EE 5611
Machine Learning Applications for Wireless Communications
Final Project

Bhavsar Jeel Alpesh: ES16BTECH11005
Vignatha Vinjam: ES17BTECH11024

Experiments Conducted:

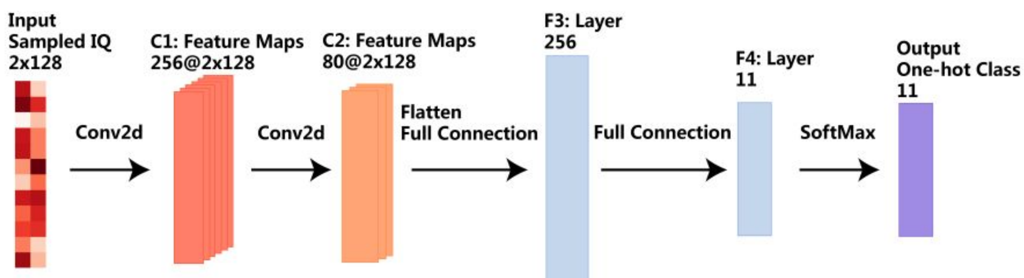
1. Implementing Baseline LSTM network, Baseline Convolutional network and Base SCRNN network as described in Sequential Convolutional Recurrent Neural Networks for Fast Automatic Modulation Classification; arXiv:1909.03050v1
2. Implementing a New-LSTM network, New-SCRNN network and comparing their performance with the baselines.
3. Training Baseline SCRNN on only High SNRs, only few High SNRs, only Low SNRs. Training Baseline SCRNN with tanh activation for the LSTM layers (since it tanh is preferred for LSTM layers) instead of ReLU. (These experiments did not show distinct improvement and hence are not included in this report.)
4. Checking Visualisations of the intermediate outputs first Convolution layers of Baseline SCRNN

Features Used:

a. Independent-Quadrature components (128,2)
b. Amplitude-Phase components (128,2)
c. Independent-Quadrature-Amplitude-Phase components (128,4)

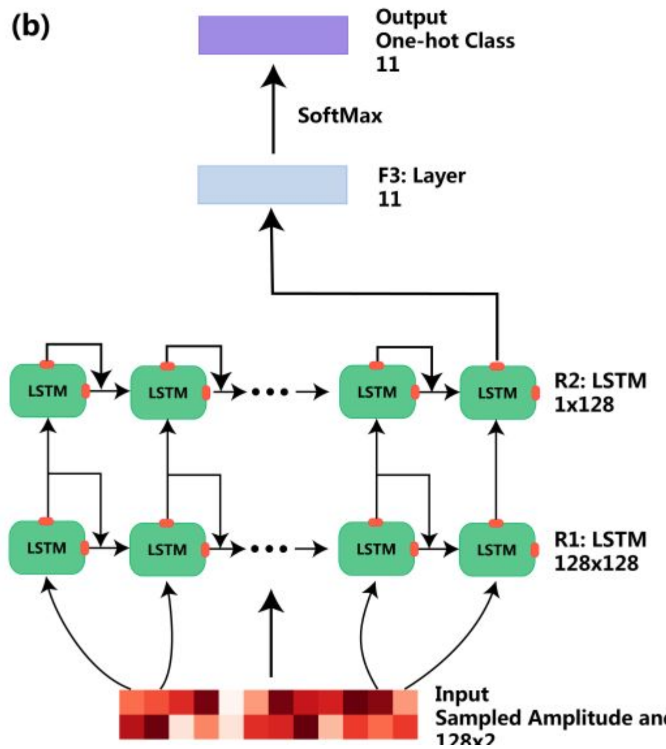
Model Architectures:

1. **Baseline Convolutional Architecture**



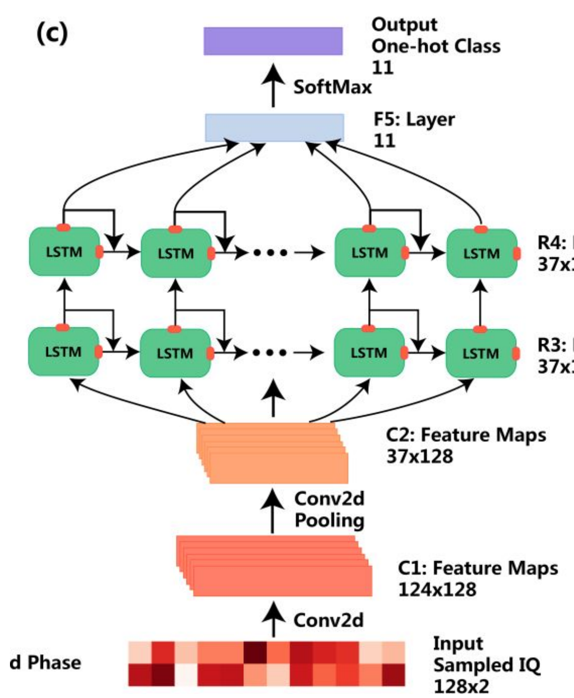
This architecture uses Independent-Quadrature components (128,2) features as input and ReLU activation for all the layers except the output layer.

