

Data Pre-Processing for Hands-on Keyword Spotting

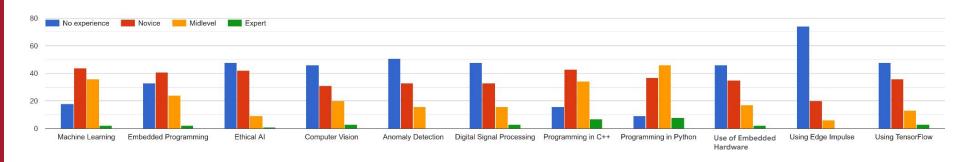
Brian Plancher
Harvard John A. Paulson School of Engineering and Applied Sciences
Barnard College, Columbia University
brianplancher.com



Quick Disclaimer: Today will be both too fast and too slow!

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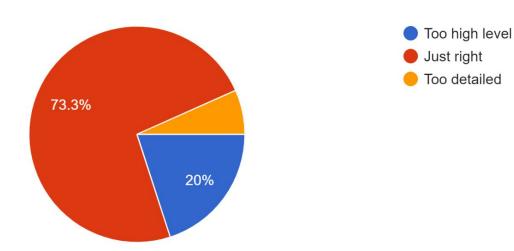
Do you have experience in?



Feedback from yesterday:

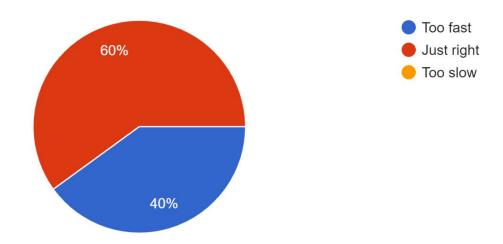
The depth of material covered today was

15 responses



Feedback from yesterday:

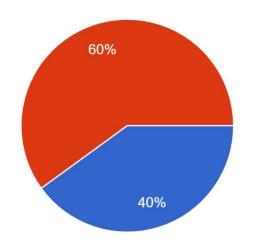
The pace of the lab today was 15 responses

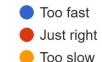


Feedback from yesterday:

The pace of the lab today was

15 responses

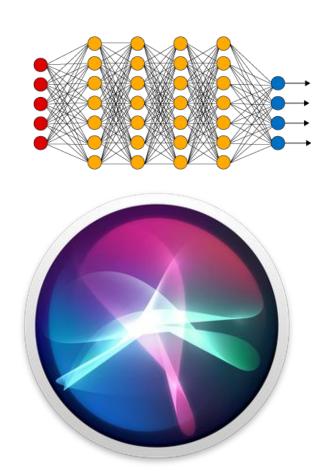


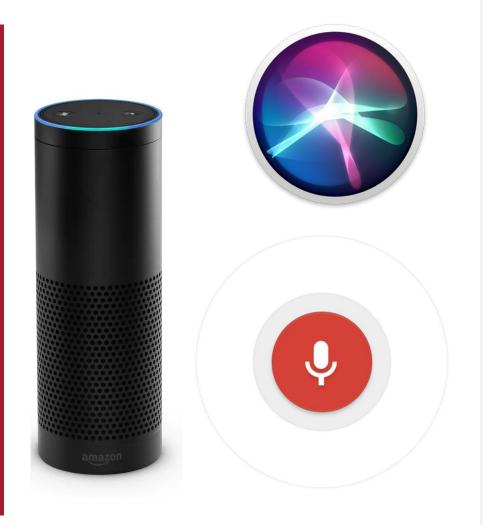


Please add more information about how to use your cell phone!

Keyword Spotting in One Slide

If we pick a simple task to only identifying a few key words we can then use a small model and train it with little data and fit it onto an embedded device





By the end of today: Hands-on Keyword Spotting (KWS)

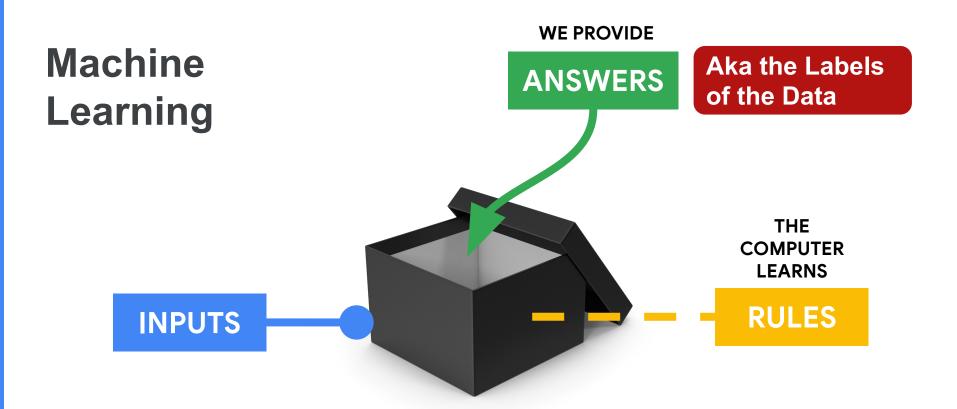
We will explore the science behind KWS and collect data and train our own custom model to recognize "yes" vs. "no" using Edge Impulse

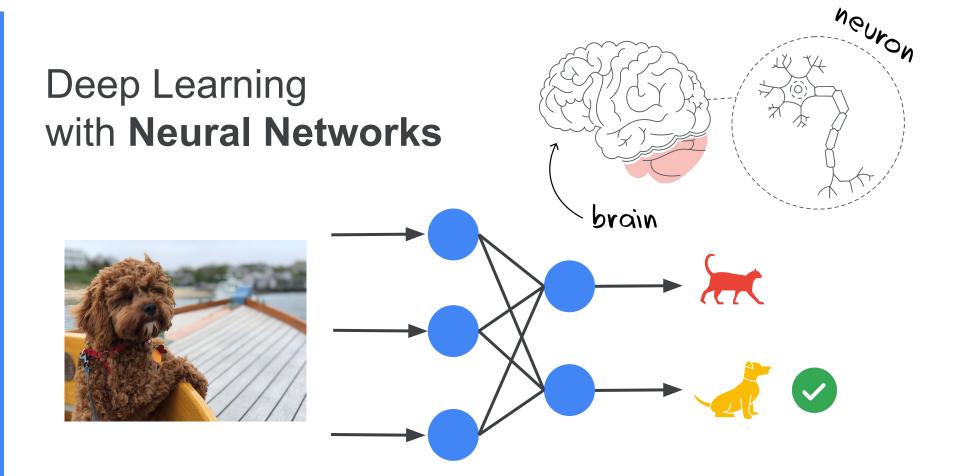
Today's Agenda

- A Quick Review of What We've Learned
- Data Engineering for KWS
- Hands-on KWS Data Collection with Edge Impulse
- Training our Model using Transfer Learning
- Deploying our Model onto our Arduino
- Summary

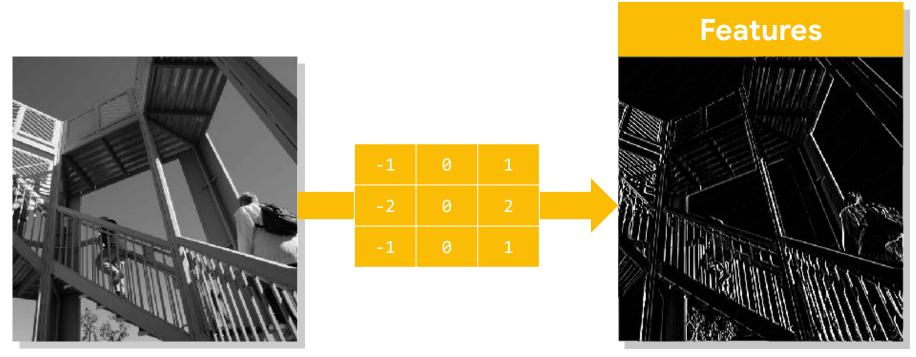
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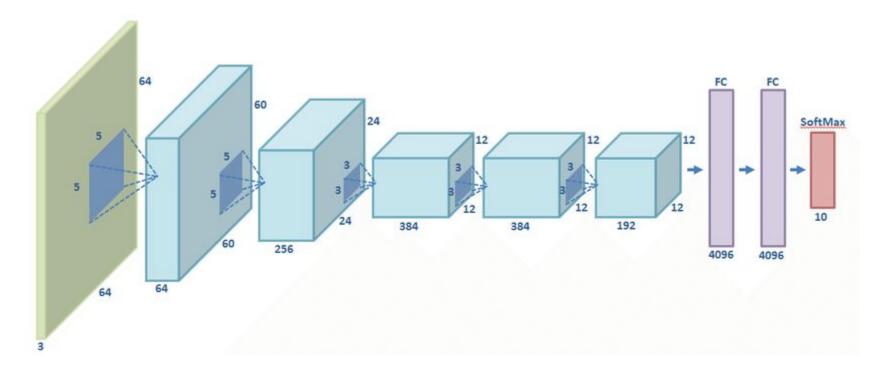




Features can be found with Convolutions



Convolutional Neural Networks



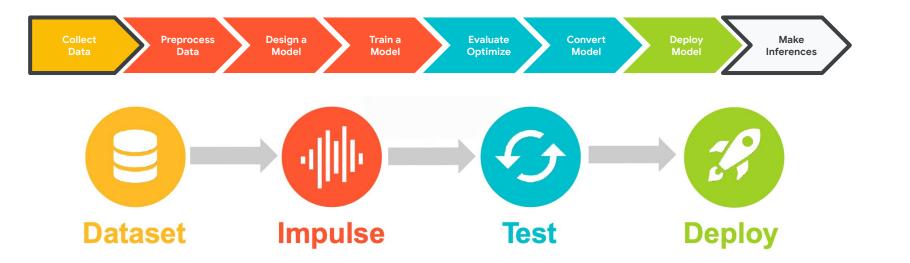
The **TinyML** Workflow



Starting inferencing in 2 seconds... Taking photo...

Predictions (DSP: 9 ms., Classification:

car: 0.07812 truck: 0.92188



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(How to collect good data)

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Who will use your ML model?

- What languages will they speak?
- What accents will they have?
- Will they use slang or formal diction?

(How to collect good data)

Who will use your ML model?

Where will your ML model be used?

- What languages will they speak?
- What accents will they have?
- Will they use slang or formal diction?
- Will there be background noise?
- How far will users be from the microphone?
- Will there be echos?

(How to collect good data)

Who will use your ML model?

Where will your ML model be used?

Why will your ML model be used? Why those Keywords?

- What languages will they speak?
- What accents will they have?
- Will they use slang or formal diction?
- Will there be background noise?
- How far will users be from the microphone?
- Will there be echos?

- What tone of voice will be used?
- Are your keywords commonly used? (aka will you get a lot of false positives)
- What about false negatives?

(How to collect good data)

There are a lot more things to consider to eliminate bias and protect privacy when collecting data that we will talk about in future sessions!

