Automatic Modulation Classification

Using
Efficient Convolutional Neural Networks
For Low Powered IOT Devices

GROUP 11

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LIST OF CONTENT PRESENTATION

Introduction

Objectives

- An efficient convolutional neural network based on depthwise separable convolution has been proposed to classify the modulation of the received signals.

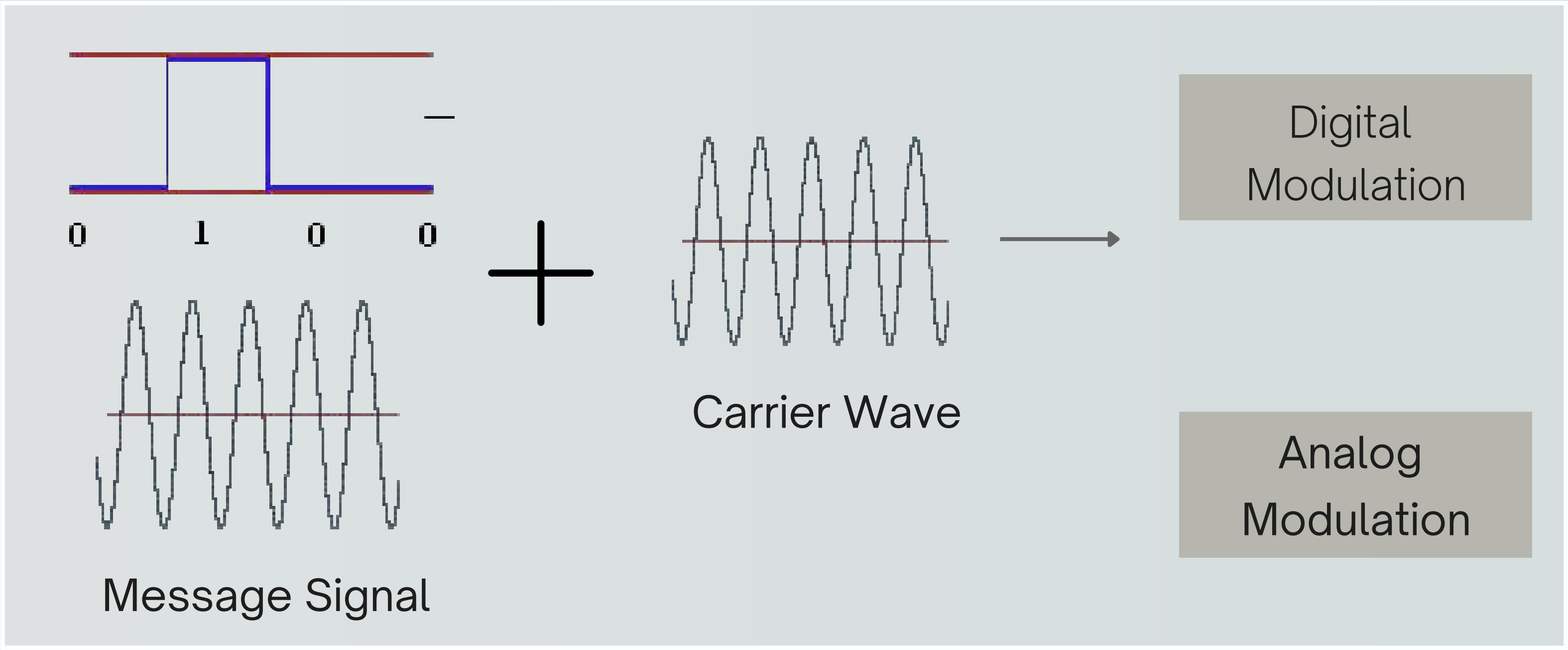
- Finding the best CNN architechture for low powered IOT devices

Modulation & Demodulation

- Modulation is the process of converting data into radio waves by adding information to an electronic or optical carrier signal

There are 2 types of Modulation

1. Digital Modulation
2. Analog Modulation



- Demodulation is defined as extracting the original information-carrying signal from a modulated carrier wave

Types Of Modulation Techniques

- The Dataset We have taken contains 8 Digital Modulation Techniques and 3 Analog Modulation Techniques

Digital Modulations	Analog Modulations
8PSK	AM-DSB
BPSK	AM-SSB
CPFSK	WBFM
GFSK	
PAM4	
QAM16	
QAM64	
QPSK	

Automatic Modulation Classification

What is AMC?

- Automatic modulation classification (AMC), which aims to blindly identify the modulation type of an incoming signal at the receiver in wireless communication systems, is a fundamental signal processing technique in the physical layer to improve the spectrum utilization efficiency.

Why AMC is needed?

- In the Non-Coperative Systems, transmitters can freely choose the modulation type of signals. however, the knowledge of modulation type is necessary to the receivers to demodulate the signals so that the transmission can be successful. AMC is a sufficient way to solve this problem with no effects on spectrum efficiency

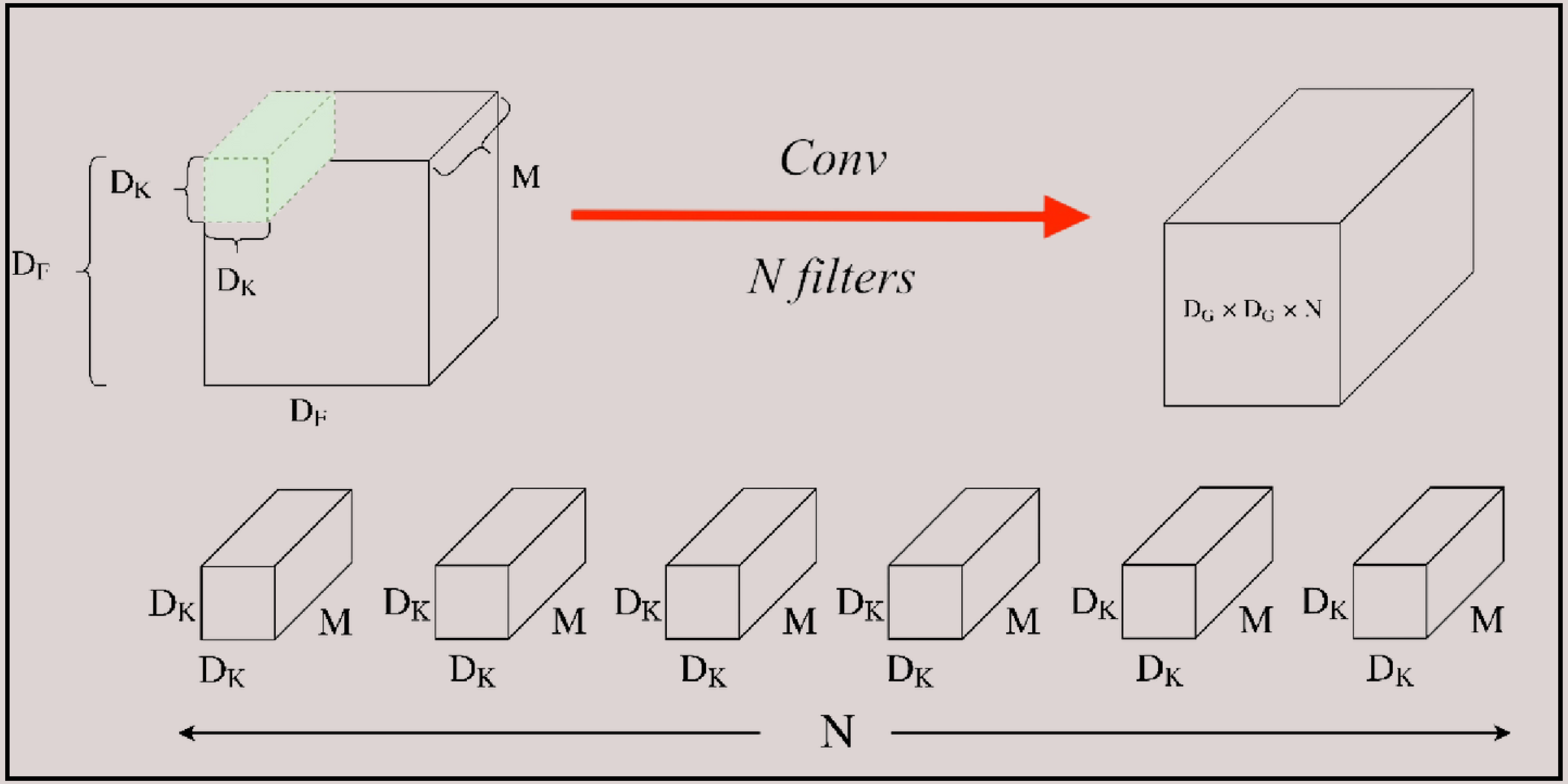
Need Of AMC In IOT Devices

Many IOT devices use MIMO in which the signals are received from various sources so there is a need to find the modulation type

The advent of internet of things (IOT) and the evolution in the mobile networks is driven by the need to satisfy the consumer's demand of enhanced performance, high speeds, seamless links elasticity, and portability in the telecommunication network.

