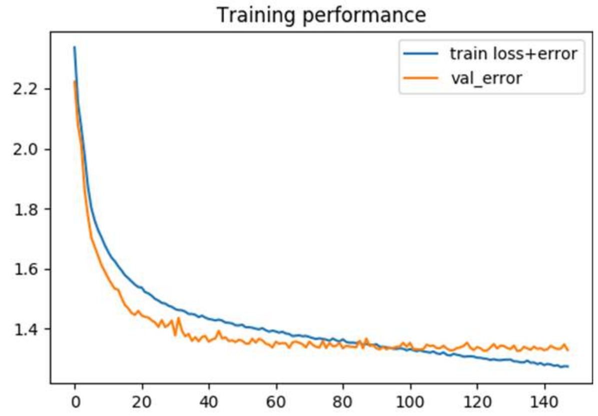
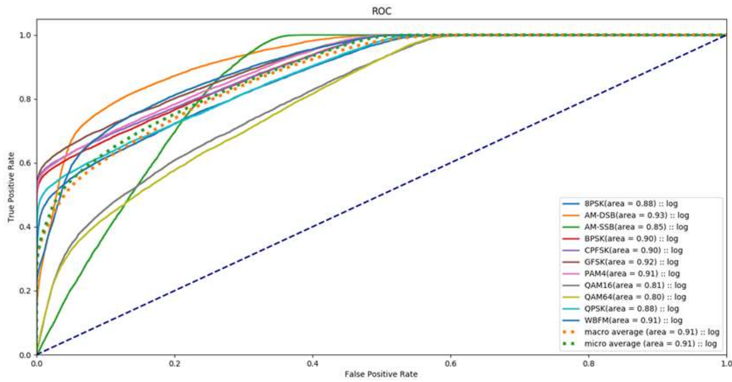
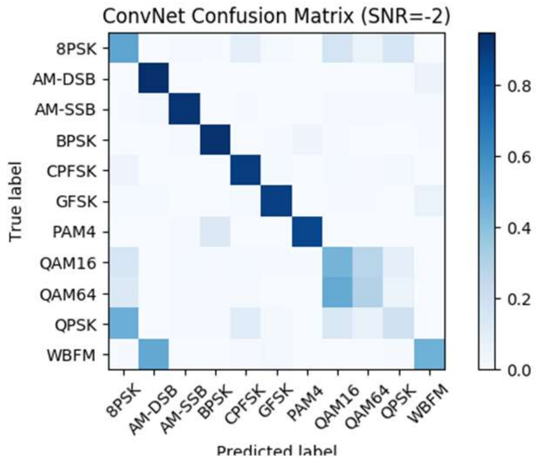
CLASSIFICAÇÃO DE MODULAÇÃO UTILIZANDO DEEP LEARNING

LETÍCIA C. DE SOUZA

GUSTAVO DE ANDRADE C. POLICARPO







AGENDA

- Motivação
- Proposta
- *Convolutional Neural Network* – CNN
- *Residual Networks* – ResNet
- *Densely Connected Networks* – DenseNet
- *Long Short-Term Memory* – LSTM
- *Convolutional Long Short-term Deep Neural Network* – CLDNN
- Conclusões
- Trabalhos Futuros

Fast Deep Learning for Automatic Modulation Classification

Sharan Ramjee, *Student Member, IEEE*, Shengtai Ju, *Student Member, IEEE*, Diyu Yang, *Student Member, IEEE*, Xiaoyu Liu, *Student Member, IEEE*, Aly El Gamal, *Member, IEEE* and Yonina C. Eldar, *Fellow, IEEE*

Abstract

In this work, we investigate the feasibility and effectiveness of employing deep learning algorithms for automatic recognition of the modulation type of received wireless communication signals from subsampled data. Recent work considered a GNU radio-based data set that mimics the imperfections in a real wireless channel and uses 10 different modulation types. A Convolutional Neural Network (CNN) architecture was then developed and shown to achieve performance that exceeds that of expert-based approaches. Here, we continue this line of work and investigate deep neural network architectures that deliver high classification accuracy. We identify three architectures - namely, a Convolutional Long Short-term Deep Neural Network (CLDNN), a Long Short-Term Memory neural network (LSTM), and a deep Residual Network (ResNet) - that lead to typical classification accuracy values around 90% at high SNR. We then study algorithms to reduce the training time by minimizing the size of the training data set, while incurring a minimal loss in classification accuracy. To this end, we demonstrate the performance of Principal Component Analysis in significantly reducing the training time, while maintaining good performance at low SNR. We also investigate subsampling techniques that further reduce the training time, and pave the way for online classification at high SNR. Finally, we identify representative SNR values for training each of the candidate architectures, and consequently, realize drastic reductions of the training time, with negligible loss in classification accuracy.

Convolutional Radio Modulation Recognition Networks

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Abstract. We study the adaptation of convolutional neural networks to the complex-valued temporal radio signal domain. We compare the efficacy of radio modulation classification using naively learned features against using expert feature based methods which are widely used today and e show significant performance improvements. We show that blind temporal learning on large and densely encoded time series using deep convolutional neural networks is viable and a strong candidate approach for this task especially at low signal to noise ratio.

Keywords: Machine learning · Radio · Software radio · Convolutional networks · Deep learning · Modulation recognition · Cognitive radio · Dynamic spectrum access

Radio Machine Learning Dataset Generation with GNU Radio

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Abstract

This paper surveys emerging applications of Machine Learning (ML) to the Radio Signal Processing domain. Provides some brief background on enabling methods and discusses some of the potential advancements for the field. It discusses the critical importance of good datasets for model learning, testing, and evaluation and introduces several public open source synthetic datasets for various radio machine learning tasks. These are intended to provide a robust common baselines for those working in the field and to provide a benchmark measure against which many techniques can be rapidly evaluated and compared.

cations researchers are now increasingly considering these methods, but lack common benchmarks and open datasets for evaluating advances as seen in other application areas.

1.1. Early Methods

Deep Neural Networks have been rapidly maturing and being applied to many new and old machine learning applications and problem spaces. Many key ideas have been around for many years. Hebbian Learning (Hebb, 1949), the notion that the brain as a network of neurons, slowly learns based on some form of corrective feedback which adjusts neural firing parameters and synaptic weights. The perceptron (Rosenblatt, 1958), a probabilistic model for a Hebbian neuron using a simple activation function on inputs using a set of weights which could be used for classifi-

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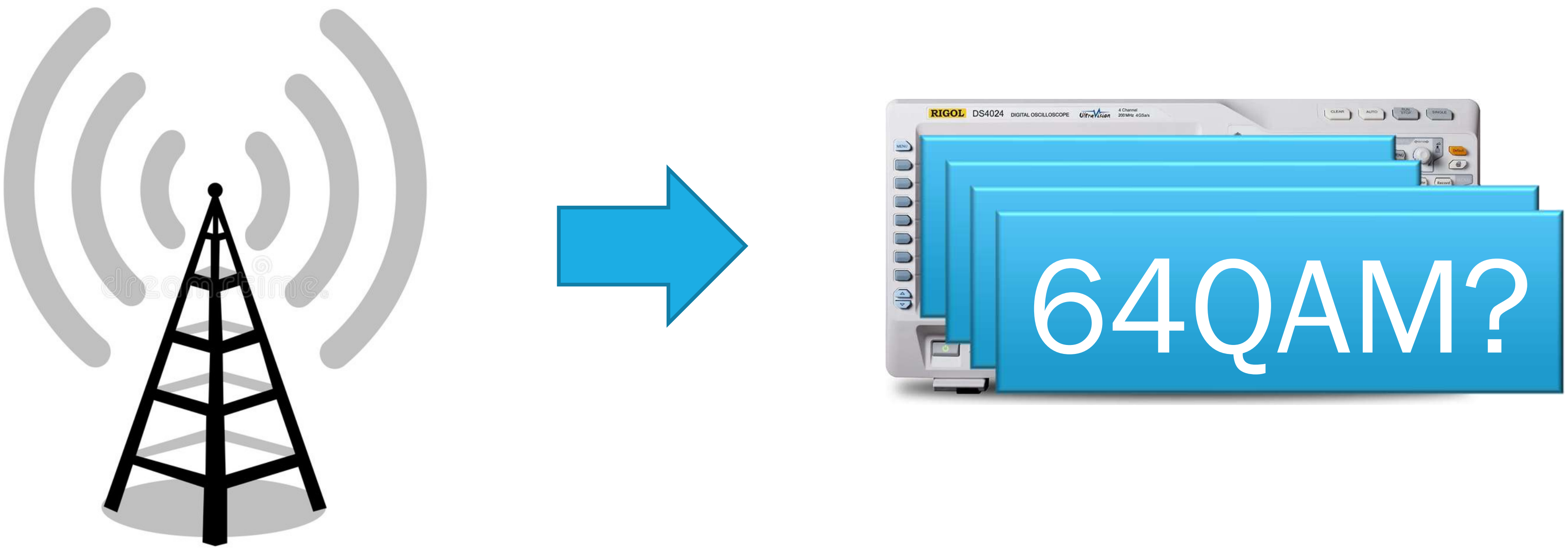
MOTIVAÇÃO