ML model be used?
Why those Keywords?

you get a lot of false positives)

What about false negatives?

taka Will

Tips and Tricks for Custom KWS

- Pick uncommon words for Keywords
- Record lots of "other words"
- Record in the location you are going to be deploying
- Get your end users to help you build a dataset
- Record with the same hardware you will deploy
- Always test and then improve your dataset and model

Tips and Tricks for Custom KWS

Today we are just working on a demo so to give our demo the the best chance of working we will:

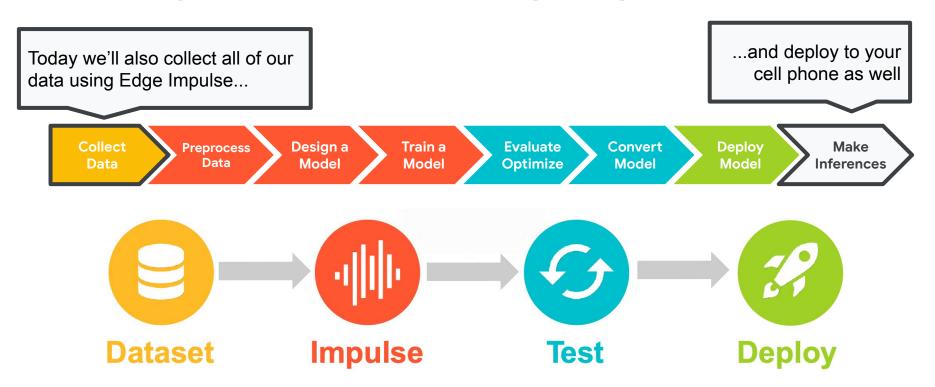
1. Stay in one spot

- (we're cheating)
- 2. Only record ourselves
- 3. Use common words (yes, no)
- 4. Only test ourselves

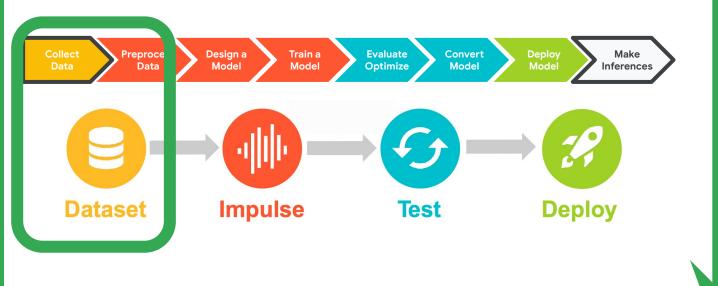
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The TinyML Workflow using Edge Impulse



Edge Impulse Project Dashboard

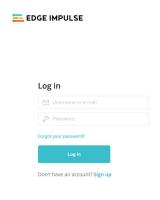


- Dashboard
- Devices
- **D**ata acquisition
- ↓ Impulse design
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Create an Edge Impulse Account

 Create an Edge Impulse account: https://studio.edgeimpulse.com/signup

2. Validate your email by clicking the link in the email sent to your account's email address





Activity: Create a Keyword Spotting Dataset

Collect ~30 samples each of the following classes of data:

- Keyword #1 "yes" (label: yes) (length: 1 seconds)
- Keyword #2 "no" (label: no) (length: 1 seconds)
- "Unknown" words that are not the keyword and background noise (label: unknown) (length: 1 seconds)

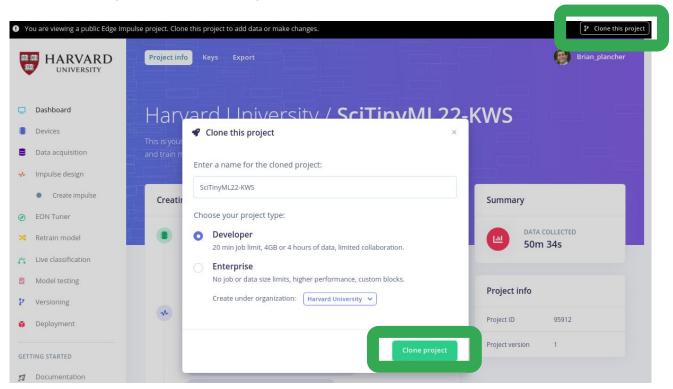
Activity: Create a Keyword Spotting Dataset

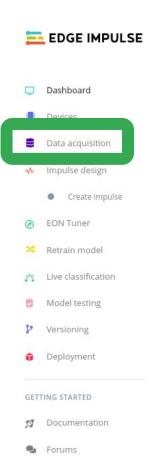
Collect ~30 samples each of the following classes of data:

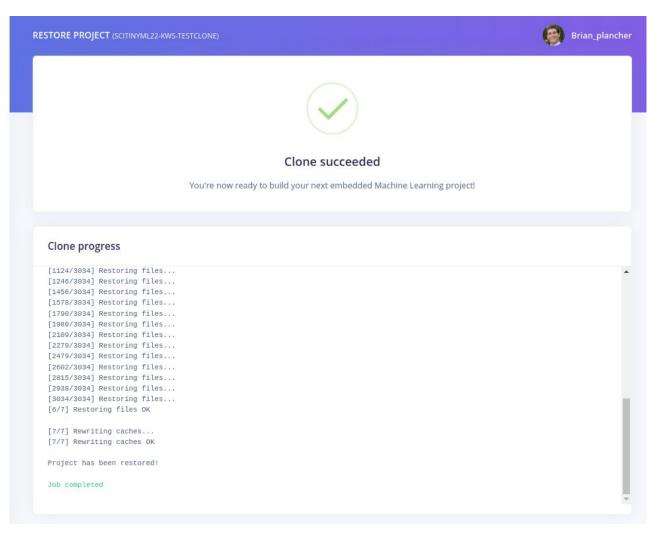
- Keyword #1 "yes" (label: yes) (length: 1 seconds)
- Keyword #2 "no" (label: no) (length: 1 seconds)
- "Unknown" words that are not the keyword and back live pre-loaded in a bunch of background noise and unknown words!

Clone my starter KWS project:

https://bit.ly/SciTinyML22-KWS





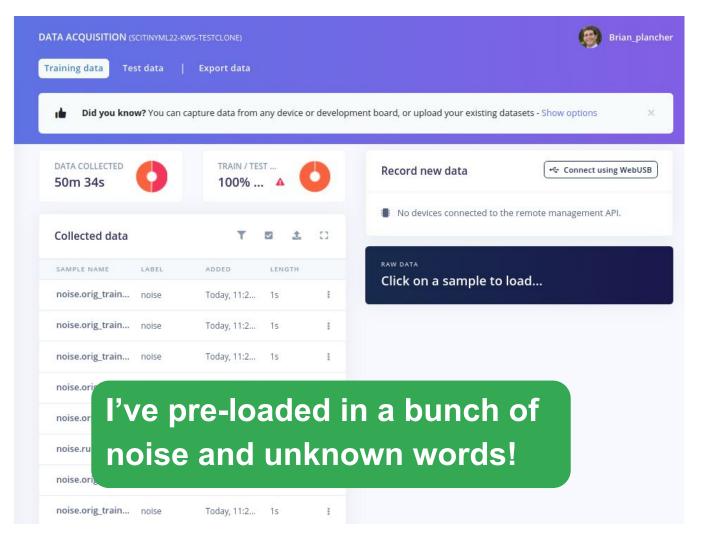


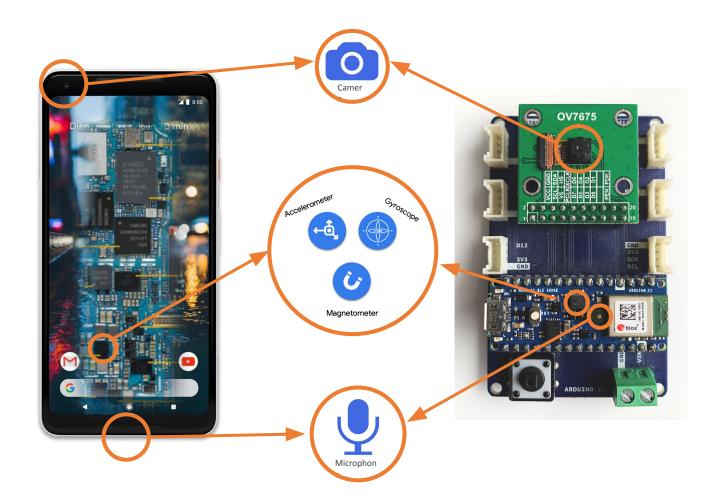


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GETTING STARTED

- Documentation
- Forums



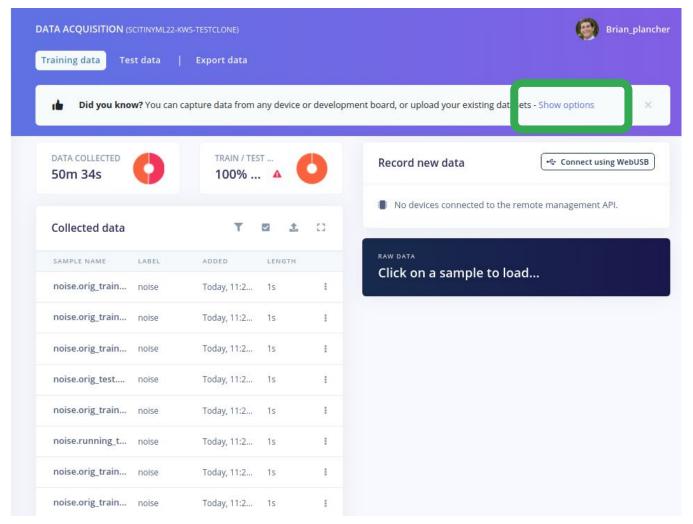


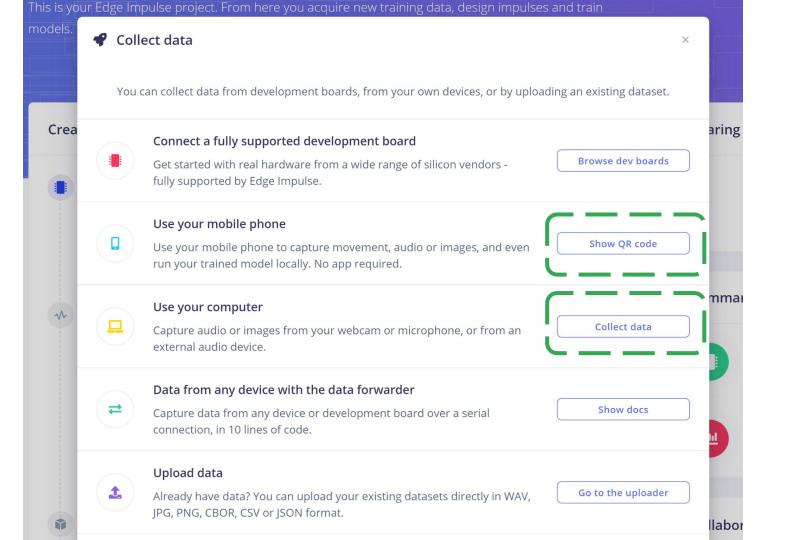


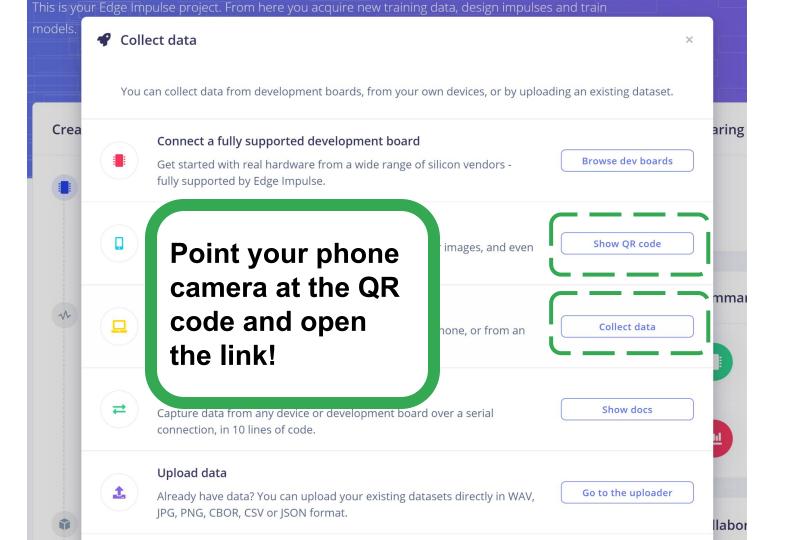
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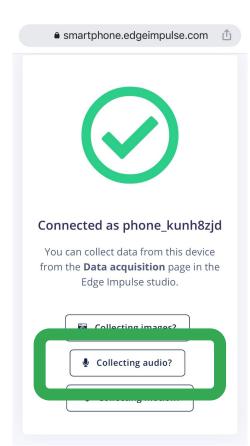


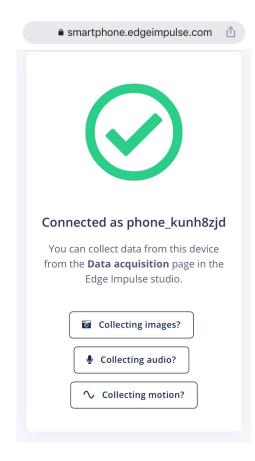


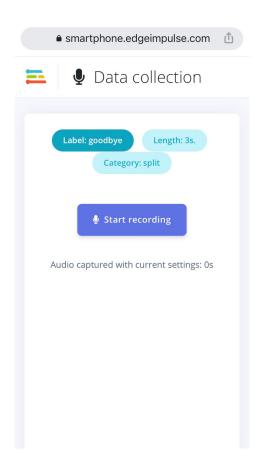
Connected as phone_kunh8zjd

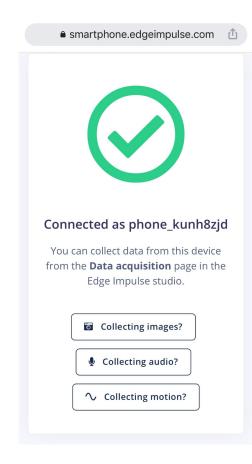
You can collect data from this device from the **Data acquisition** page in the Edge Impulse studio.

