

MATLAB EXPO

2021

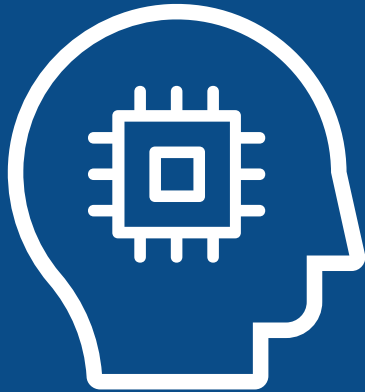
신호 및 시계열 데이터를 위한 인공지능

김종남 부장



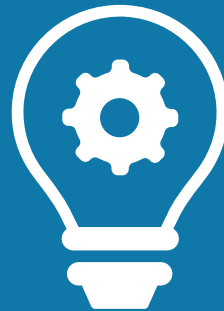
Machine Learning and Deep learning have grown rapidly over the last decade

ARTIFICIAL INTELLIGENCE



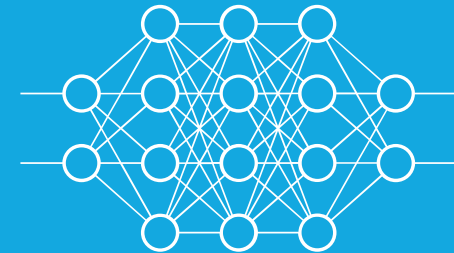
MACHINE LEARNING

Supervised and Unsupervised Statistical Models...



DEEP LEARNING

Neural networks, GANs, Autoencoders....

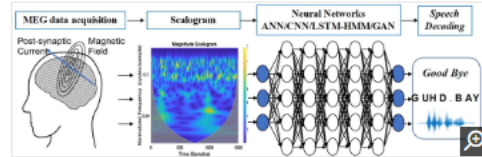


Use of AI in signal processing applications is growing rapidly

UT Austin Researchers Convert Brain Signals to Words and Phrases Using Wavelets and Deep Learning

"MATLAB is an industry-standard tool, and one that you can trust. It is easier to learn than other languages, and its toolboxes help you get started in new areas because you don't have to start from scratch."

— Dr. Jun Wang, UT Austin



Classifying the brain signals corresponding to the imagined word "goodbye" using feature extraction and deep neural networks.

Shell performs Seismic Event Detection with Deep Learning

Challenges

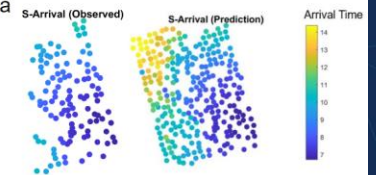
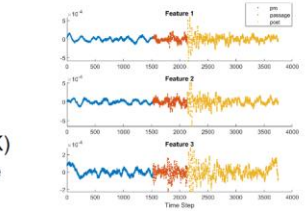
- Terabytes of passive seismic data from geophones
- Traditional methods time/labor intensive (5 months & ~\$100K)
- Event detection inconsistent/unreliable in 'low' signal to noise records

Solution

- Train LSTM network to detect P-wave and S-wave arrivals via sequence-to-sequence classification

Results

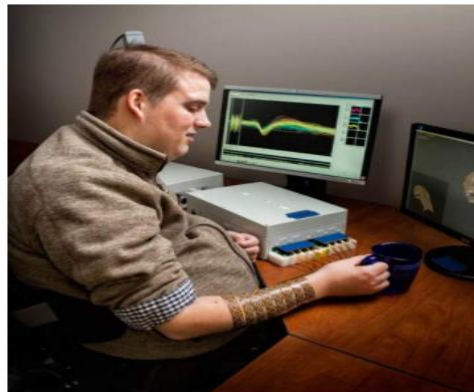
- >98% accuracy for arrival prediction
- Networks generalizes to other data (sites, source mechanisms)



Battelle Neural Bypass Technology Restores Movement to a Paralyzed Man's Arm and Hand

"The algorithms we developed using MATLAB gave the participant back basic control of his arm and hand. By the end of the study, he could grip a bottle, pour out its contents, and set it down, as well as pick up a stir stick and execute a stirring motion."

— David Friedenberg, Battelle



Patient using the Battelle NeuroLife system.

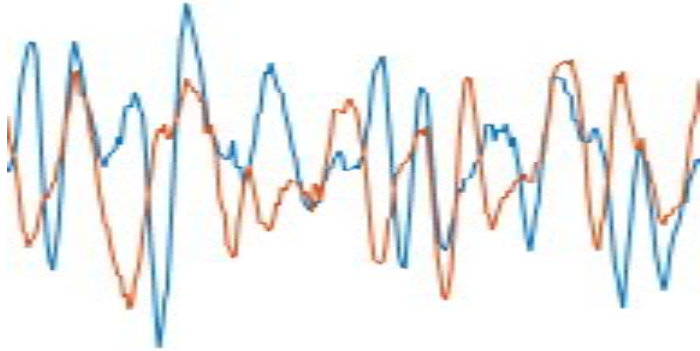


Voice Interface: The Touchscreen of the Next Century

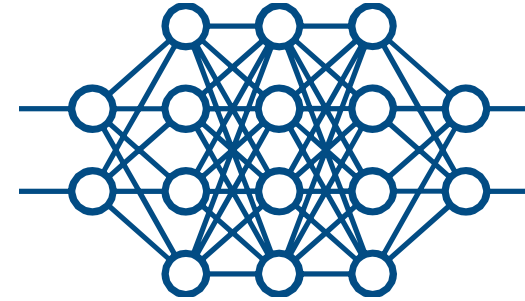
How AI and Signal Processing Came Together to Track the DNA of Sound

Modulation Classification of RF waveforms

TRANSMITTER
(Software
Defined Radio)



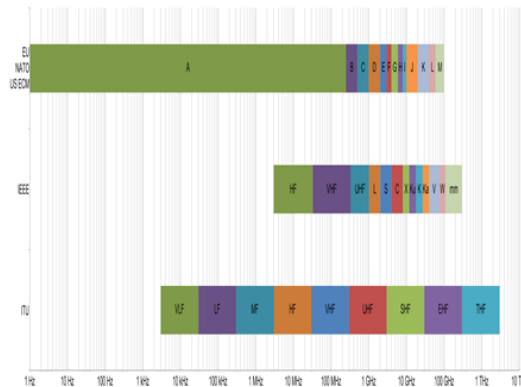
RECEIVER
(Software
Defined Radio)



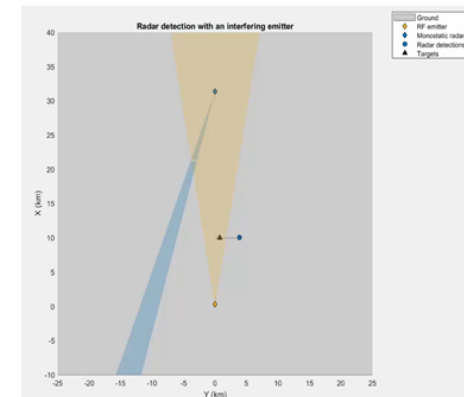
**Modulation
Type**



Intelligent Receivers

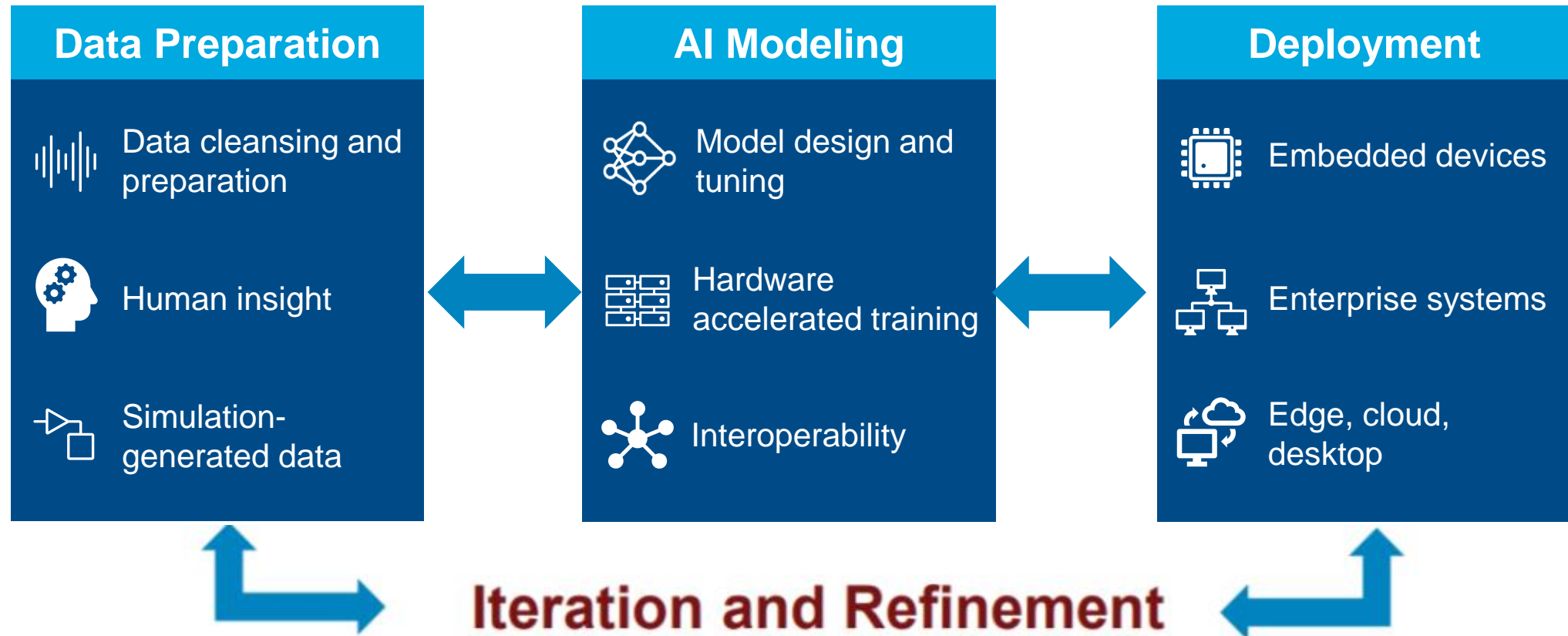


Spectrum Management



Radar Interference Detection

AI-driven system design



Preparing and labelling data

Data Preparation



Data cleansing and preparation



Human insight

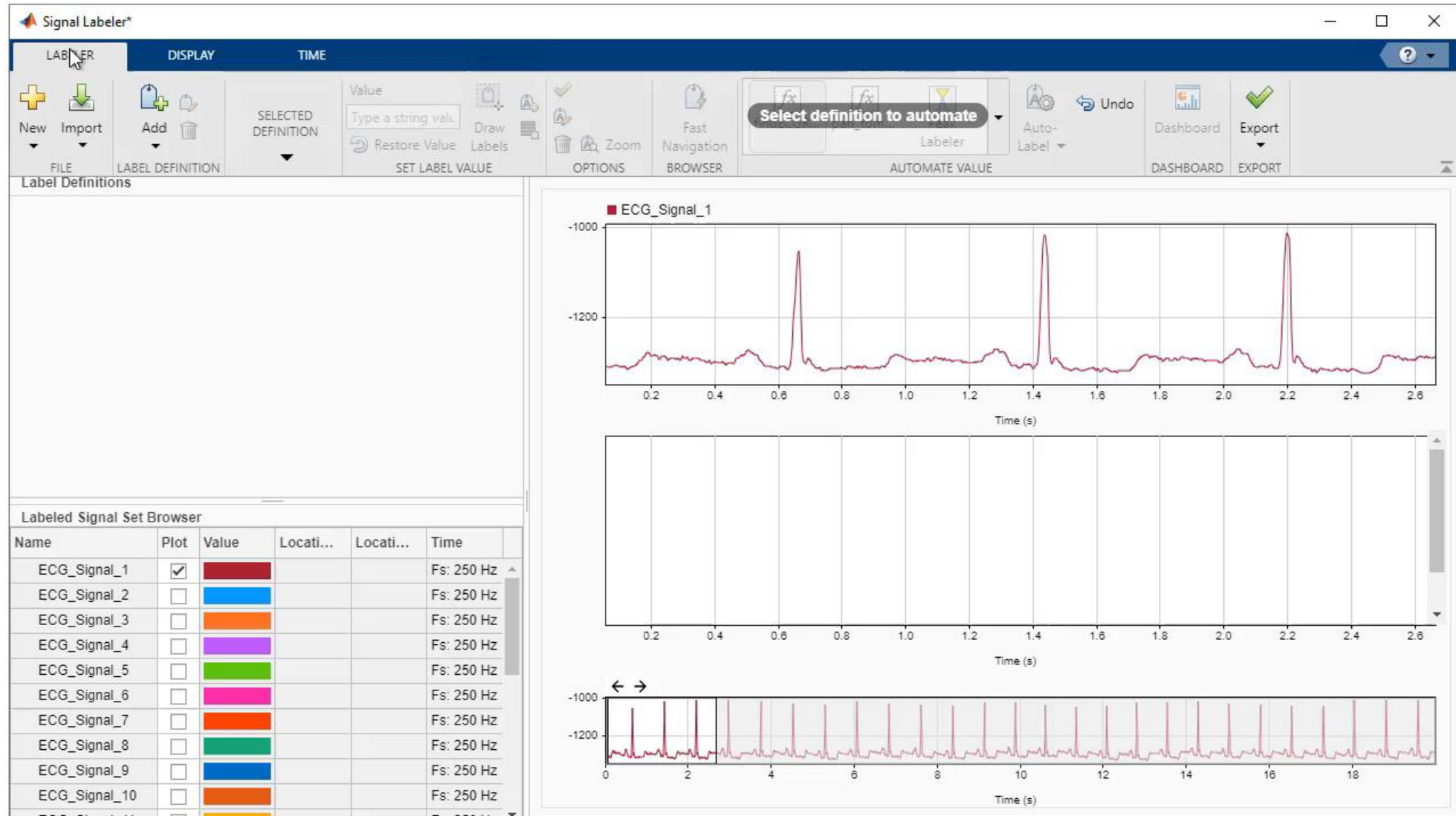


Simulation-generated data

Q. How to label collected data?

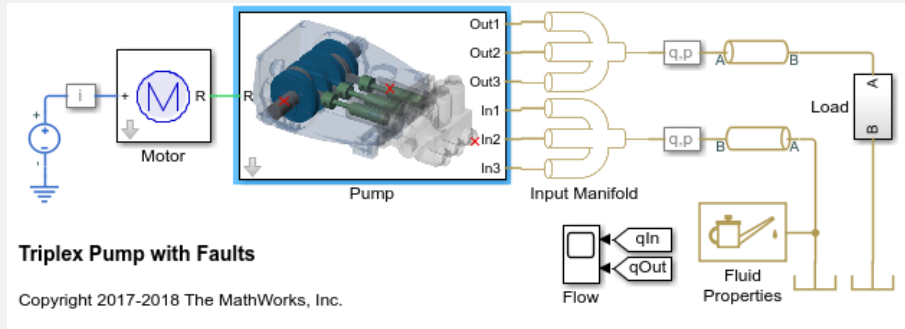
Q. What if it is not possible to collect data?