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PROPOSTA

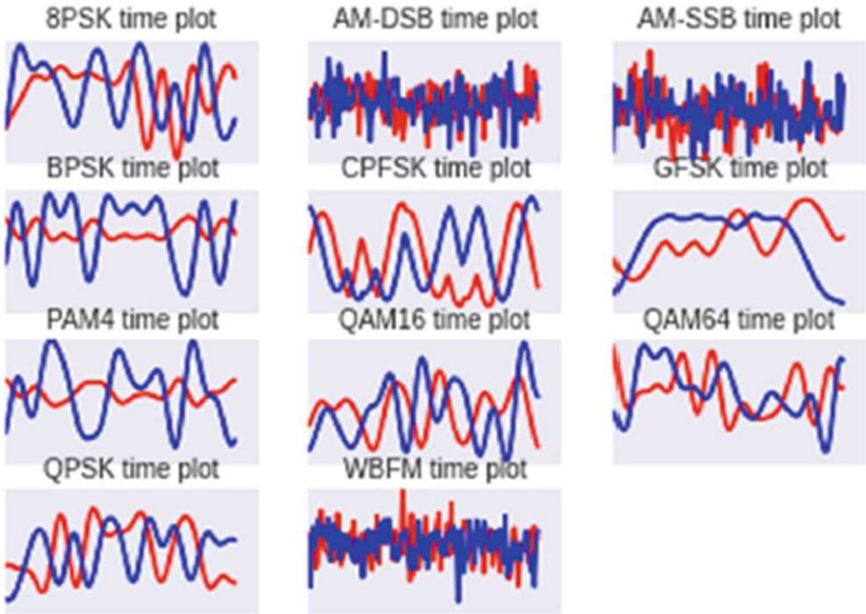

Fig. 1. Time domain of high-SNR example classes

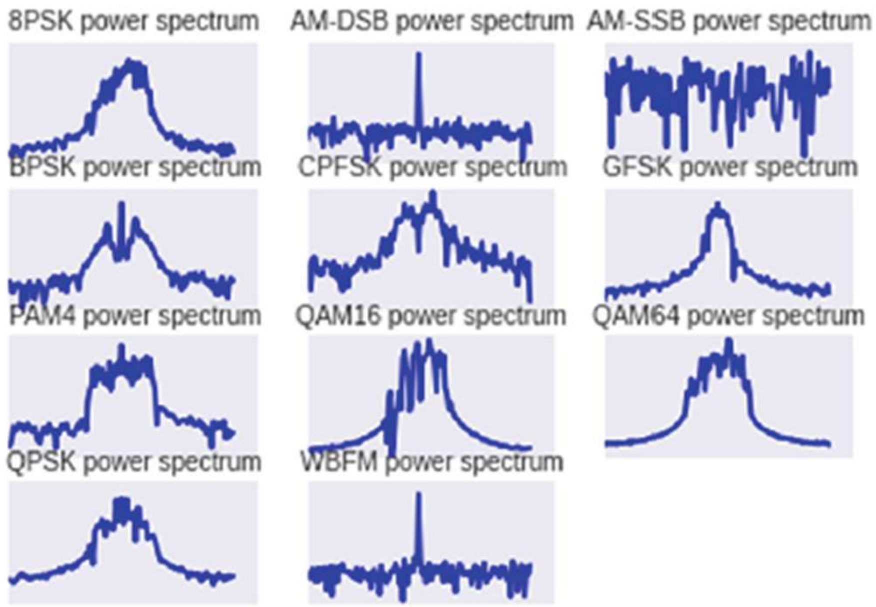

Fig. 2. Power spectrum of high-SNR example classes

DATASET

- Foi utilizado o dataset RadioML2016.10a.
- Para **modulações digitais**, foram utilizadas as obras de Shakespeare em ASCII de Gutenberg.
- Para **modulações analógicas**, um sinal de voz continuo é usado, que consiste principalmente em voz acústica com alguns interlúdios e intervalos.
- **O modelo de canal** foi simulado adicionando-se efeitos como ruído térmico e desvanecimento de multipercurso.

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CONVOLUTIONAL NEURAL NETWORK – CNN

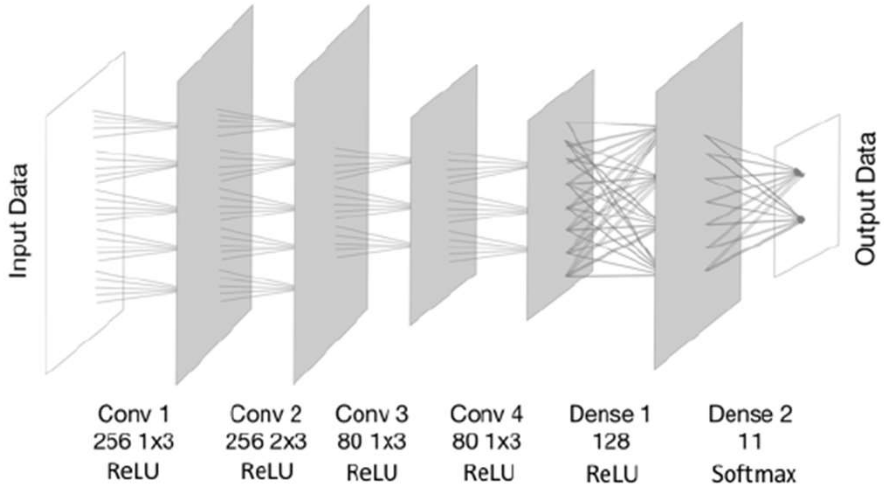
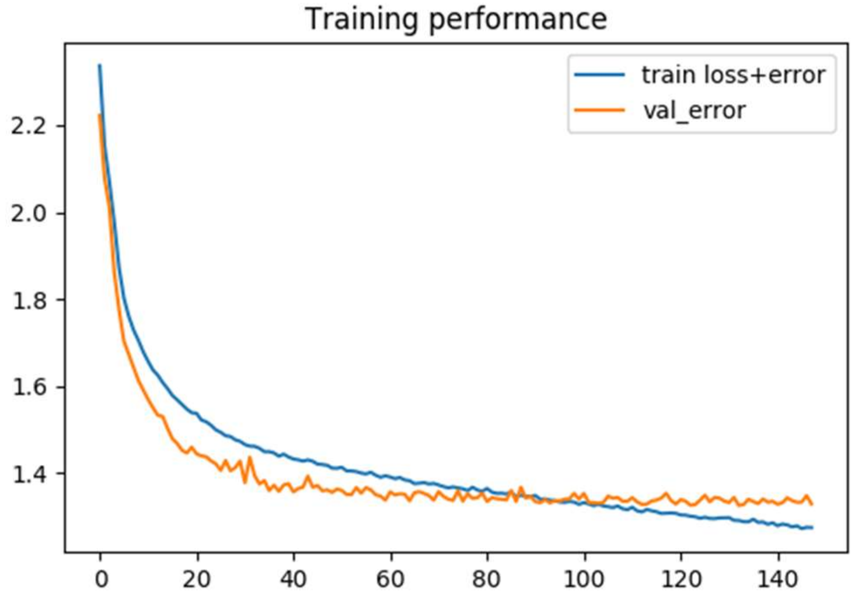
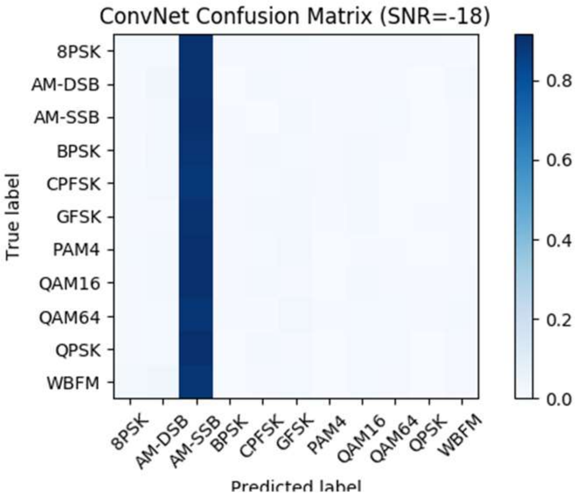
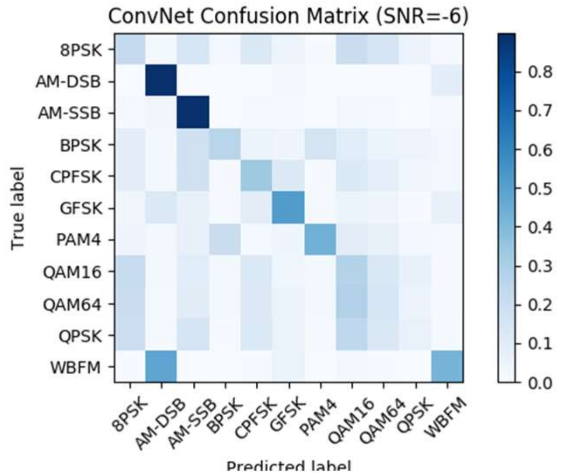


Fig. 2: CNN architecture.