2. **Baseline LSTM Architecture**



This architecture uses Amplitude-Phase components (128,2) features as input and tanh activation for the LSTM layers

3. **Baseline SCRNN**



This architecture uses Independent-Quadrature components (128,2) features as input. The Convolutional layers and ReLU activation for all the layers except the output layer.

4. **New-LSTM**

   This architecture is the same as Baseline LSTM architecture, except it uses Independent-Quadrature-Amplitude-Phase components (128,4) as the input features

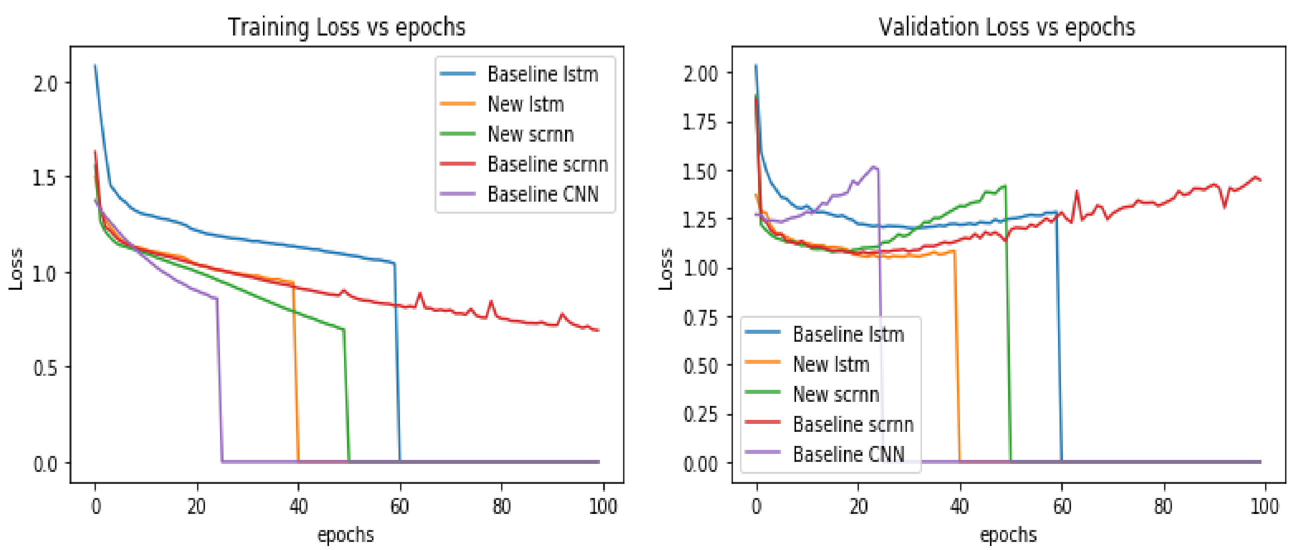
5. **New-SCRNN**

   This architecture is the same as Baseline SCRNN architecture, except it uses Independent-Quadrature-Amplitude-Phase components (128,4) as the input features and the LSTM layers have tanh activation instead of ReLU

Results

Training over limited SNR range did not provide a substantial improvement. The data available for each SNR was equal and training over only a few SNRs reduced our training dataset. Hence the results displayed here are for training over the entire SNR range of [-20dB, -18dB, -16dB, … , 18dB]