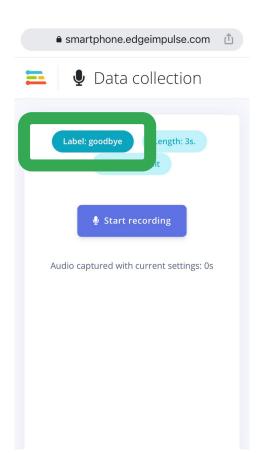
- **o** Collecting images?
- Collecting audio?
- \sim Collecting motion?

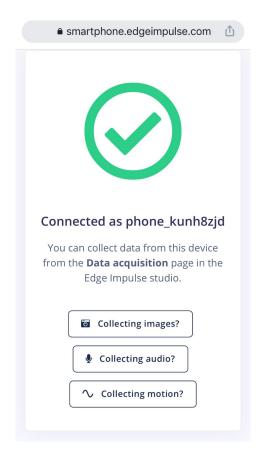


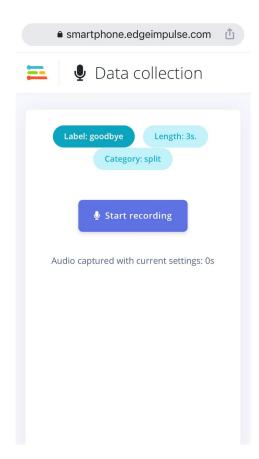


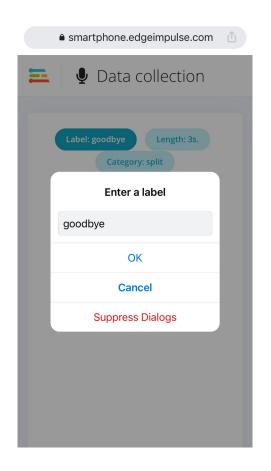


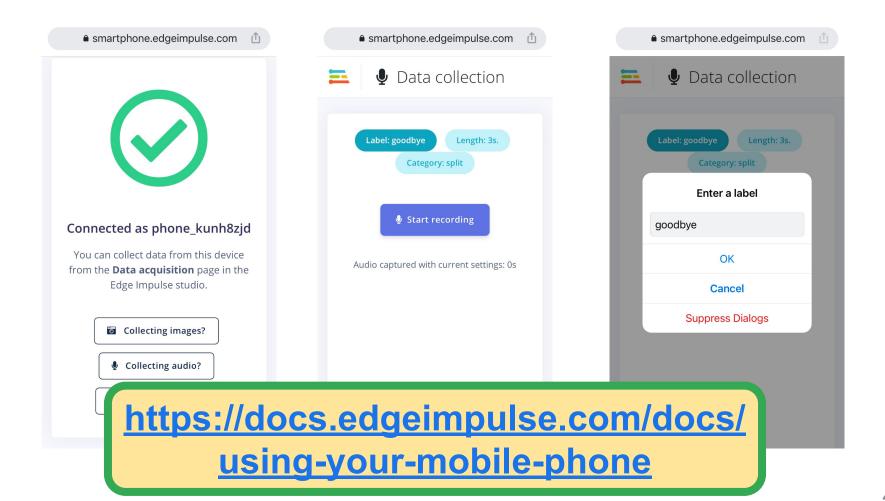










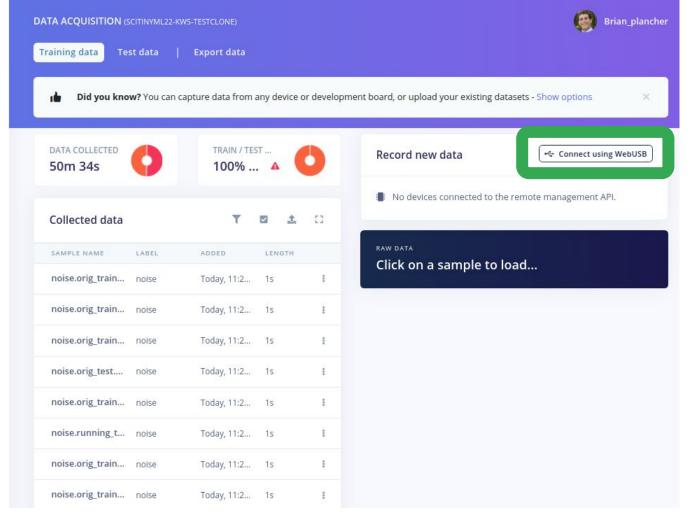




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You may need to re-flash the El Firmware!



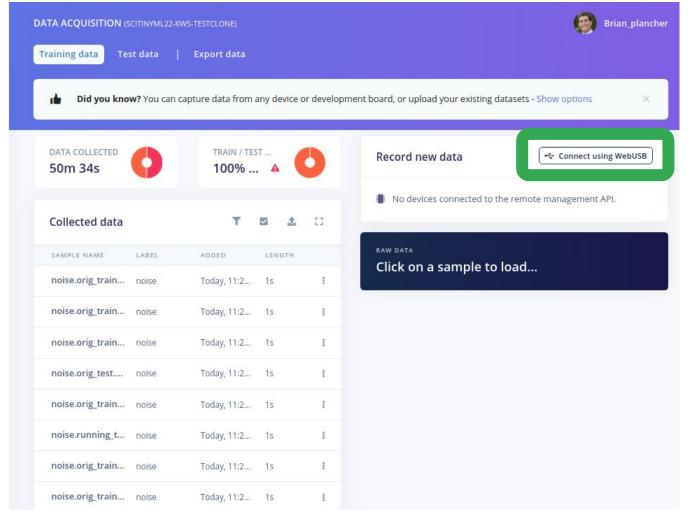
- 1. Double tap RESET to enter bootloader mode
- 2. Download the firmware: bit.ly/El-Nano33-Firmware
- 3. Run the flash script for your operating system (flash_windows.bat, flash_mac.command or flash linux.sh).
- 4. Wait until flashing is complete, and press the RESET button once to launch the new firmware.

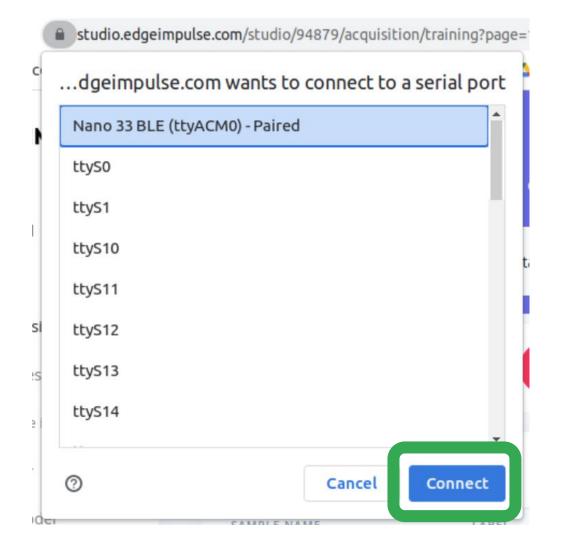


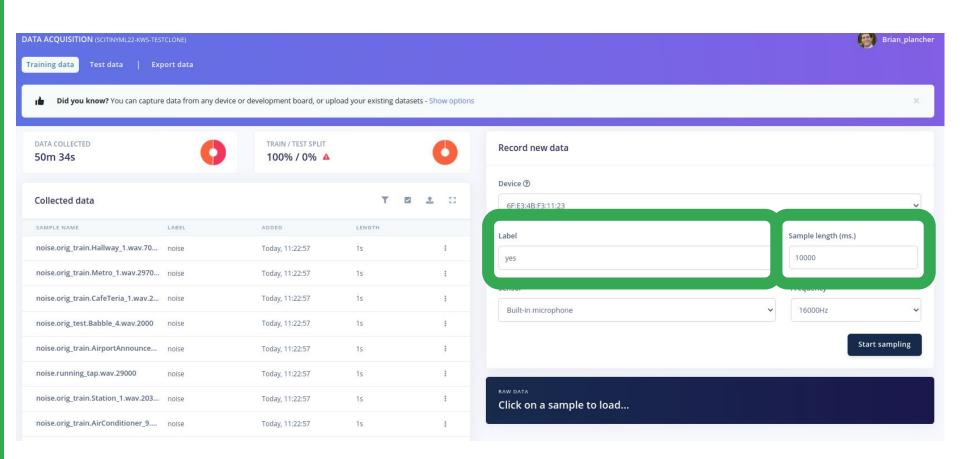
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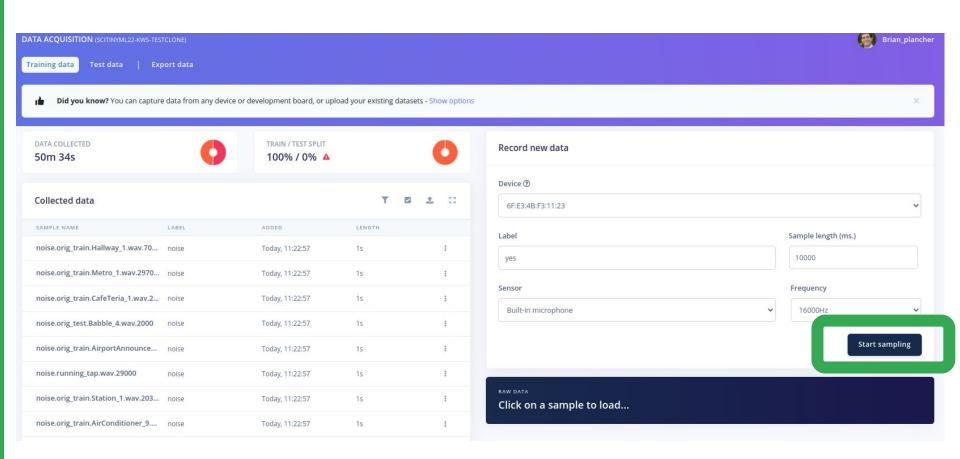
GETTING STARTED

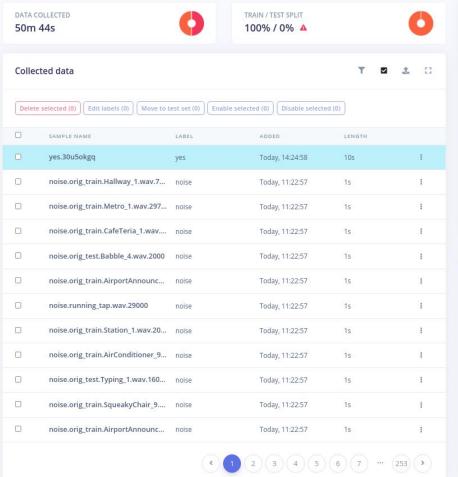
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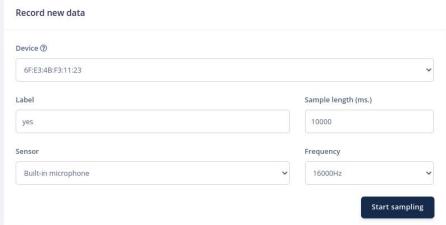