CNN Architechtures Proposed

Normal Convolution



$$\text{Mults once} = D_K^2 \times M$$

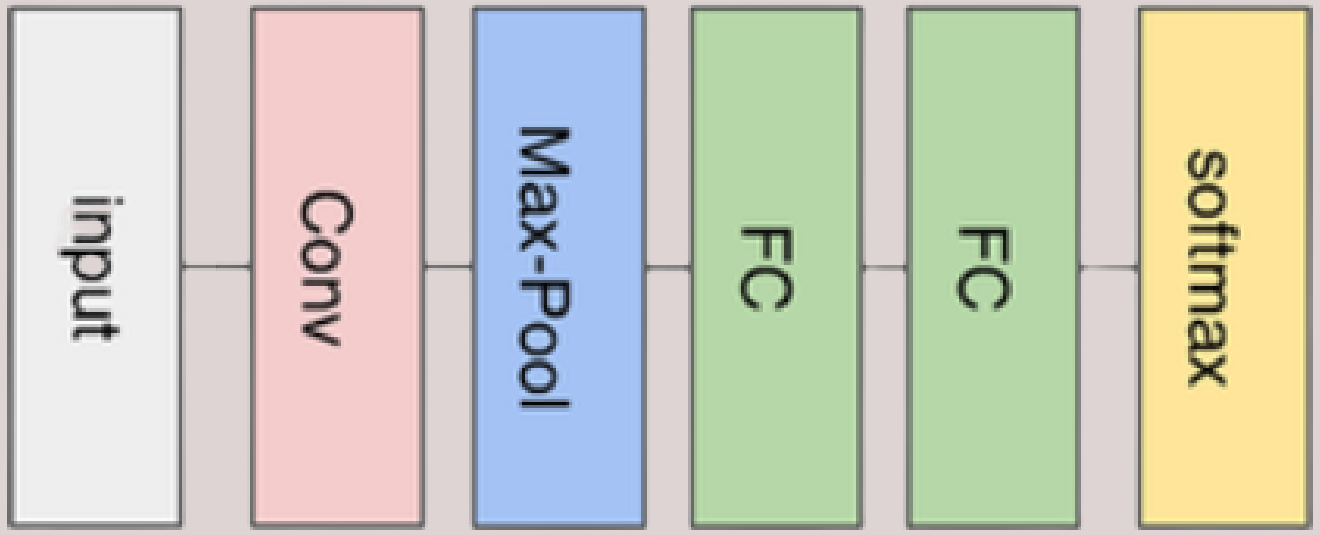
$$\text{Mults per Kernel} = D_G^2 \times D_K^2 \times M$$

$$\text{Mults N Kernels} = N \times D_G^2 \times D_K^2 \times M$$

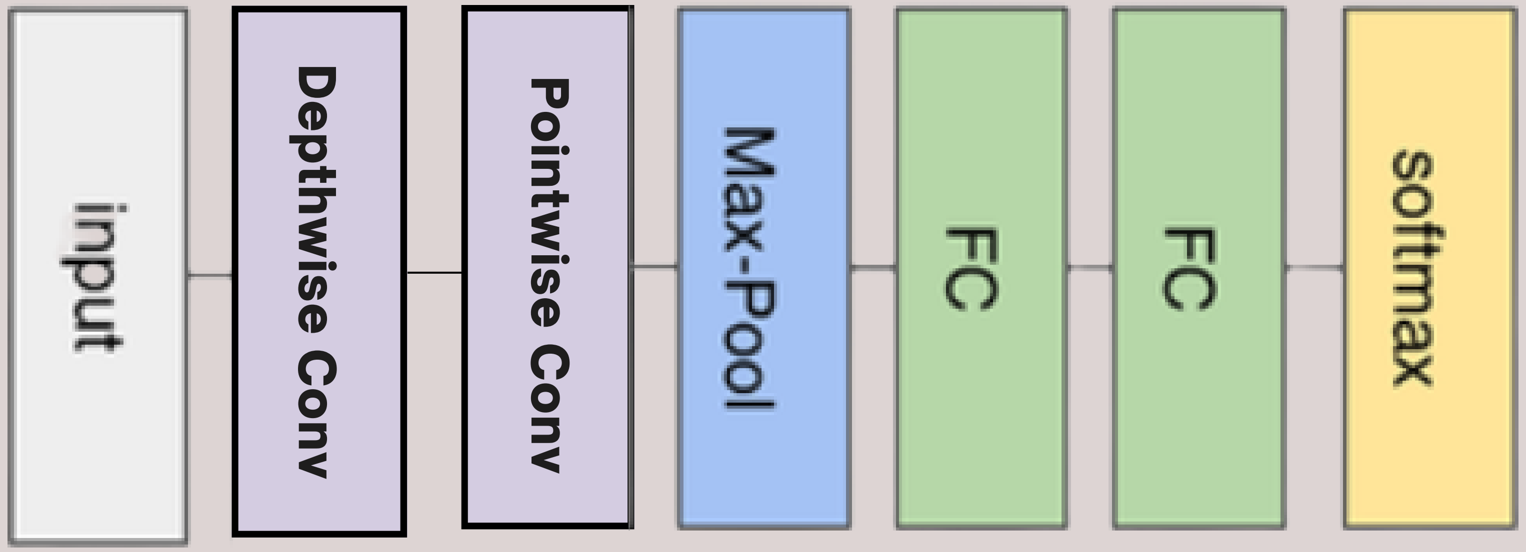
Depthwise Seperable Convolution

While standard convolution performs the channelwise and spatial-wise computation in one step, Depthwise Separable Convolution splits the computation into two steps:

1. **Depth-wise convolutions**
2. **Point-wise convolutions**

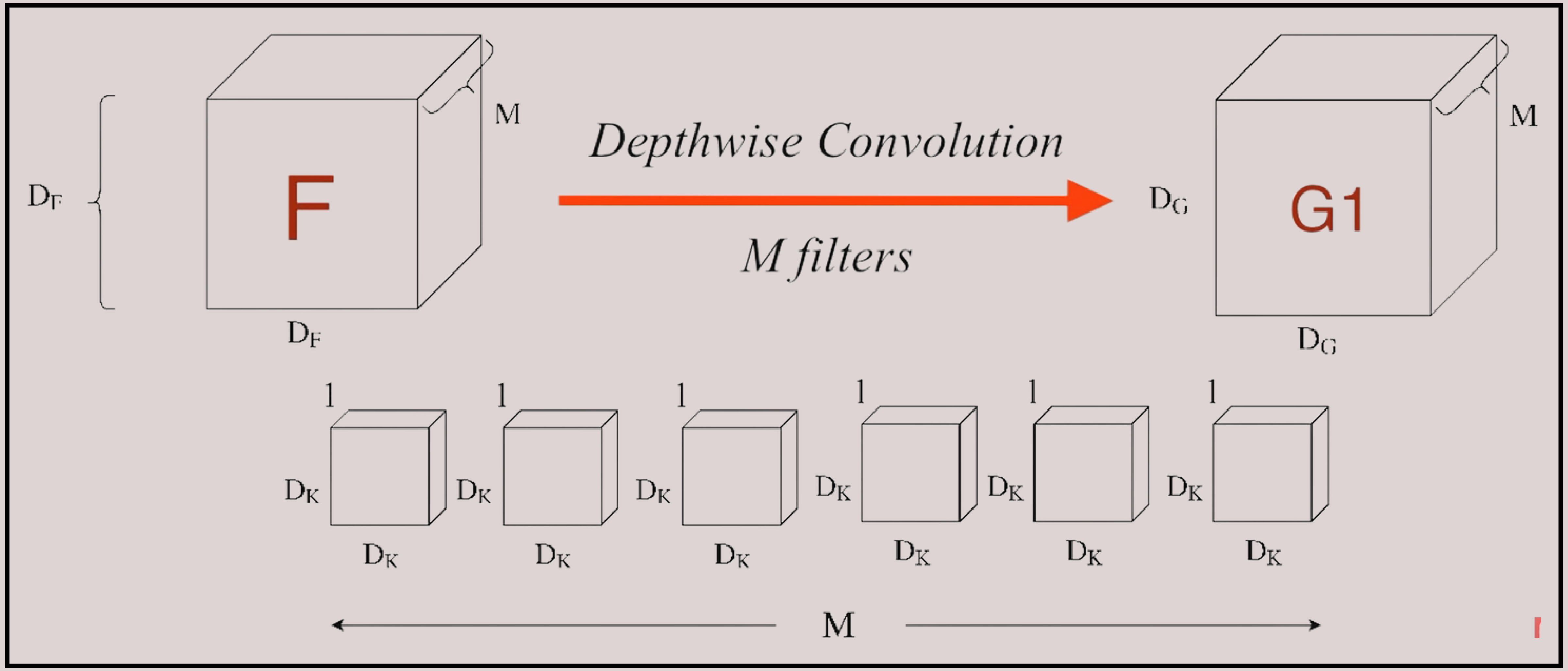


Normal CNN



Depthwise seperable CNN

Depthwise Convolution

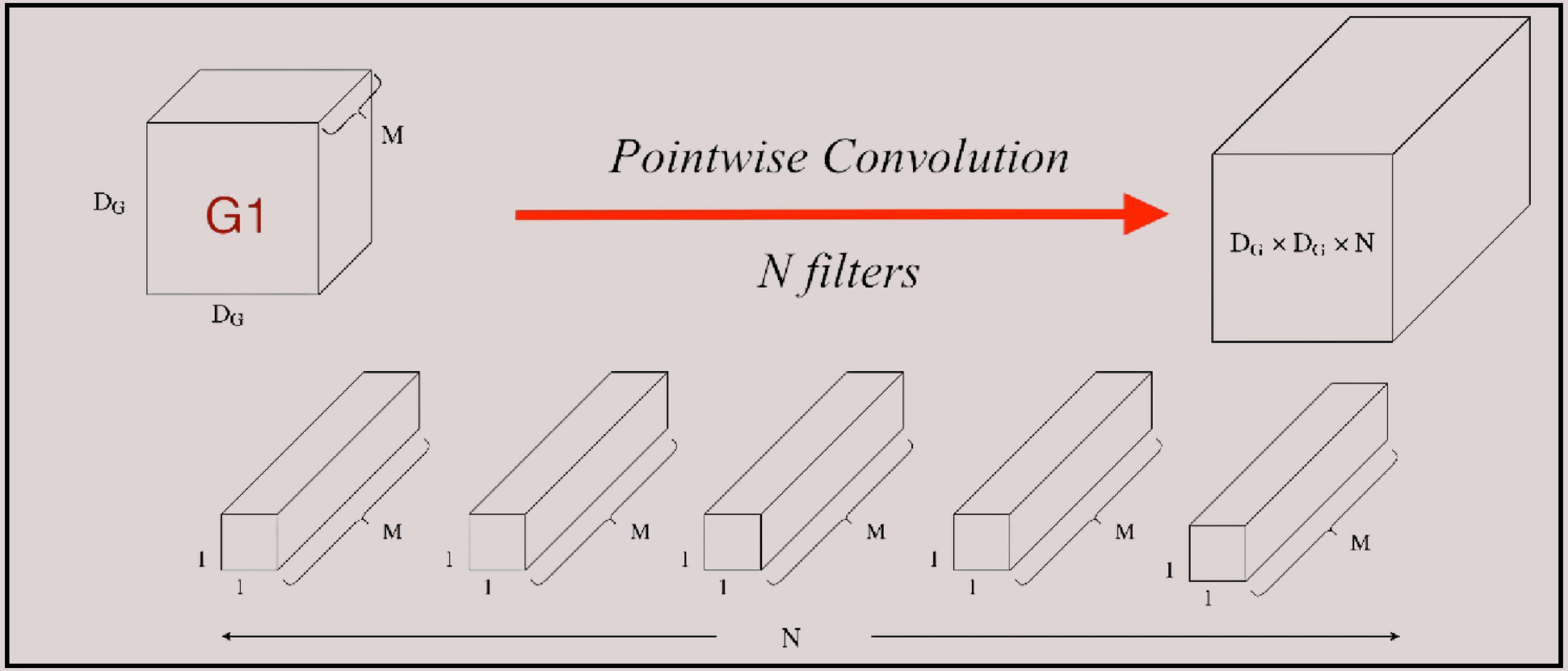


Mults once = D_K^2

Mults 1 Channel = $D_G^2 \times D_K^2$

DC Mults = $M \times D_G^2 \times D_K^2$

Pointwise Convolution



$$\text{Mults once} = M$$

$$\text{Mults 1 Kernel} = D_G \times D_G \times M$$

$$\text{PC Mults} = N \times D_G \times D_G \times M$$

Total Mults in Depthwise = DC Mults + PC Mults

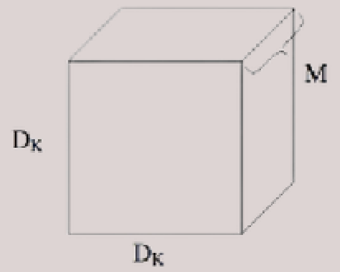
$$M \times D_G^2 \times D_K^2 + N \times D_G^2 \times M$$

$$M \times D_G^2 (D_K^2 + N)$$

Comparison Standard vs . Depthwise

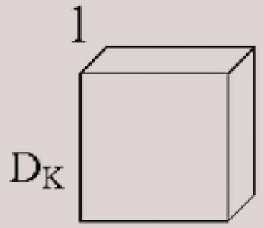
$$\frac{No.Mults\ in\ Depthwise\ Separable\ Conv}{No.Mults\ in\ Standard\ Conv} = \frac{M \times D_G^2\ (D_K^2 + N)}{N\ \times D_G \times D_G \times D_K \times D_K \times M}$$

$$\frac{No.\ Mults\ in\ Depthwise\ Separable\ Conv}{No.\ Mults\ in\ Standard\ Conv} = \frac{D_K^2 + N}{(D_K^2 \times N)} = \frac{1}{N} + \frac{1}{D_K^2}$$



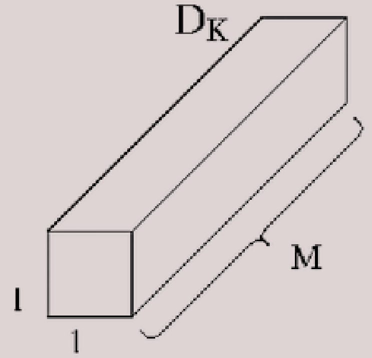
Param 1 Kernel = $D_K^2 \times M$

Param N Kernels = $N \times M\ \times D_K^2$



Param 1 Kernel = D_K^2

Param M Kernels = $M \times D_K^2$



Param 1 Kernel = M

Param N Kernels = $N \times M$

$M(D_K^2 + N)$

$$\frac{No.params\ in\ Depthwise\ Separable\ Conv}{No.params\ in\ Standard\ Conv} = \frac{M \times (D_K^2 + N)}{N\ \times D_K^2 \times M} = \frac{1}{N} + \frac{1}{D_K^2}$$