Convergence of all models vs epochs

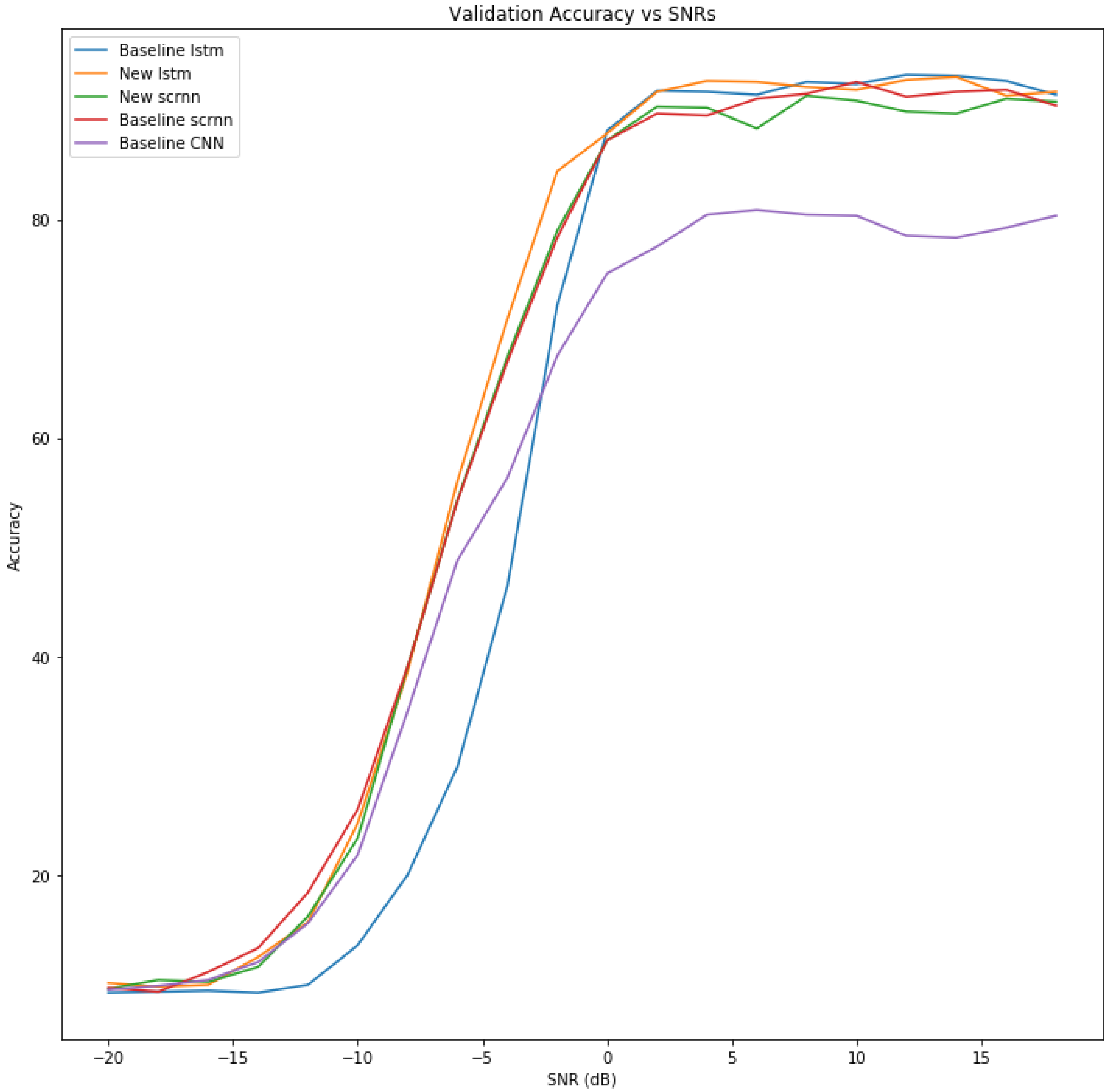


We can observe that the rate of convergence is:

$$BaselineCNN \geq NewSCRNN \geq NewLSTM = BaselineSCRNN \geq BaselineLSTM$$

The overall validation accuracies saturate somewhere around 60%. This number is very low because the performance at low SNR values is very bad and it contributes substantially to the overall accuracy. Hence, We have not included the validation accuracy plots here.

<u>Validation accuracy comparison of all models vs SNR range</u>



The baseline approach papers have not mentioned the max_norm constraint values and the positions of Dropout layers. We added a Dropout of 0.2 after each LSTM layer and put the max_norm as 2.0 for the output layer for our experiments. These experiment conditions are probably not the same as the ones used by the authors and hence we have been unable to replicate the exact results.

The Baseline SCRNN is supposed to outperform Baseline LSTM but we see that is not the case. We can even see that **the Baseline LSTM and the New LSTM approach that we have tried, provides comparable performance to the Baseline SCRNN and even outperforms it a few high SNRs**.