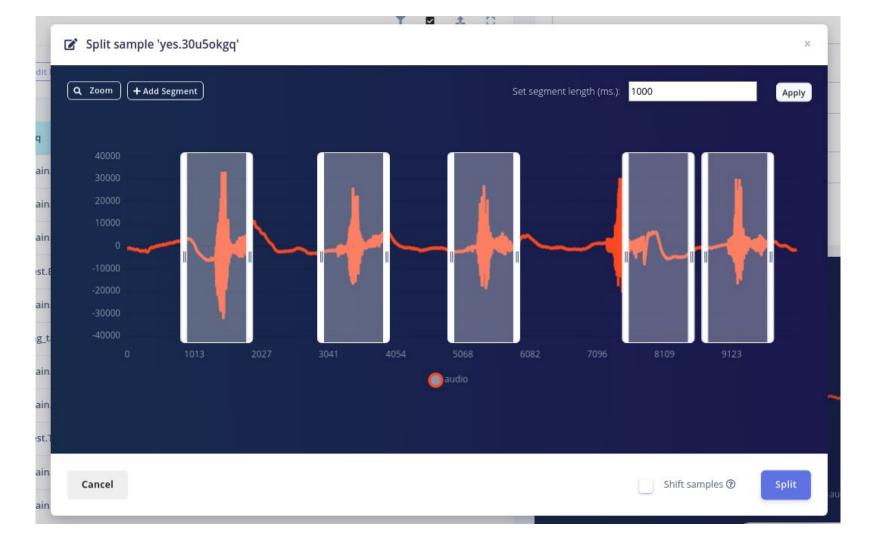


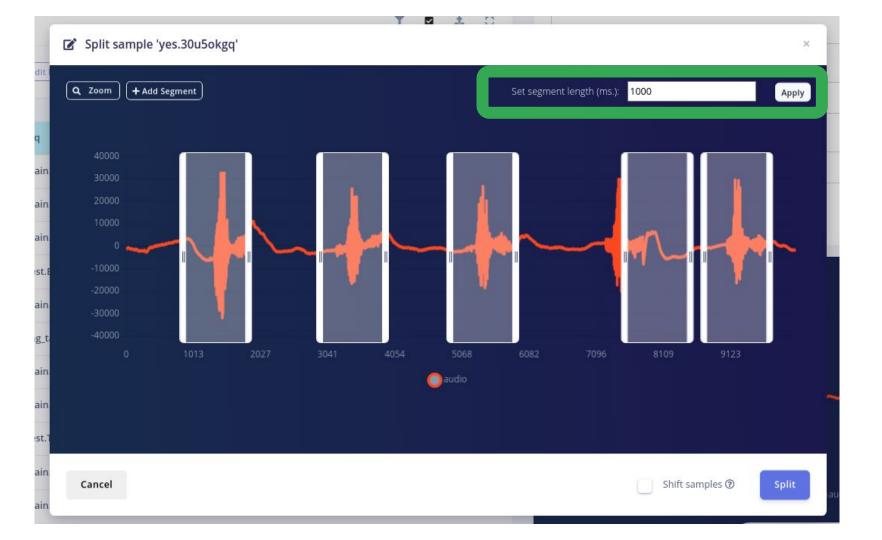




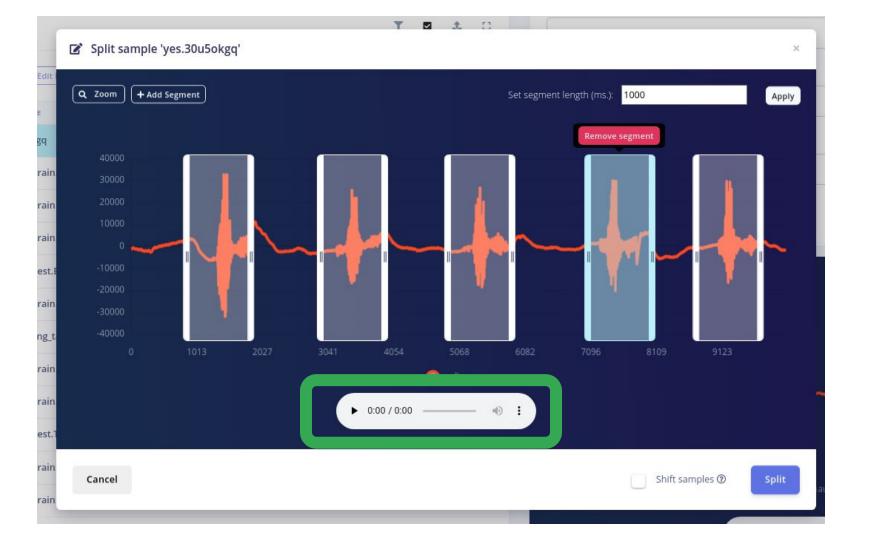


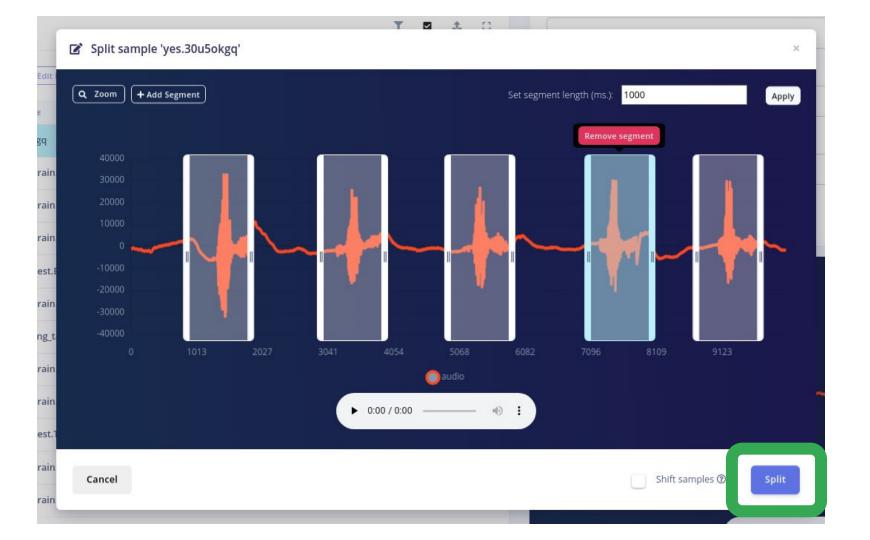
0	SAMPLE NAME	LABEL	ADDED	LENGTH	
	yes.30u5okgq	yes	Today, 14:24:58	10s i	
)	noise.orig_train.Hallway_1.wav.7	noise	Today, 11:22:57	Rename Edit label Move to test set Disable	
	noise.orig_train.Metro_1.wav.297	noise	Today, 11:22:57		
)	noise.orig_train.CafeTeria_1.wav	noise	Today, 11:22:57		
	noise.orig_test.Babble_4.wav.2000	noise	Today, 11:22:57	Crop sample	
)	noise.orig_train.AirportAnnounc	noise	Today, 11:22:57	Split sample Download	
)	noise.running_tap.wav.29000	noise	Today, 11:22:57	Delete	
7	noice origitation Station 1 way 20	poico	Today 11:22:57	16 1	

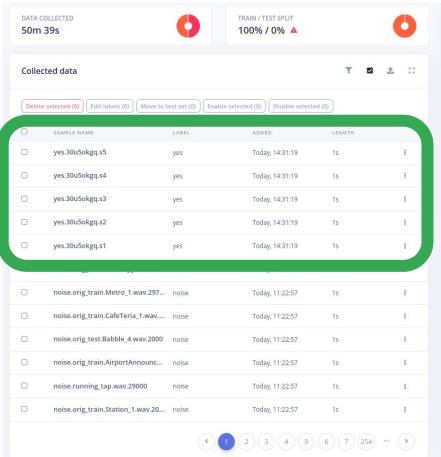


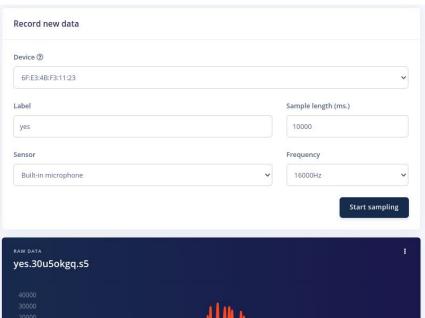












0:00 / 0:00 —

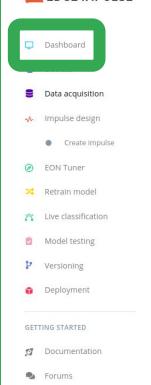
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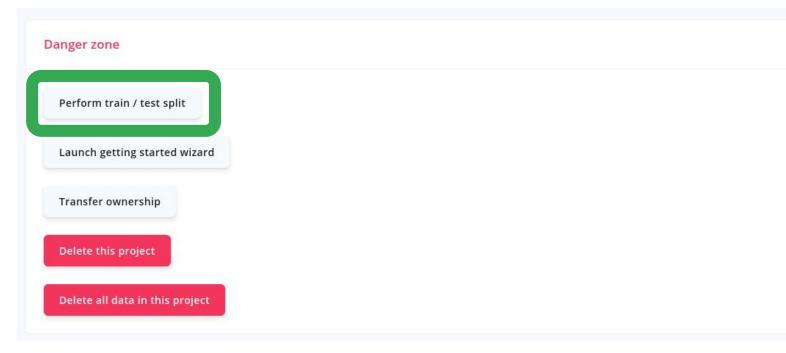
- Keyword #1 "yes" (label: yes) (length: 1 seconds)
- Keyword #2 "no" (label: no) (length: 1 seconds)

We'll resume in 10 minutes!

EDGE IMPULSE



Scroll Down to the Bottom

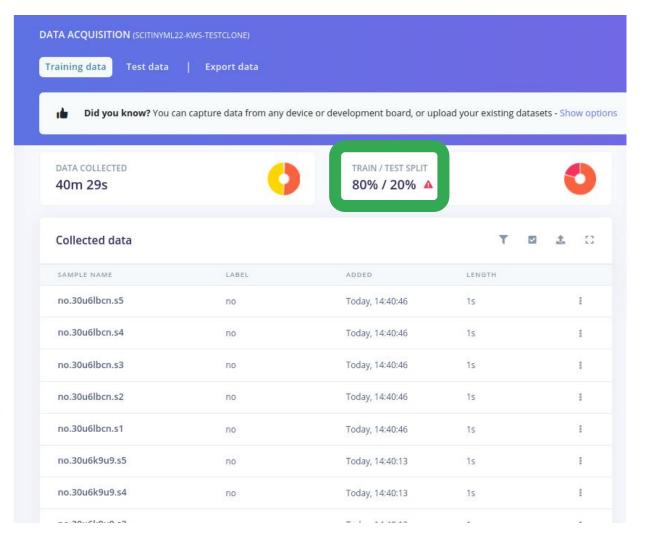


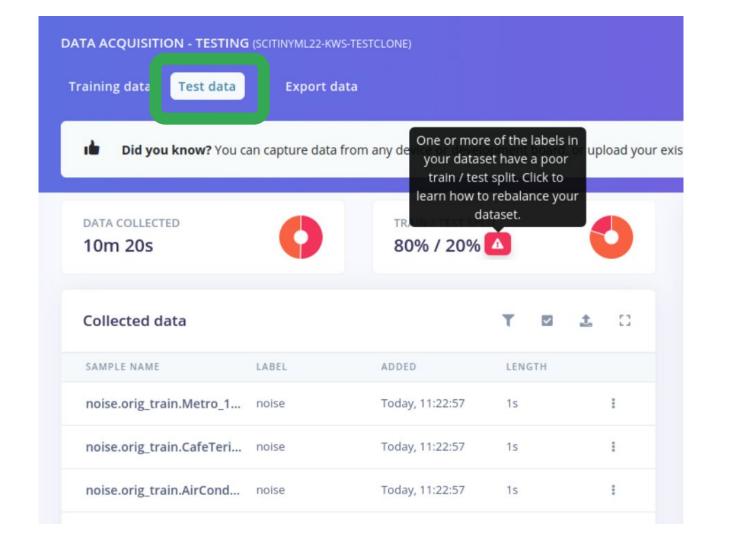
EDGE IMPULSE

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Training data is used to train your model, and **testing data** is used to test your model's accuracy after training. We recommend an approximate 80/20 train/test split ratio for your data for every class (or label) in your dataset, although especially large datasets may require less testing data.

