Electrical Engineering Department

Signal Detection and Demodulation at the Wireless Physical Layer using Deep Learning

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Introduction

In cognitive radios, automatic modulation classification (AMC) is a method used by the receiver to automatically determine the modulation scheme of a transmitted signal, regardless of various channel effects.Traditionally, there are two methods :

1. **Likelihood-Based Methods**
   - **Advantages:** Minimizes classification error, thereby giving the most optimal estimation out of all the methods.
   - **Disadvantages:** Extremely complex and requires a-priori knowledge of the signal and channel parameters, which is usually not available in the real world. In the presence of unpredictable channels, it is no longer optimal.
2. **Feature-Based Methods**
   - **Advantages:** Computationally simple and does not require a-priori knowledge of the channel.
   - **Disadvantages:** Requires de-noising of signals, data preprocessing, and expert feature engineering prior to applying a machine learning (ML) classifier.

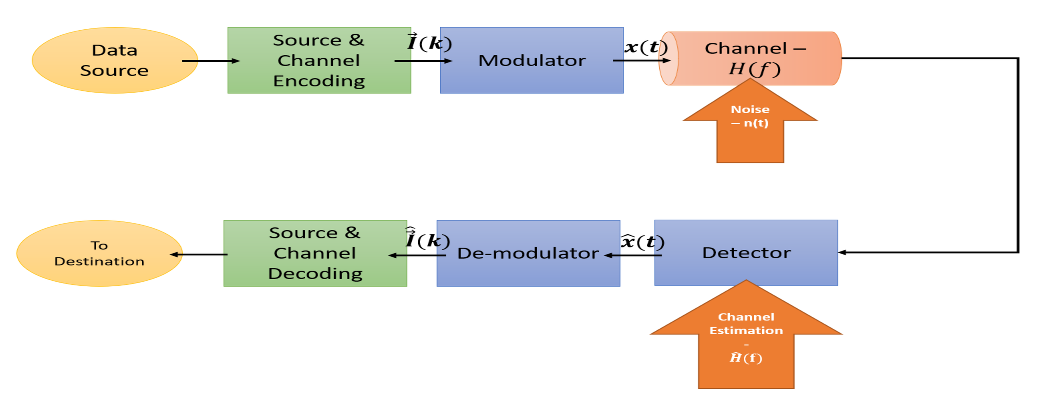


Fig. 1. A wireless communication system. Before decoding, the modulation scheme used must be determined.

In the past three years, researchers have started exploring a new method that has seen widespread success in other fields such as computer vision and speech processing:

3. **Deep-Learning (DL) Methods**
   - **Advantages:** Neural networks (NNs) have been shown to be universal function approximators, suggesting they might be capable of competing with likelihood-based AMC methods. DL inherently learns features from the dataset and does not require signal preprocessing or feature engineering.
   - **Disadvantages:** It is still an emerging field! More research on various DL methods needs to be conducted to create a solid body of knowledge on its effectiveness for wireless communication channels.

Motivation

The work in [1] demonstrates that convolutional neural networks (CNNs) can achieve comparable accuracy to traditional AMC methods, even in the presence of severe channel impairments. In [2], the authors apply a hierarchical approach and provide a proof-of-concept that hierarchical deep neural nets (DNNs) are feasible for AMC. However, their hierarchies are manually chosen, based on expert knowledge of modulation type.

Hierarchical classification has been used to improve classification in other fields, such as text-classification. In [5], the authors developed a method to automatically induce a hierarchy of ML classifiers based on a confusion matrix of a base classifier. The hierarchical approach performed better on text classification than flat classifiers [3].

Motivation

We propose a CNN architecture framework determined using induced class hierarchies to completely remove the need for expert domain knowledge for feature engineering and hierarchy determination. Moreover, to the best of our knowledge, previous works have not applied induced class hierarchies to deep learning architectures.