Labeling Signals with Signal Labeler App

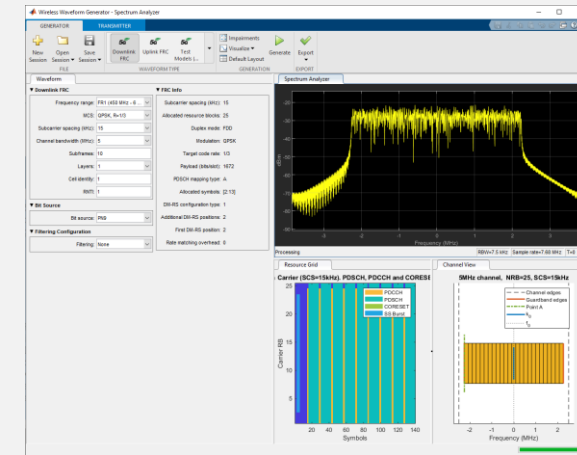


Generate Synthetic Data for various applications in MATLAB

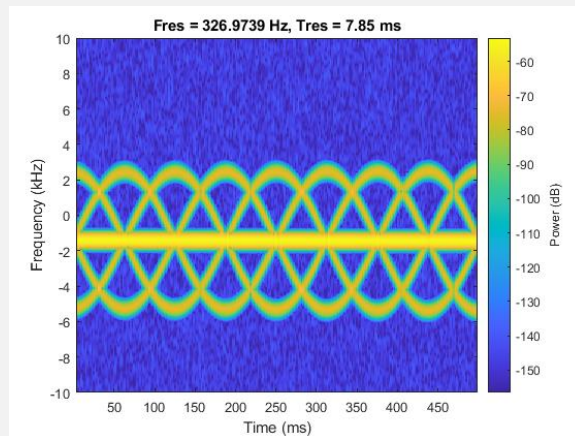
Simulate data using Simulink models



Generate wireless waveforms

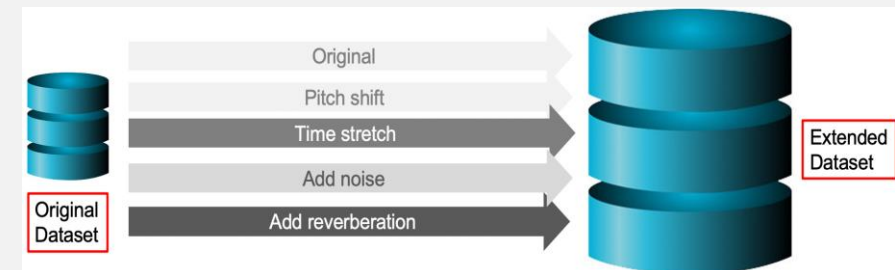


Generate Radar Returns



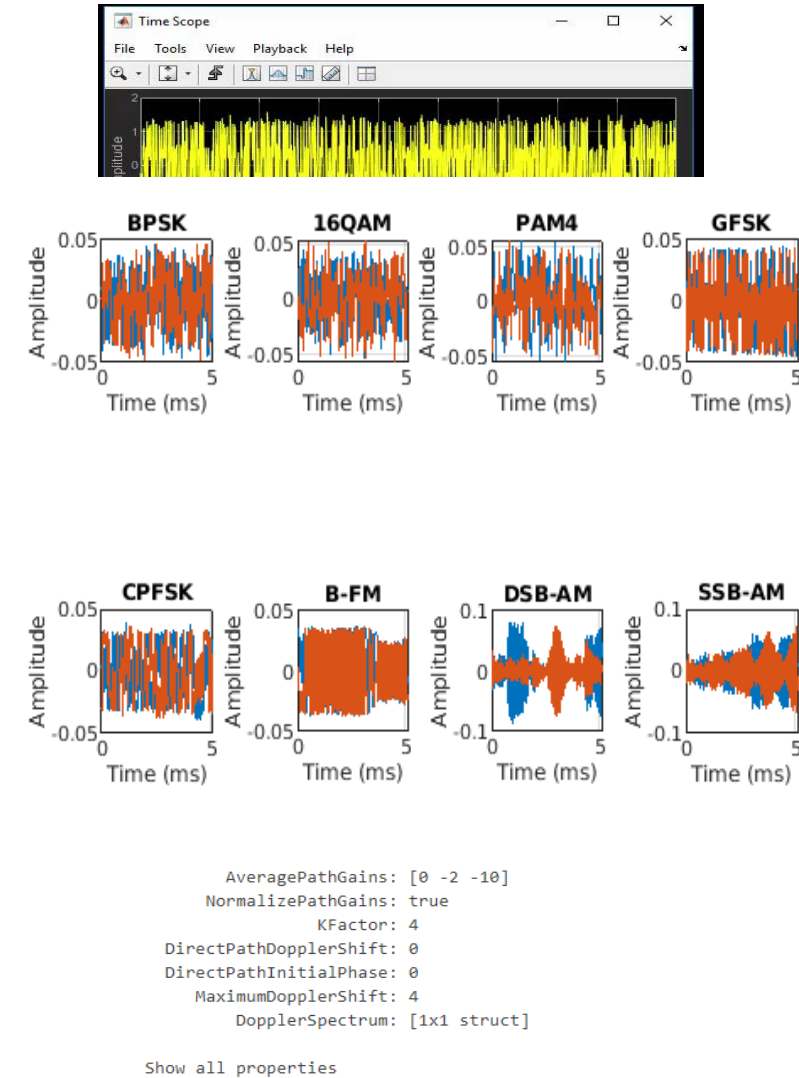
Generate and Augment Audio Data

text2speech



Generation of wireless communication waveforms with impairments

- Modulate digital baseband signals using built-in functions
 - BPSK, QPSK, 8PSK, FM, DSB-AM, SSB-AM, GFSK, PAM4
- Easily account for various impairments
 - RF / Hardware impairments (Frequency/ Phase Offsets etc.)
 - Channel Impairments (Multipath Fading Channels)
- Generate Datasets for Deep Learning
 - 5000 frames generated for each modulation type
 - 80% data – Training; 10% data – Validation; 10% data - Test



Feature Extraction

Data Preparation



Data cleansing and preparation



Human insight

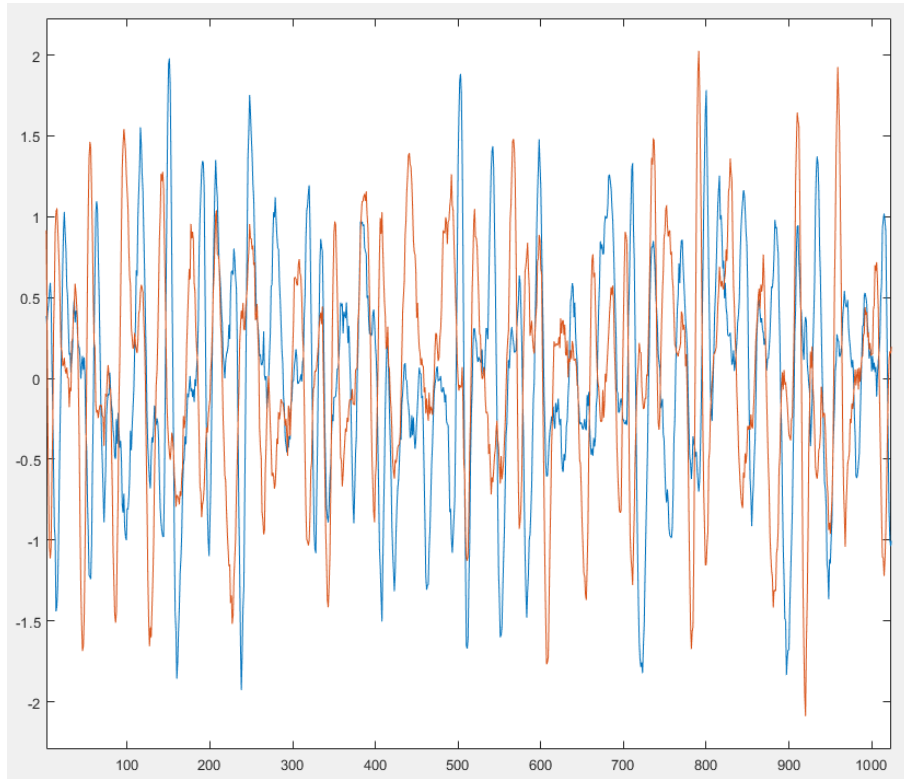


Simulation-generated data

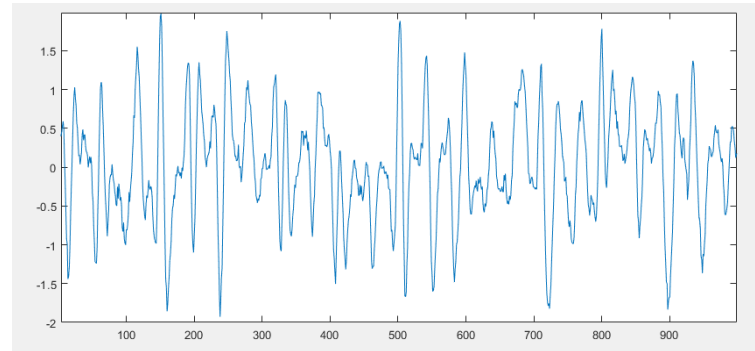
Q. Can I use raw data?

Q. How do I extract the right features for my data?

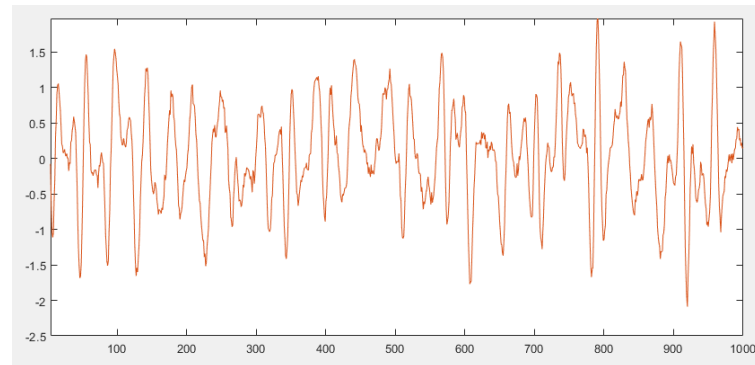
Use of raw data for AI models



IQ waveform



I waveform



Q waveform

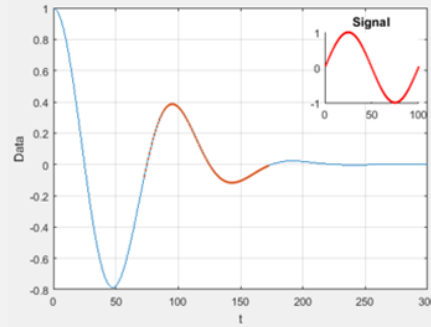
**High
Dimensionality**

Need for more data

**Need for
specialized models**

Feature extraction with signal processing techniques

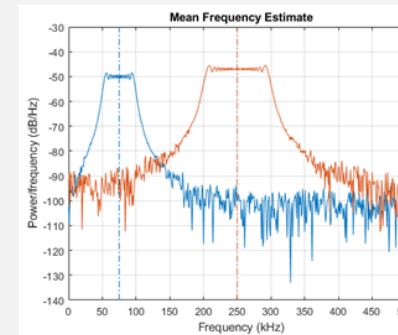
Time-Domain Features



- Signal Patterns
- Changepoints
- Peaks
- Signal Envelope

.....