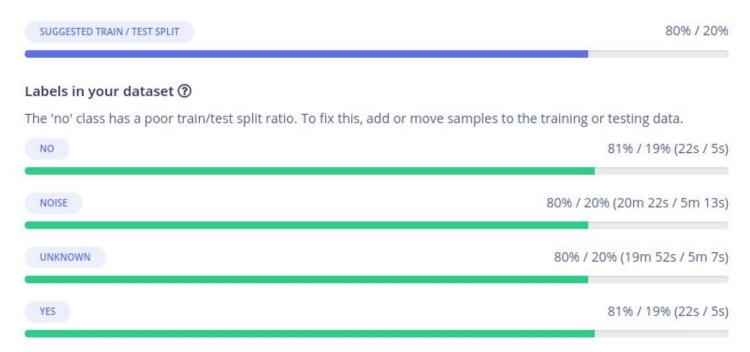


Perform train / test split

Use this option to rebalance your data, automatically splitting items between training and testing datasets. **Warning: this action cannot be undone.**

Collected data			T 🗷	t. []
SAMPLE NAME	LABEL	ADDED	LENGTH	
no.30u8qcvh.s1	no	Today, 15:22:58	1s	1
no.30u6k9u9.s5	no	Today, 15:22:5	Rename	
no.30u6k9u9.s1	no	Today, 15:22:5	Edit label Move to test set	
no.30u8qcvh.s9	no	Today, 15:22:4	Disable	
no.30u8qcvh.s7	no	Today, 15:22:4	Crop sample	
yes.30u8rq7l.s8	yes	Today, 15:20:1	Split sample	
yes.30u8rq7l.s7	yes	Today, 15:20:1	Download Delete	

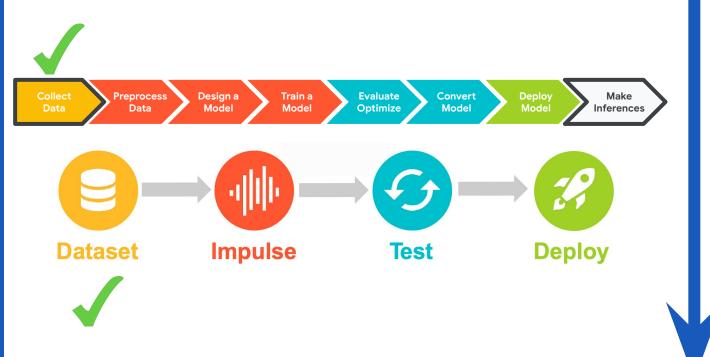
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Edge Impulse Project Dashboard



- Dashboard
- Devices



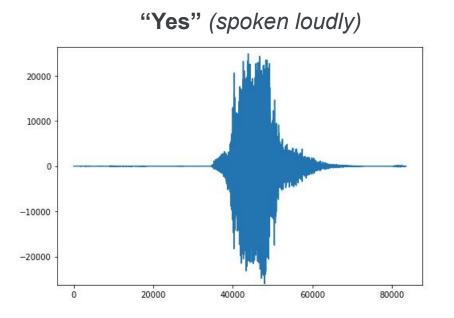
Data acquisition

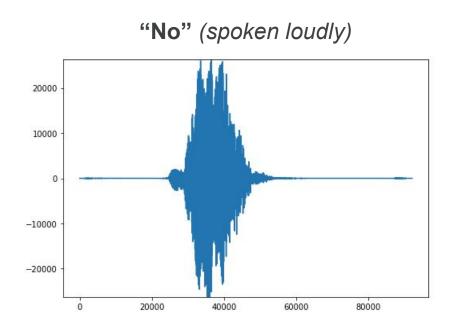
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Why might we want to **preprocess** data and not send the raw data to the neural network?

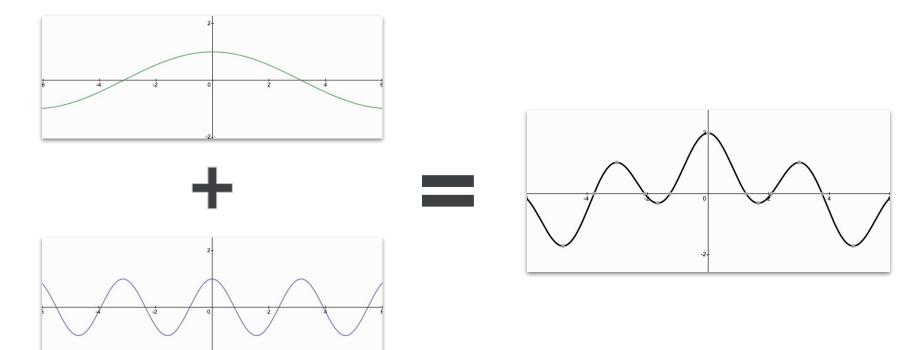


Can you tell these two signals apart?

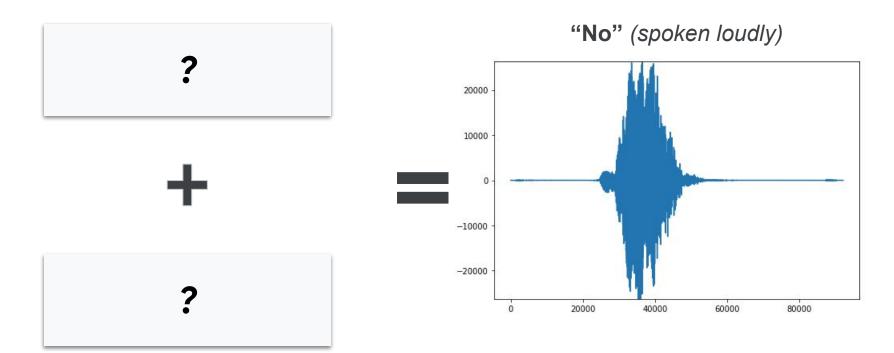




Signal Components?

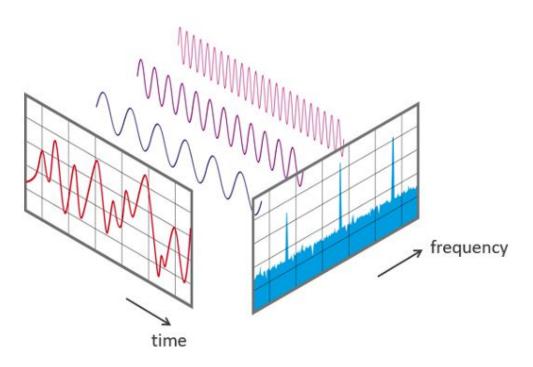


Signal Components?

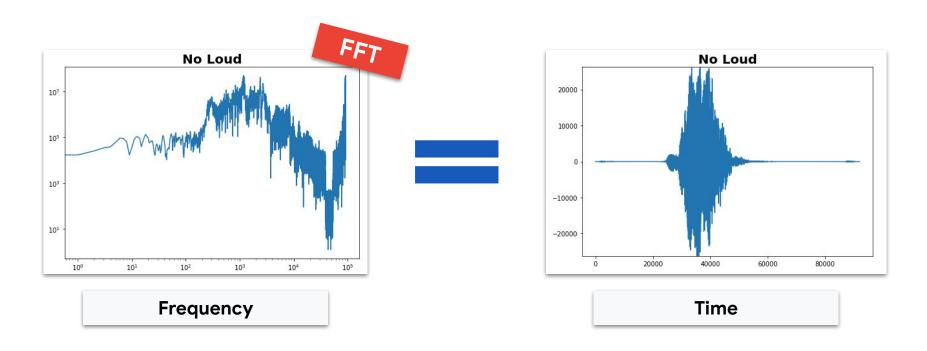


Fast Fourier Transform:

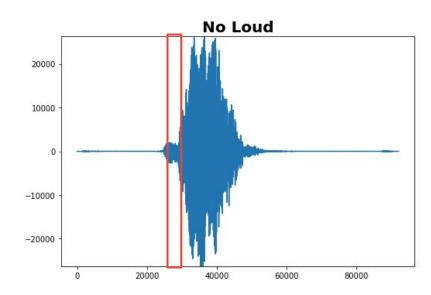
extract the frequencies from a signal



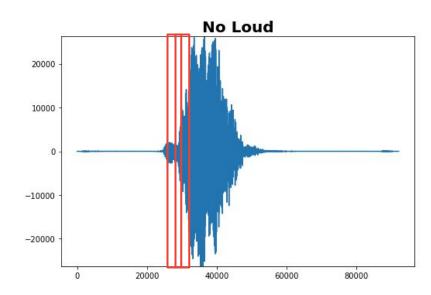
Fast Fourier Transform



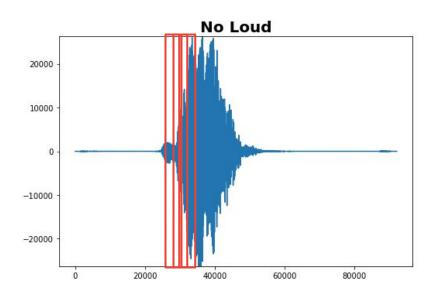
Building a **Spectrogram** using FFTs



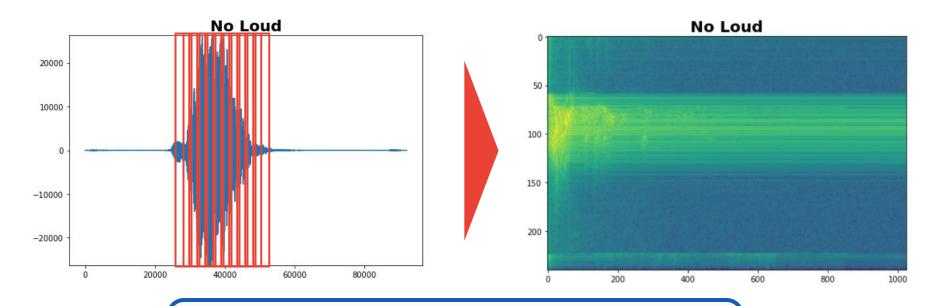
Building a **Spectrogram** using FFTs



Building a **Spectrogram** using FFTs

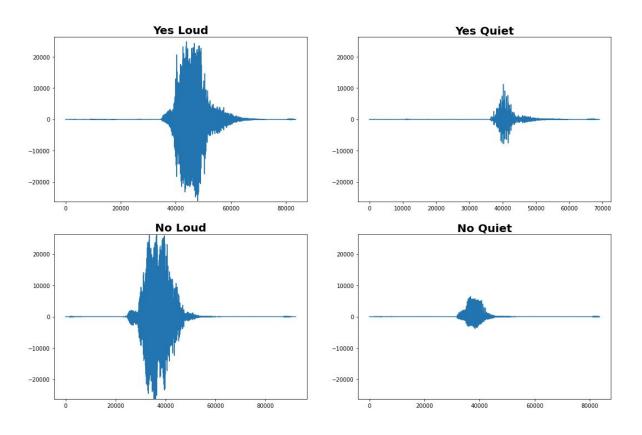


Building a **Spectrogram** using FFTs

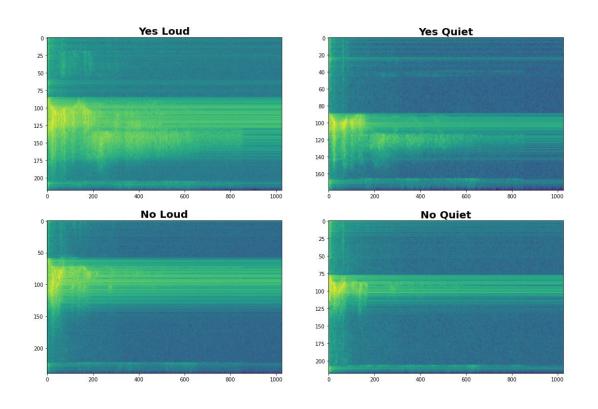


Essentially if you stack up all the FFTs in a row then you get the Spectrogram (time vs. frequency with color indicating intensity)

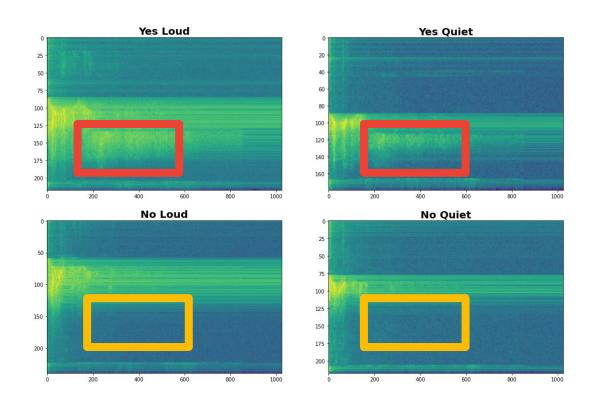
Spectrograms help differentiate the data



