An Evaluation of Neural Network Performance using Complex-Valued Input Data

- **Authors:** *Kushal Thapa, Dr. Stan McClellan*
- **Presenter:**

  Kushal Thapa

  Ingram School of Engineering

  Texas State University

  San Marcos, TX, USA

  email: k_t260@txstate.edu

TEXAS STATE UNIVERSITY®

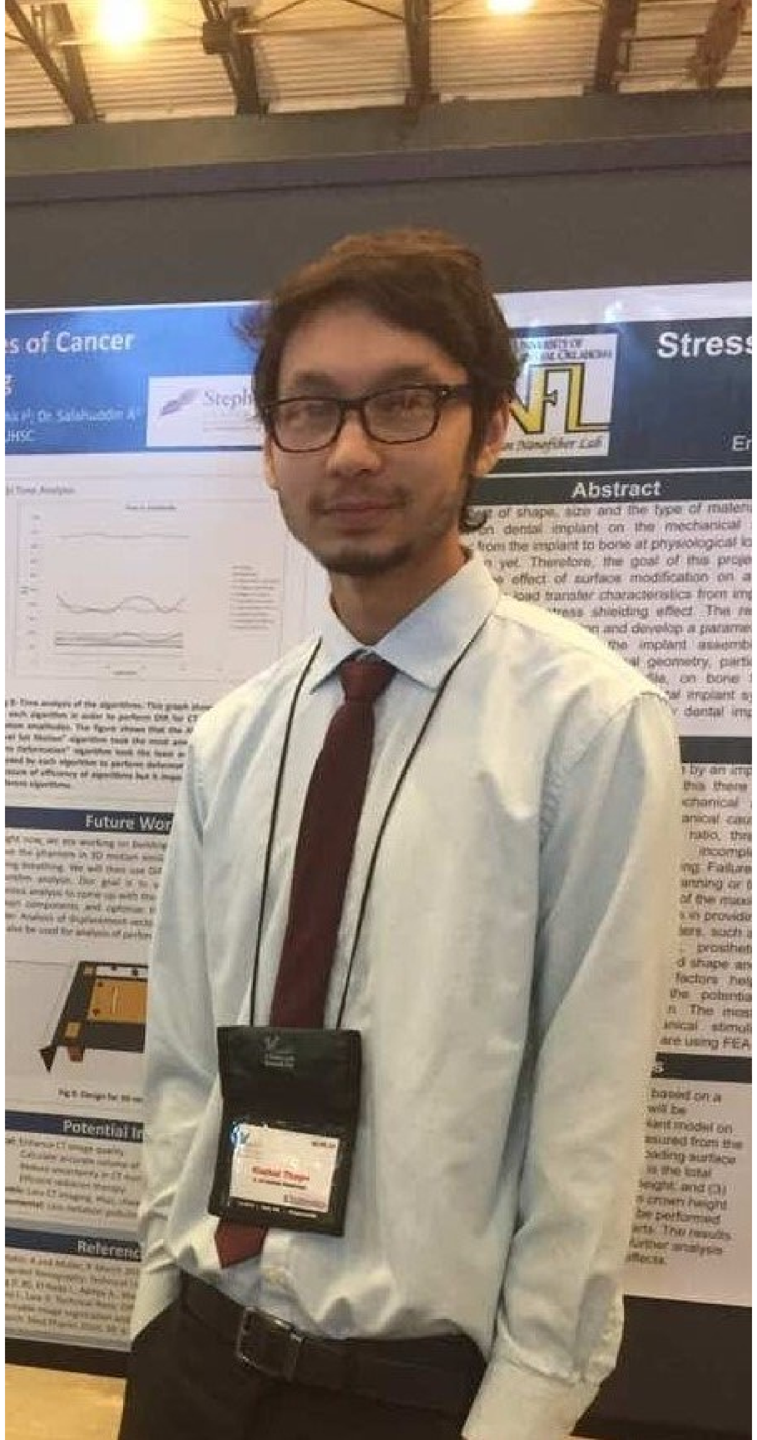
The rising STAR *of Texas*

IARIA

Presenter’s Bio

- B.S. in Biomedical Engineering from *University of Central Oklahoma*
- Currently a M.S. in Engineering- Electrical Engineering student at *Texas State University*
- Graduate Research Assistant for Dr. Stan McClellan in Ingram School of Engineering
- Website: kushalthapa.wordpress.com

  https://github.com/kushal-thapa



Research Interest

- Power line communications
- Machine Learning in communications
- Distributed network architecture
- Remote filesystem monitoring
- Characterization of heat trace cable