Methodology

The Dataset: The benchmark synthetic radio dataset from [4] is used.
- SNR Levels: Range from -20dB to 18dB
- 11 Modulation schemes: QPSK, QAM16, QAM64, AM-DSB, AM-SSB, CPSK, BPSK, 8PSK, WBFM, GFSK, PAM4

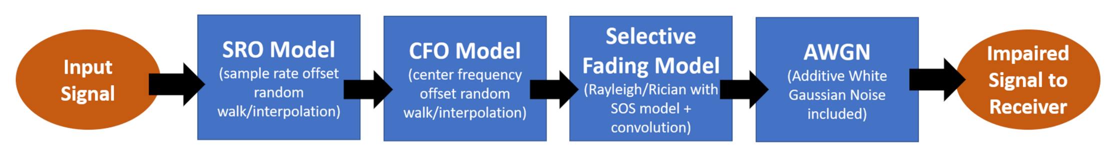


Fig. 2. Channel simulation process - the transmitted data undergoes severe channel effects to simulate the real world [4].

Baseline, Flat CNN Model: Taken from [1], consists of 2 convolutional layers, followed by two fully-connected (FC) layers.
- **Input Vectors:** 220,000 IQ samples – half for training, half for validation and test. A vector is 128 time stamps long.

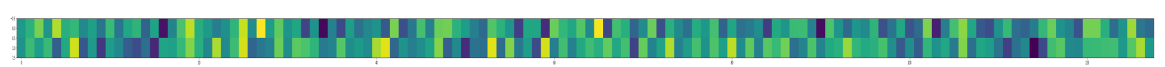


Fig. 3. A CPSK input vector of length 128, as an "image" input to the CNN model. The first row consists of the In-phase (I) components, the second row of the Quadrature-phase (Q) components.

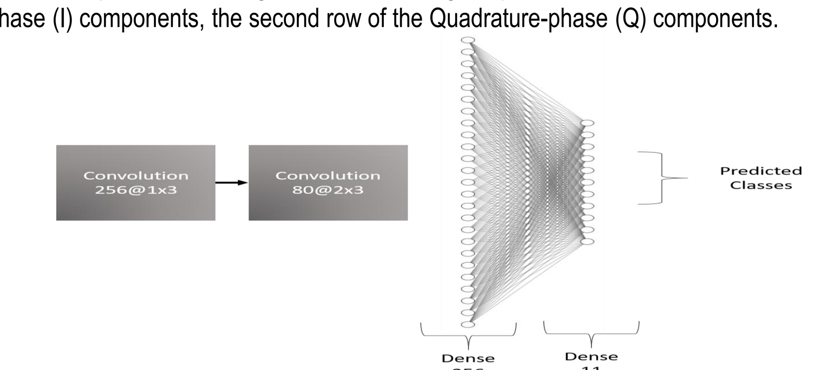


Fig. 4. The base, 11-way CNN model developed in [1].

Inducing a Class Hierarchy: We follow the method in [3]. We choose the class hierarchy generated from the standardized Euclidian distance, which yields the highest cophenetic pair-wise correlation of 95%.