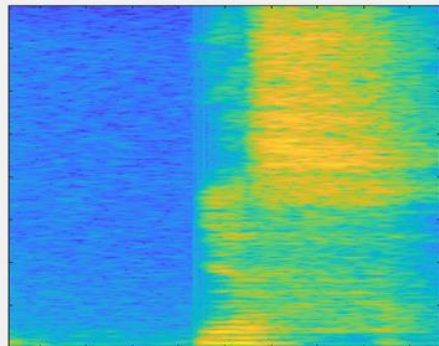
Frequency-Domain Features



- BW measurements
- Spectral Statistics
- Octave Spectrum

.....

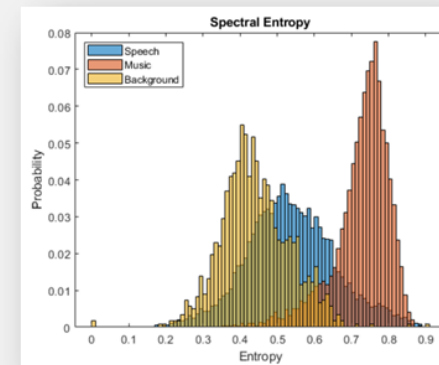
Time-Frequency features



- STFT
- CWT
- Constant-Q Transform

.....

Domain-Specific Features



- Speech and audio
- Navigation and Sensor Fusion
- Radar
- Communication

.....

Building the AI models

AI Modeling



Model design and
tuning



Hardware
accelerated training



Interoperability

Q. How do I select the right model for my application:

- If I do not have enough data?
- If I do not have domain expertise?
- If I need an easily interpretable model?

.....

Start by using published literature and MATLAB examples

Deep Neural Network Architectures for Modulation Classification

Xiaoyu Liu, Diyu Yang, and Aly El Gamal
School of Electrical and Computer Engineering
Purdue University
Email: {liu1962, yang1467, elgamala}@purdue.edu

Abstract—In this work, we investigate the value of employing deep learning for the task of wireless signal modulation recognition. Recently in [1], a framework has been proposed by generating a dataset using GNU radio that overcomes imperfections in a real wireless channel, and uses modulation types. Further, a convolutional neural network architecture was developed and shown to deliver a performance that exceeds that of expert-based approaches. Here, we first tune the CNN architecture of [1] and find deep neural network that deliver higher accuracy than the state of the art. The architecture of [1] and found it to achieve an accuracy of approximately 75% of correctly recognizing the modulation type. We first tune the CNN architecture of [1] and find deep neural network that deliver higher accuracy than the state of the art. The architecture of [1] and found it to achieve an accuracy of approximately 75% of correctly recognizing the modulation type. We first tune the CNN architecture of [1] and find deep neural network that deliver higher accuracy than the state of the art. The architecture of [1] and found it to achieve an accuracy of approximately 75% of correctly recognizing the modulation type.

I. INTRODUCTION

Signal modulation is an essential process in wireless communication systems. Modulation recognition is typically used for both signal detection and demodulation. Signal receiver demodulates the signal correctly. However, the fast development of wireless communication and more high-end requirements, the number of modulation methods and parameters used in wireless communication systems is increasing rapidly. The problem of how to recognize modulation methods accurately is hence becoming increasingly challenging.

Traditional modulation recognition methods use prior knowledge of signal and channel parameters. However, they are inaccurate under mild circumstances and need to be trained through a separate control channel. Hence, autonomous modulation recognition arises in wireless communication systems where modulation schemes are expected to change as the environment changes. This leads to continuous modulation recognition methods using deep neural networks (DNN) have played a significant role in modulation recognition.

Automatic Modulation Recognition Using Wavelet Transform and Neural Networks in Wireless Systems

K. Hassan, I. Dayoub, W. Hamouda & M. Berbineau

Time-Frequency Analysis based Blind Modulation Classification for Multiple-Antenna Systems

Weiheng Jiang^a, Xiaogang Wu^a, Bolin Chen^a, Wenjiang Feng^a, Yi Jin^b

^aSchool of Microelectronics and Communication Engineering, Chongqing University, Chongqing 400044, China.
^bXi'an Branch of China Academy of Space Technology, Xi'an 710100, China.

Abstract

Blind modulation classification is an important step to implement cognitive radio networks. The multiple-input multiple-output (MIMO) technique is widely used in military and civil communication systems. Due to the lack of prior information about channel parameters and the overlapping of signals in the MIMO systems, the traditional likelihood-based and feature-based approaches cannot be applied in these scenarios directly. Hence, in this paper, to resolve the problem of blind modulation classification in MIMO systems, the time-frequency analysis method based on the windowed short-time Fourier transform is used to analyse the time-frequency characteristics of time-domain modulated signals. Then the extracted time-frequency characteristics are converted into RGB spectrogram images, and the convolutional neural network based on transfer learning is applied to classify the modulation types according to the RGB spectrogram images. Finally, a decision fusion module is used to fuse the classification results of all the receive antennas. Through simulations, we analyse the classification performance at different signal-to-noise ratios (SNRs), the results indicate that, for the single-input single-output (SISO) network, our proposed scheme can achieve 92.37% and 99.12% average classification accuracy at SNRs of -4 dB and 10 dB, respectively. For the MIMO network, our scheme achieves 80.42% and 87.92% average classification accuracy at -4 dB and 10 dB, respectively. This outperforms the existing classification methods based on baseband signals.

Keywords: Time-Frequency Analysis, Blind Modulation Classification, Multiple-Antenna Systems, RGB Spectrogram Image

1. Introduction

The increase in communication demands and the shortage of spectrum resources has caused the cognitive radio (CR) and multiple-input multiple-output (MIMO) techniques to be implemented in wireless communication systems. As one of the essential steps of CR, modulation classification (MC) is widely applied in both civil and military applications, such as spectrum surveillance, electronic surveillance, electronic warfare, and network control and management [1]. It improves radio spectrum utilisation and enables intelligent decision-making for context-aware autonomous wireless spectrum monitoring systems [2]. However, most of the existing MC methods are focussed on single-input single-output (SISO) scenarios, which cannot be directly applied when multiple transmit antennas are equipped at the transceivers [3]. Therefore, it is crucial to research the performance of the MC method for MIMO communication systems.

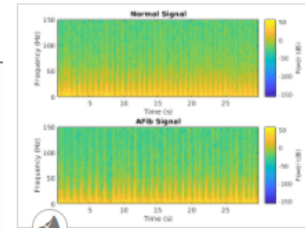
Traditional MC approaches for the SISO systems discussed in the literature can be classified into two main categories: likelihood-based and feature-based methods. In the likelihood-based methods, the authors in [13] presented convolutional long short-term

fast modulation classification and blind modulation classification (BMC). By contrast, the FB approaches cannot obtain the optimal result, but they have lower computational complexity and do not require prior information. The FB methods usually include two steps: feature extraction and classifier design. The higher-order statistics, instantaneous statistics, and other features are calculated in the feature extraction. Then the popular classification methods, such as decision tree [7], support vector machine [8] [9], and artificial neural network (ANN) [10] [11] are adopted as the classifiers.

With the rapid rise of artificial intelligence and the emerging requirements of intelligent wireless communication, deep learning-based approaches are now becoming widely studied and used in different aspects of wireless communication, such as the transceiver design at the physical layer [12] and BMC problems [13] [14] [15] [16] [17] [18]. As for BMC in SISO scenarios, the raw in-phase and quadrature phase (IQ) data or the time-domain amplitude and phase data can be directly used as the input of the deep learning neural network. More specifically, the authors in [13] presented convolutional long short-term

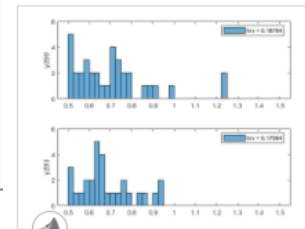
g 2010, Article number: 532898 (2010) | [Cite this article](#)
[Metrics](#)

ent characteristics used in signal waveform or automatic digital modulation recognition is ed using higher-order statistical moments (HOM) a features set. A multilayer feed-forward neural tion learning algorithm is proposed as a classifier. rent M-ary shift keying modulation schemes and gnal information. Pre-processing and features analysis is used to reduce the network complexity . The proposed algorithm is evaluated through ability. The proposed classifier is shown to be me with high accuracy over wide signal-to-noise Gaussian noise (AWGN) and different fading



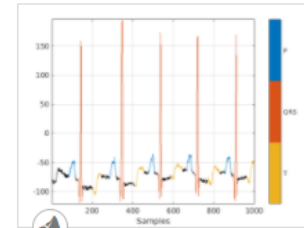
Classify ECG Signals Using Long Short-Term Memory Networks

Classify heartbeat electrocardiogram data using deep learning and signal processing.



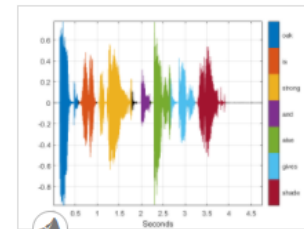
Label QRS Complexes and R Peaks of ECG Signals Using Deep Learning...

Use Signal Labeler to locate and label QRS complexes and R peaks of ECG signals.



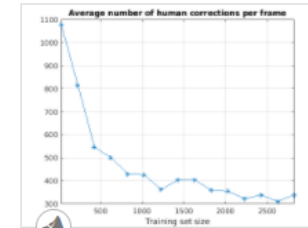
Waveform Segmentation Using Deep Learning

Segment human electrocardiogram signals using time-frequency analysis and deep learning.



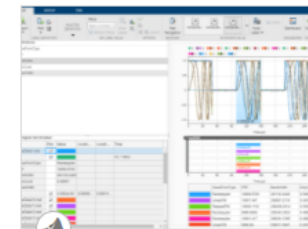
Label Spoken Words in Audio Signals Using External API

Use Signal Labeler to label spoken words in an audio signal.



Iterative Approach for Creating Labeled Signal Sets with Reduced Human Effort

Use deep learning to decrease the human effort required to label signals.



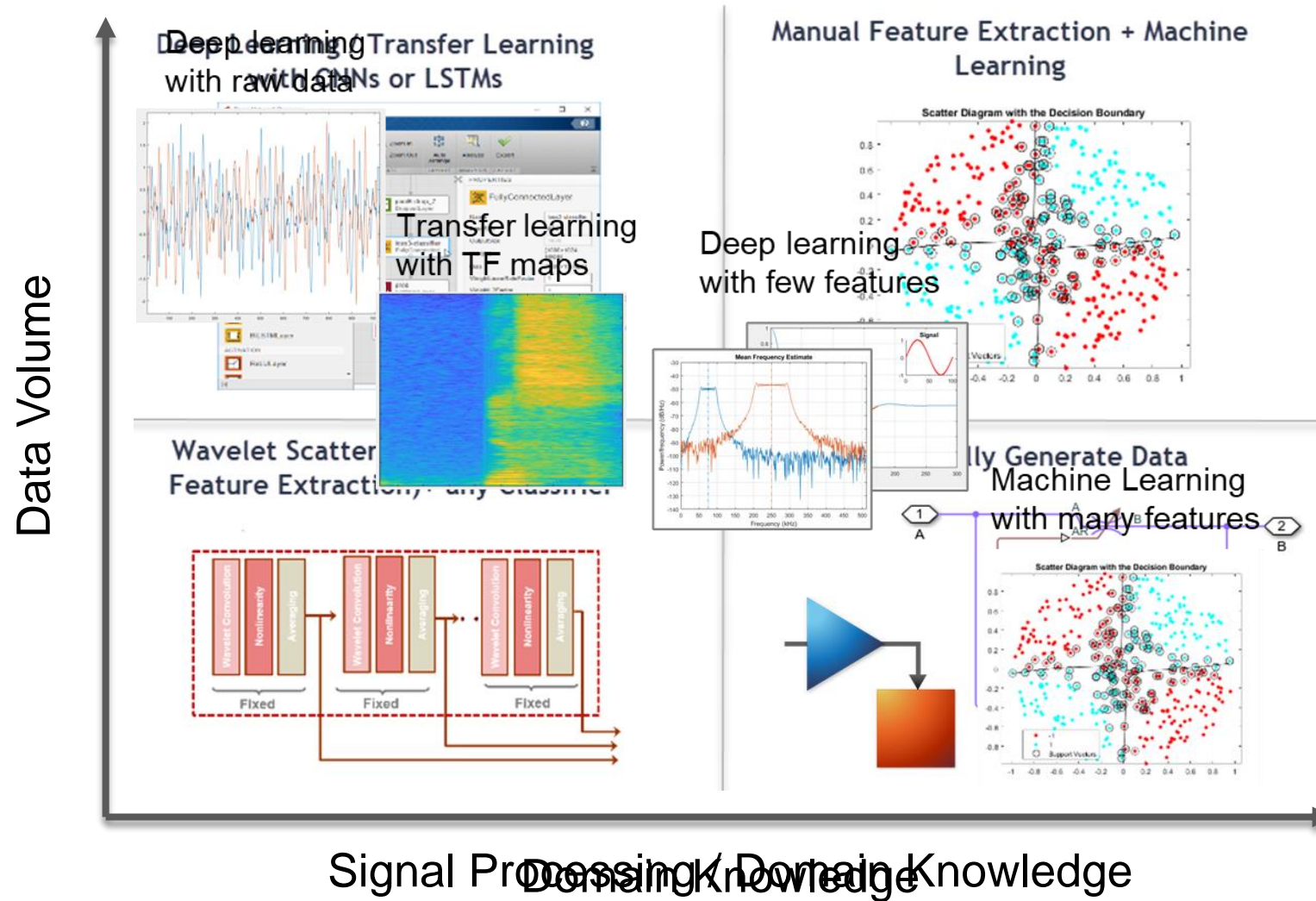
Labeling Radar Signals with Signal Labeler