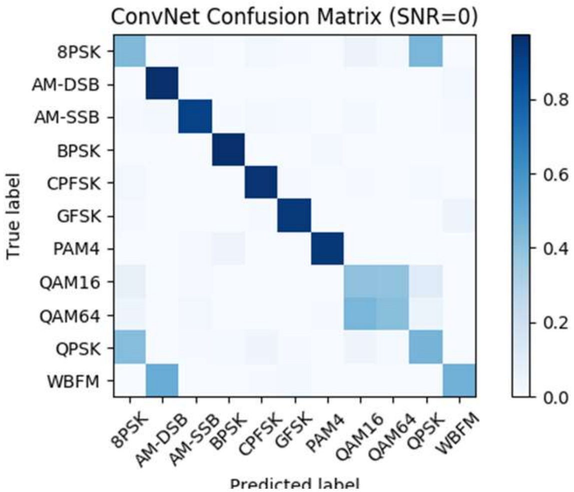
SNR = -18 dB

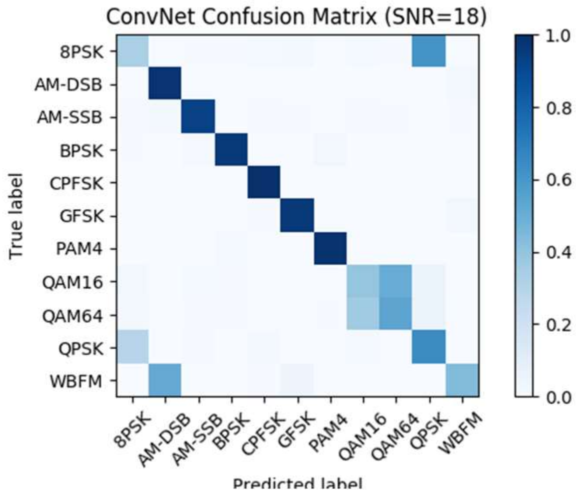




SNR = -6 dB

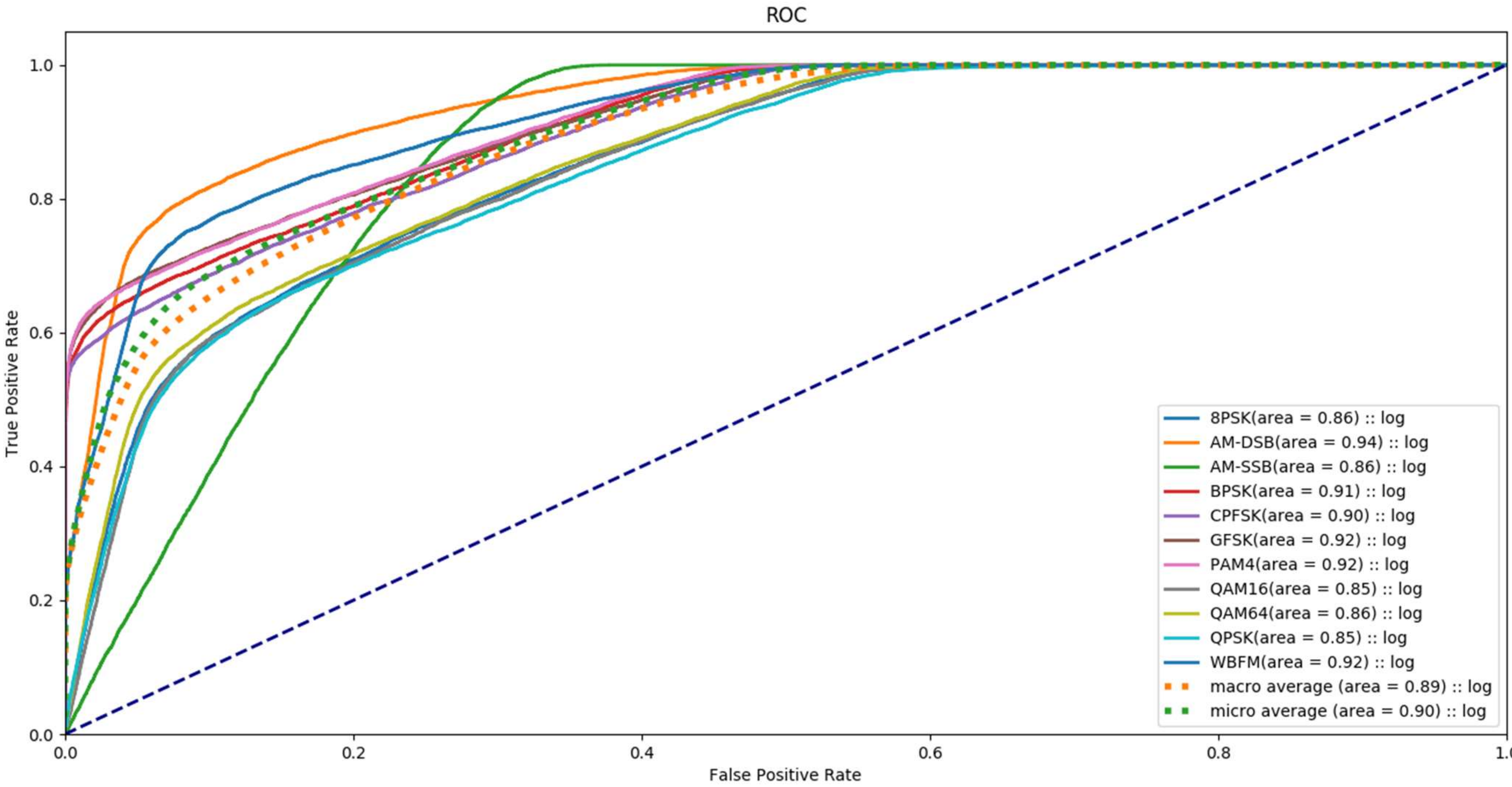
SNR = 0 dB





SNR = 18 dB

CURVA ROC - CNN



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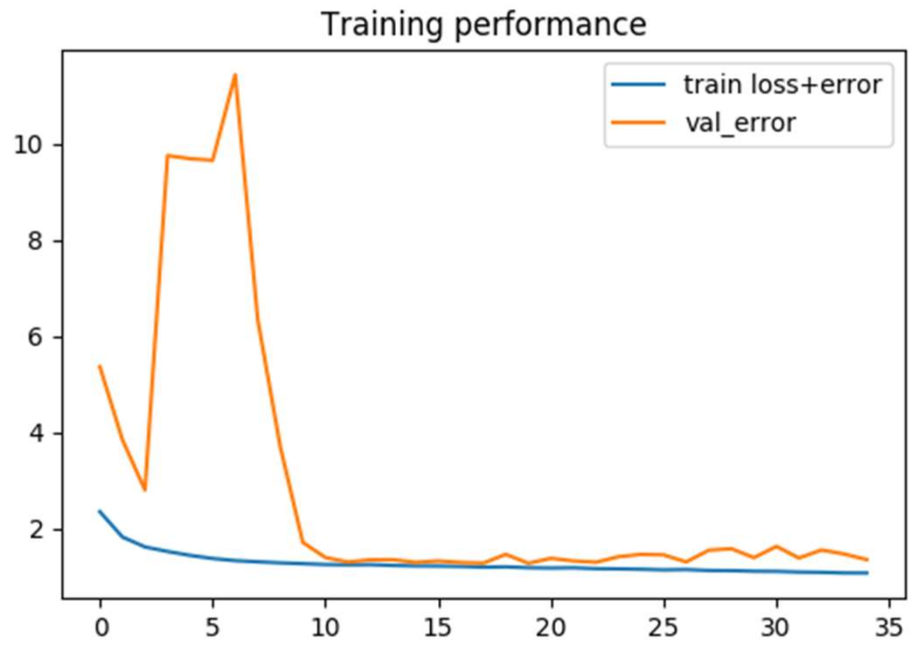
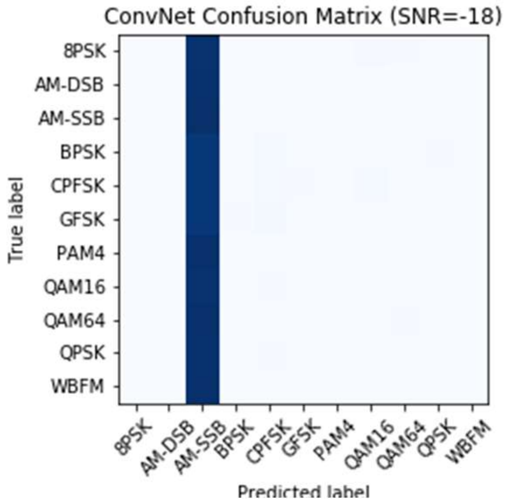
RESIDUAL NETWORKS – RESNET

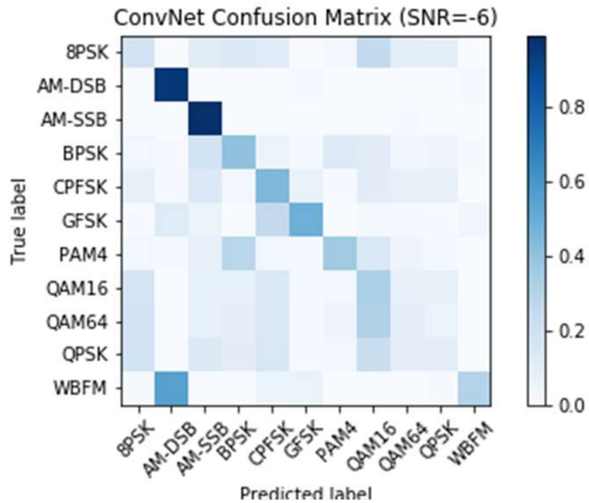
Layer	Output dimensions
Input	2x128
Residual Stack	32x64
Residual Stack	32x32
Residual Stack	32x16
FC/ReLU	128
FC/ReLU	128
FC/Softmax	10

TABLE I: ResNet Architecture.