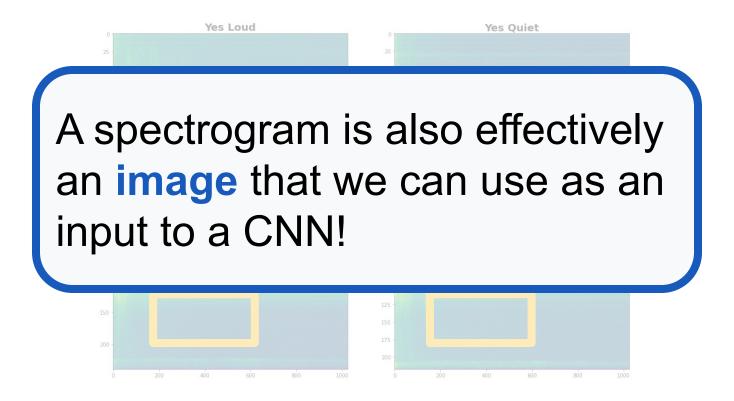
Spectrograms help differentiate the data



Spectrograms help differentiate the data

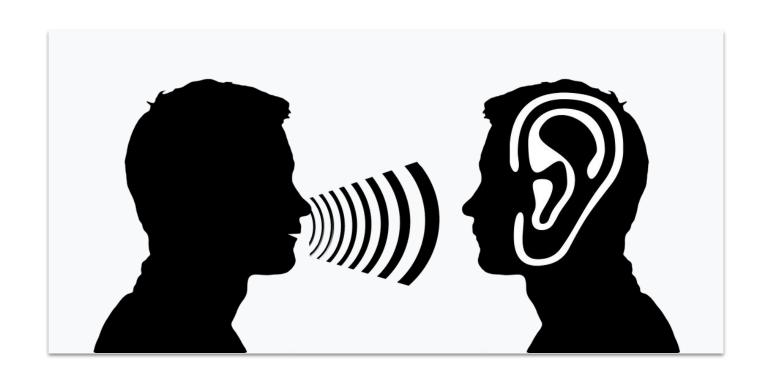


Data Preprocessing: Spectrograms

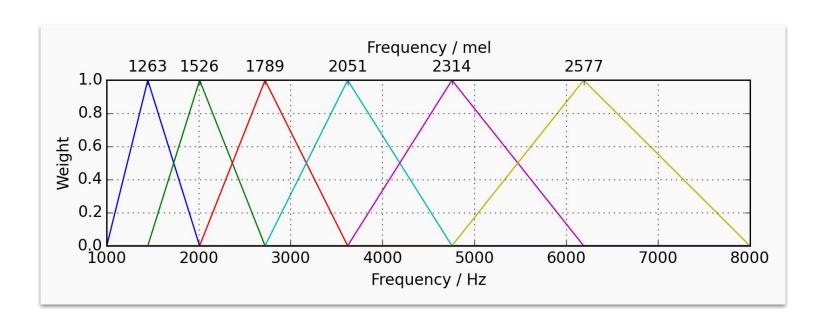


Can we do **better** than a spectrogram?

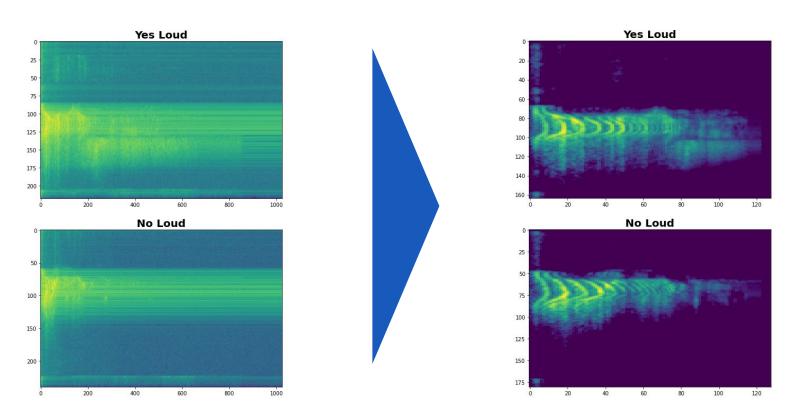
Can we take domain knowledge into account?



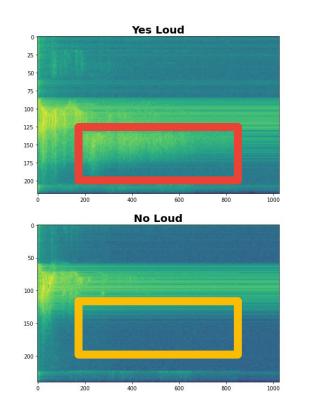
Mel Filterbanks

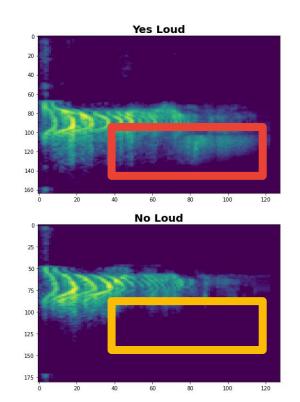


Spectrograms v. MFCCs

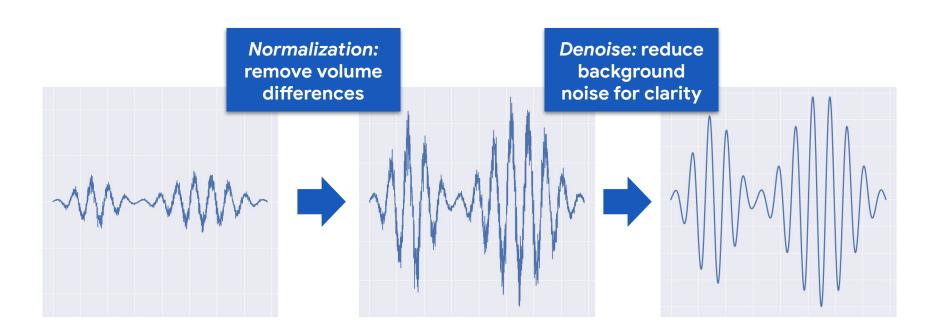


Spectrograms v. MFCCs

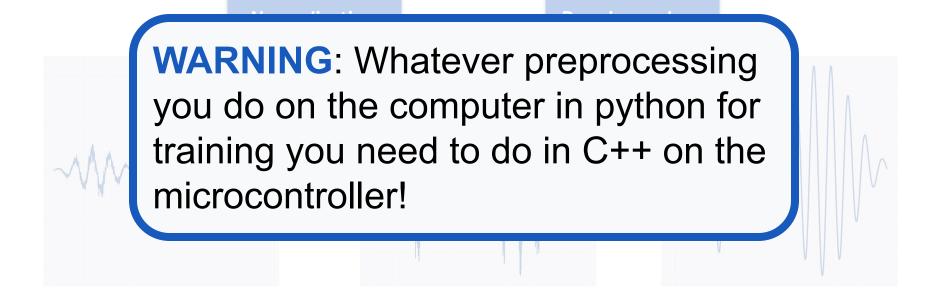




Additional Feature Engineering



Additional Feature Engineering



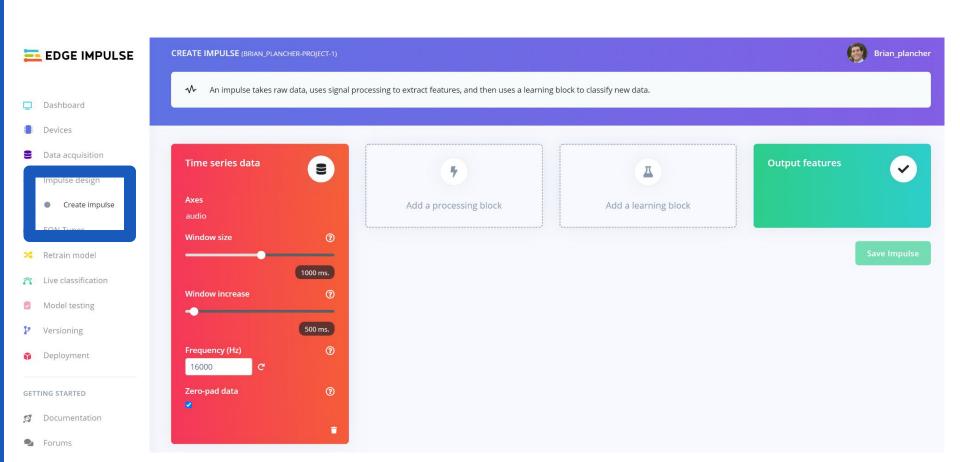
Today's Agenda

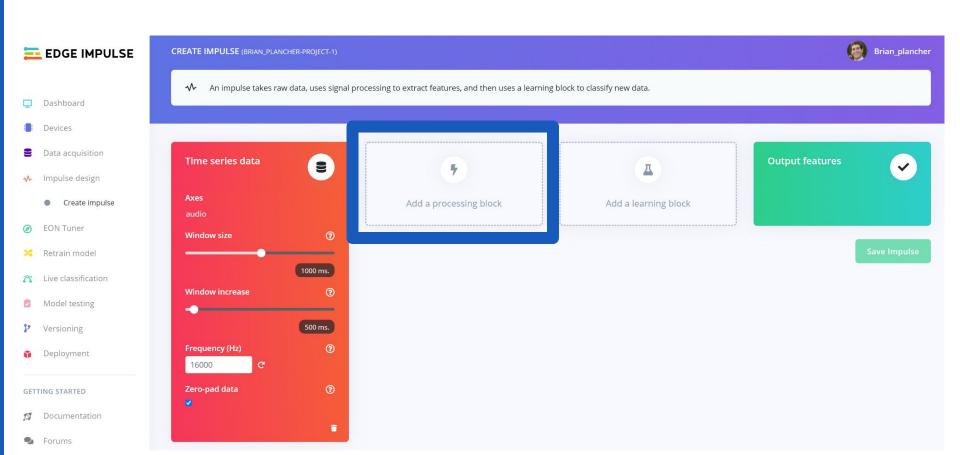
- Deep ML Background
- Hands-on Computer Vision: Thing Translator
- The Tiny Machine Learning Workflow
- Keyword Spotting (KWS) Data Collection
- KWS Preprocessing and Training

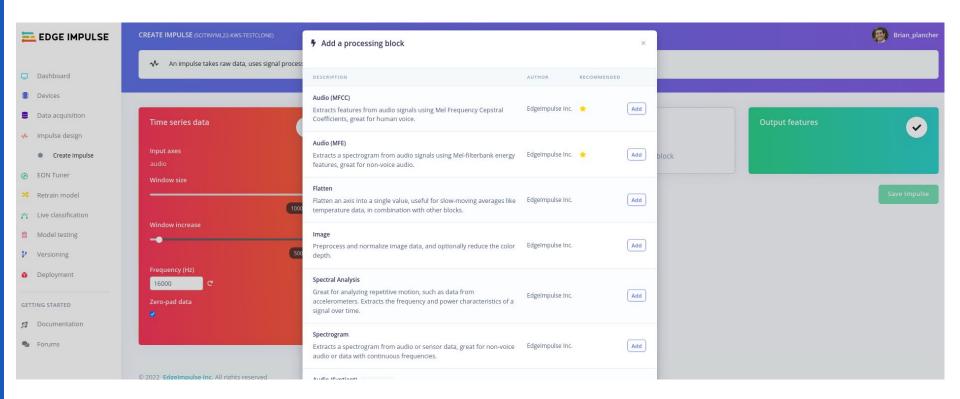
Preprocessing (for KWS)

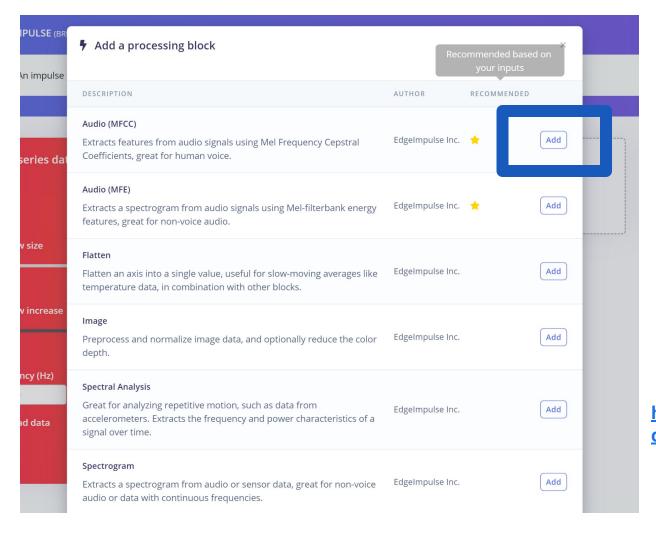
Hands-on Preprocessing and Training with Edge Impulse