Label the time and frequency features of pulse radar signals with added noise.

arXiv:1712.00443v3 [cs.LG] 5 Jan 2018

arXiv:2004.00378v1 [cs.LG] 1 Apr 2020

Understanding tradeoffs for model selection

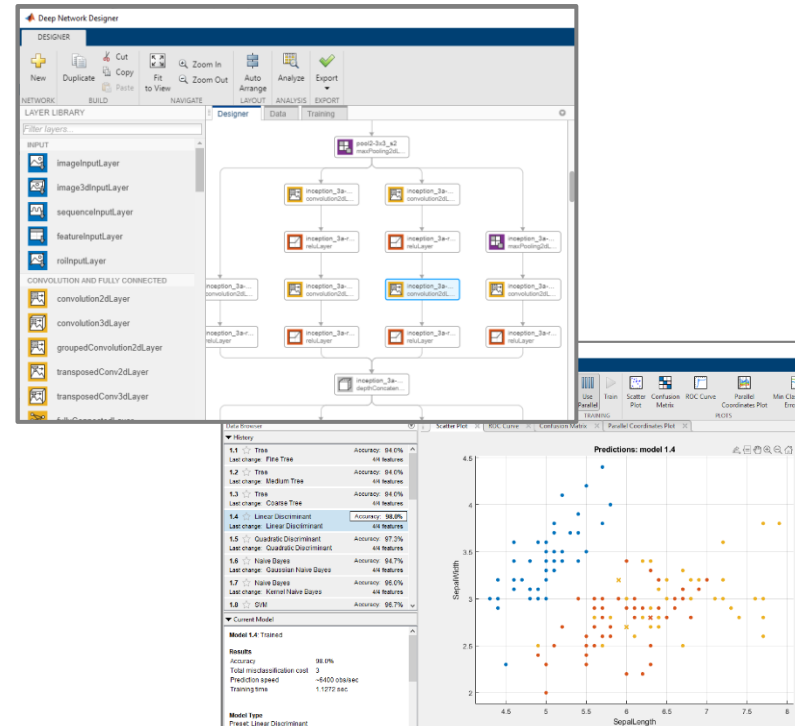


There are three ways to build AI models in MATLAB

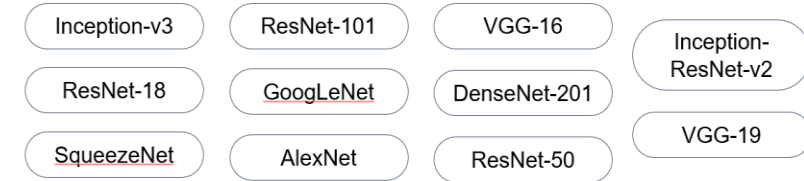
```
imageInputLayer([2 spf 1], 'Name', 'Input Layer')
convolution2dLayer(filterSize, 'Name', 'CNN1')
batchNormalizationLayer('Name', 'BN1')
reluLayer('Name', 'ReLU1')
maxPooling2dLayer(poolSize, 'Name', 'MaxPool1')
```

fitcauto/fitrauto

Writing code

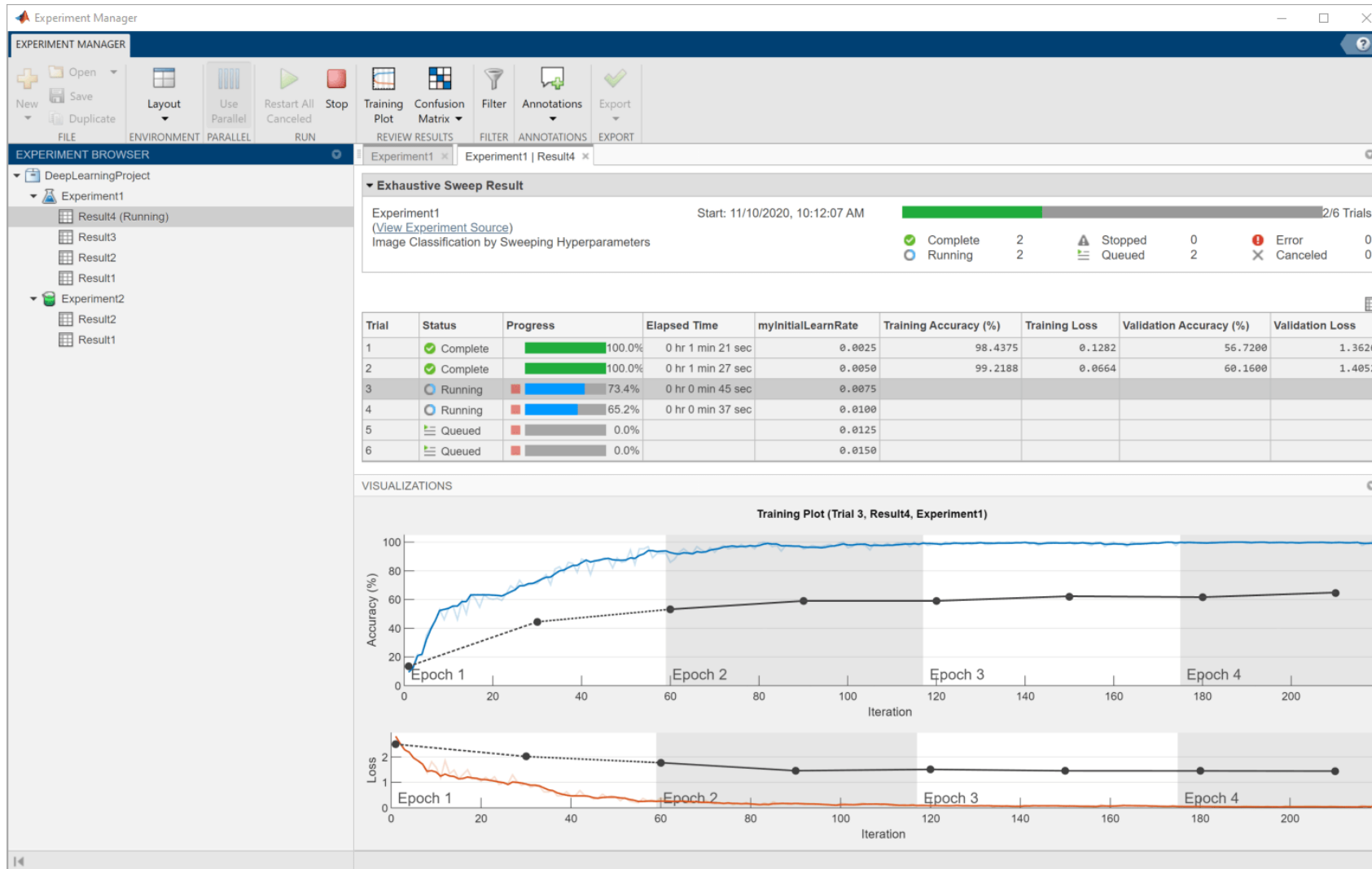


Interactively Design Models with Apps



Use Transfer Learning for Deep Learning

Iterate to find the best model with Experiment Manager App



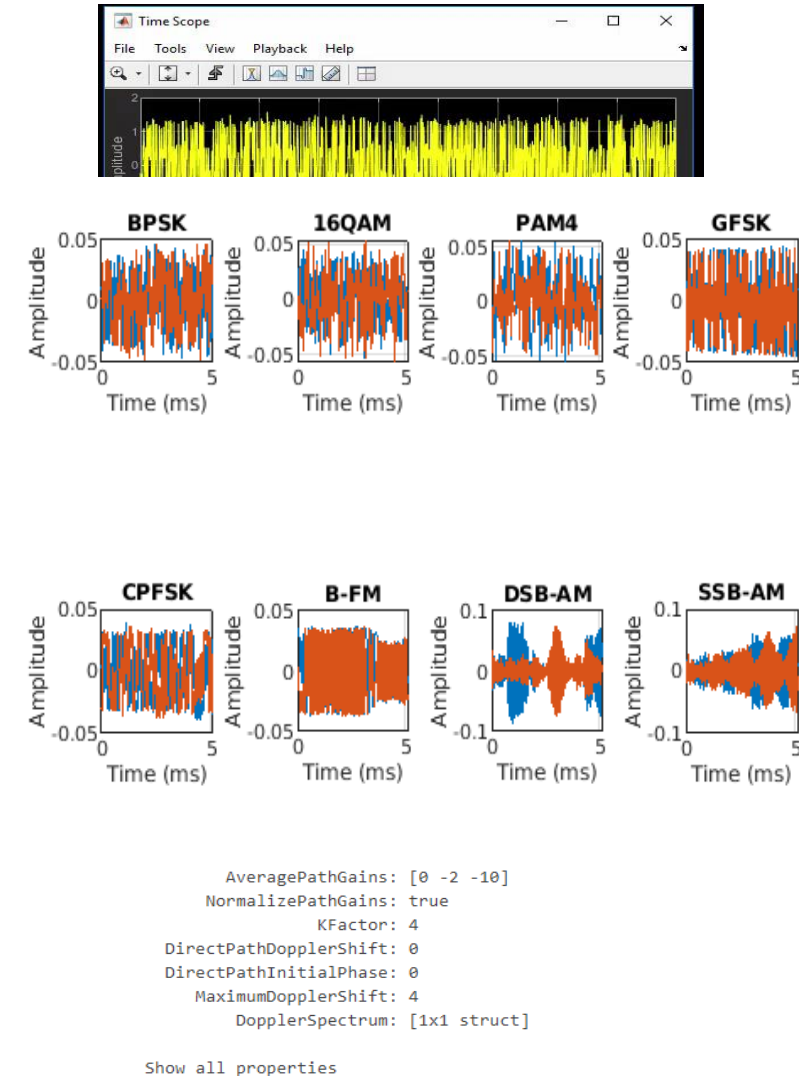
Find optimal training options

Compare the results of using different data sets

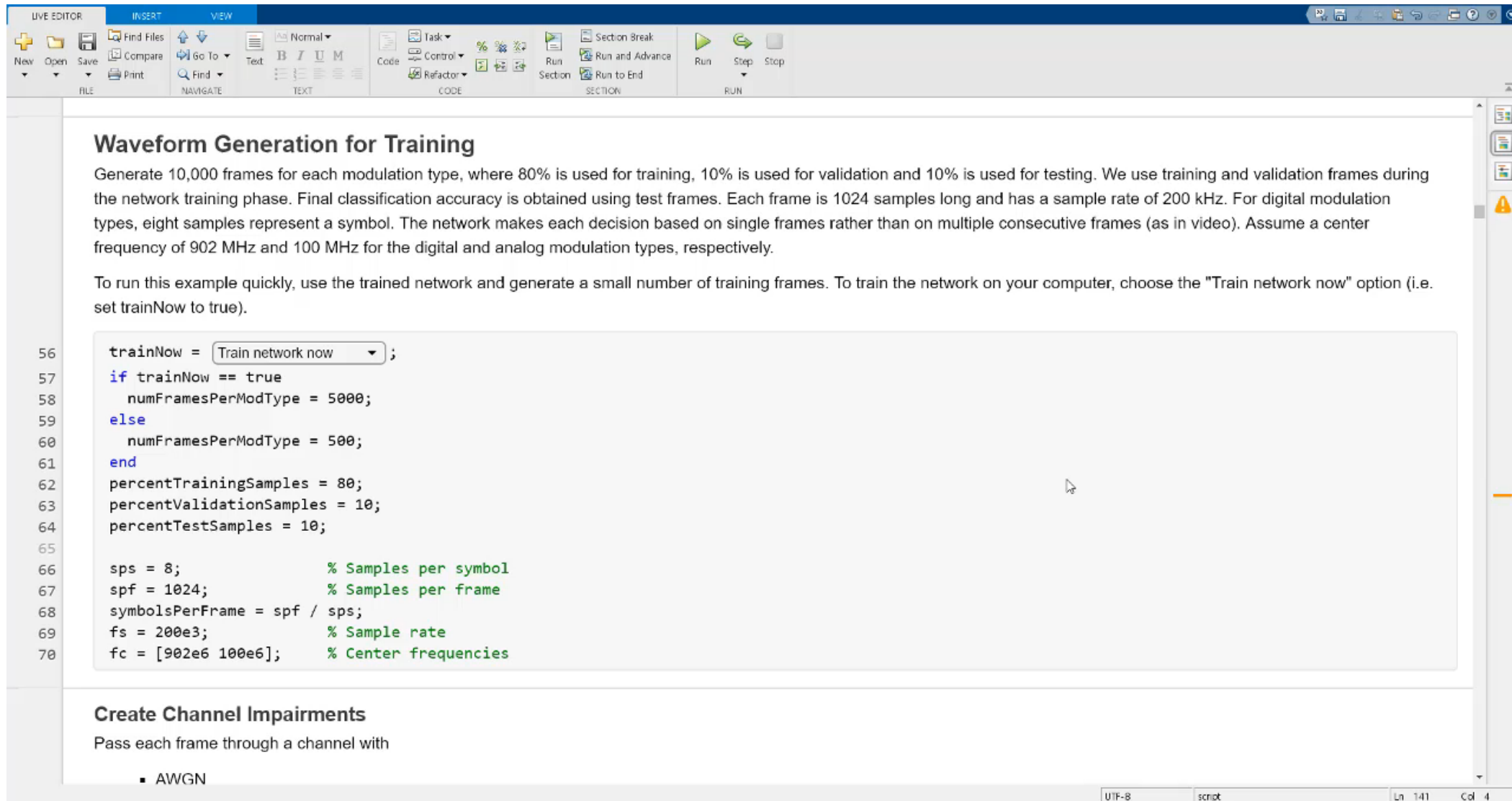
Compare the results of using different models

Generation of wireless communication waveforms with impairments

- Modulate digital baseband signals using built-in functions
 - BPSK, QPSK, 8PSK, FM, DSB-AM, SSB-AM, GFSK, PAM4
- Easily account for various impairments
 - RF / Hardware impairments (Frequency/ Phase Offsets etc.)
 - Channel Impairments (Multipath Fading Channels)
- Generate Datasets for Deep Learning
 - 5000 frames generated for each modulation type
 - 80% data – Training; 10% data – Validation; 10% data - Test



Data generation with Wireless Comm



The screenshot shows the MATLAB Live Editor interface. The top toolbar includes tabs for LIVE EDITOR, INSERT, and VIEW, along with various icons for file operations, navigation, text formatting, code execution, and debugging. The main workspace is divided into two sections: "Waveform Generation for Training" and "Create Channel Impairments".

