# AaronNet: Light and Fast CNN for Modulation Classification

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## 1 Introduction

Deep Neural Networks (DNNs) have become a commonly used method to analyze raw data in different domains for prediction and classification. DNNs are used frequently in the RF domain for different tasks such as modulation classification , RF interference identification and RF Fingerprint detection . DNNs have several advantages over other methods, including the high generalization ability leading to high accuracy and automatic feature extraction. However, they have their own drawbacks. Designing DNNs is usually a complicated and time-consuming process. In addition, DNNs are computationally expensive and resource demanding.

In this work, we develop a AaronNet, a Deep Neural Network (DNN) specialized for Radio Frequency (RF) applications. The proposed network has a very low inference cost and is highly energy-efficient. We test AaronNet on RadioML2018dataset, and achieve a high accuracy. We further prune the network to reduce the inference cost.

## 2 DNN for Modulation Classification

In the RF domain, some transmitters can freely choose the modulation type of the transmitter signals. However, for the receiver to demodulate the signal, knowledge of the modulation type is necessary. In such systems, Automatic Modulation Classification (AMC), which identifies the modulation type of a received signal, is a way to identify the modulation type based on the incoming signal. Some applications of AMC include spectrum interference monitoring, radio fault detection, dynamic spectrum access and numerous regulatory and defense applications. AMC requires high-throughput and low latency, because the classifier needs the hardware implementation and it is important to reduce the computation cost of the network. This is contradictory with the nature of DNNs, so DNNs have to be further optimized to support the RF domain.

There are various methods for optimizing DNNs. The first type of optimizations include modifying the number of layers or filters used in the network. The second type of optimization consists of the network compression techniques. These methods include knowledge distillationlayer-wise quantization and pruning unstructued pruning and structured pruning.

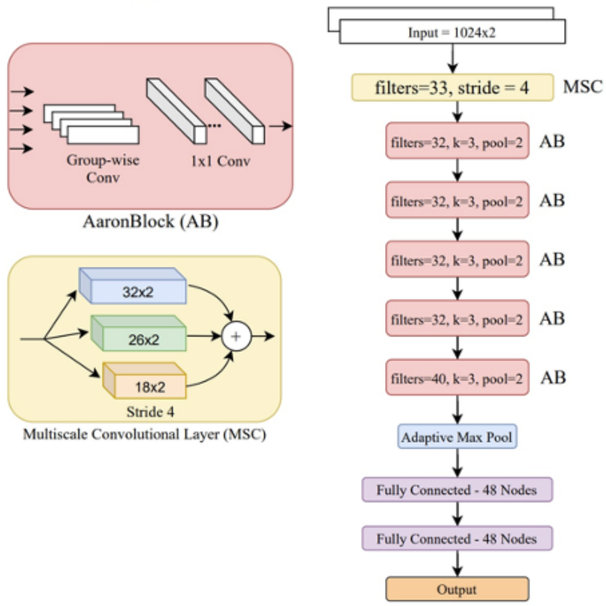


**Fig. 1.** AaronNet architecture.

## 3 AaronNet

In this work we propose AaronNet as a light and fast CNN for the RF domain. Figure 1 shows the architecture of AaronNet. As the figure shows, this network consists of point-wise and depth-wise convolutional layers to reduce the computation cost and to increase the processing power. In addition, we introduce the Multi-Scale Convolutional (MSC) layer to extract features from the RF input signal. The combination of these two, ensures a obtaining a light network capable of obtaining a high accurate. Finally, we use an adaptive max pooling to reduce the number of parameters even more before feeding the extracted features to the fully-connected layers.

## 4 Dataset

To evaluate the performance of AaronNet, we test it on RadioML2018 dataset. This dataset includes over-the-air recordings and simulated channel effects for 24 different analog and digital types. The input signal is $2x1024$ in size, that consists of the quadrature and in-phase components of the input RF signal.

## 5 Results

Table 1 shows the accuracy and the inference cost for 3 different variations of AaronNet. Apart from the original AaronNet, there are two more variations,

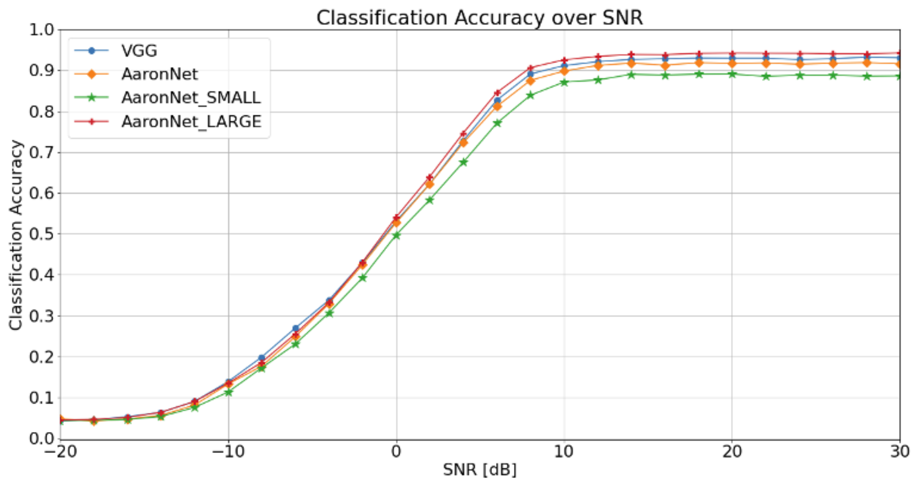


**Fig. 2.** Classification Accuracy for different SNRs for different combinations of AaronNet, compared to the baseline network (VGG).

including AaronNet-Large and AaronNet-Small. The former is a find-pruned dense version of AaronNet, including more number of filters per layer. The latter is the pruned version of the original AaronNet.

Figure 2 shows the network classification accuracy for different Signal to Noise Ratios (SNRs). As the figure shows, AaronNet-Large achieves a higher classification accuracy for a wide range of SNRs, despite having 23x smaller inference cost. On the other hand, AaronNet-Small obtains a slightly lower accuracy among all, while having 64x smaller inference cost. the original AaronNet stands in between other networks, in terms of the classification accuracy.

**Table 1.** Accuracy and Inference of different AaronNet combinations.

| **Network** | **Inference Cost** | **Accuracy** |
|---|---|---|
| $AaronNet$ | 0.05722 | 58.48% |
| $AaronNet_{LARGE}$ | 0.04320 | 60.07% |
| $AaronNet_{SMALL}$ | 0.01539 | 56.07% |

## 6 Conclusion

In this work, AaronNet is designed as a light and accurate network for the RF modulation classification problem. The network is tested on the RadioML2018 dataset, and compared to the VGG network, it has a significantly lower inference cost while obtaining a higher accuracy. AaronNet is a highly potential network for deep learning applications in the RF domain.