EVALUATION OF CNN AND CLDNN ARCHITECTURES ON RADIO MODULATION DATASETS

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Abstract: This paper presents an evaluation of deep learning architectures designed for modulation recognition. The evaluation inspects, whether the architectures behave in the same way as they did on the dataset they were designed on. The architectures are trained and tested on two different radio modulation datasets. This results in proposing additional binary classification as a method to reduce misclassification of QAM modulation types in one of the datasets.

Keywords: Radio modulation, classification, neural network, deep learning, CNN, CLDNN

1 INTRODUCTION

Deep learning (DL) has been on the rise over the last ten years. Even though many may have heard about DL in combination with computer vision or natural language processing, it has been used in other fields as well, including wireless communications [1].

One of the applications of DL in wireless communications is automatic modulation recognition (AMR), which is also the topic of this work. A decision-theoretic approach and a statistical pattern recognition approach are commonly used for the AMR. Both of them rely on extracting features from received data before classification. Meanwhile, with the deep learning approach, the received data can be pasted directly into the DL model. This is due to the ability of a neural network to find patterns (features) in data during training.

A design of a convolutional neural network (CNN) and a convolutional long-short-term memory deep neural network (CLDNN) architectures for AMR were described in [2]. This paper, therefore, includes only a brief overview of these architectures and focuses on an evaluation of achieved accuracies on two radio modulation datasets.

2 ARCHITECTURES

Architectures designed for the AMR introduced in papers such as [3, 4] very often use either convolutional neural network, recurrent neural network (RNN), or their combination. This led me to design CNN and CLDNN architectures. Even though the architectures often have over a million trainable parameters, the parameters of the proposed CNN and CLDNN were kept low. While a high number of parameters means, that the model can learn more features, it can cause overfitting on smaller datasets, requires more computational power and results in a larger model size. A more detailed description of the proposed CNN and CLDNN architectures can be found in [2]. An overview of the used architectures is shown in Figures 1 and 2.

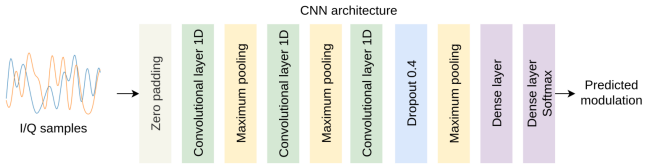

Figure 1: CNN architecture

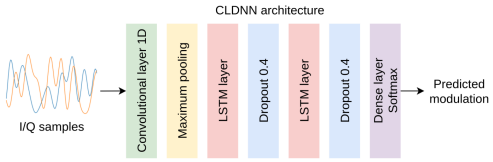

Figure 2: CLDNN architecture

3 EXPERIMENTAL RESULTS

In [2], the CLDNN achieved better results in accuracy than the CNN, and both networks were able to achieve high accuracy even on a smaller dataset. This section presents results achieved by the CNN and CLDNN architectures and shows, that these conclusions apply to other datasets as well.

3.1 MIGOU-MOD DATASET

The MIGOU-MOD dataset [5] includes 8.8 million samples of over-the-air measurements with 11 different modulations - QPSK, QAM16, QAM64, CPFSK, BFSK, GFSK, 8PSK, PAM4, AM-SSB, AM-DSB, and WBFM. The measurements were taken indoors at two distances from a transmitter at 1 and 6 meters. This corresponds to the average signal-to-noise ratio (SNR) of 37dB and 22dB respectively. More details on this dataset can be found in [6].

Figure 3 shows confusion matrices of the dataset. Voice records used for the signal generation contain pauses, during which the only present signal is a carrier frequency. The authors in [6] mention, that this causes confusion between the AM-SSB and AM-DSB. Why these pauses do not affect the third analog modulation WBFM the same way as they did in [2] on a RadioML dataset, is, however, unclear to me.

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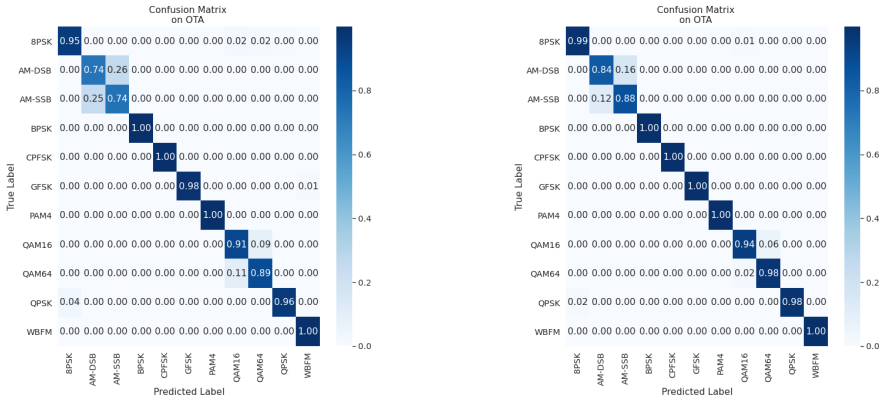