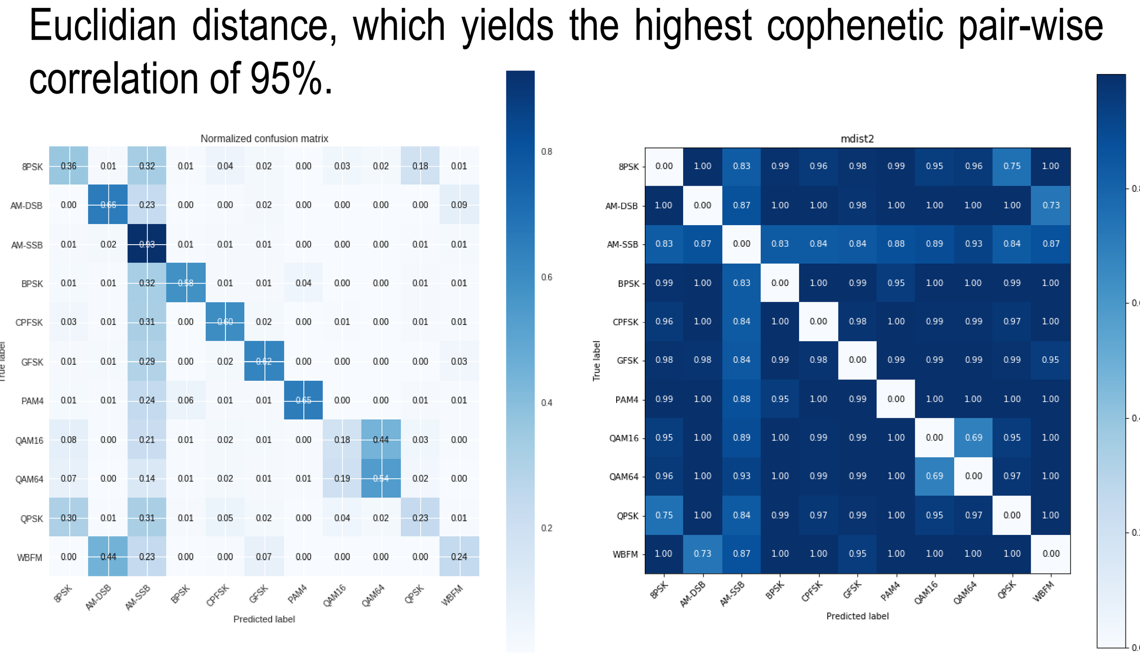
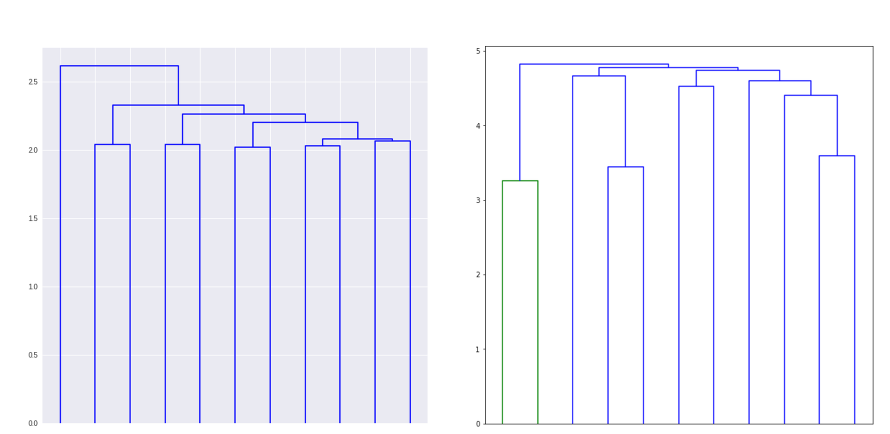


Fig. 5. The normalized confusion matrix of the baseline model and the final distance matrix after following the methods in [3]

Fig. 6. Left – Dendrogram generated using Canberra Measure, Cophenet value of 94.4%.

Right – Dendrogram generated using standardized Euclidean measure, Cophenet value of 95.9%. We chose this as our final hierarchy structure.



Methodology

Hierarchical Models: First, we generate a two-level hierarchical-CNN (h-CNN), Model A. Each CNN in the hierarchy is individually finetuned and trained on its specific modulation inputs to achieve the highest accuracy possible for that set of inputs. We then generate a three-level h-CNN (Model B). We experimented with various modifications to the base CNN architecture from [1], and found that a deeper network of three convolution layers and three dense layers produces the highest accuracy. Variations of this are used for each sub-CNN in the hierarchy.

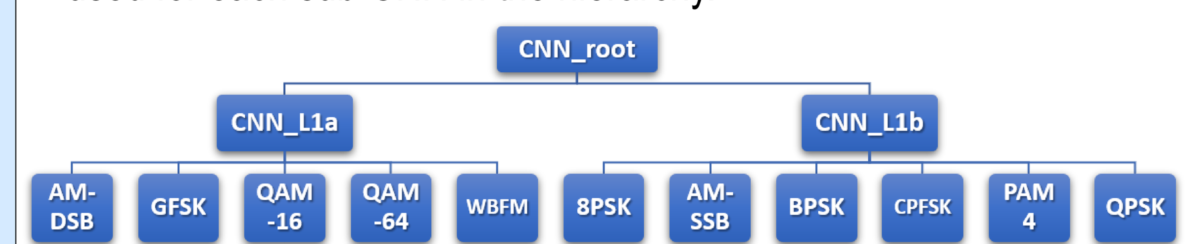


Fig. 7. Model A, a two-level hierarchy of 3 separately trained CNNs.