Example -

$N = 1{,}024 \qquad D_K = 3$

$$\frac{No.\ Mults\ in\ Depthwise\ Separable\ Conv}{No.\ Mults\ in\ Standard\ Conv}$$

$$= \frac{1}{1024} + \frac{1}{3^2} = 0.112$$

Results and Evalution

Datasets

The dataset used in this project is obtained from GNU Radio

Radio Signals essential 2d data, like an image, so CNN's, which are great for image classification, can be used. The raw RF data is called IQ data and that stands for In-Phase and Quadrature. These are vectors containing complex numbers that represent the signal. Various RF equipment (such as a rtl-sdr USB dongle) can capture and record the data to your hard drive. GNU Radio software can also generate data for analysis, as was done by DeepSig

Classification Accuracy Of CNN Architechtures

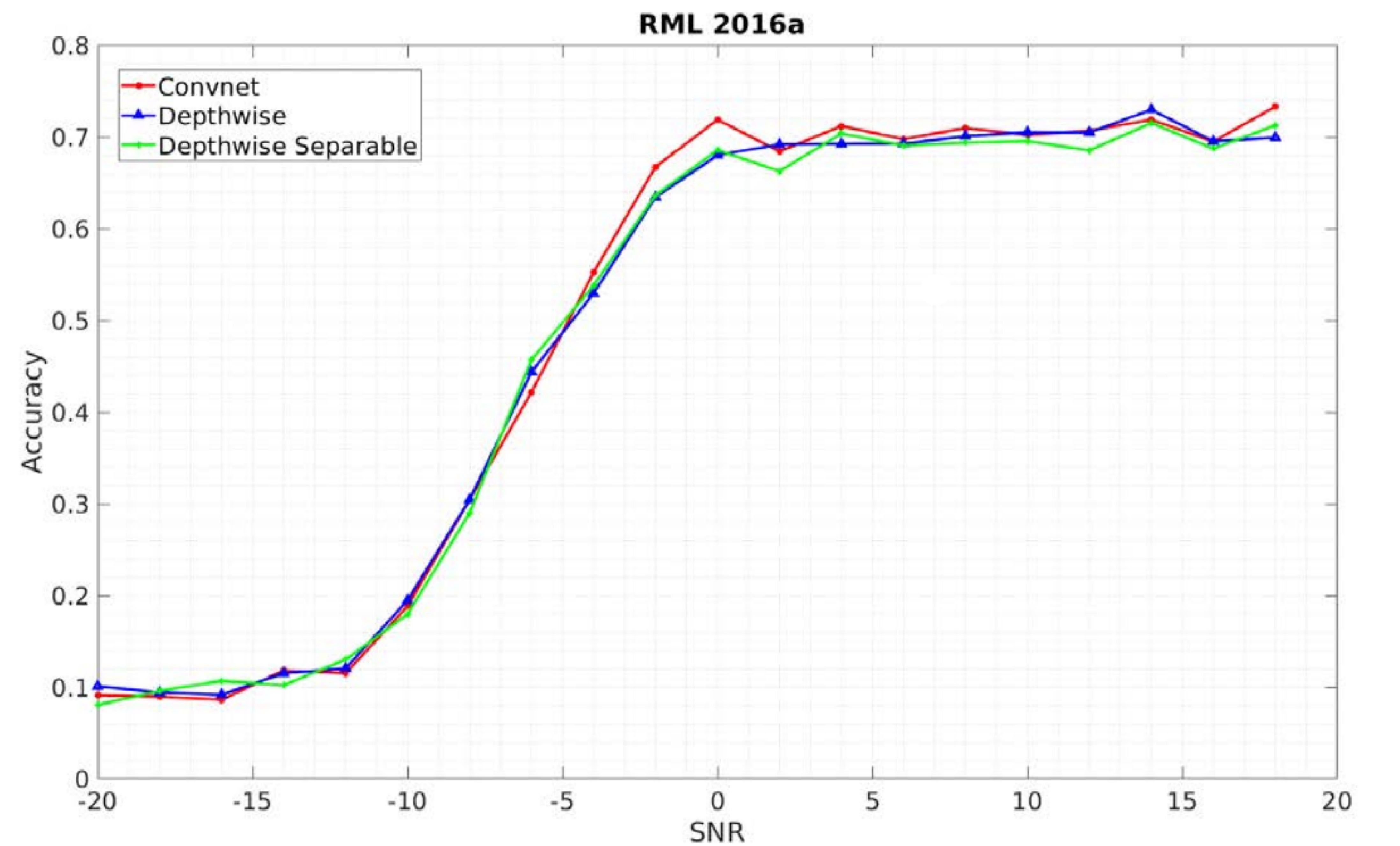


Fig. 1

Here Fig. 1 represents Classification Accuracy of the convolutional neural network architectures on RML2016a dataset