Waveform Generation for Training

Generate 10,000 frames for each modulation type, where 80% is used for training, 10% is used for validation and 10% is used for testing. We use training and validation frames during the network training phase. Final classification accuracy is obtained using test frames. Each frame is 1024 samples long and has a sample rate of 200 kHz. For digital modulation types, eight samples represent a symbol. The network makes each decision based on single frames rather than on multiple consecutive frames (as in video). Assume a center frequency of 902 MHz and 100 MHz for the digital and analog modulation types, respectively.

To run this example quickly, use the trained network and generate a small number of training frames. To train the network on your computer, choose the "Train network now" option (i.e. set `trainNow` to true).

```
56 trainNow = Train network now ;
57 if trainNow == true
58     numFramesPerModType = 5000;
59 else
60     numFramesPerModType = 500;
61 end
62 percentTrainingSamples = 80;
63 percentValidationSamples = 10;
64 percentTestSamples = 10;
65
66 sps = 8;           % Samples per symbol
67 spf = 1024;        % Samples per frame
68 symbolsPerFrame = spf / sps;
69 fs = 200e3;        % Sample rate
70 fc = [902e6 100e6]; % Center frequencies
```

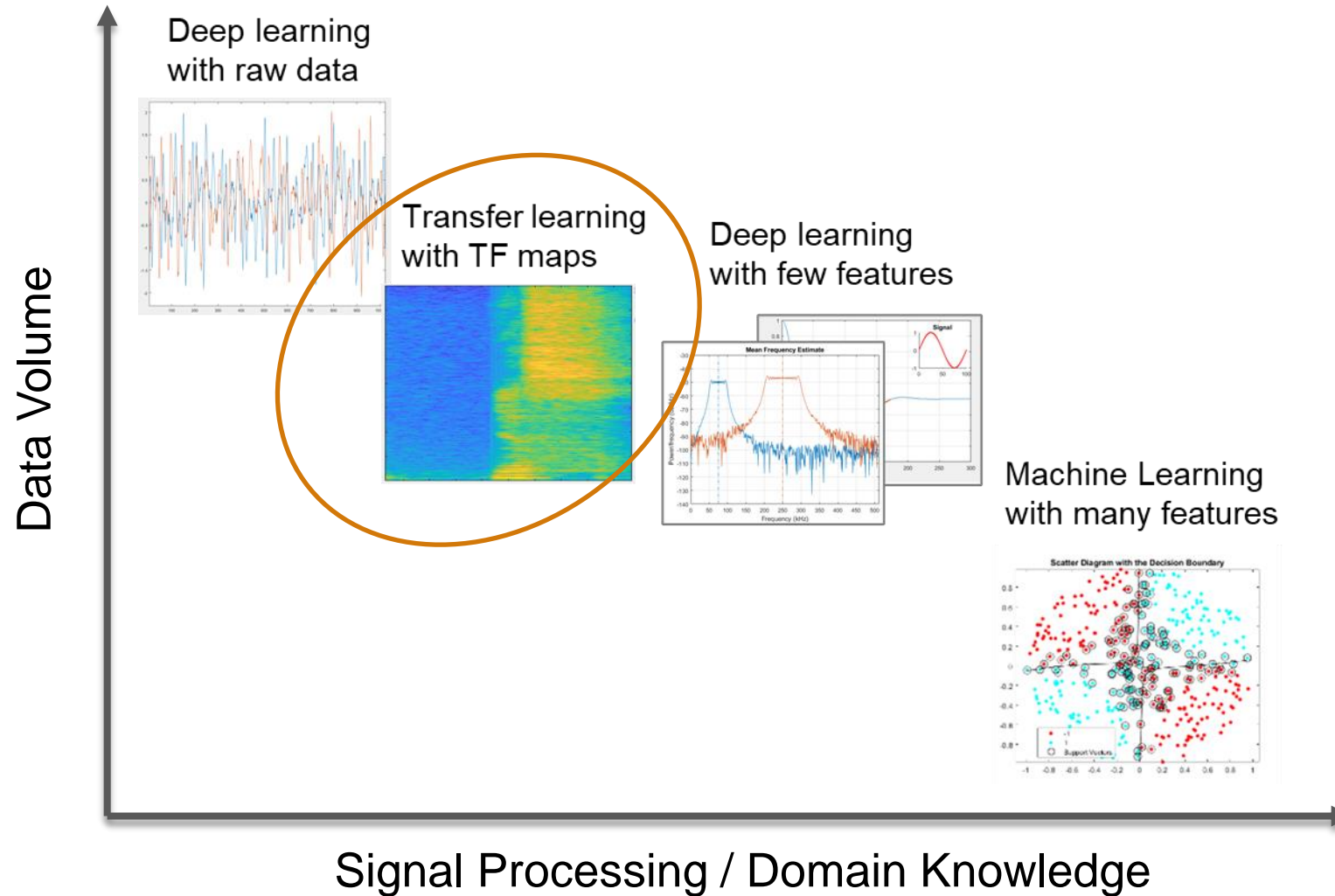
Create Channel Impairments

Pass each frame through a channel with

- AWGN

The bottom status bar shows the file encoding as UTF-8, the file name as script, and the cursor position as Ln 141, Col 4.

Selecting the Right Model : Understanding Tradeoffs

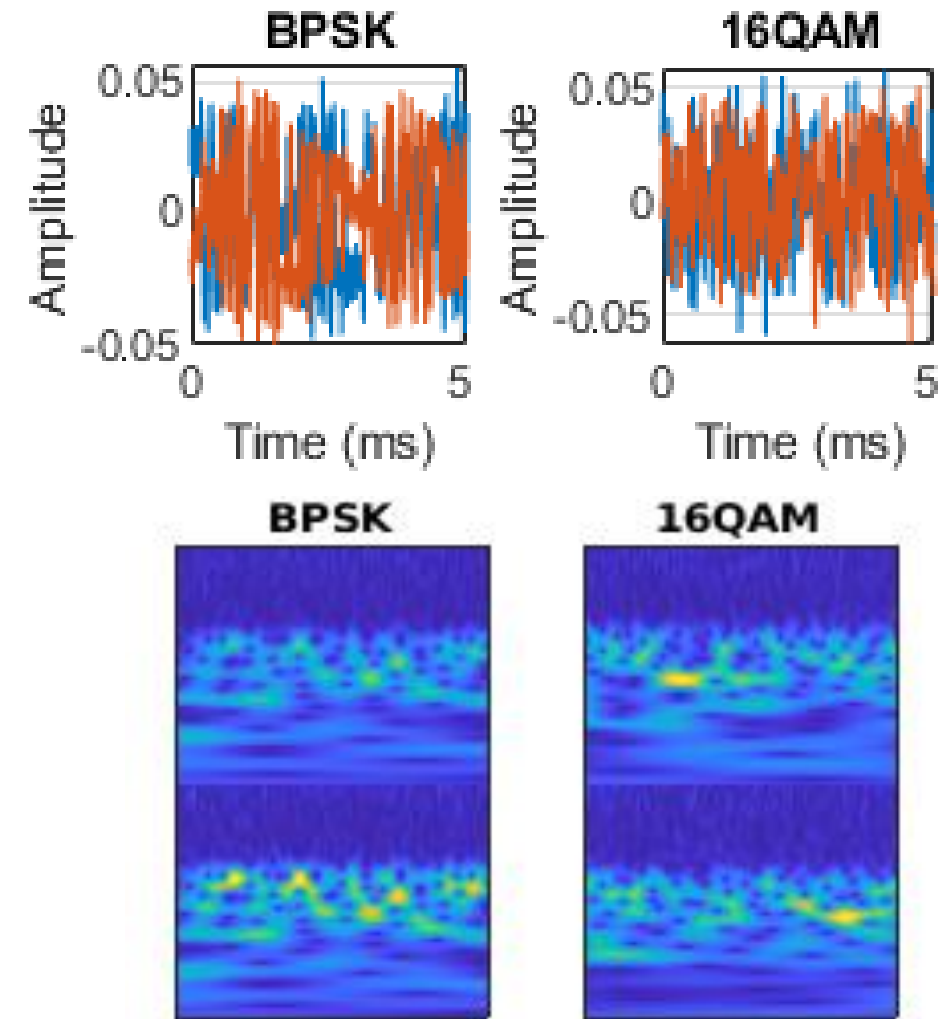


Continuous Wavelet Transform is used to extract the Time-Frequency maps

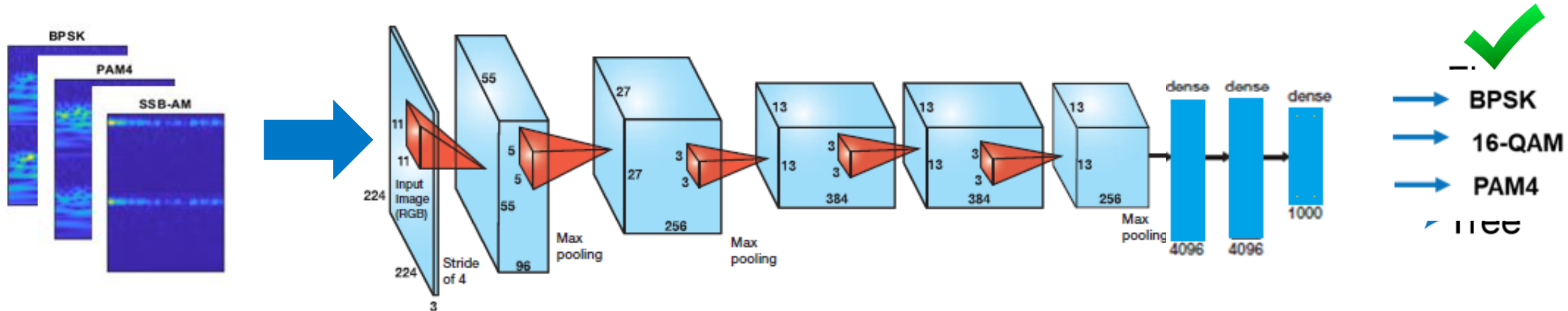
- One line of code for generating wavelet time-frequency visualization in MATLAB. Works for any signal

```
>> cwt(inputSignal)
```