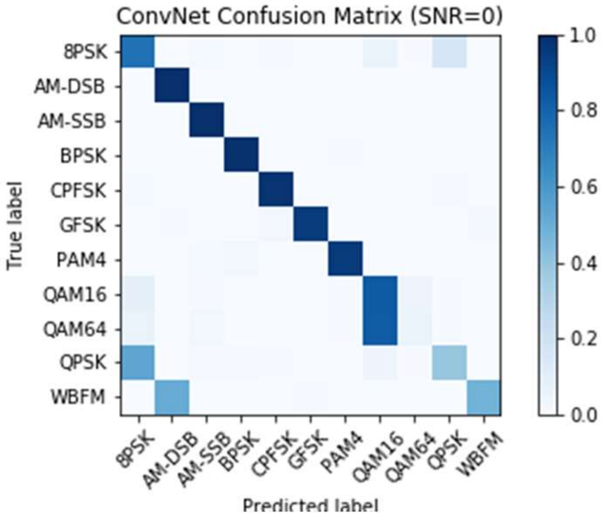
SNR = -18 dB

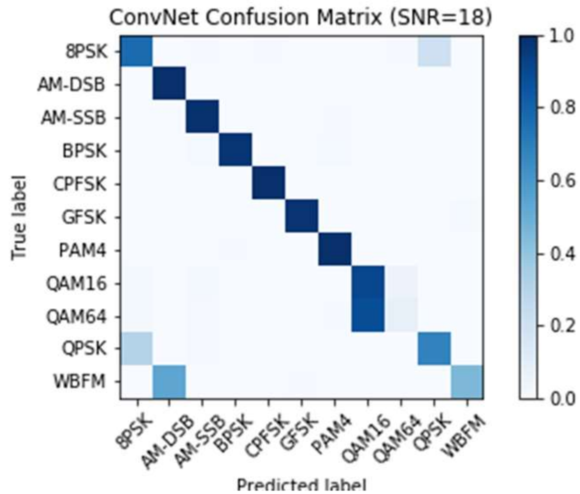




SNR = -6 dB

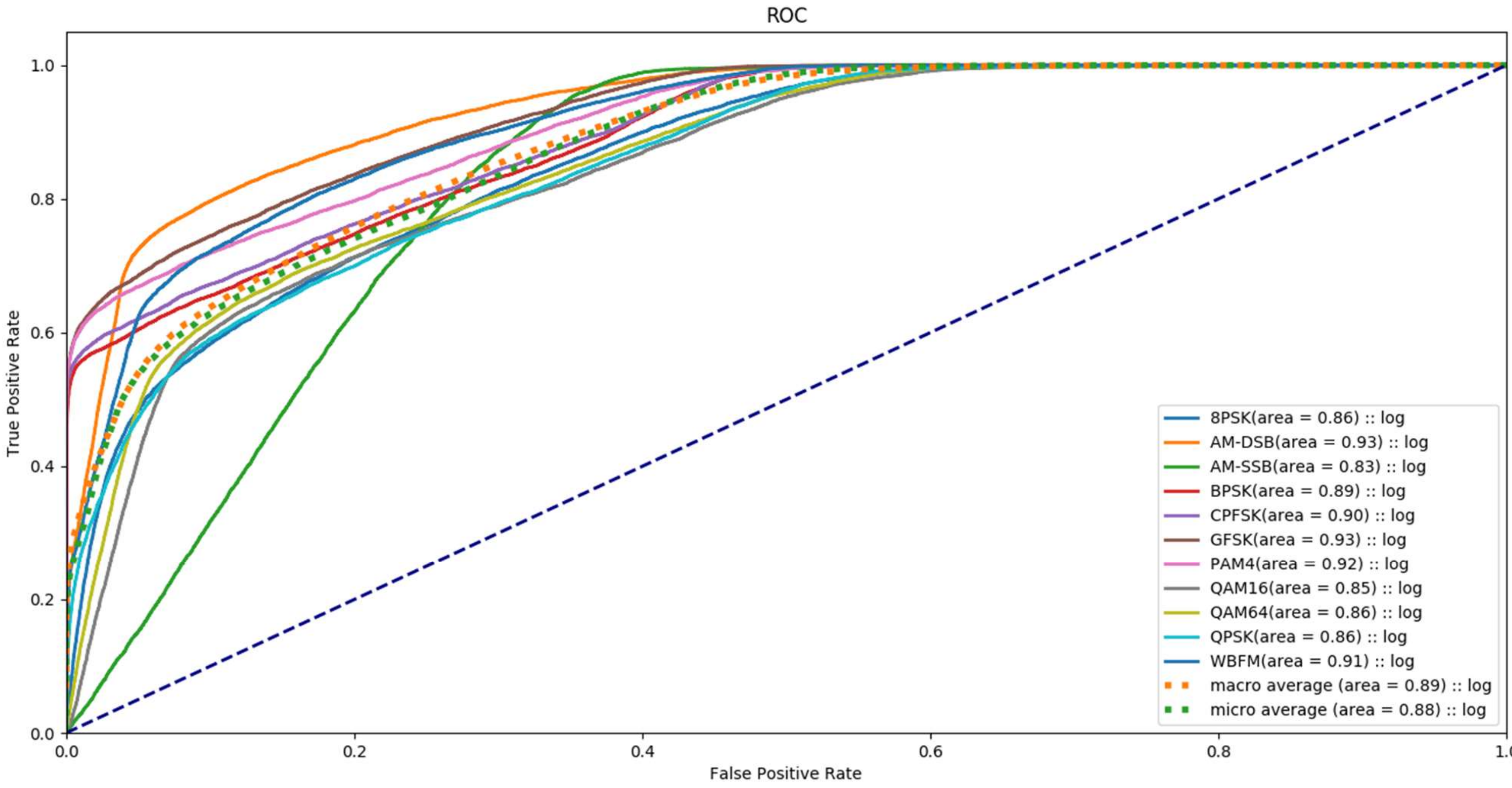
SNR = 0 dB





SNR = 18 dB

CURVA ROC - RESNET



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DENSELY CONNECTED NETWORKS – DENSENET

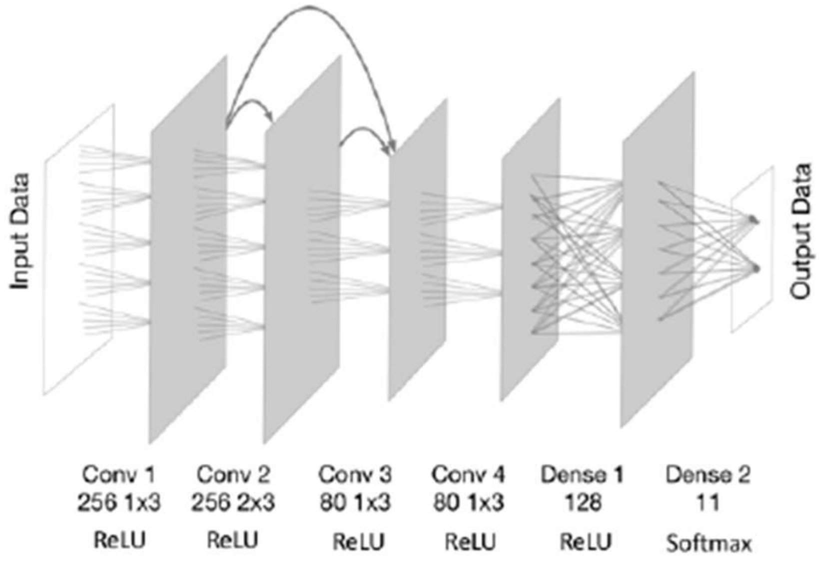
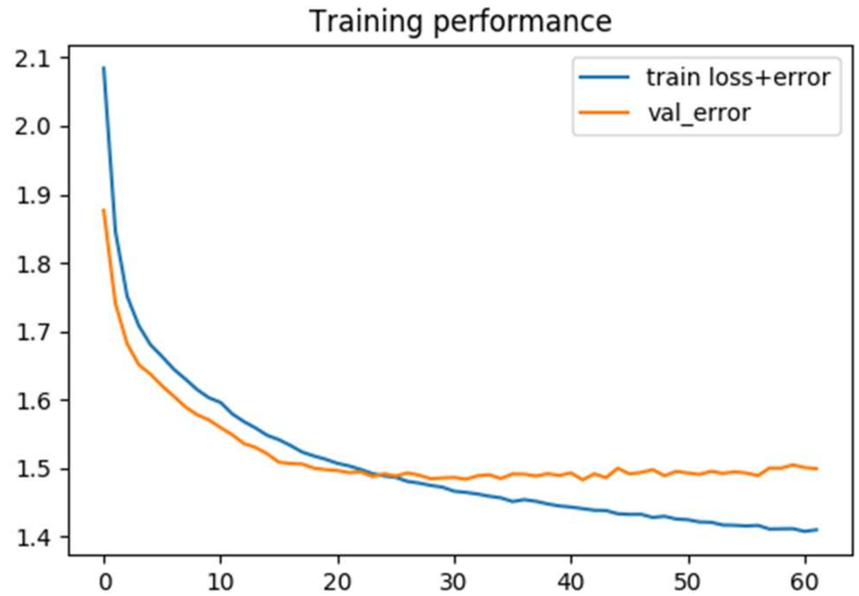


Fig. 3: DenseNet architecture.