Hence, further experiments need to be conducted here to check if we can substantially outperform the Baseline SCRNN approach which was supposed to be state of the art.

Validation Accuracy (%) vs SNR (dB)		SNR (dB)																			
		-20	-18	-16	-14	-12	-10	-8	-6	-4	-2	0	2	4	6	8	10	12	14	16	18
Model Architecture	Baseline CNN	9	9	9	9	9	13	20	29	46	72	88	91	91	91	92	92	93	93	92	91
	Baseline LSTM	9	9	10	12	15	21	35	48	56	67	75	77	80	80	80	80	78	78	79	80
	Baseline SCRNN	9	9	11	13	18	26	39	54	67	78	87	89	89	91	91	92	91	91	91	90
	New SCRNN	9	10	10	11	16	23	39	54	67	79	87	90	90	88	91	90	89	89	91	90
	New LSTM	10	9	9	12	15	24	38	56	70	84	87	91	92	92	92	91	92	93	91	91

We can see in the above table the SNR values at which the New LSTM and New SCRNN approaches have outperformed the Baseline SCRNN approach.

Confusion Matrices

New LSTM

6 dB	BPSK	QPSK	PAM4	AM_DSB	GFSK	QAM64	AM_SSB	8PSK	QAM16	WBFM	CPFSK
BPSK	97	0	0	0	0	0	3	0	0	0	0
QPSK	0	99	0	0	0	0	1	0	0	0	0
PAM4	0	0	99	0	0	0	1	0	0	0	0
AM_DSB	0	0	0	99	0	0	0	0	0	1	0
GFSK	0	0	0	0	100	0	0	0	0	0	0
QAM64	0	0	0	0	0	96	2	0	2	0	0
AM_SSB	1	0	0	3	1	0	95	0	0	0	0
8PSK	0	0	0	0	0	0	0	100	0	0	0
QAM16	0	0	0	0	0	5	1	0	94	0	0
WBFM	0	0	0	60	0	0	0	0	0	40	0
CPFSK	0	0	0	0	0	0	0	0	0	0	100

Baseline SCRNN

6 dB	BPSK	QPSK	PAM4	AM_DSB	GFSK	QAM64	AM_SSB	8PSK	QAM16	WBFM	CPFSK
BPSK	100	0	0	0	0	0	0	0	0	0	0
QPSK	0	98	0	1	0	1	0	0	0	0	0
PAM4	0	0	100	0	0	0	0	0	0	0	0
AM_DSB	0	0	0	100	0	0	0	0	0	0	0
GFSK	0	0	0	0	100	0	0	0	0	0	0
QAM64	0	0	1	0	0	89	2	0	8	0	0
AM_SSB	1	1	6	3	1	1	83	0	2	2	0
8PSK	0	0	0	0	0	0	1	99	0	0	0
QAM16	0	0	0	0	0	10	0	0	90	0	0
WBFM	0	0	0	57	0	0	0	0	0	43	0
CPFSK	0	0	0	0	0	0	0	0	0	0	100

The confusion matrices for New LSTM and Baseline SCRNN have been displayed for testing at 6 dB SNR. The confusion matrices for the rest of the experiments and at more SNRs can be found in this Google Sheet.

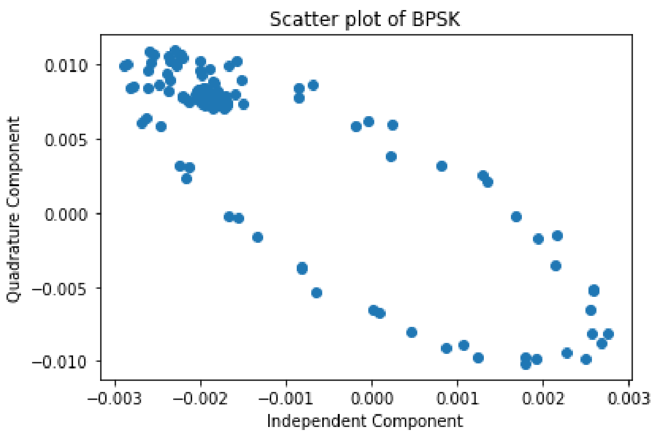
In the Google Sheet we can observe that the diagonals become gradually sharper with increasing SNR, yet two primary confusions exist even at high SNRs.

