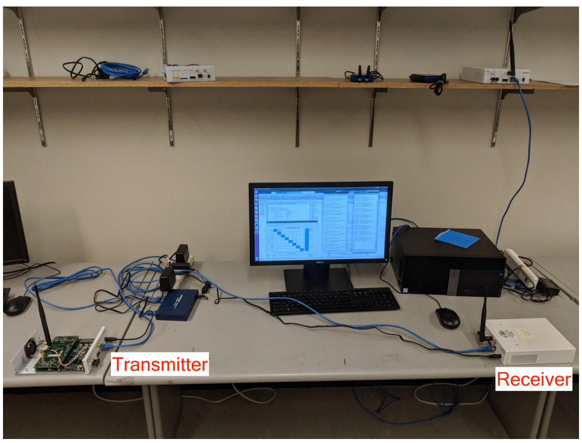

FIGURE 9. Physical system using USRPs.

In order to further demonstrate the efficacy of the CNN used in [73], we introduce USRPs in place of the PLUTO radios to show the example is scalable and not hardware dependent. The physical system is similar to the previous and is shown in Fig. 9. Notice that the distance between the radio peripherals is larger, about six feet; however, there are still no obstructions in the same low-noise environment. Certain parameters must be changed in order for the demonstration to be optimized for the USRPs as opposed to the PLUTO radios. A center frequency of 2.483 GHz is used with a sample rate of 400KHz. The gain is manually set to be 15dB which we found to be the best value for this demonstration under the specified conditions.

A classification accuracy of 96.25% is achieved using USRPs. The resultant confusion matrix is shown in Fig. 10. The classification accuracy is similarly high compared to the demonstration using PLUTO radios, indicating further that such a CNN implementation is feasible in classifying over-the-air signals and can work with different hardware peripherals.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

As stated in the existing literature, compared with the traditional modulation recognition methods, the application of deep learning can simplify the signal processing steps and improve the system recognition performance as well as provide more accurate and efficient modulation recognition methods.

However, many papers are based on ideal assumptions and depend on a large number of labeled signal samples. Most of the research work stays in the simulation stage. In the practical application scenario, the communication environment is more complex, the signal frame length is diverse, the length and systems are usually different. Although LSTM model can partially solve the problem of variable input vector length, there is an urgent need for effective variable length learning algorithm to make up for the current gap in the field of signal processing. Another challenge is how to extract features effectively under negative signal-to-noise ratio (NSNR). In the complex communication environment, the quality of communication is often too difficult to be guaranteed. The classification effect of existing algorithms in harsh environments still needs to be greatly improved. How to use learning algorithms to effectively separate noise and excavate deeper features still requires effective investigation.

The dataset is a key factor in the application of deep learning. In the existing works, some authors [39]–[42], [44], [45] used the same dataset (RadioML2016.10a or RadioML2016.10b) to train the different DL models. Others used the dataset generated by themselves. However, with the increasing complexity of the communication environment and the increasing demand for various specific tasks, it is impossible to ensure that a large training data set is carefully constructed for each task. To solve this problem, the construction of semi-supervised algorithm systems is desired. By collecting a large amount of data, only a few of which are labeled samples, effective semi-supervised algorithms can meet the rapid growth of various signal processing needs.

Another challenge in the future is how to build hardware platforms, transplant programs and validate the algorithms through measured data. In this direction, the authors of [22] propose a flexible end-to-end wireless communications prototype platform for real physical environments. The authors of [24] design an intelligent system for the proposed low complexity DBN targeting Xilinx-vertex6 FPGA chip. They apply the system to identify the micro unmanned aerial systems and realize automated modulation classification in cognitive radio. However, the micro unmanned aerial systems in the experiment is indoor static. The detecting accuracy of ASK, BPSK, and QPSK modulation is lower than that achieved via conventional DBN due to more constrained parameters in the low-complexity DBN. In the future, it is necessary to consider how to implement DL-based communication signal modulation identifier on the FPGA, which requires further research on data quantization, model compression and other related research. Finally, as an effective tool for analyzing data and extracting features, DL techniques have great application and expansion value. Combining the DL model with other intelligent algorithms can achieve more powerful performance in different fields.

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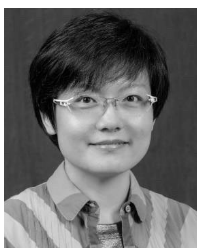

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