- Deployment Challenges and Opportunities for Embedded ML
- Summary





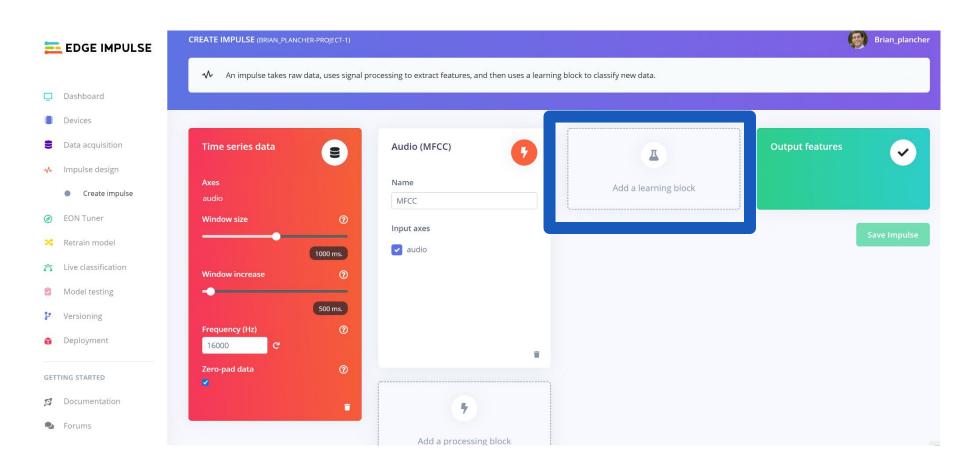


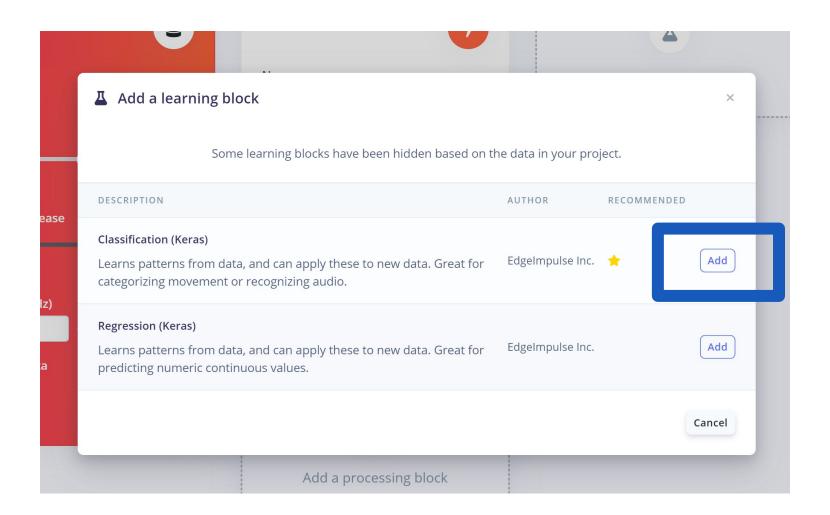


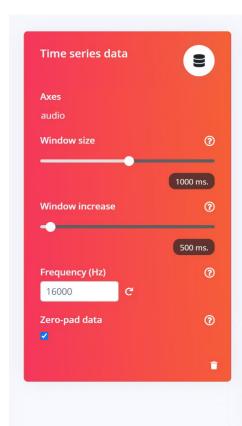
We'll keep things simple today and just add an MFCC but/and in future projects you can:

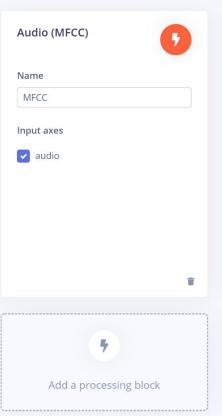
- create your own blocks
- use multiple blocks

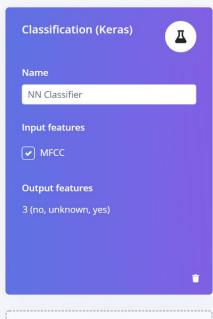
https://docs.edgeimpulse.com/docs/custom-blocks