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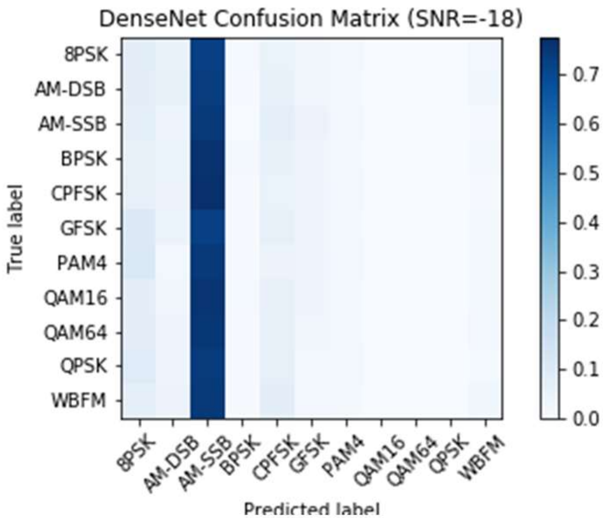
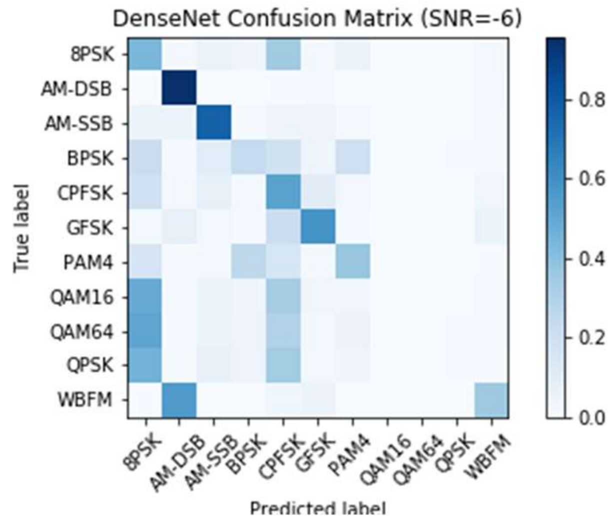
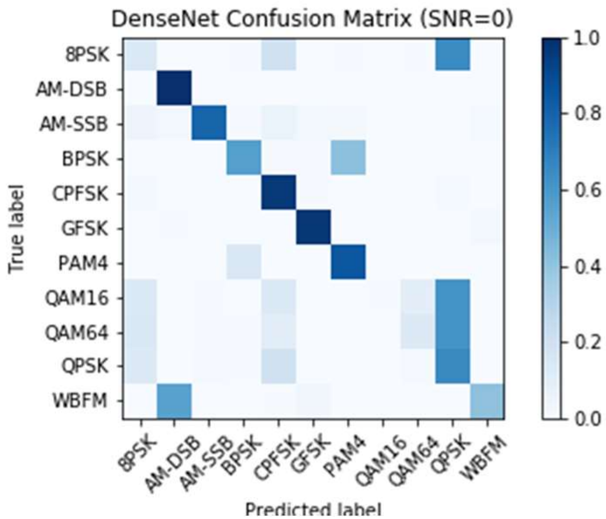
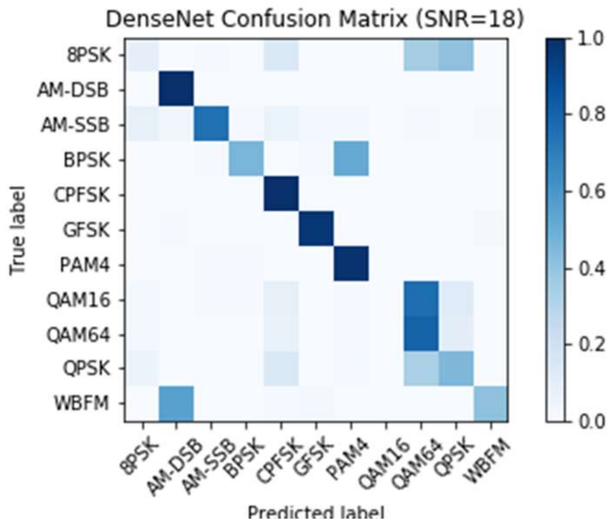




SNR = -6 dB

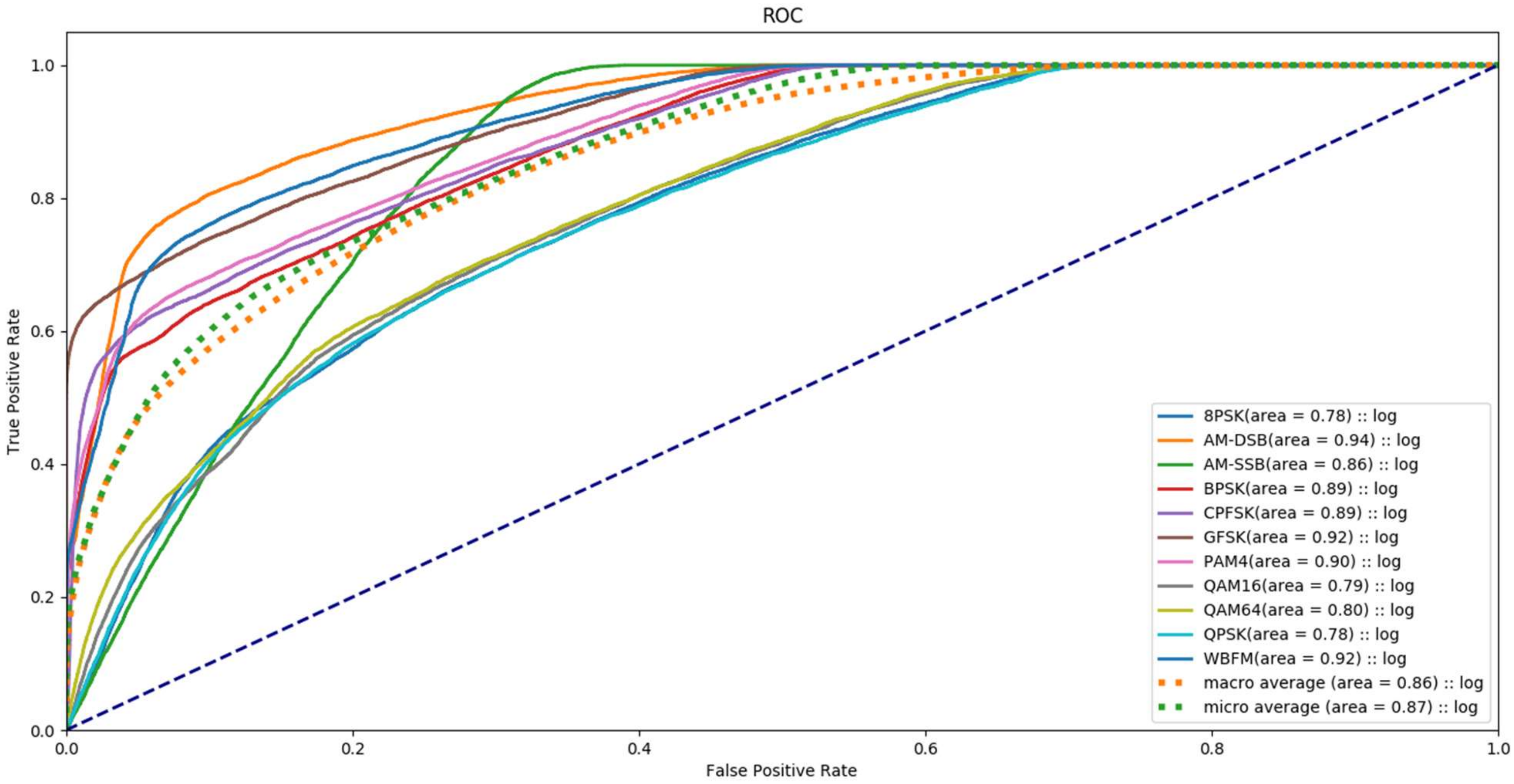
SNR = 0 dB





SNR = 18 dB

CURVA ROC - DENSENET



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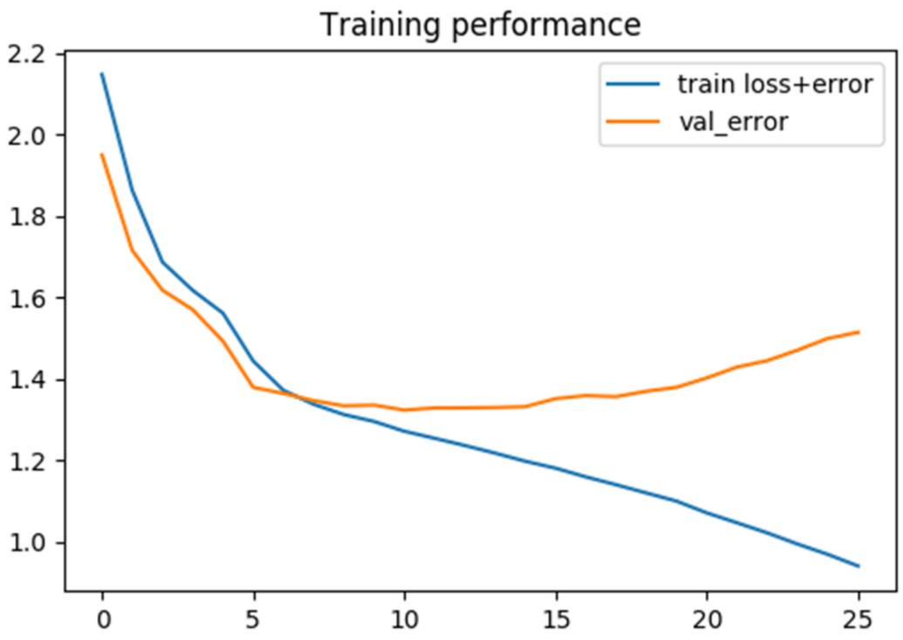
LONG SHORT-TERM MEMORY – LSTM