(a) CNN

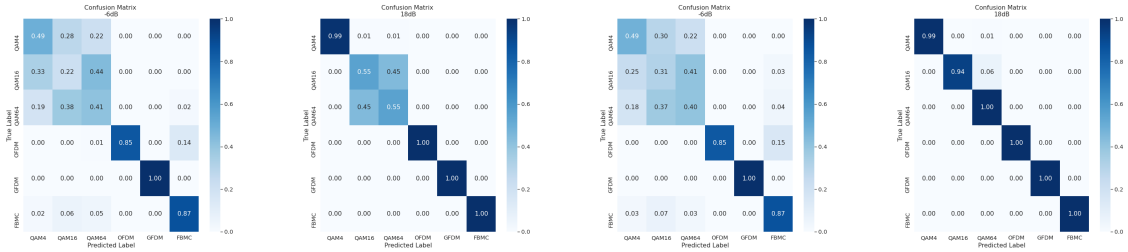
(b) CLDNN

Figure 3: MIGOU-MOD dataset - Confusion Matrices

3.2 VUT DATASET

This dataset was provided to me by my supervisor and it was generated using MATLAB. This dataset is rather small and contains 120,000 samples of 6 modulations - QAM4, QAM16, QAM64, OFDM,

GFDM, and FBMC. The data are again stored as 2x128 vectors of I/Q signals and the SNRs are in a range from -20dB to 18dB.

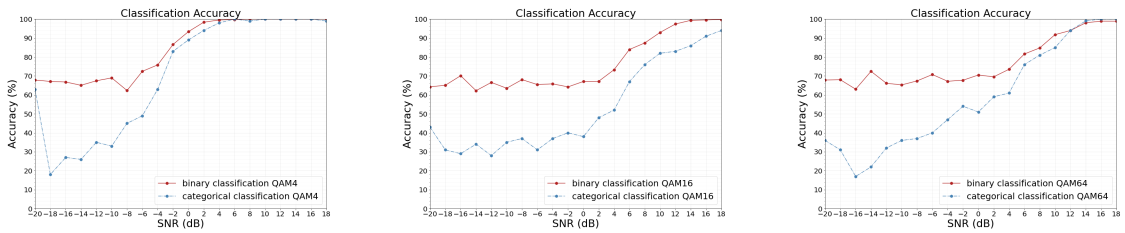


(a) CNN at SNR = -6dB **(b)** CNN at SNR = 18dB **(c)** CLDNN at SNR = -6dB **(d)** CLDNN at SNR = 18dB

Figure 4: VUT dataset - Confusion Matrices

Figure 4 shows confusion matrices of CNN and CLDNN architectures both at low and high SNRs. It is easy to see, that both of the networks have troubles telling the QAM modulation types apart at low SNRs. The FBMC modulation, which uses overlapping QAM, gets confused at low SNRs for QAM as well. Since the QAM64 may contain the same constellation points as QAM16, it can be challenging to tell them apart at times, especially with 128 sample points only.

The accuracy improved by more than 30% at low SNRs when the CNN and CLDNN architectures were used as binary classifiers. The significant improvement can be seen in Figure 5. Adding binary classification after the current categorical classification has, however, its downsides. Binary classifiers can only tell if the input sample is a certain modulation type or not. This means, that three additional models would be needed for the QAM modulation types in this dataset, and would increase the overall model size. Two possible options to solve this problem are either designing another architecture for the binary classification, that is small in size, or using quantization on the binary classifiers to reduce their size.



(a) QAM4 **(b)** QAM16 **(c)** QAM64

Figure 5: Accuracy improvement of QAM with binary classification

4 CONCLUSION

This paper presented an evaluation of the CNN and CLDNN on two additional datasets. The results confirmed expectation from [2], that the CLDNN architecture achieves higher accuracy and both models can work well with smaller datasets. The CLDNN outperformed the best result in [6] by 2.35% on the MIGOU-MOD dataset, even though it was trained on a 10 times smaller training set. The accuracy of the CLDNN was better at SNRs above 0dB for the VUT dataset generated by MATLAB as well. The quadrature amplitude modulations at SNR below 0dB were challenging for

both architectures. Proposed binary classifiers at the end of the current architectures might increase the classification accuracy by more than 30%. This option should be further examined, as the extra classifiers would increase the overall size of the model.

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