Classification Accuracy Of CNN Architechtures

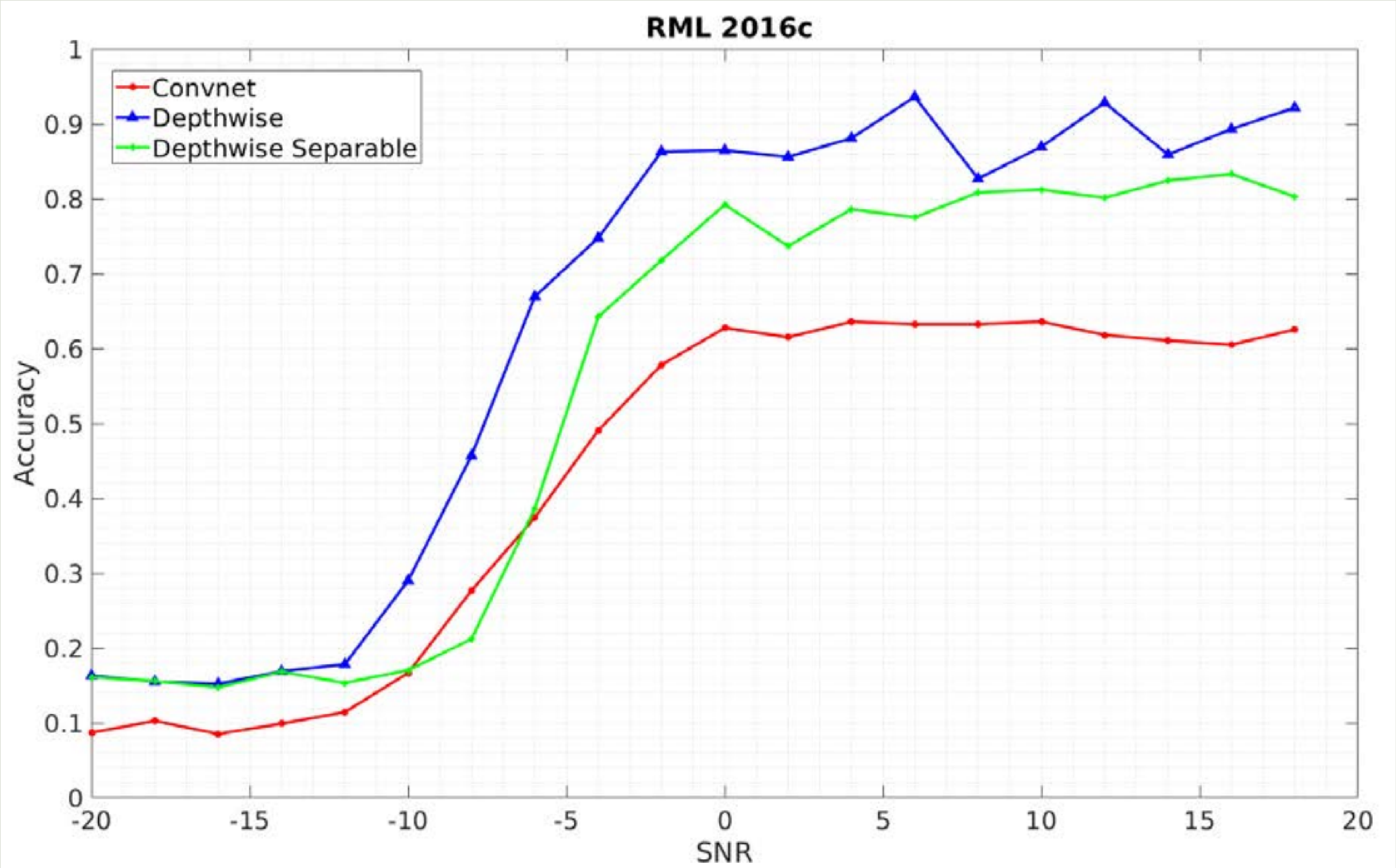


Fig. 2

Here Fig. 2 represents Classification Accuracy of the convolutional neural network architectures on RML2016c dataset

Conv2D vs Depthwise

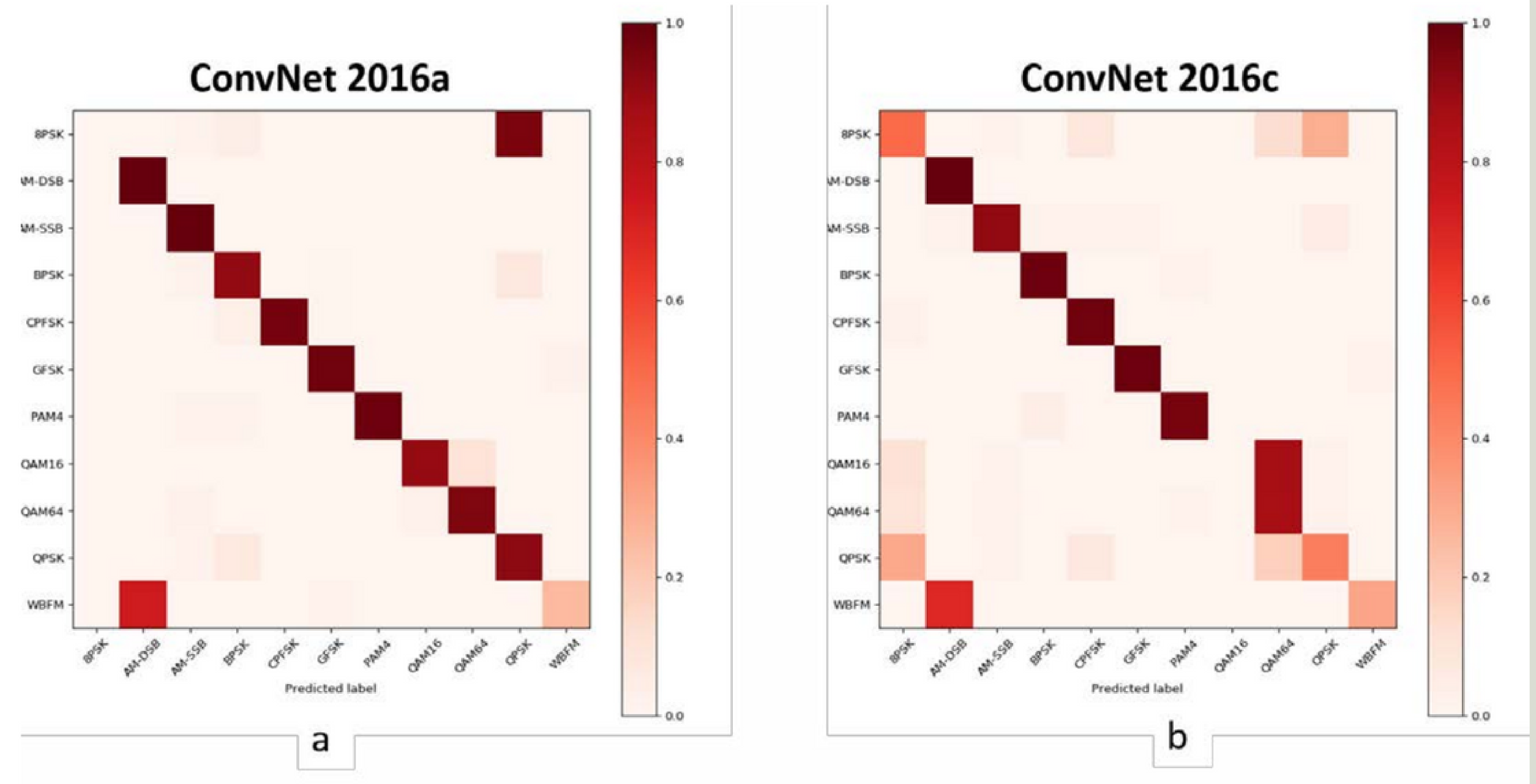
Architecture	Parameters	Reduction	Accuracy	
			RML2016a	RML2016c
Conv2D	921611	–	71.30%	83.40%
Depthwise	596491	35.2%	69.90%	92.10%
Separable	385307	58.2%	71.25%	83.03%

TABLE 1

COMPARISON OF ACCURACY ACHIEVED ON 18 DB SNR OF BOTH DATESETS ON DIFFERECT ARCHITECTURE CONFIGURATIONS

- Although, In some cases the proposed models accuracy is 0-2 % lower than traditional convolution model but the parameters are getting reduced from 35% - 60%