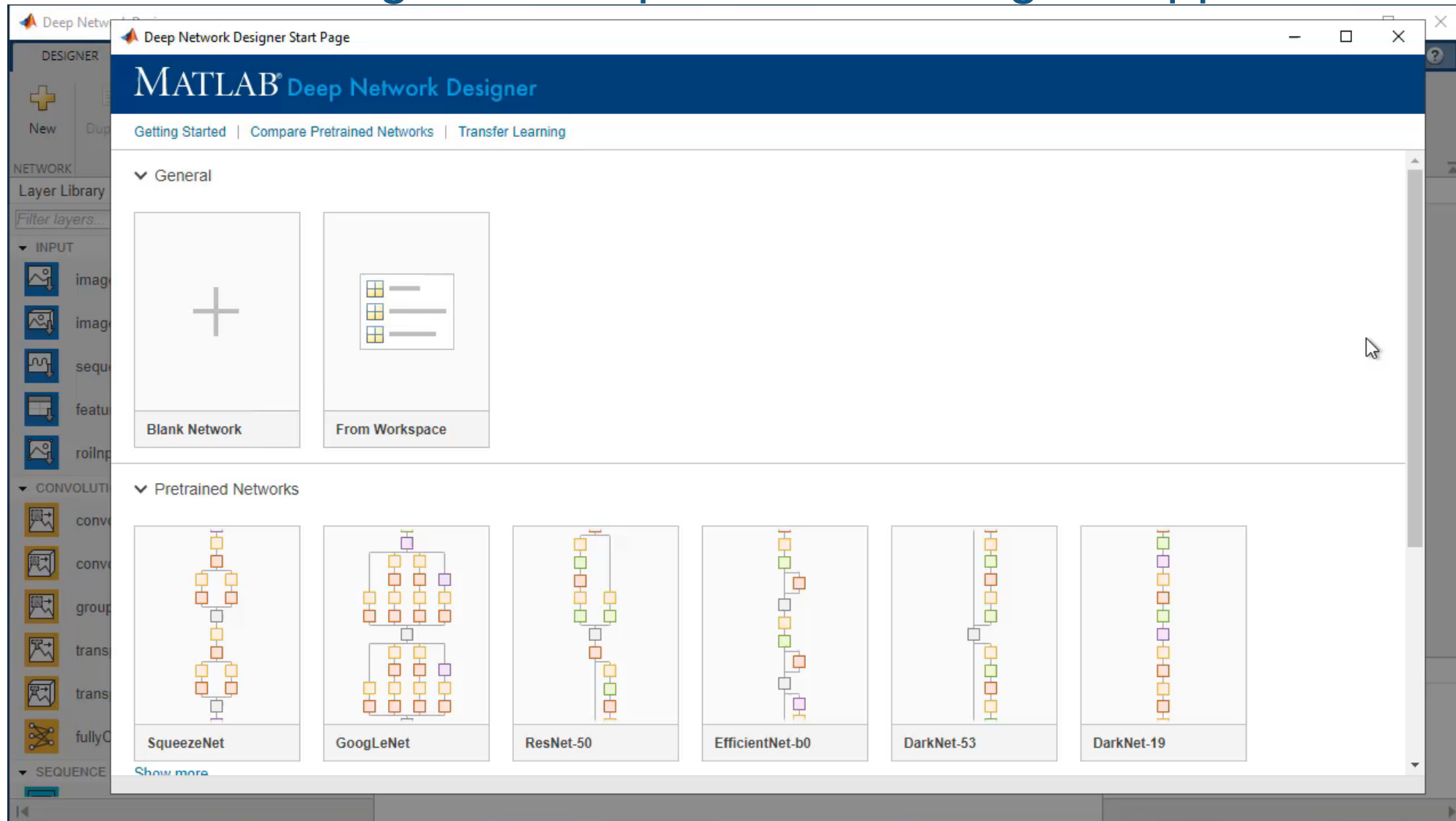
- Localizes sharp transients and slowly varying oscillations simultaneously
- Works with complex data



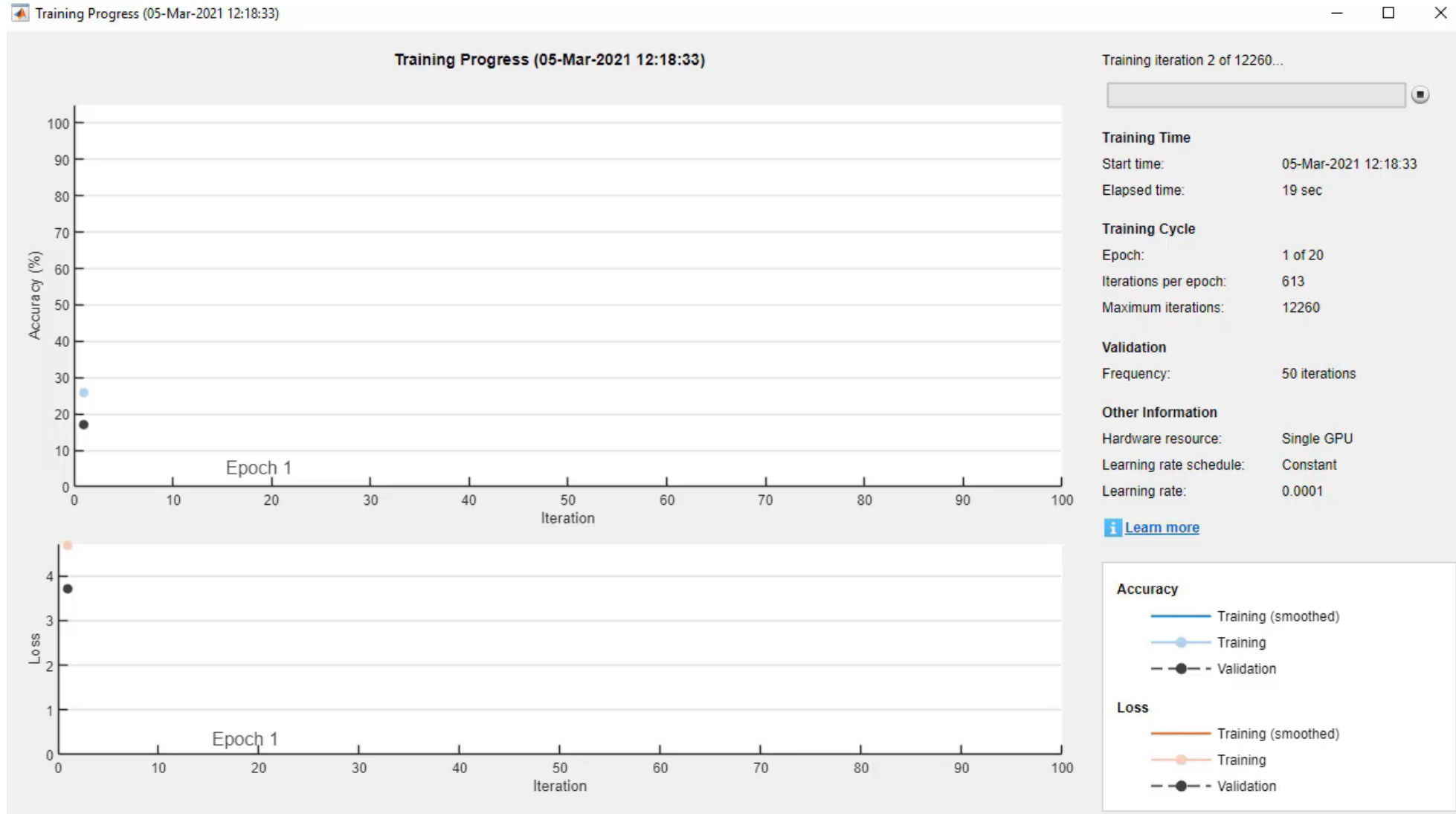
Using time-frequency maps as inputs to a pretrained CNN



Transfer Learning with Deep Network Designer App

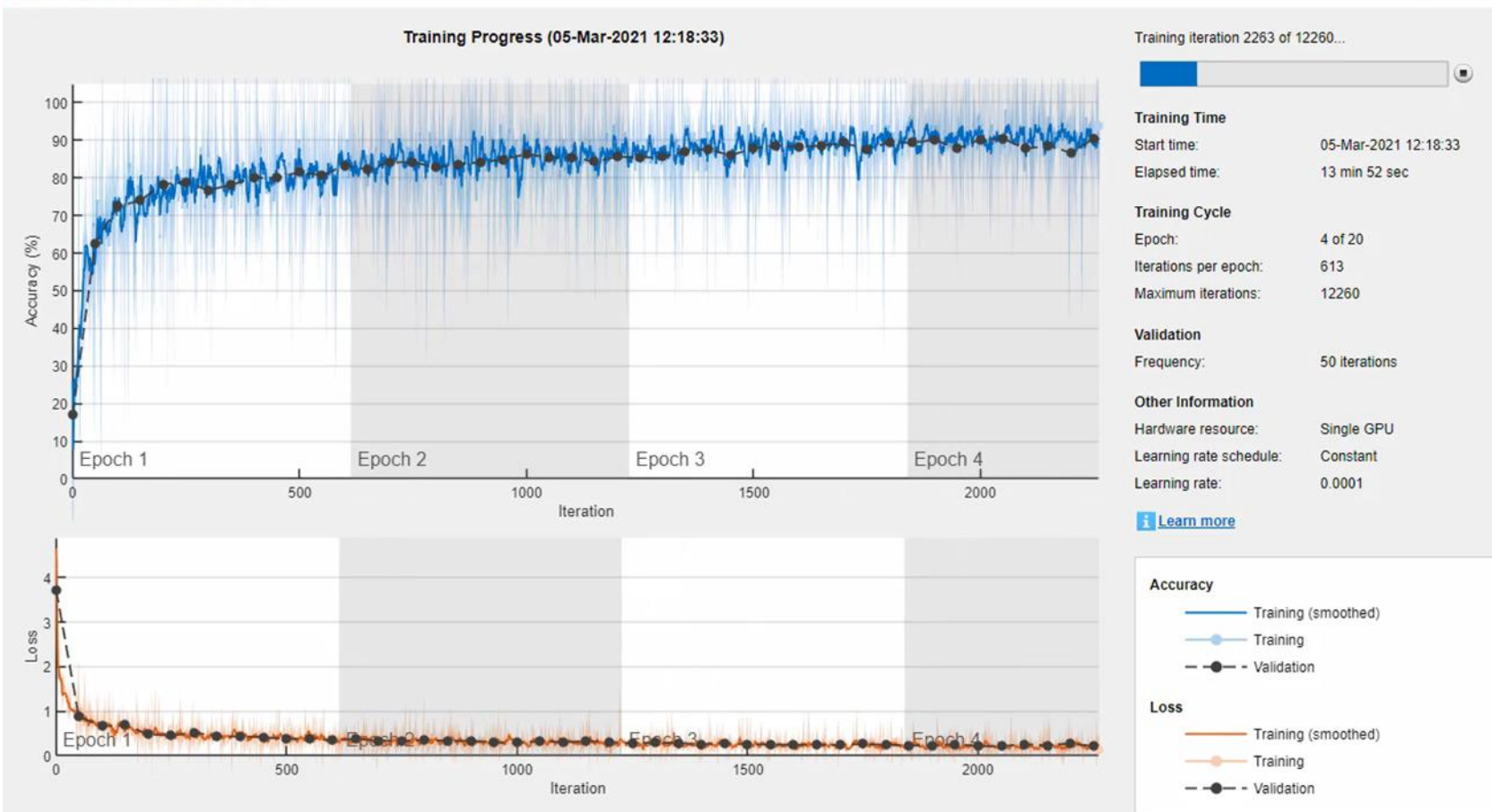


Train and Test Deep Network



Train and Test Deep Network

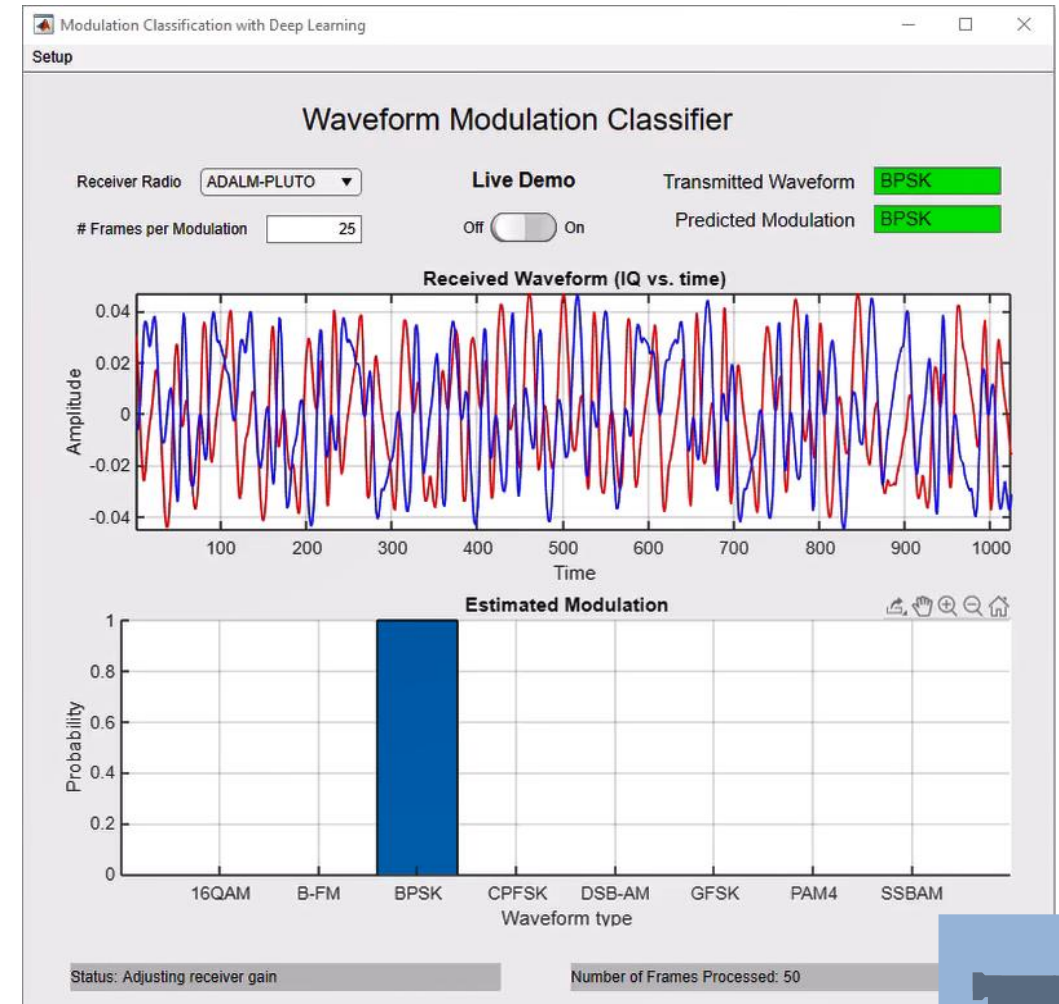
Training Progress (05-Mar-2021 12:18:33)