Introduction

- Complex-valued data
  - MRI in Biomedical Imaging
  - Seismic data in Geosciences
  - Signal Processing in Communication systems
- Problem
  - ML/NN doesn’t like complex-valued input
- Possible solutions
  - Approach a) Ignore the imaginary component
  - Approach b) Combine the real and imaginary component
  - Approach c) Stack the real and imaginary component
- Objective
  - Compare approaches b) and c)

Experimental Setup

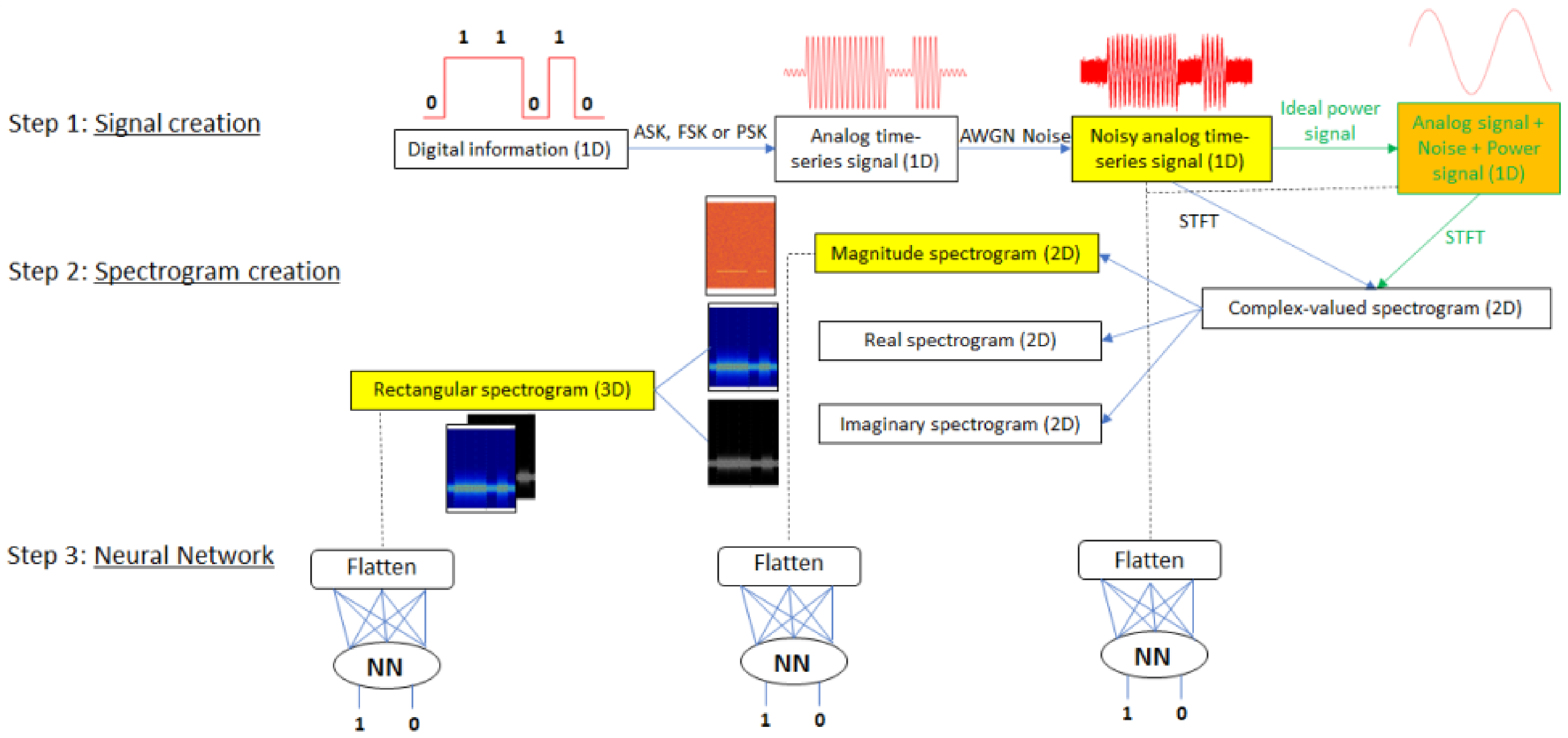


Figure 1. Flow of experiment showing creation of raw time-series modulated signal, transformation to various spectrograms and the use of the three datasets (highlighted) in NN. The extra sub-step of addition of power signal for 'Test 2' is shown in green.

Hyperparameters of the NN

Total number of samples	10,000
Training to Test ratio	70:30
No. of hidden layers	1
No. of nodes in the hidden layer	64
No. of nodes in the output layer	2
Activation function for the hidden layer	Relu
Activation function for the output layer	Softmax
Optimizer	RMSProp
Loss function	Categorical Entropy
No. of training epochs	10
Batch size for training	16