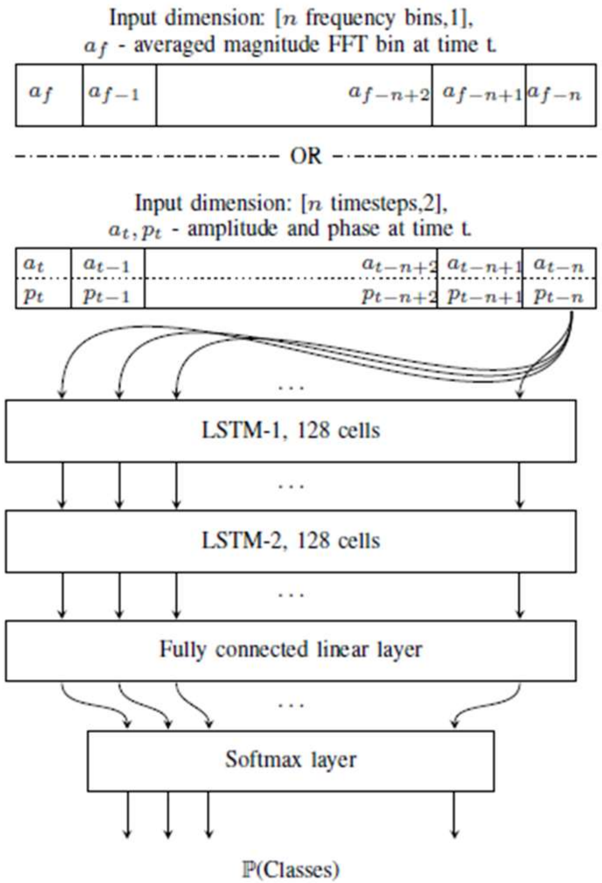
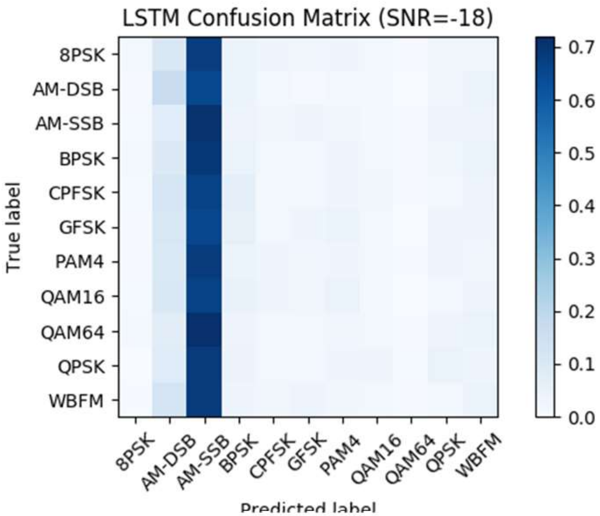
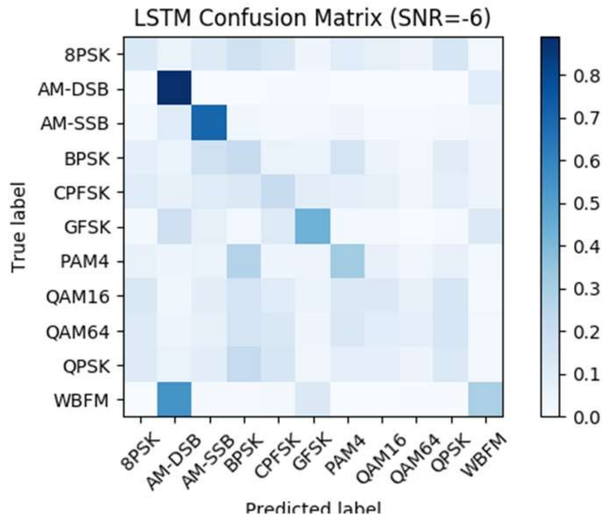


Fig. 2: Two layer LSTM model for classification. The model is trained and deployed for modulation classification using either amplitude-phase signal or the averaged magnitude-FFT signal as input.