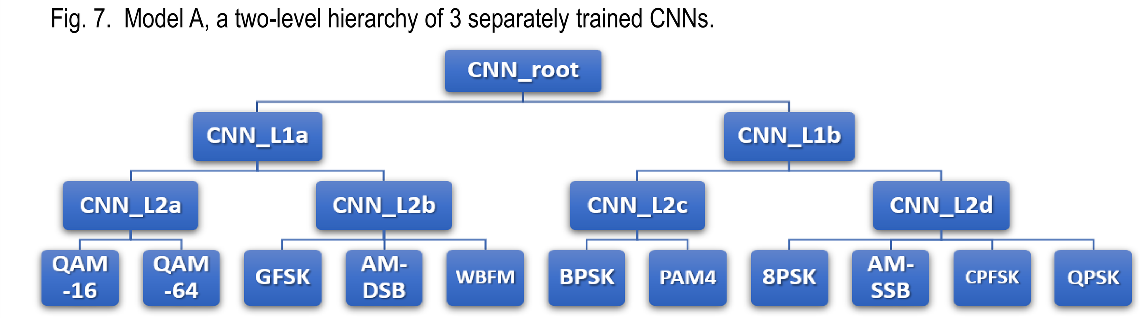


Fig. 8. Model B, a three-level hierarchy of 7 separately trained CNNs.

Results and Analysis

The following table shows the accuracies of all three models and their subclasses, and the overall training time.

Model	Accuracy (All-SNR)		Training (seconds)
Base [1]	50%		900s
Model A	Overall	51%	568s
	CNN root	84%	
	CNN_L1a, L2a	54%, 59%	
Model B	Overall	50%	708s
	CNN_L2a, L2b	50%, 62%	
	CNN_L2c, 2d	83%, 55%	

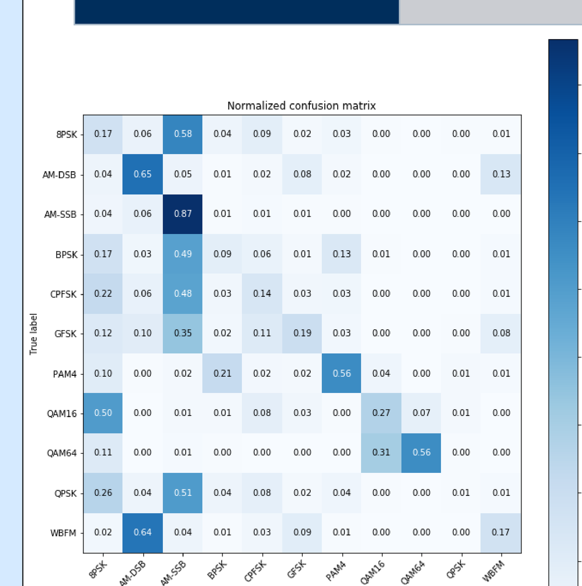


Fig. 9. Confusion matrix of the base CNN model at -8 dB SNR.

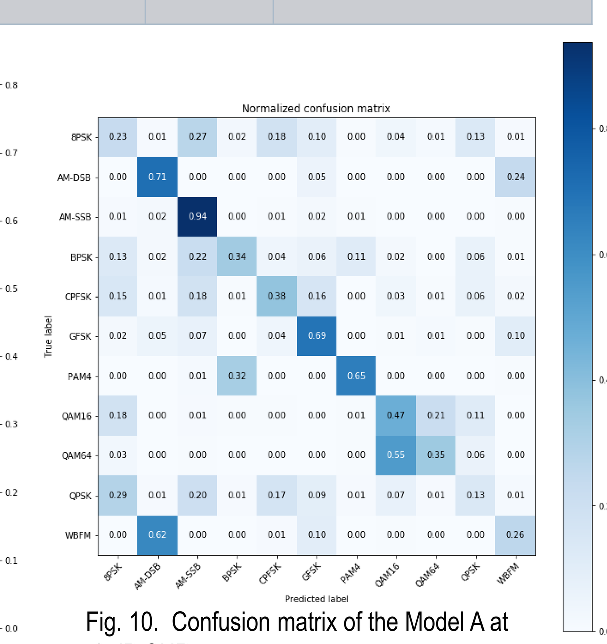


Fig. 10. Confusion matrix of the Model A at -8 dB SNR.