Results

Modulation Intensity

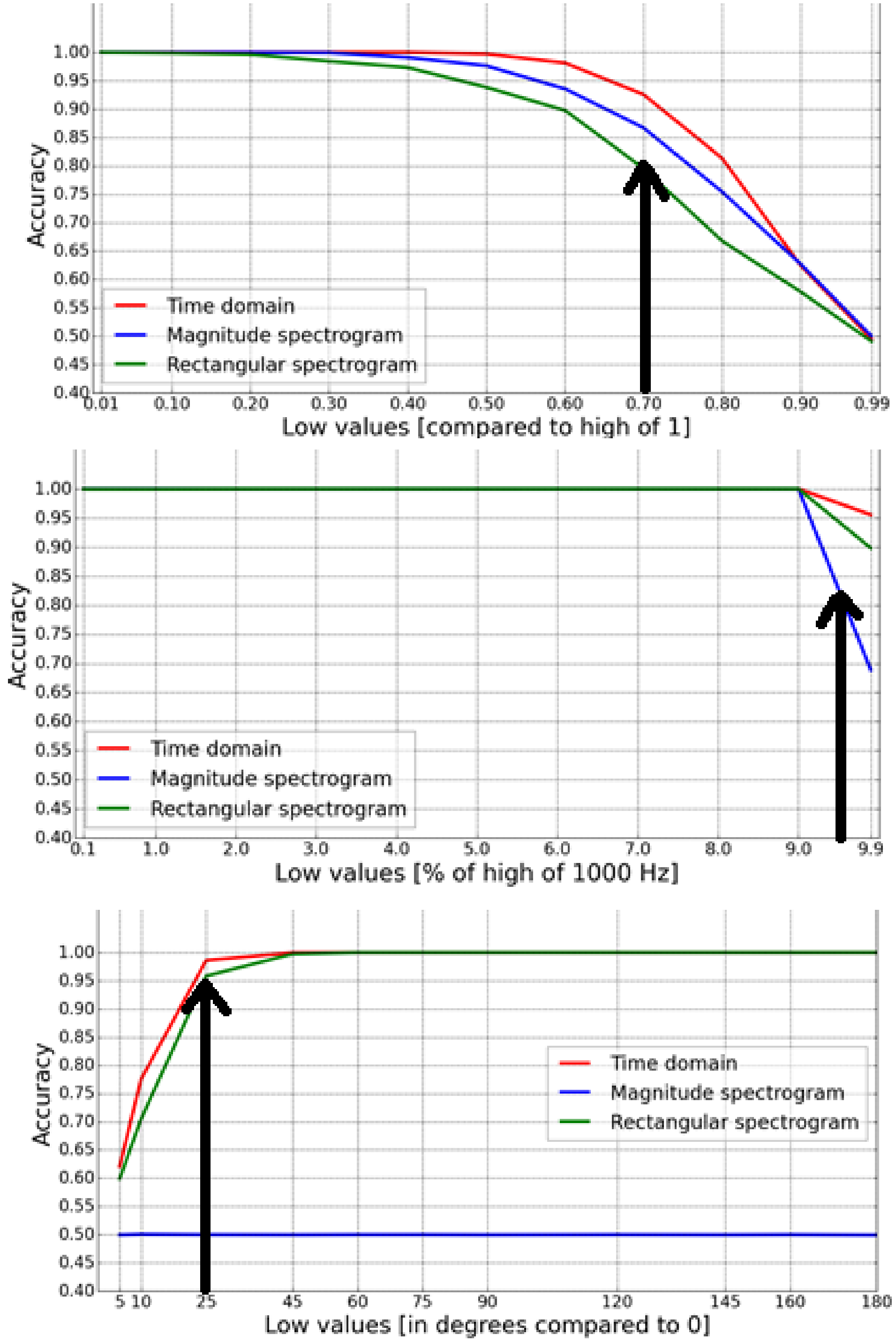


Figure 2. The NN model's test accuracy for a range of 'low values' (compared to a high of '1') for ASK signal (top), FSK signal (mid), and PSK signal (bottom) with SNR=0dB. The plot shows general decrease in accuracy as 'low-values' get closer to the high-value, i.e., as modulation intensity decreases. The plot also shows arrows placed on the low-value of interest pointing towards the subjective "inflection point". These low values were used in succeeding experiments.