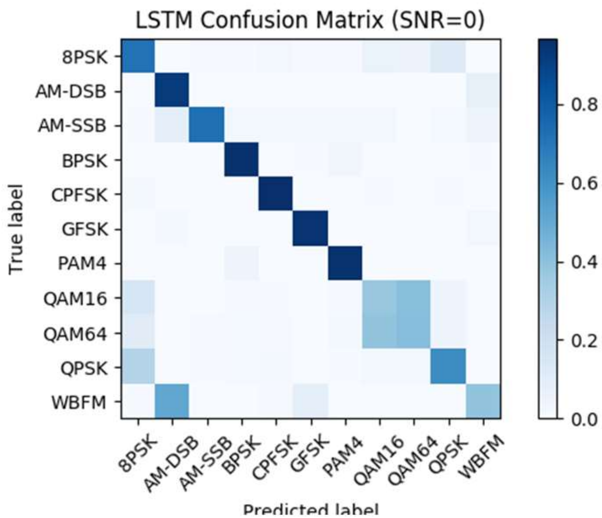
SNR = -18 dB



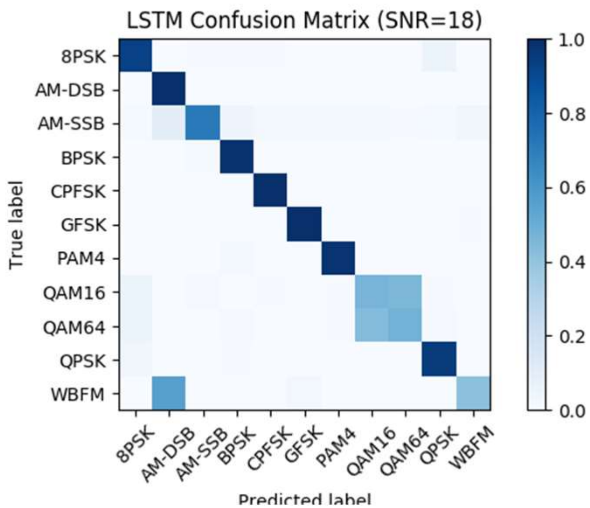
SNR = -6 dB



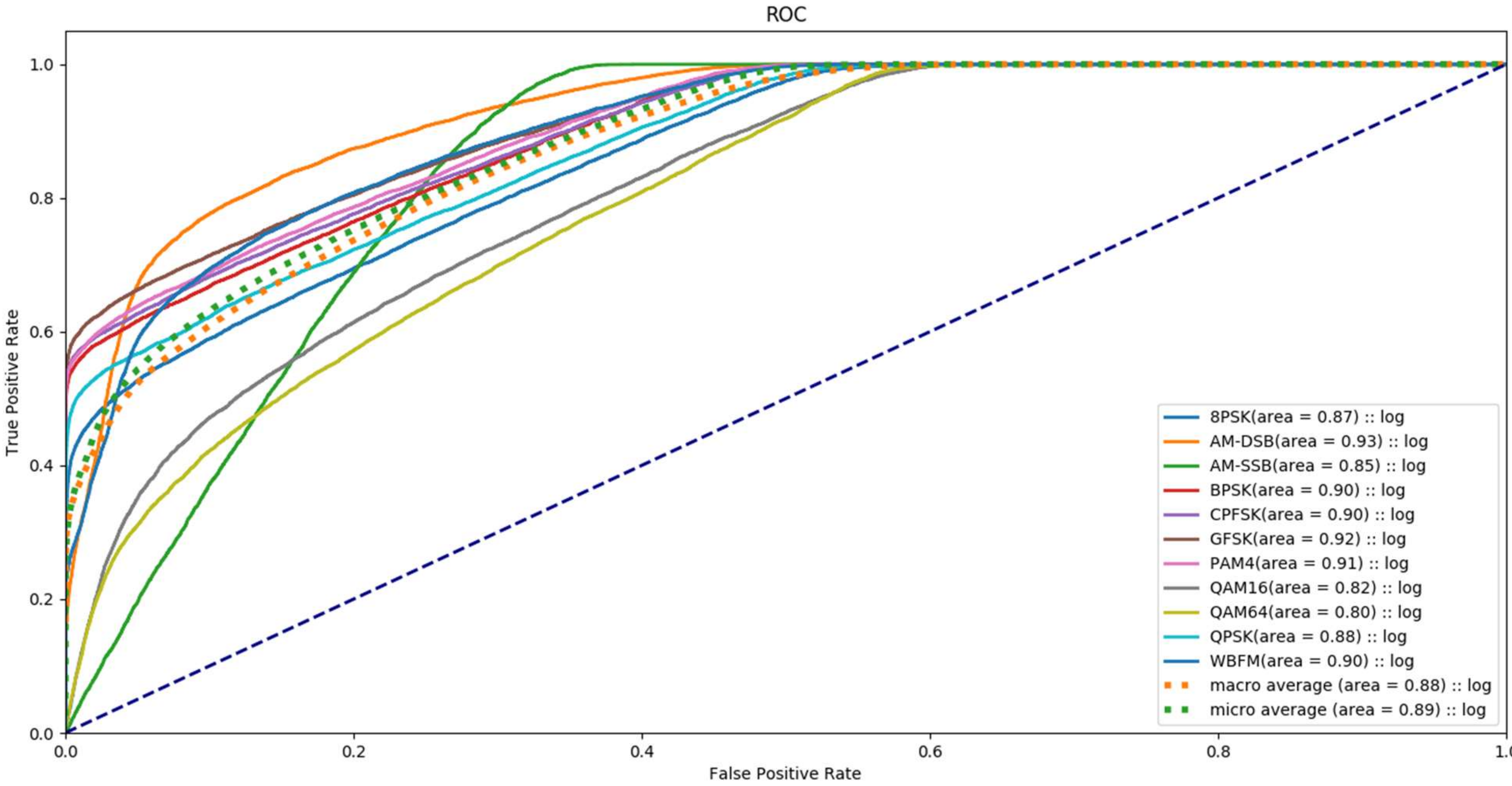
SNR = 0 dB



SNR = 18 dB



CURVA ROC - LSTM



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CONVOLUTIONAL LONG SHORT-TERM DEEP NEURAL NETWORK – CLDNN

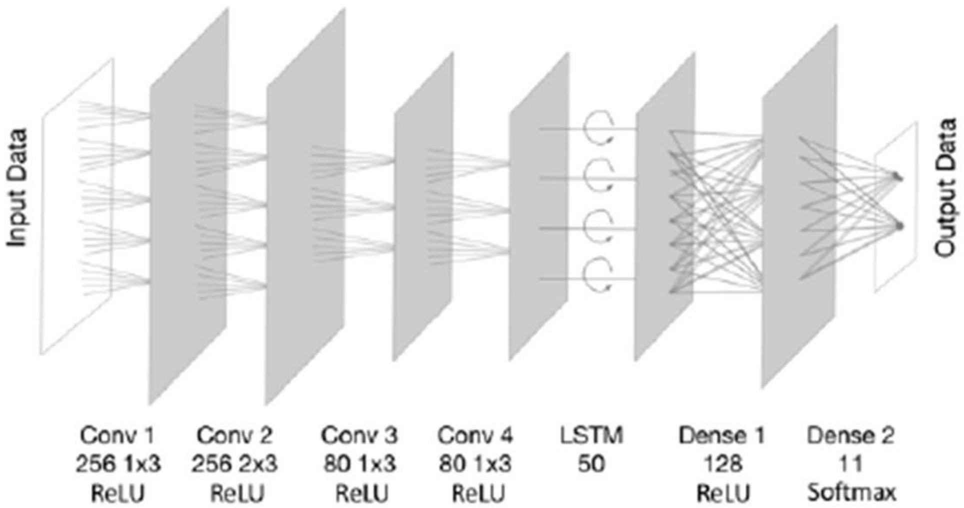
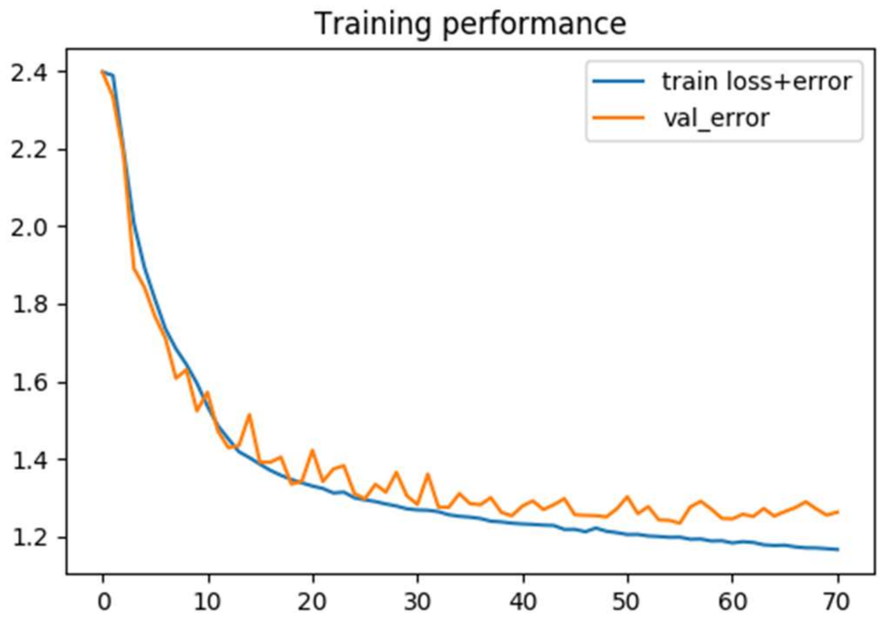
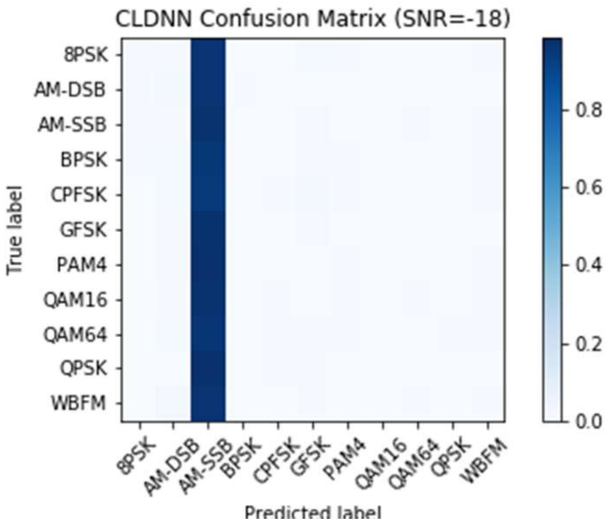
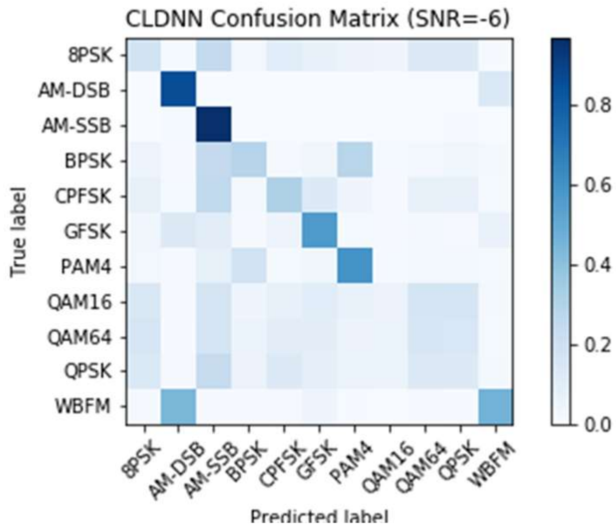


Fig. 4: CLDNN architecture.