Convnet Vs Seperable Convolution



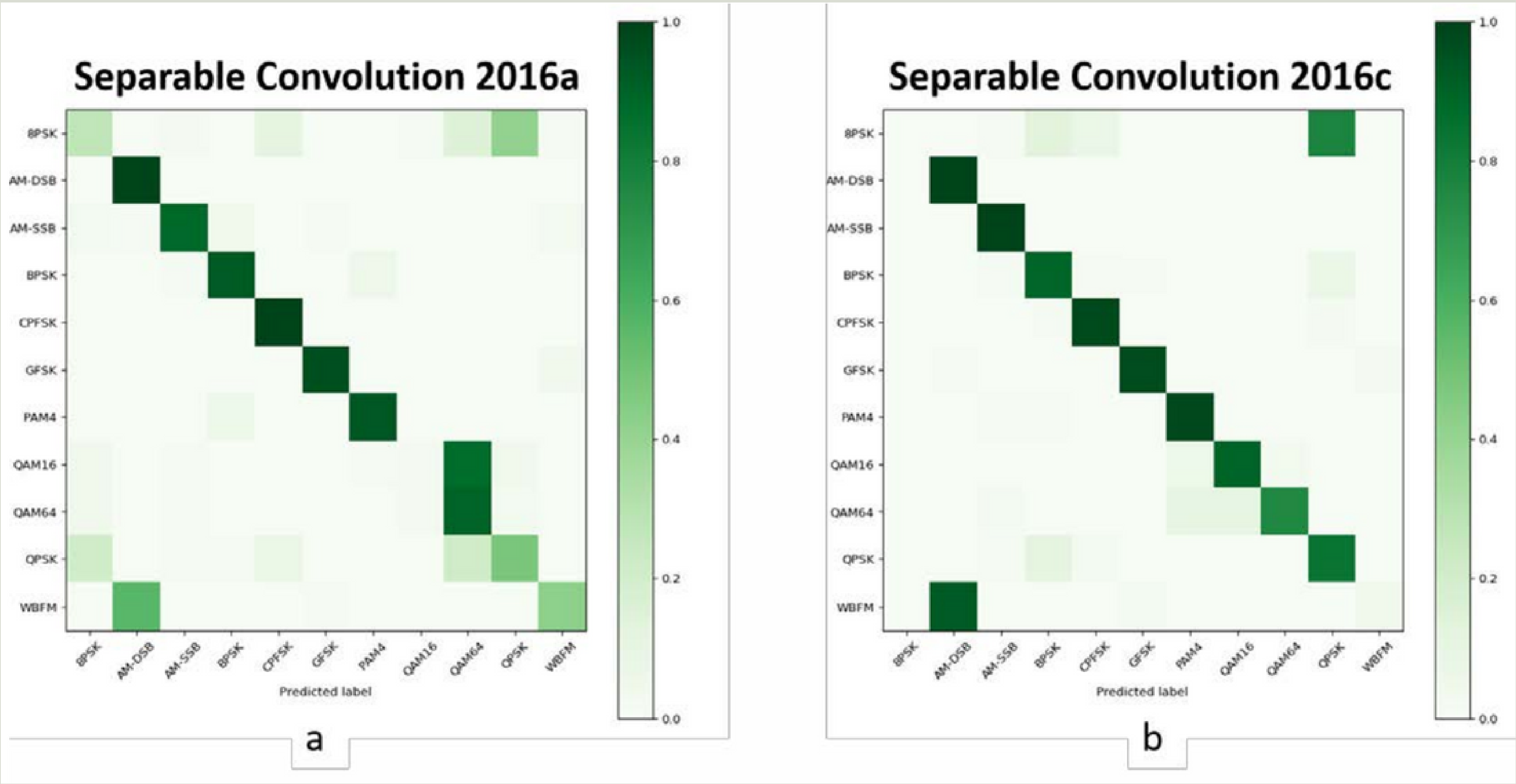


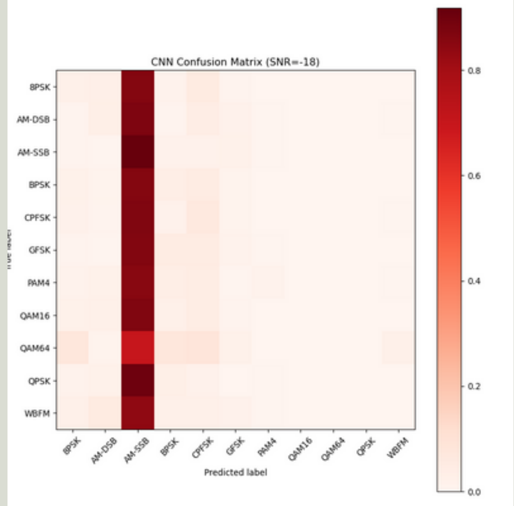
Fig. 3a

Confusion matrix depicting the ability of the conventional CNN to classify several modulation schemes at SNR=18 on RML2016a dataset (a) and RML2016c dataset (b)

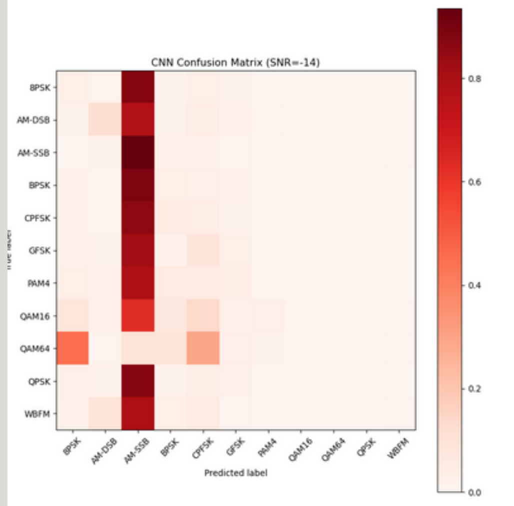
Fig. 3b

Confusion matrix depicting the ability of the separable CNN to classify several modulation schemes at SNR=18 on RML2016a dataset (a) and RML2016c dataset (b)