Results
Training time comparison

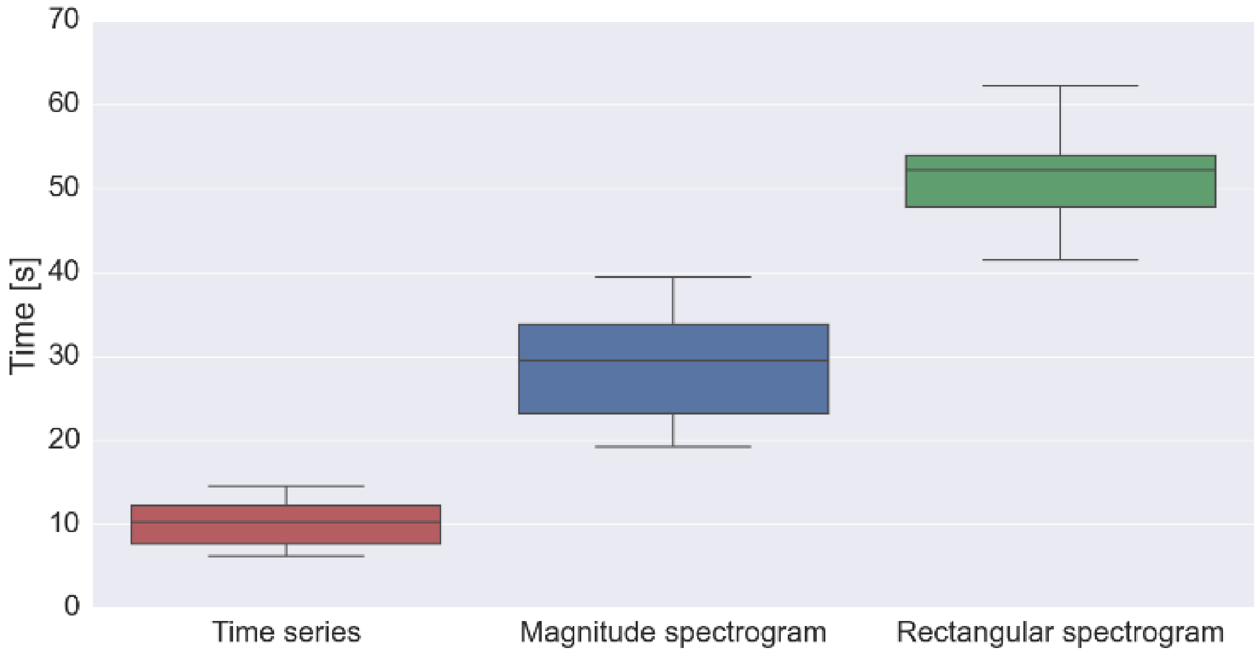
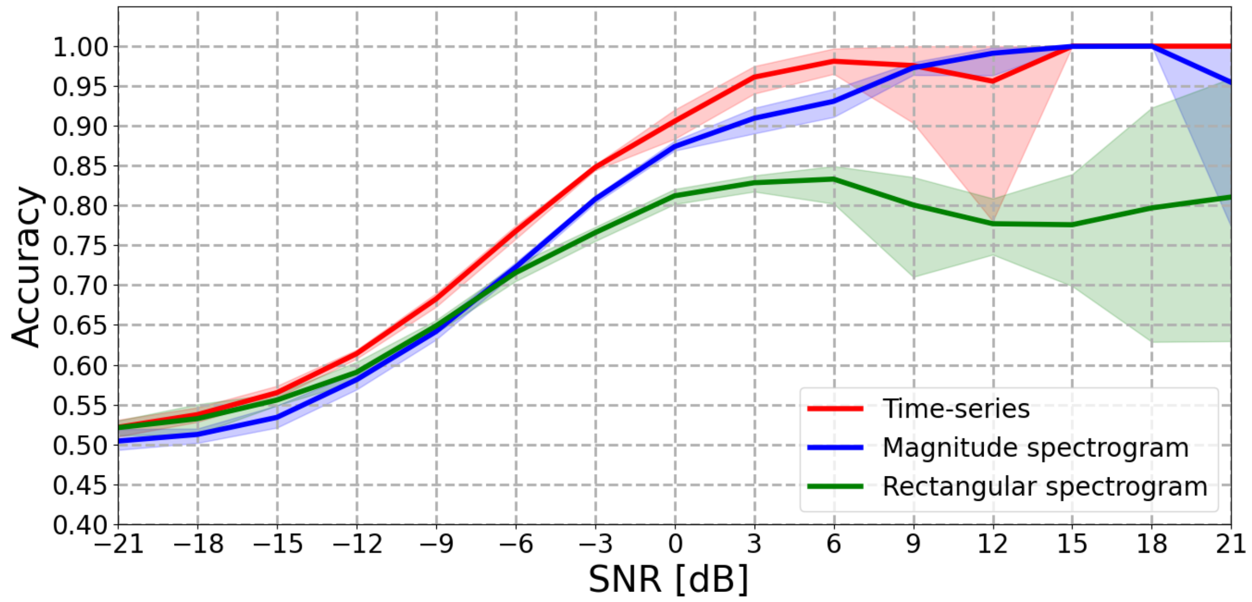


Figure 3. Boxplot showing the total training time distribution for the timeseries (red), magnitude spectrogram (blue) and rectangular spectrogram (green) NN models.

Results

Test 1: ASK

Figure 4. Test accuracy of NN models trained with time domain, magnitude spectrogram and rectangular spectrogram datasets containing ASK signals (high=1, low=0.7) with SNR ranging from -21dB to 21dB. Time-series model had generally highest accuracy while the rectangular spectrogram model shows better performance than magnitude spectrogram model only in low SNR conditions.