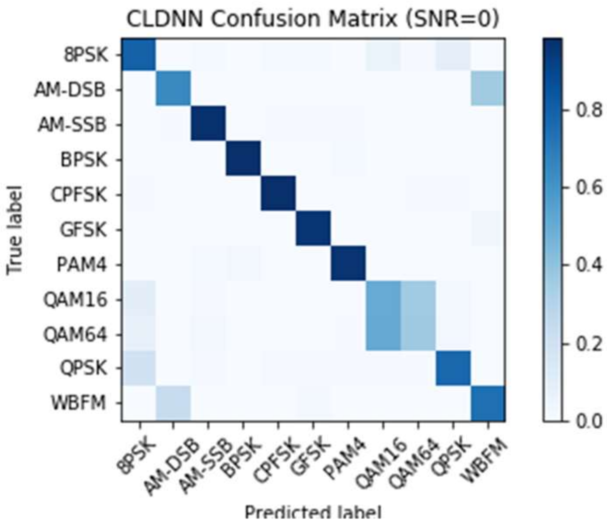
SNR = -18 dB

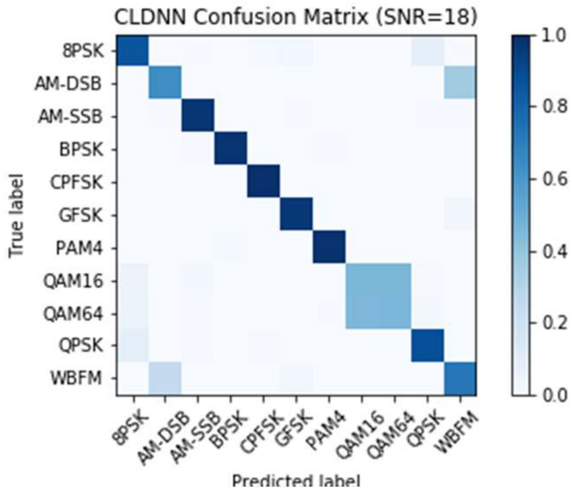




SNR = -6 dB

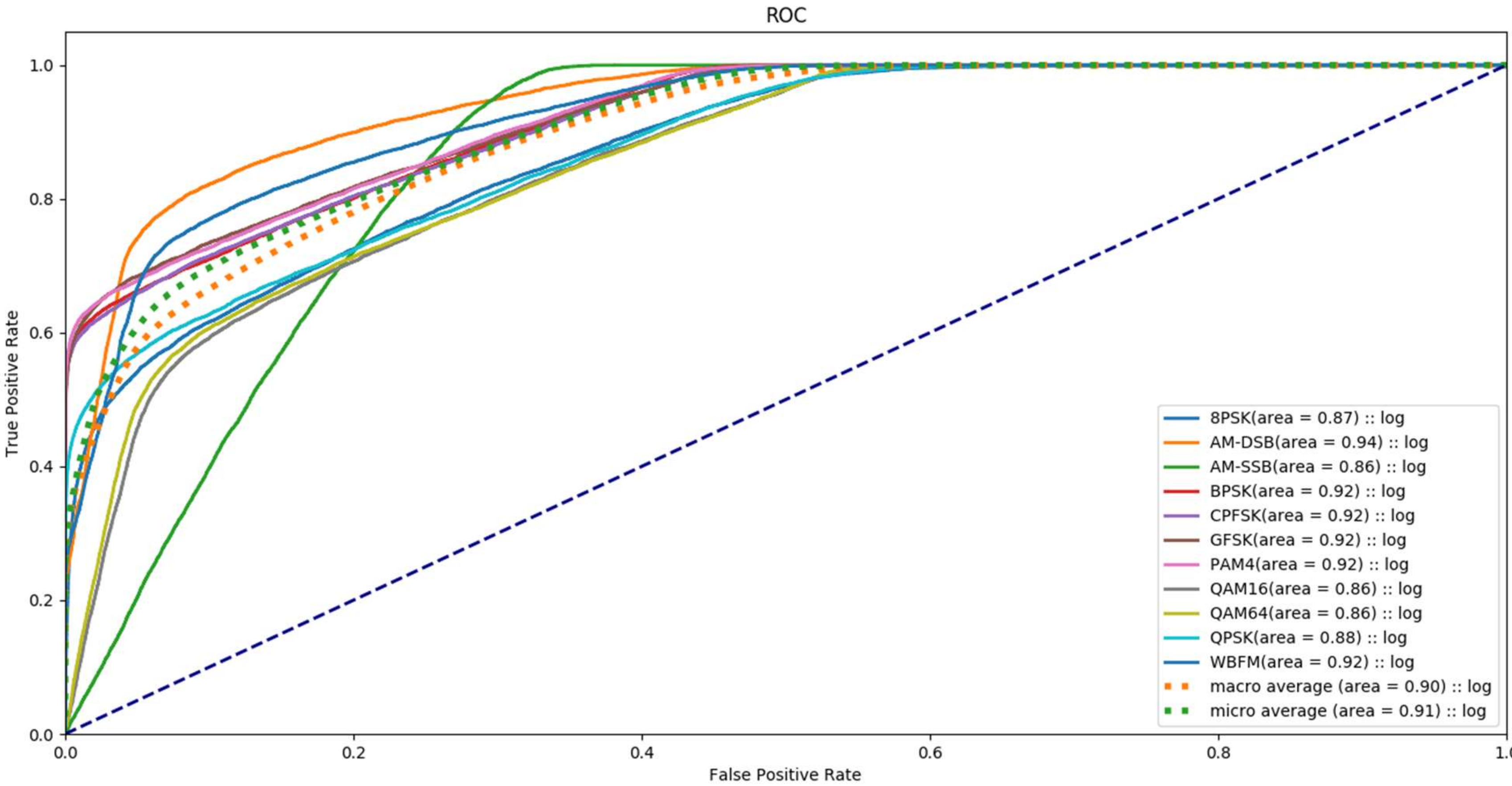
SNR = 0 dB





SNR = 18 dB

CURVA ROC - CLDNN



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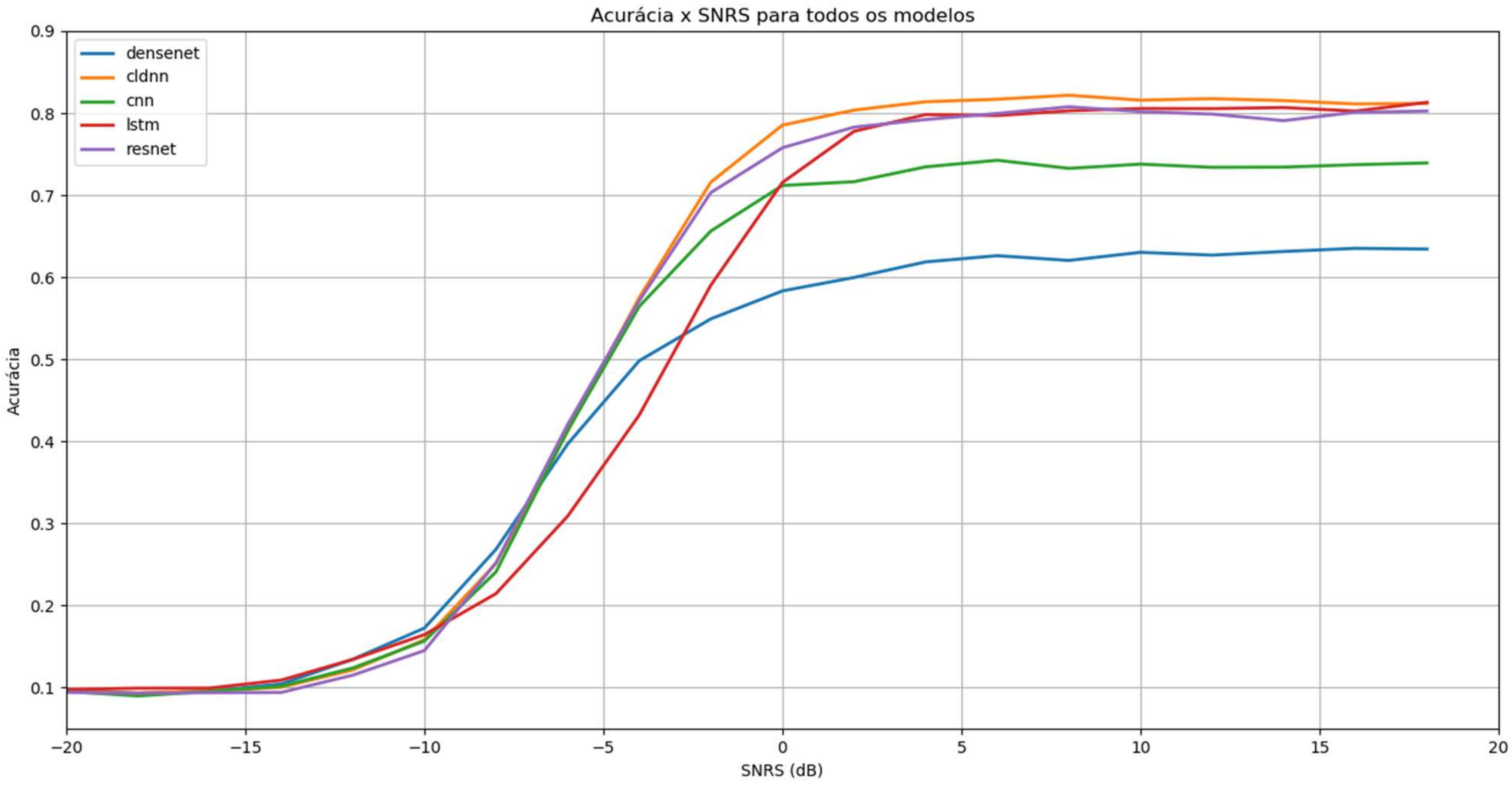
CONCLUSÕES



Acurácia x SNRS para todos os modelos
densenet
cldnn
cnn
lstm
resnet
Acurácia
SNRS (dB)
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
−20
−15
−10
−5
0
5
10
15
20

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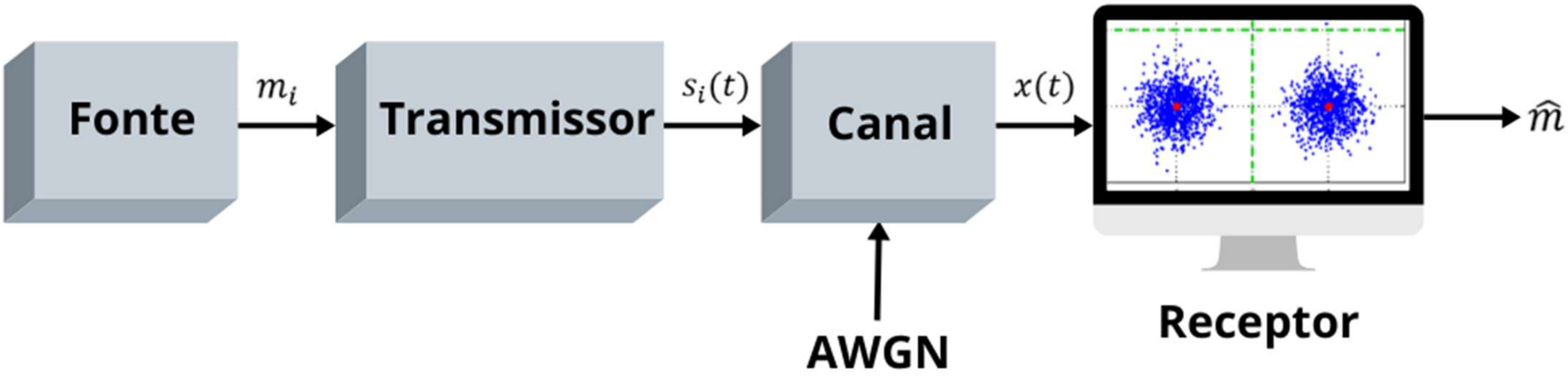
TRABALHOS FUTUROS

- Atualização do código

- Implementação prática



OBRIGADO!