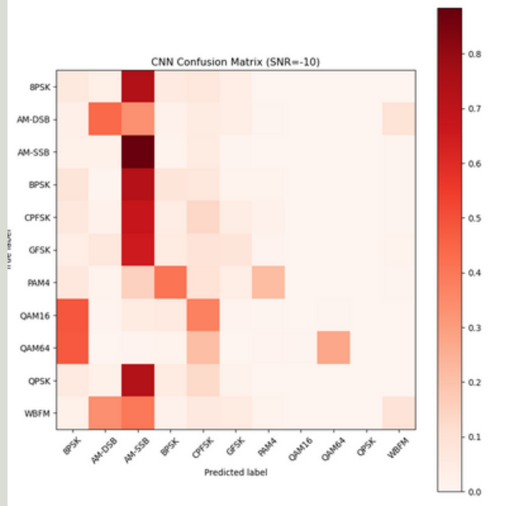
Confusion Matrixes For RML2016a



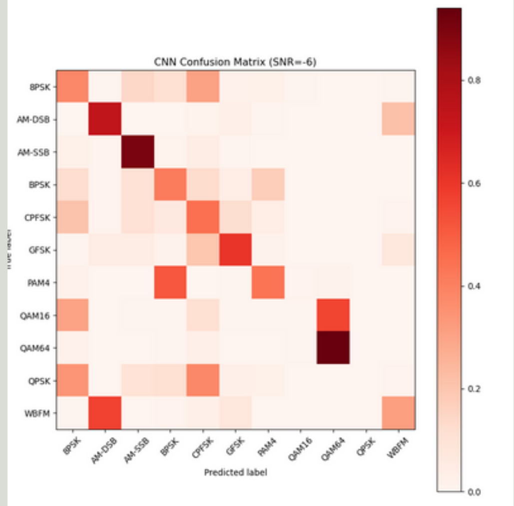
SNR = -18 DB



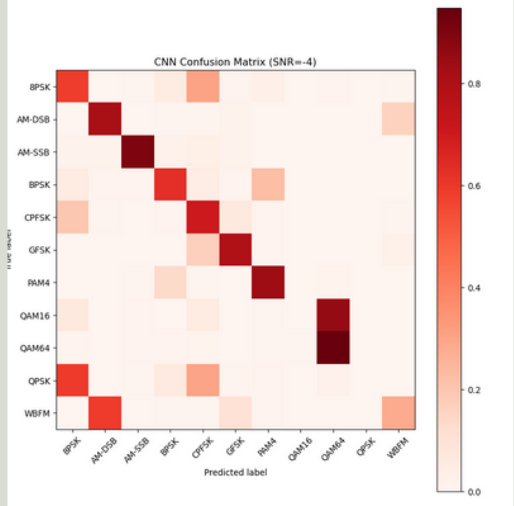
SNR = -14 DB



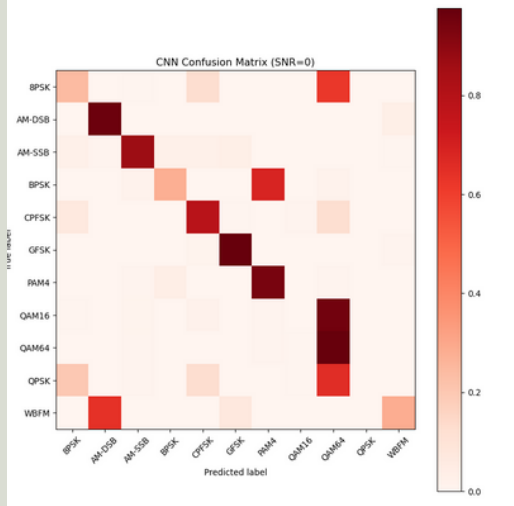
SNR = -10 DB



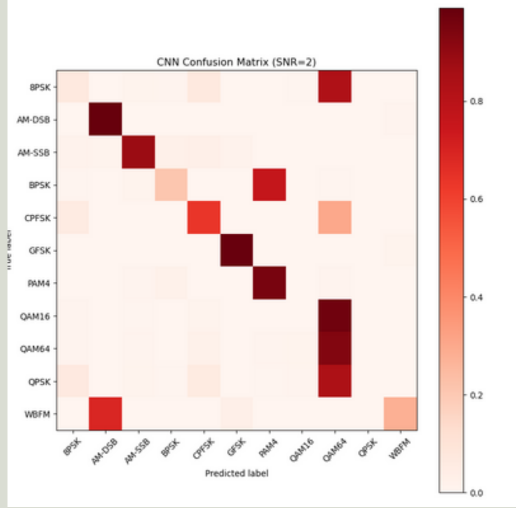
SNR = -6 DB



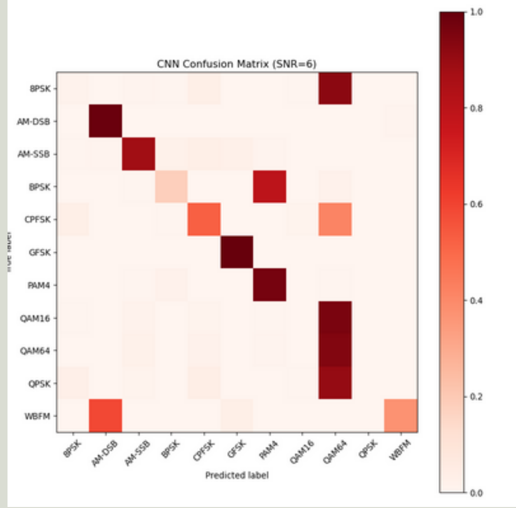
SNR = -4 DB



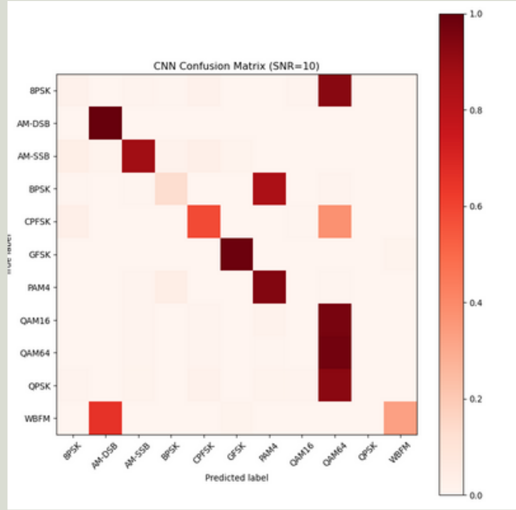
SNR = 0 DB



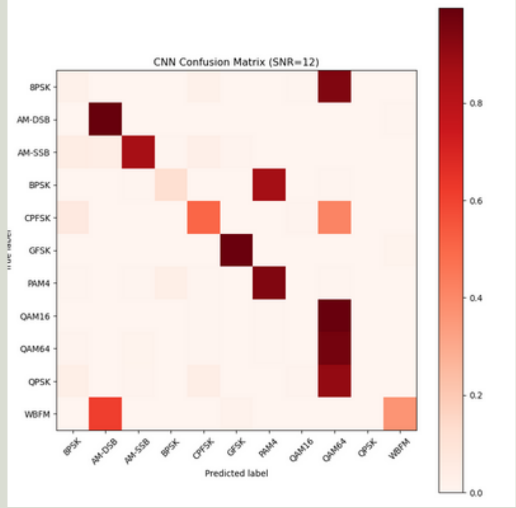
SNR = 2 DB



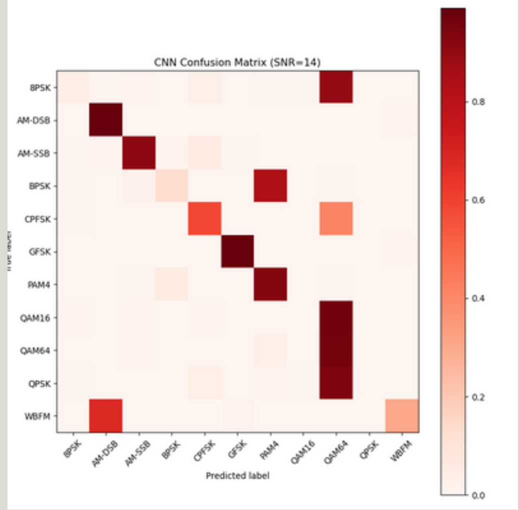
SNR = 6 DB



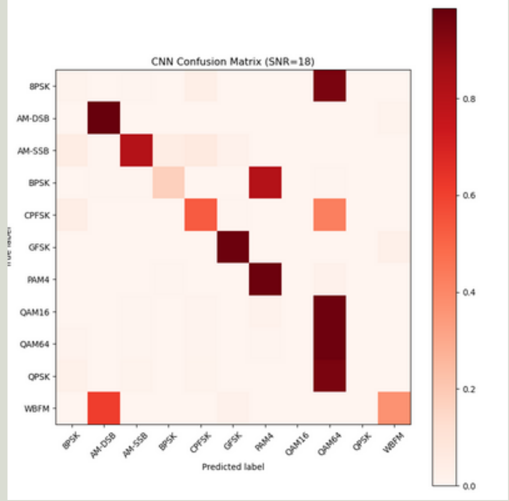
SNR = 10 DB



SNR = 12 DB



SNR = 14 DB

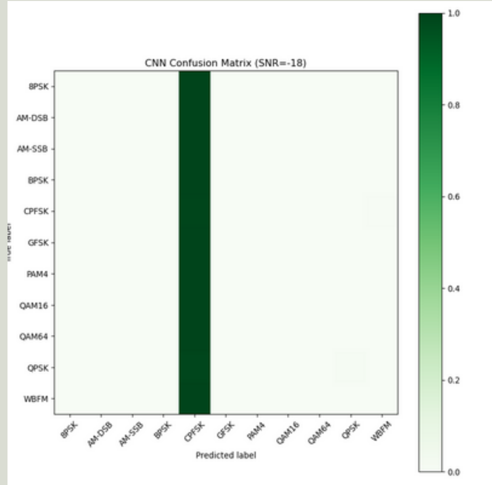


SNR = 18 DB

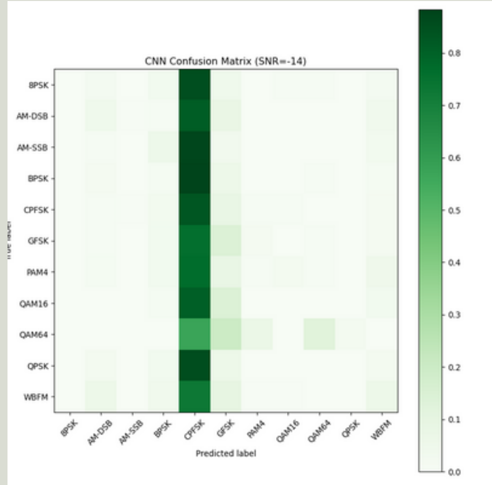
Fig. 5

Confusion matrix for depthwise seperable on RML2016a dataset (a)