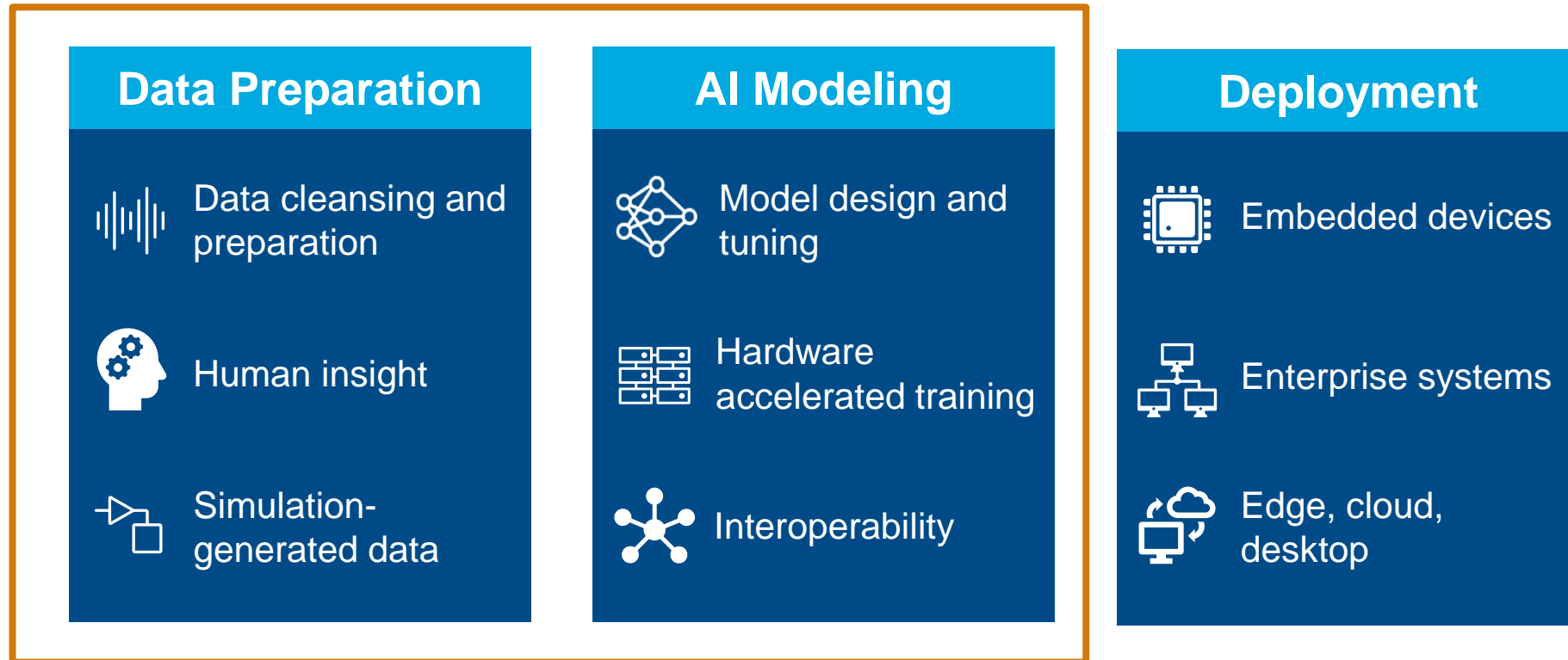
Confusion Matrix (overall accuracy: 0.9769)

True Class \ Predicted Class	16QAM	B-FM	BPSK	CPFSK	DSB-AM	GFSK	PAM4	SSB-AM		
16QAM	996							4	99.6%	0.4%
B-FM		1000							100.0%	
BPSK			993					7	99.3%	0.7%
CPFSK			3	997					99.7%	0.3%
DSB-AM					919			81	91.9%	8.1%
GFSK						999	1		99.9%	0.1%
PAM4							972		97.2%	2.8%
SSB-AM					61			939	93.9%	6.1%
	100.0%	100.0%	97.0%	100.0%	93.8%	100.0%	98.8%	92.1%		
			3.0%		6.2%		1.2%	7.9%		
	16QAM	B-FM	BPSK	CPFSK	DSB-AM	GFSK	PAM4	SSB-AM		

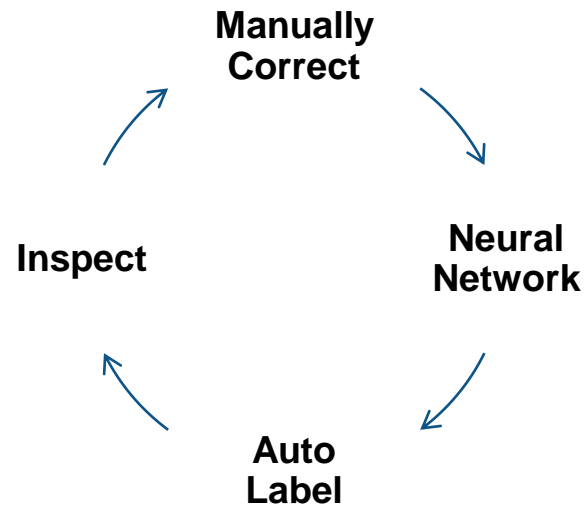
Testing network with connected hardware



AI-assisted system design

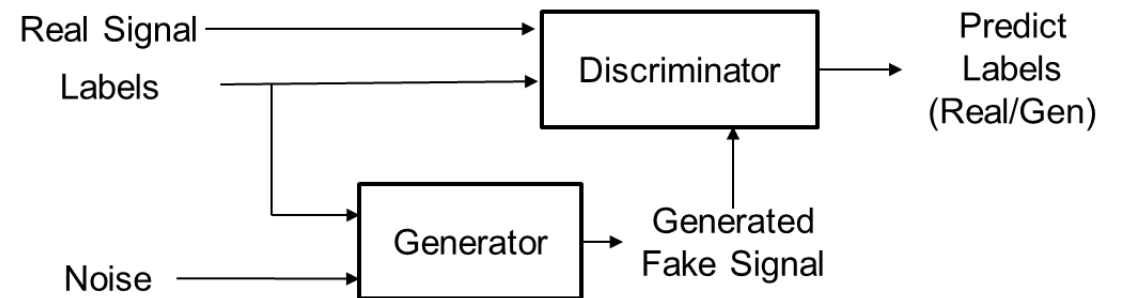


Deep Learning can be used in each step of the AI workflow



Labeling assistance

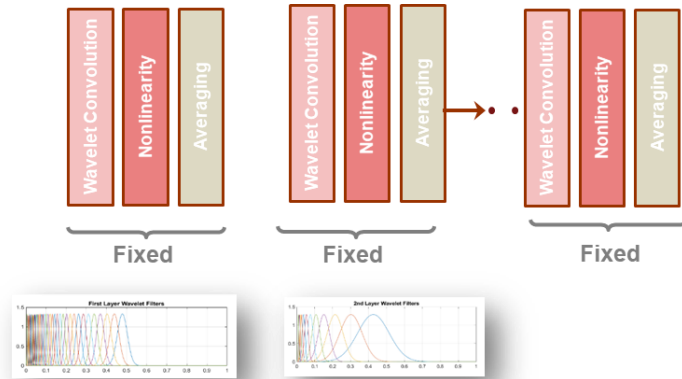
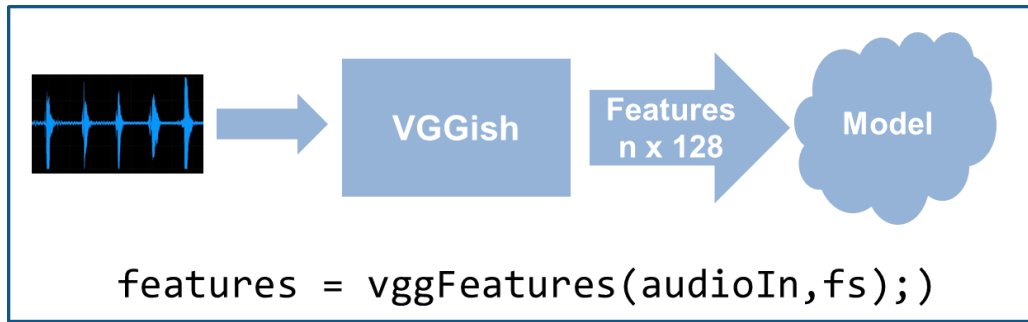
`classifySound (YAMNet)`, `GoogLeNet`,
`fitcecoc (ResNet18)`



Synthetic Data Generation

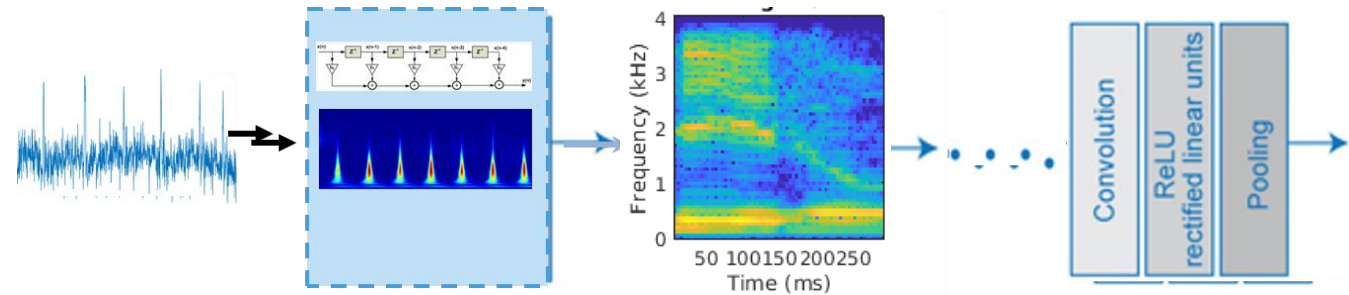
**Generative Adversarial Networks
(GANs)**