Results

Test 1: FSK

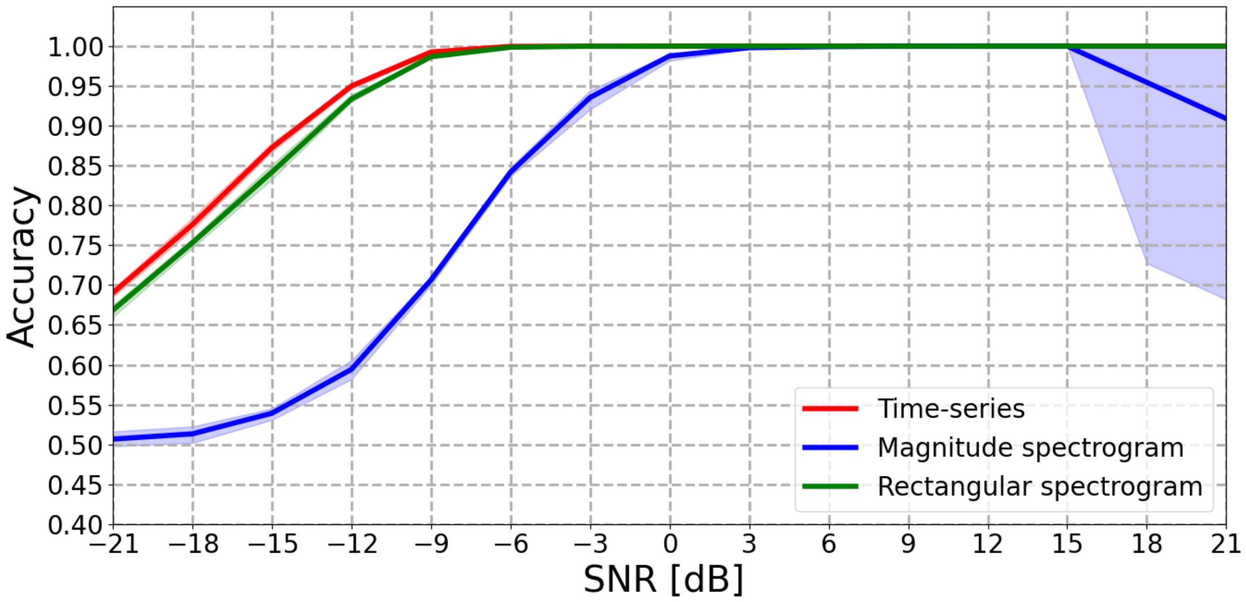
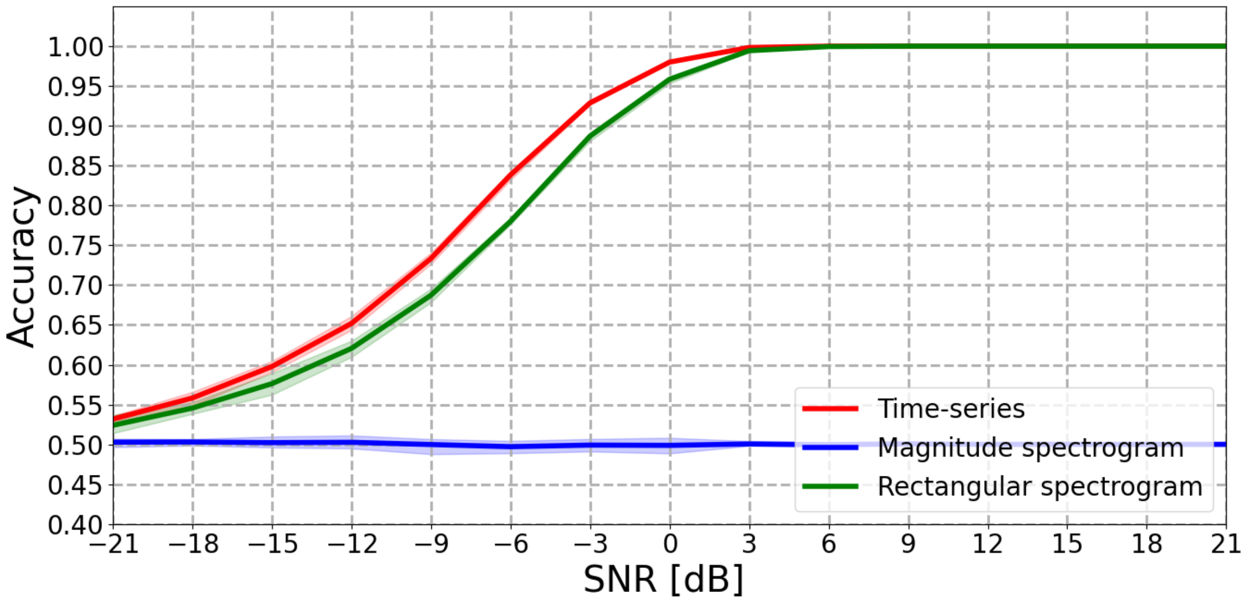


Figure 5. Accuracy versus SNR plot for NN models of FSK signals (high=1000 Hz, low=950 Hz) showing similar performance of time-series and rectangular spectrogram models while the magnitude spectrogram model performed worst across all SNR levels.