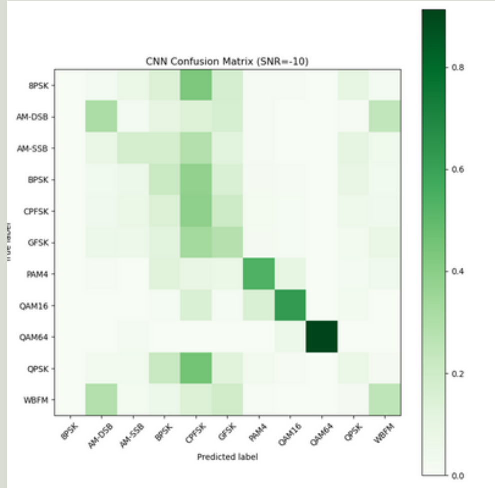
Confusion Matrixes For RML2016c



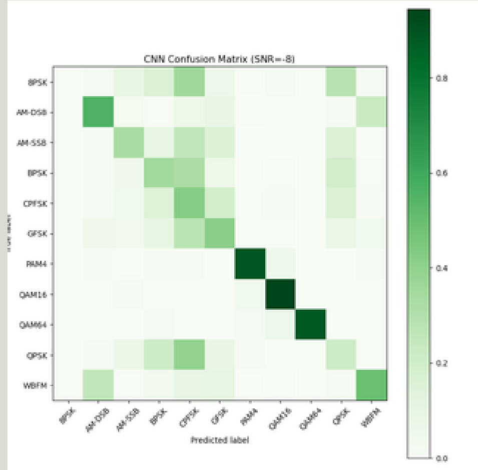
SNR = -18 DB



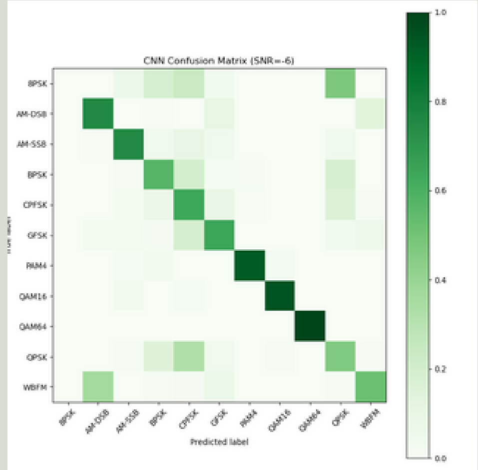
SNR = -14 DB



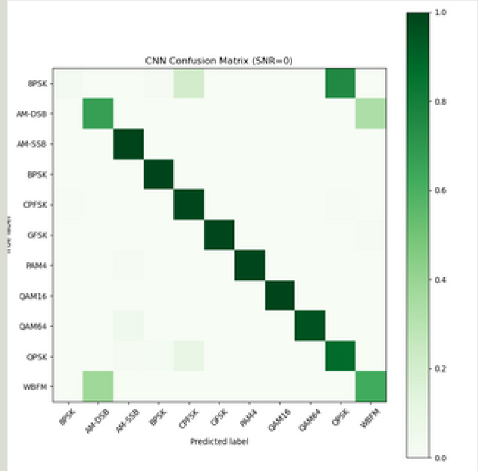
SNR = -10 DB



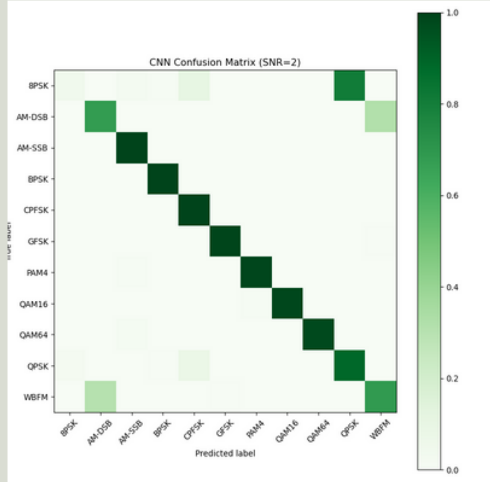
SNR = -6 DB



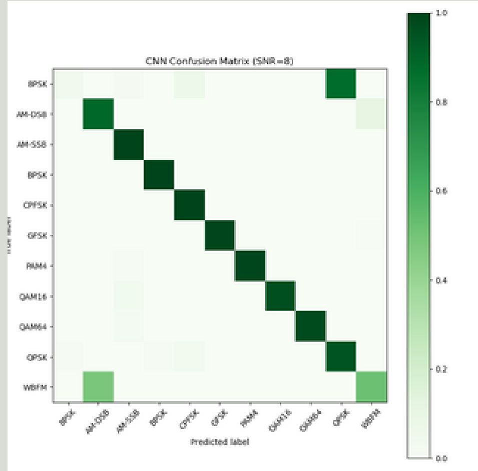
SNR = -4 DB



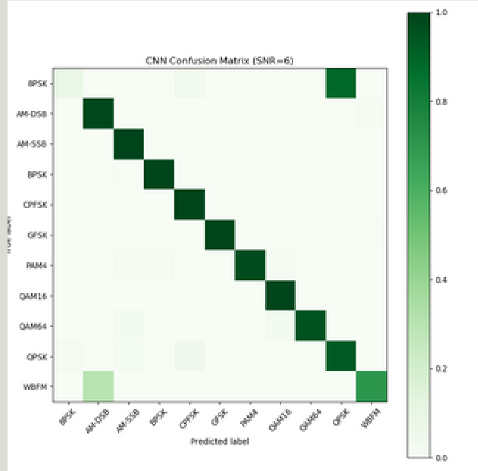
SNR = 0 DB



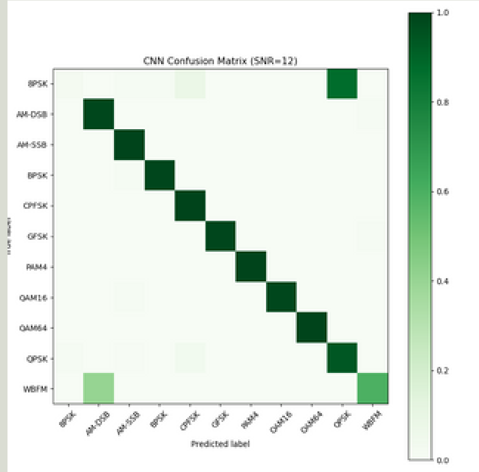
SNR = 2 DB



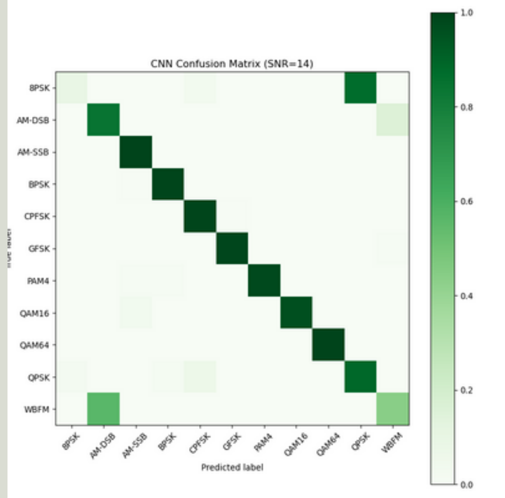
SNR = 6 DB



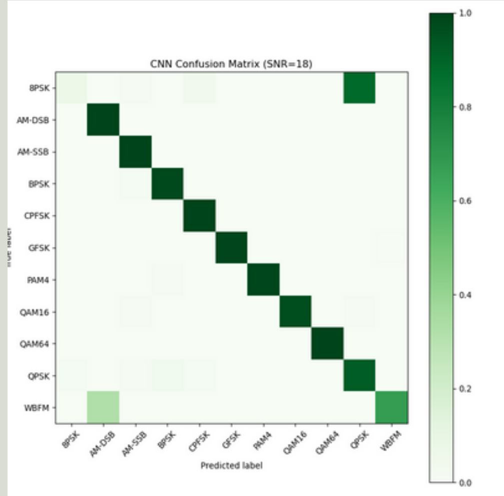
SNR = 10 DB



SNR = 12 DB



SNR = 14 DB



SNR = 18 DB

Fig. 6

Confusion matrix for depthwise seperable on RML2016c dataset

Conclusion

Conclusion

- Depthwise and separable convolutional neural network architectures have been presented to classify the modulation schemes.

- The low powered IOT devices does not have the capability to process large number of parameters as in the conventional neural networks so the proposed methods achieves similar and in some cases better performance compared to the conventional convolution approaches with significantly less number of parameters.(Such architectures are highly favorable for implementation in the devices that are constrained by power and area)

Acknowledgment

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THANK YOU