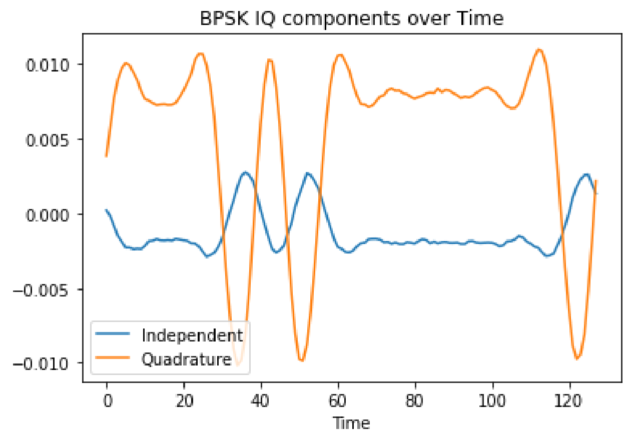
1. One is among the analog modulations. This is mainly due to the silent period exiting in the analog audio signal.
2. The confusion between QAM16 and QAM64 occurs because the former is a subset of the latter).

Convolutional Layer Intermediate Outputs

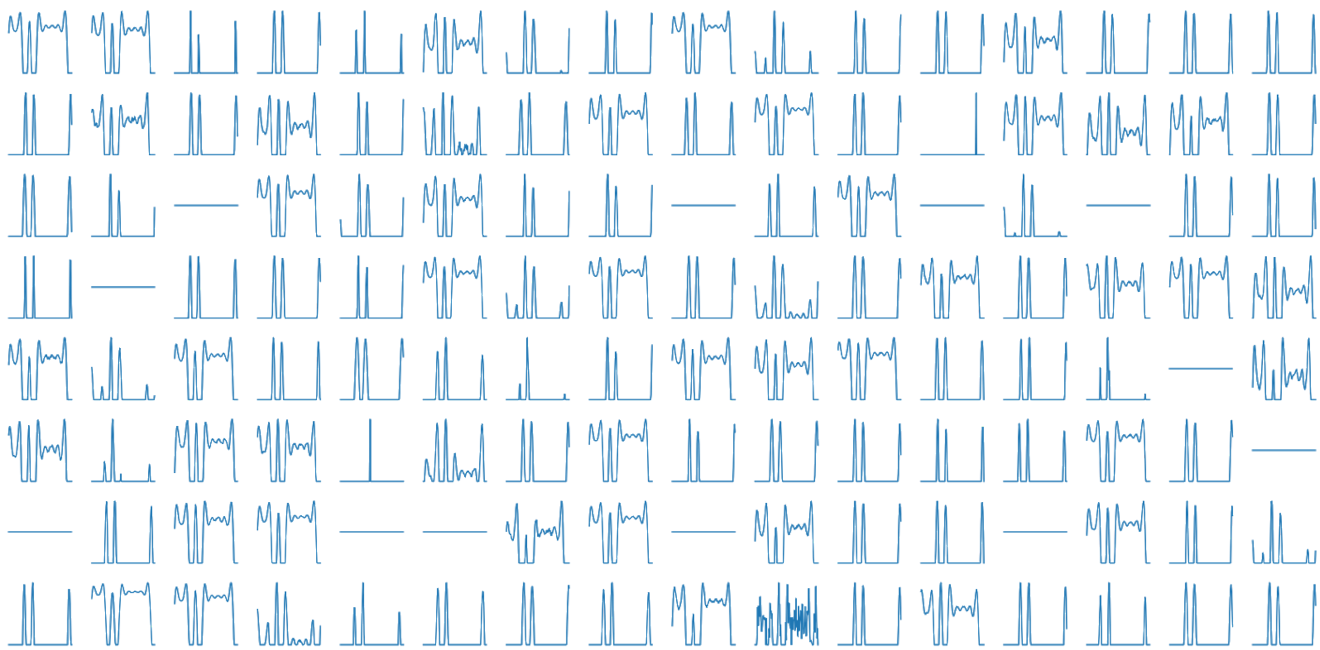
1. BPSK

   We fed a BPSK input signal to the trained Baseline SCRNN Model to visualise the intermediate output of the first convolutional layer.





The intermediate output that we received was:



Its hard to decipher these visualisations of the filters and we have been unable to notice any distinct patterns exclusive to a particular modulation scheme which can show that the SCRNNs act as a front end distillation. The visualisations for BPSK, QPSK and an impulse signal can be found in Conv_layer_visualisations.ipynb