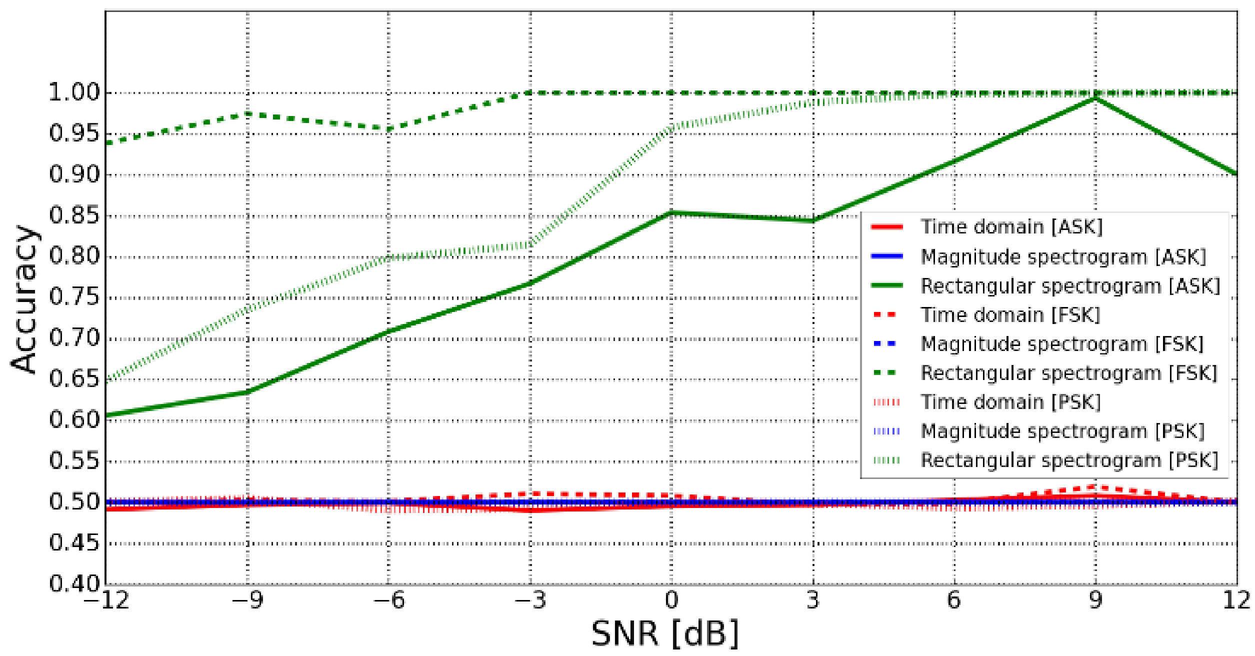
Results
Test 1: PSK

Figure 6. Accuracy versus SNR plot for NN models of PSK signals (high=0°, low=25°) showing the similar performance of time-series and rectangular spectrogram models. The magnitude spectrogram models' accuracy was approximately 50% for all SNR levels because of its inherent inability to retain phase information.



Results
Test 2

Figure 7. Accuracies of the time-series, magnitude spectrogram and rectangular spectrogram NN models for ASK, FSK and PSK signals with added ideal power signal. The SNR levels in the X-axis of the plot is discounting the power signal (i.e., this SNR=Energy of the core modulated signal/Energy of the AWGN).



Conclusion

- Time-series and rectangular spectrogram training data performed better than magnitude spectrogram data for FSK, PSK and low-SNR ASK signals

- Rectangular spectrogram dataset performed significantly better than others in presence of dominant out-of-band interferers.

- Stacking real and imaginary components of complex-valued data is better than combining them for a Neural Network input.