Deep Learning can be used in each step of the AI workflow



Feature Extraction

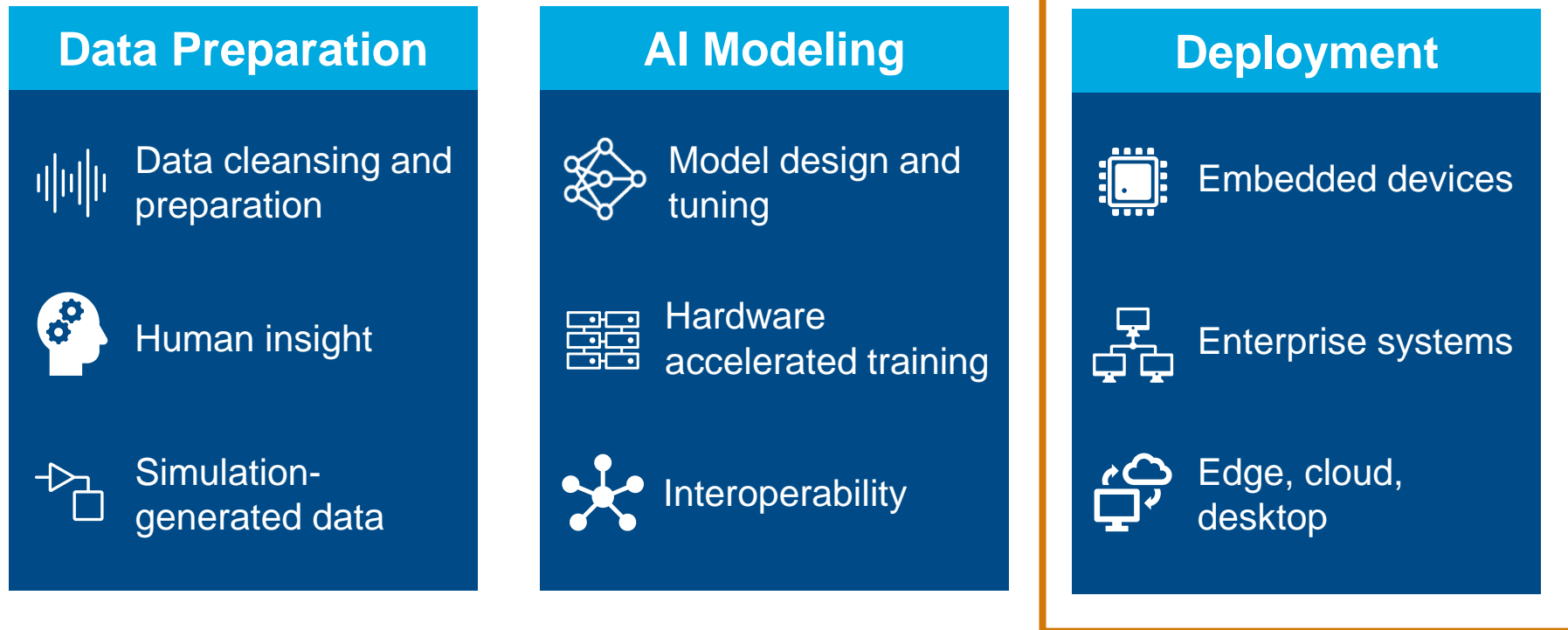
vggFeatures, **waveletScattering**



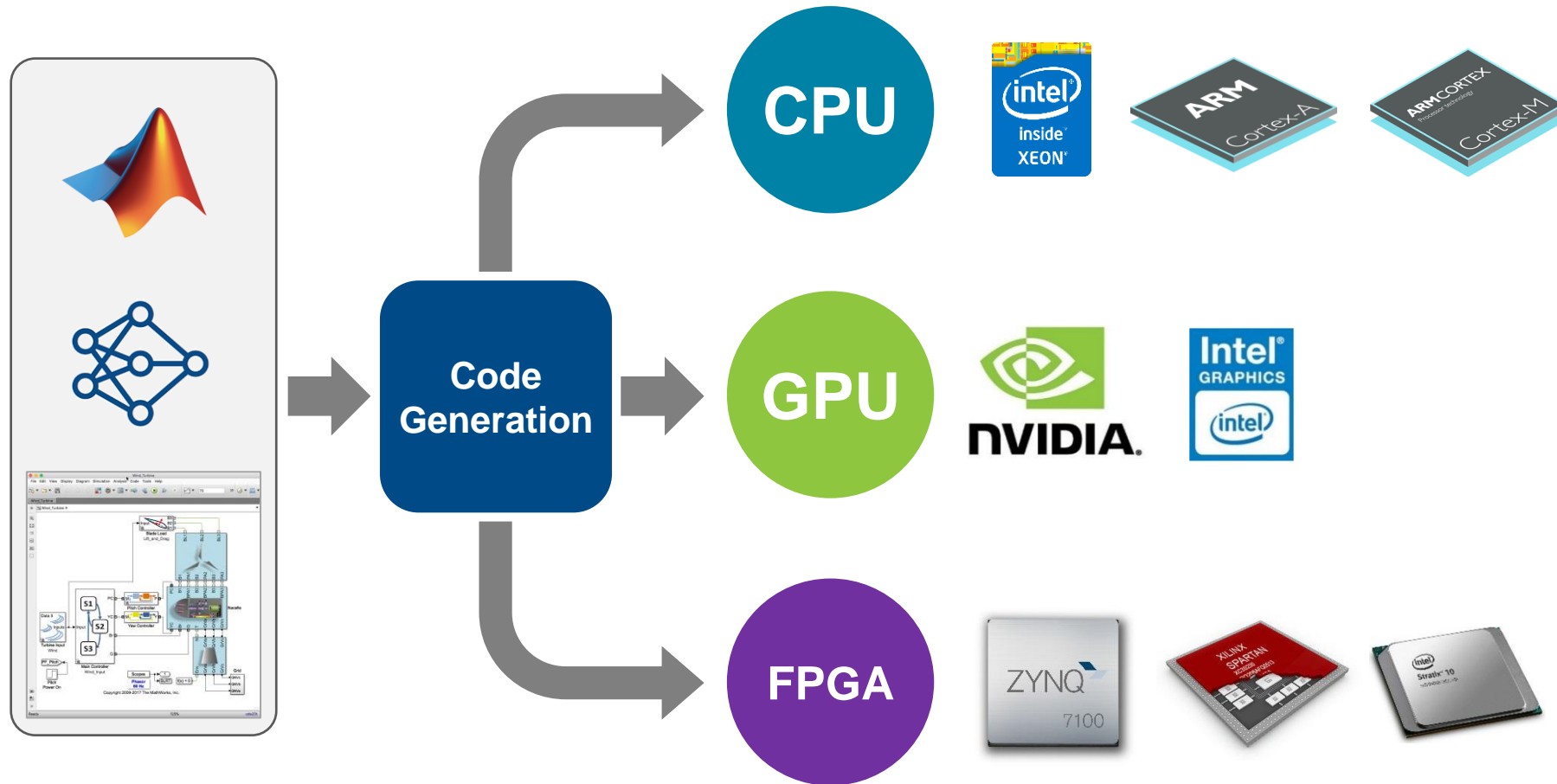
Differentiable Signal Processing

dlstft (Differentiable STFT)

AI-driven system design

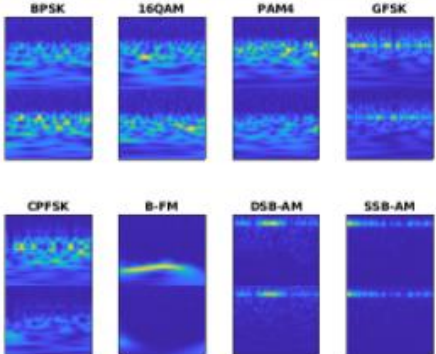


Deploy to any processor with best-in-class performance



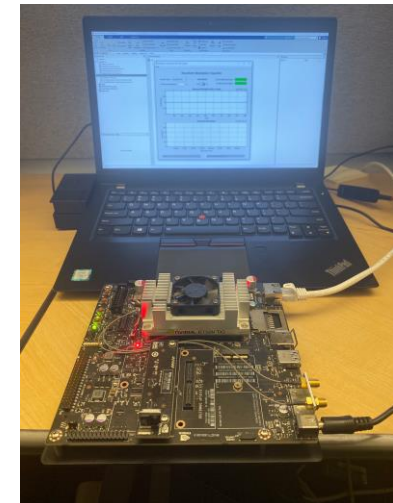
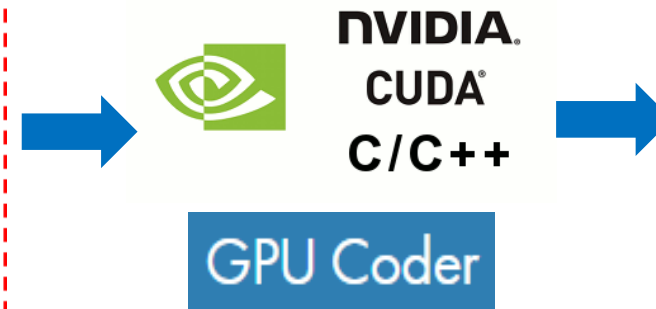
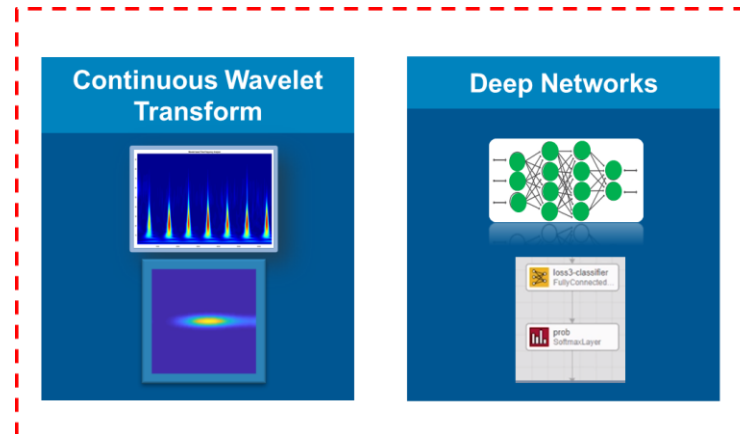
**Preprocessing, Feature
Extraction, AI Model**

Deploying complete AI algorithms to embedded processors, GPUs and FPGAs

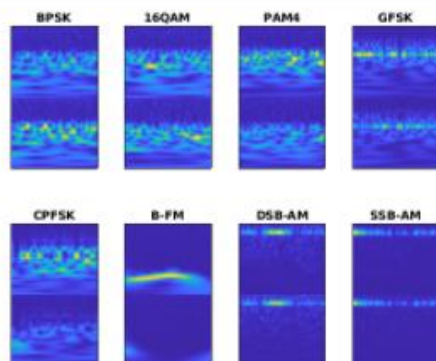


Modulation Classification Using Wavelet Analysis on NVIDIA Jetson

Generate and deploy a CUDA® executable that performs modulation classification using features extracted by the continuous wavelet

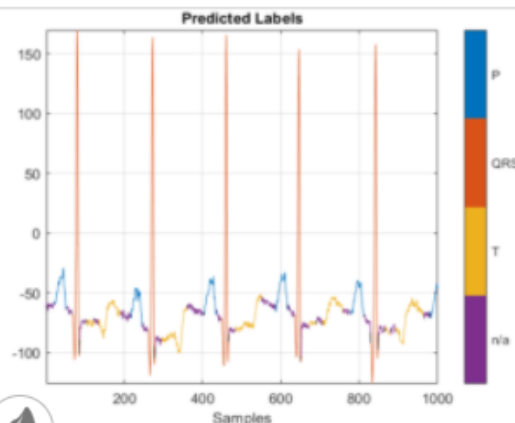


Deploying complete AI algorithms to embedded processors, GPUs and FPGAs



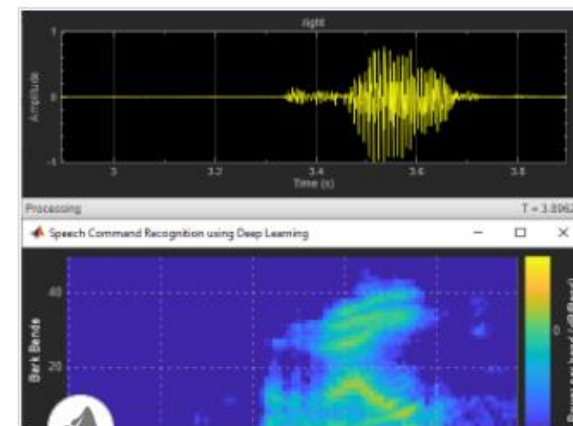
Modulation Classification Using Wavelet Analysis on NVIDIA Jetson

Generate and deploy a CUDA® executable that performs modulation classification using features extracted by the continuous wavelet



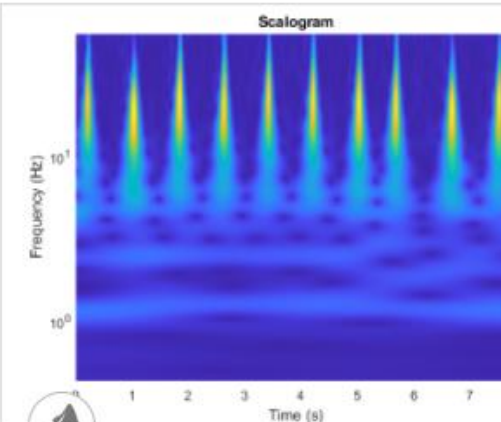
Deploy Signal Segmentation Deep Network on Raspberry Pi

Generate a MEX function and a standalone executable to perform waveform segmentation on a Raspberry Pi™.



Speech Command Recognition Code Generation with Intel MK...

Deploy feature extraction and a convolutional neural network (CNN) for speech command recognition on Intel® processors. To generate the




Classify ECG Signals Using DAG Network Deployed To FPGA




Classify human electrocardiogram (ECG) signals by deploying a trained directed acyclic graph (DAG) network.

MATLAB supports the entire AI-driven system design




Data Preparation

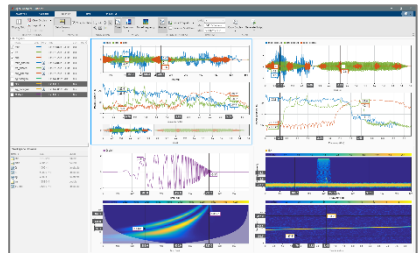
-  Data cleansing and preparation
-  Human insight
-  Simulation-generated data

AI Modeling

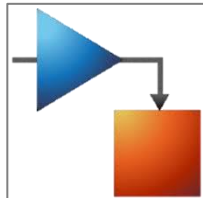
-  Model design and tuning
-  Hardware accelerated training
-  Interoperability

Deployment

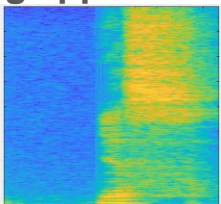
-  Embedded devices
-  Enterprise systems
-  Edge, cloud, desktop



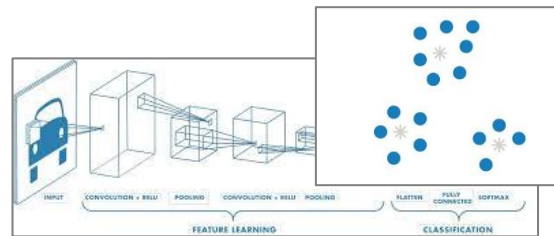
Signal Processing apps



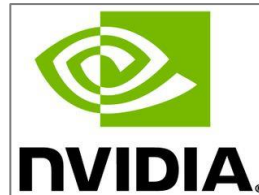
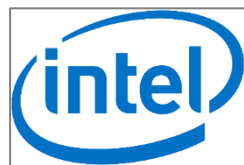
Generate Data



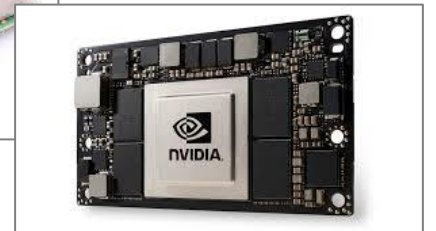
Feature Extraction Techniques



Quickly build models



Accelerate training



Deploy to targets with code generation

MATLAB EXPO 2021

감사합니다



© 2021 The MathWorks, Inc. MATLAB and Simulink are registered trademarks of The MathWorks, Inc. See [mathworks.com/trademarks](https://www.mathworks.com/trademarks) for a list of additional trademarks. Other product or brand names may be trademarks or registered trademarks of their respective holders.