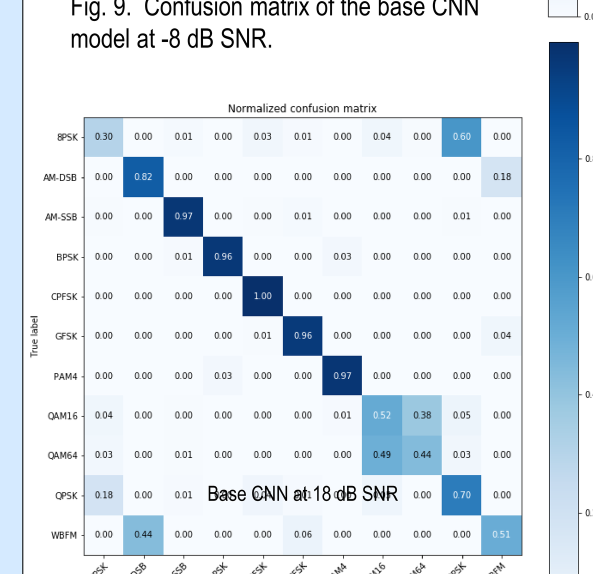


Fig. 11. Confusion matrix of the base CNN model at 18 dB SNR.

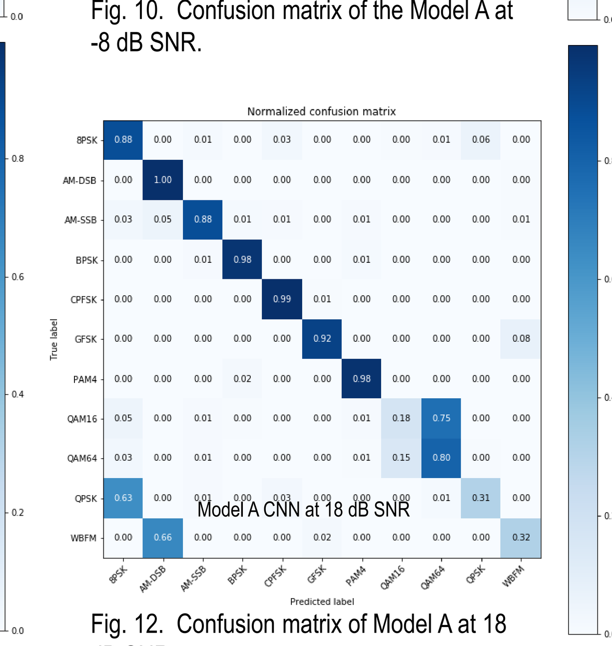


Fig. 12. Confusion matrix of Model A at 18 dB SNR.

Results and Analysis

The reduction in training time is due to each sub-CNN being trained on a smaller subset of the overall data. The root classifier learns the coarse-grained features while lower levels learn fine-grained features. Model A performs better than the base CNN at nearly all SNR levels. Model B performs comparably. Both h-CNNs perform better in low-SNR scenarios than the base model: from SNR levels -20dB to -10dB, Models A and B have a 3.7% and 2.2% average difference in accuracy from the base model.

Current Work

We are currently focusing on the following:
- Fine-tuning Model B for improved classification at lower levels.
- Exploring other CNN hierarchical architectures: experimenting with different weight and error propagation methods as well as deeper hierarchical levels
- How do induced class hierarchies translate to traditional AMC methods? We are comparing K-NN and SVM flat AMC methods to hierarchical K-NN and SVM.

Summary and Future Work

Overall, the hierarchical approach shows promise in reducing training time and improving AMC accuracy under severe channel impairments. By using an induced hierarchy, the overall neural network is guided to learn generic features at higher levels and subsequently learn more intricate features in lower levels where classes are closer in similarity in the feature space. In addition, from a computer architecture perspective, the hierarchical CNN architecture allows for a modular hardware implementation of each sub-CNN. Rather than accessing an entire block of memory containing weights, only the relevant memory locations containing the weights for a sub-CNN need to be accessed. Future work can focus on determining the hardware efficiency increase of an hierarchical CNN.

Key References

[1] T. J. O'Shea and J. Corgan, "Convolutional Radio Modulation Recognition Networks," CoRR, vol. abs/1602.04105, 2016.
[2] K. Karra, S. Kuzdeba and J. Petersen, "Modulation recognition using hierarchical deep neural networks," *2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*, Piscataway, NJ, 2017, pp. 1-3.
[3] D. Silva-Palacios, C. Ferri and M. J. Ramirez-Quintana, "Improving Performance of Multiclass Classification by Inducing Class Hierarchies," *ICCS, Zurich*, Switzerland, 2017, pp. 1692-1701.
[4] T. J. O'Shea and N. West, "Radio Machine Learning Dataset Generation with GNU radio," in Proceedings of the GNU Radio Conference, vol. 1, 2016.

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