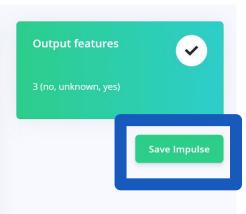




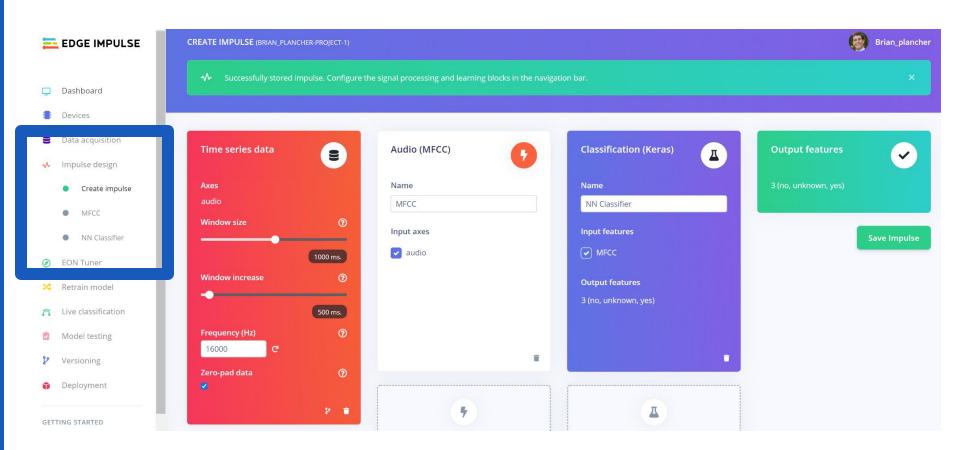


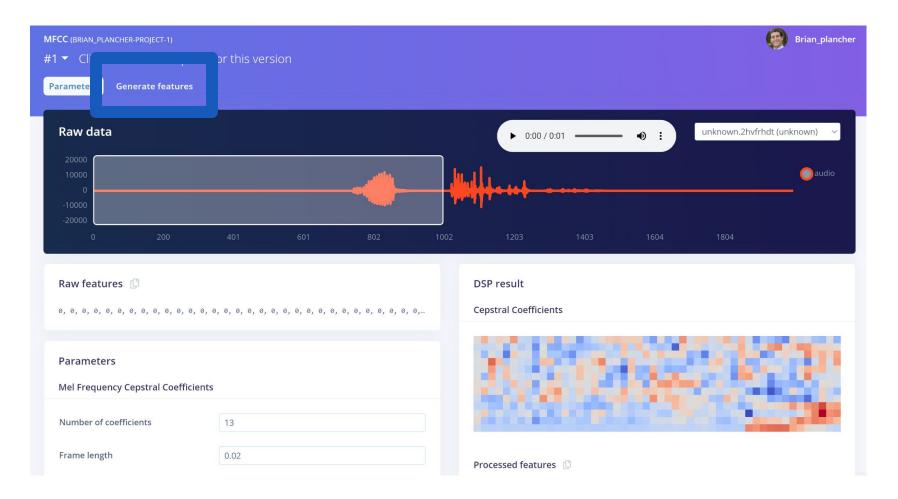


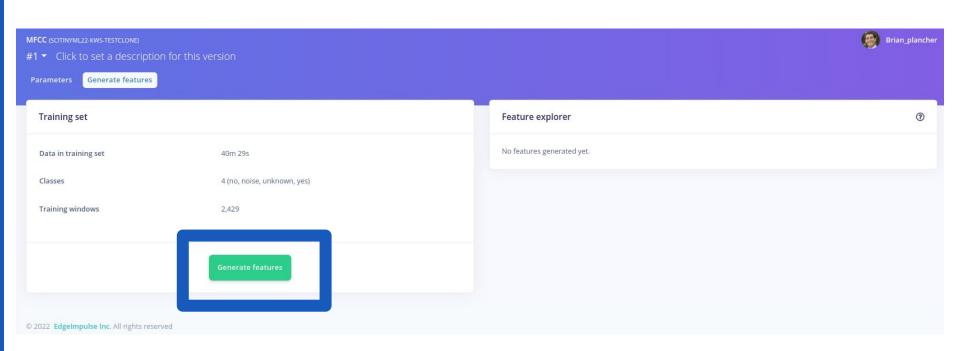


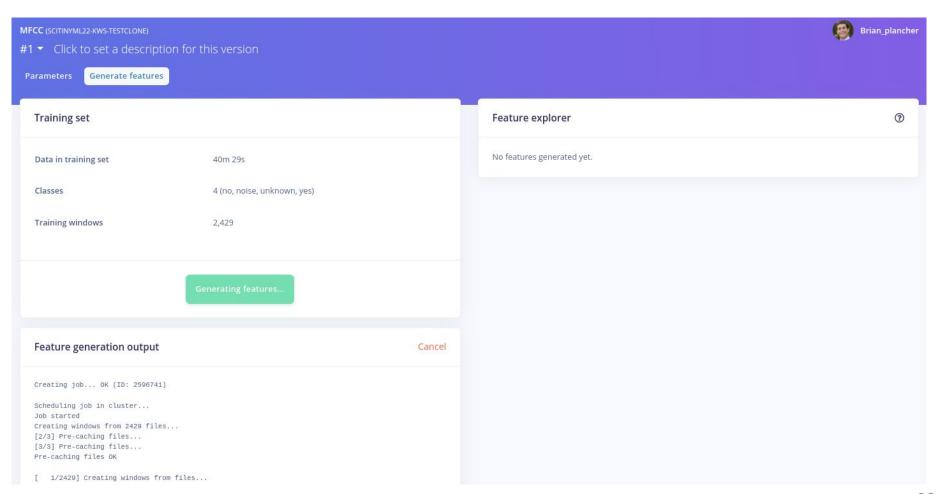


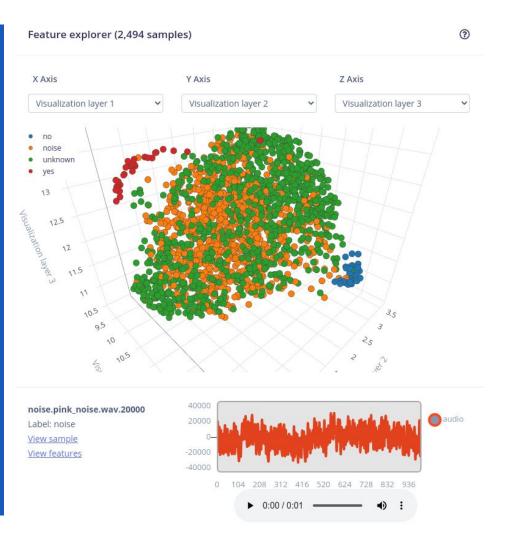
Add a learning block



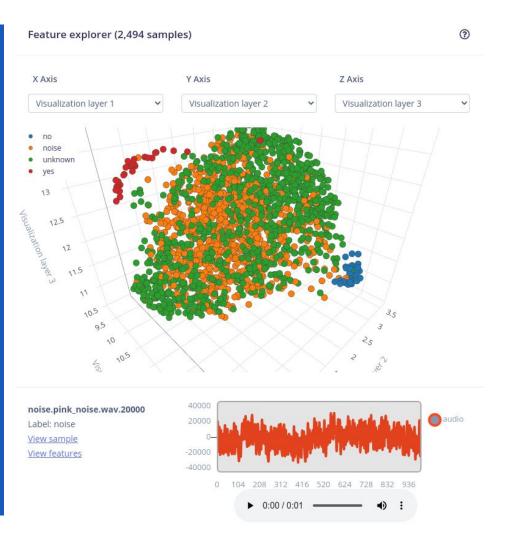


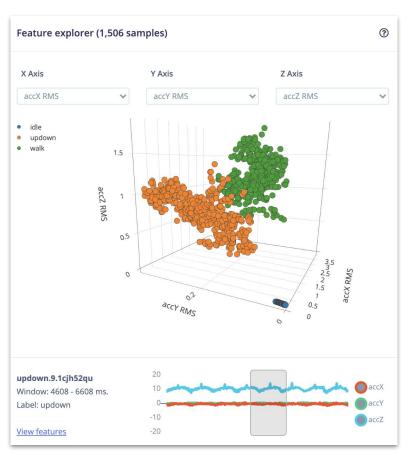


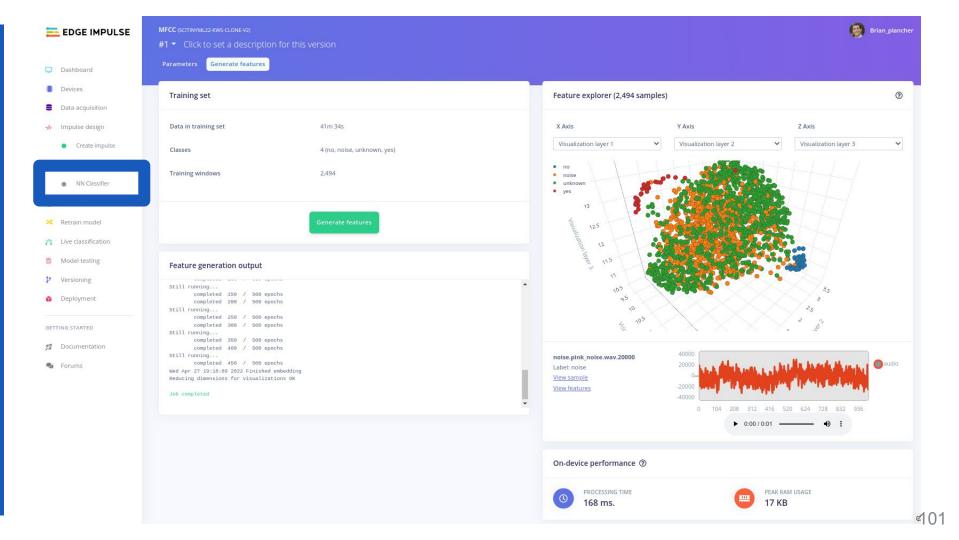


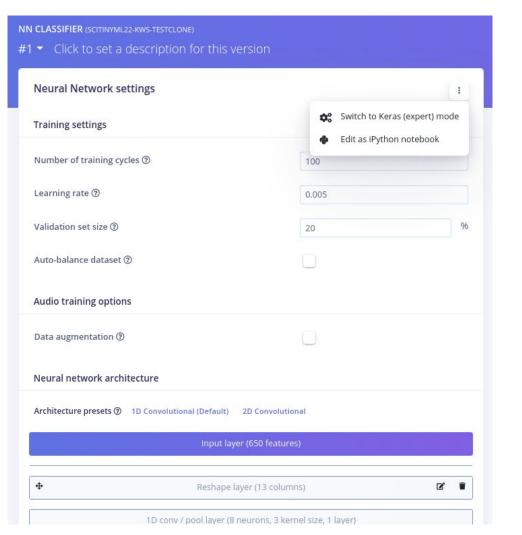


If you can visually see the clustering of the data then it is easier for the ML model to learn! (But its not required and provides no guarantees)









Model Design with Edge Impulse

Pre-made neural network "blocks" that you can add!

Neural Network settings	
Training settings	
Number of training cycles ①	50
Learning rate ⑦	0.0001
Minimum confidence rating ③	0.80
Neural network architecture	
Input layer (637 features)	
Reshape layer (13 columns)	
1D conv / pool layer (30 neurons, 5 kernel size)	
1D conv / pool layer (10 neurons, 5 kernel size)	
Flatten layer	
Add an extra layer	
Output layer (5 features)	

Model Design with Edge Impulse

"Expert" mode to write your own TensorFlow code

Neural network architecture

```
import tensorflow as tf
 2 from tensorflow.keras.models import Sequential
 3 from tensorflow.keras.layers import Dense, InputLayer,
        Dropout, Conv1D, Conv2D, Flatten, Reshape, MaxPooling1D,
        MaxPooling2D, BatchNormalization
 4 from tensorflow.keras.optimizers import Adam
    sys.path.append('./resources/libraries')
   import ei tensorflow.training
    # model architecture
    model = Sequential()
10 channels = 1
11 \quad \text{columns} = 13
12 rows = int(input_length / (columns * channels))
    model.add(Reshape((rows, columns, channels), input_shape
        =(input_lenath, )))
14 model.add(Conv2D(8, kernel_size=3, activation='relu',
        kernel_constraint=tf.keras.constraints.MaxNorm(1).
        paddina='same'))
15 model.add(MaxPooling2D(pool_size=2, strides=2, padding
        ='same'))
16 model.add(Dropout(0.25))
    model.add(Conv2D(16, kernel_size=3, activation='relu',
        kernel_constraint=tf.keras.constraints.MaxNorm(1),
        padding='same'))
18 model.add(MaxPooling2D(pool_size=2, strides=2, padding
        ='same'))
19 model.add(Dropout(0.25))
    model.add(Flatten())
    model.add(Dense(classes, activation='softmax', name='y_pred'
```

Start training

Neural network architecture Architecture presets ② 1D Convolutional (Default) 2D Convolutional Input layer (650 features) Reshape layer (13 columns) 1D conv / pool layer (8 neurons, 3 kernel size, 1 layer) Dropout (rate 0.25) 1D conv / pool layer (16 neurons, 3 kernel size, 1 layer) Dropout (rate 0.25) Flatten layer Add an extra layer Output layer (3 features) Start training

Neural network architecture

```
import tensorflow as tf
    from tensorflow.keras.models import Sequential
3 from tensorflow.keras.layers import Dense, InputLayer, Dropout, Conv1D, Conv2D,
        Flatten, Reshape, MaxPooling1D, MaxPooling2D, BatchNormalization,
        TimeDistributed
 4 from tensorflow.keras.optimizers import Adam
6 # model architecture
    model.add(Reshape((int(input length / 13), 13), input shape=(input length, )))
   model.add(Conv1D(8, kernel size=3, activation='relu', padding='same'))
10 model.add(MaxPooling1D(pool size=2, strides=2, padding='same'))
   model.add(Conv1D(16, kernel size=3, activation='relu', padding='same'))
    model.add(MaxPooling1D(pool_size=2, strides=2, padding='same'))
    model.add(Dropout(0.25))
    model.add(Flatten())
    model.add(Dense(classes, activation='softmax', name='y pred'))
17
    # this controls the learning rate
    opt = Adam(lr=0.005, beta_1=0.9, beta_2=0.999)
20 # this controls the batch size, or you can manipulate the tf.data.Dataset objects
        vourself
21 BATCH SIZE = 32
22 train_dataset = train_dataset.batch(BATCH_SIZE, drop_remainder=False)
    validation dataset = validation dataset.batch(BATCH SIZE, drop remainder=False)
    callbacks.append(BatchLoggerCallback(BATCH_SIZE, train_sample_count))
25
    # train the neural network
    model.compile(loss='categorical crossentropy', optimizer=opt, metrics=['accuracy'])
28 model.fit(train dataset, epochs=100, validation data=validation dataset, verbose=2,
        callbacks=callbacks)
```

.

Start training

Neural network architecture

```
import tensorflow as tf
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```

For now just stick with the defaults but/and you can easily design any model you want and use any optimizer you want using TensorFlow!

Start training

Neural network architecture

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    model.add(Dropout(0.25))
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21 BATCH SIZE = 32
22 train_dataset = train_dataset.batch(BATCH_SIZE, drop_remainder=False)
23 validation dataset = validation dataset.batch(BATCH SIZE, drop remainder=False)
```

For now just stick with the defaults but/and you can easily design any model you want and use any optimizer you want using TensorFlow!

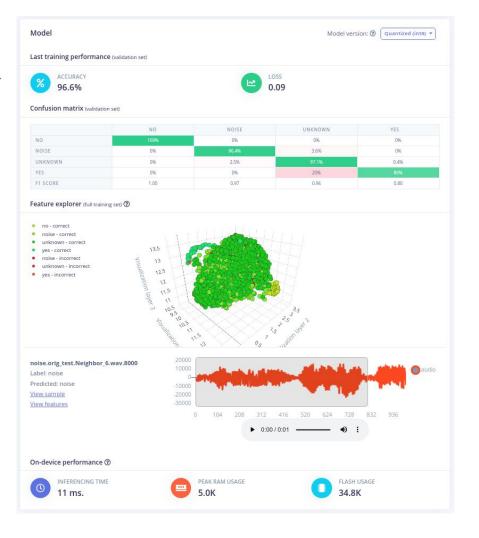
Training output

```
Epoch 95/100
4/4 - 0s - loss: 0.1044 - accuracy: 0.9500 - val_loss: 0.2934 - val_accuracy: 0.9231
Epoch 96/100
4/4 - 0s - loss: 0.0256 - accuracy: 1.0000 - val_loss: 0.3830 - val_accuracy: 0.8846
Epoch 97/100
4/4 - 0s - loss: 0.0523 - accuracy: 0.9800 - val_loss: 0.4366 - val_accuracy: 0.8462
Epoch 98/100
4/4 - 0s - loss: 0.0451 - accuracy: 0.9800 - val_loss: 0.4265 - val_accuracy: 0.8846
Epoch 99/100
4/4 - 0s - loss: 0.0514 - accuracy: 0.9900 - val_loss: 0.3926 - val_accuracy: 0.8846
Epoch 100/100
4/4 - 0s - loss: 0.0348 - accuracy: 0.9900 - val_loss: 0.3571 - val_accuracy: 0.9231
Finished training
```

Training Set

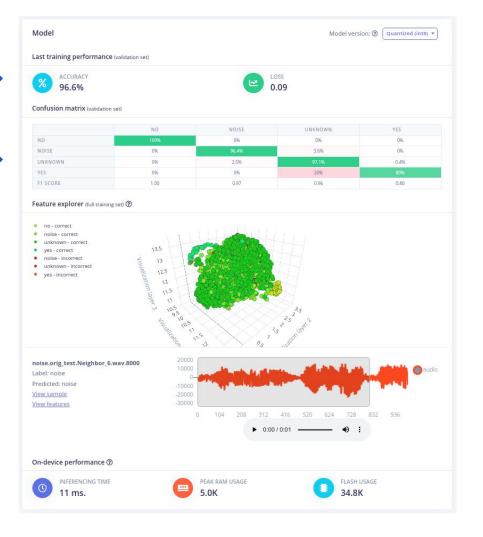
Validation Set

Final Accuracy



Final Accuracy

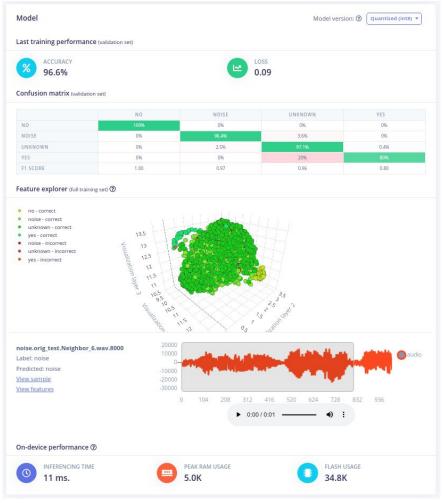
Accuracy Breakdown



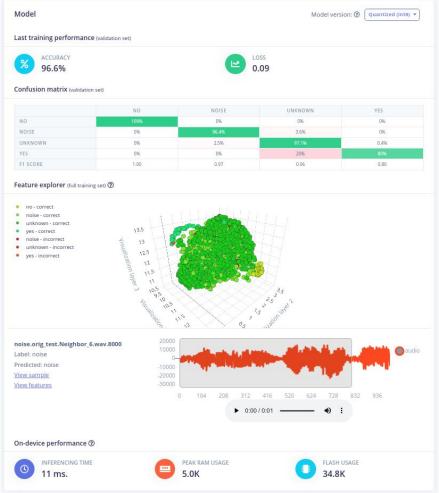
Confusion Matrix

	Actual Output = Yes	Actual Output = No
Predicted Output = Yes	# of True Positive	# of False Positive Type 1 Error
Predicted Output = No	# of False Negative Type 2 Error	# of True Negative

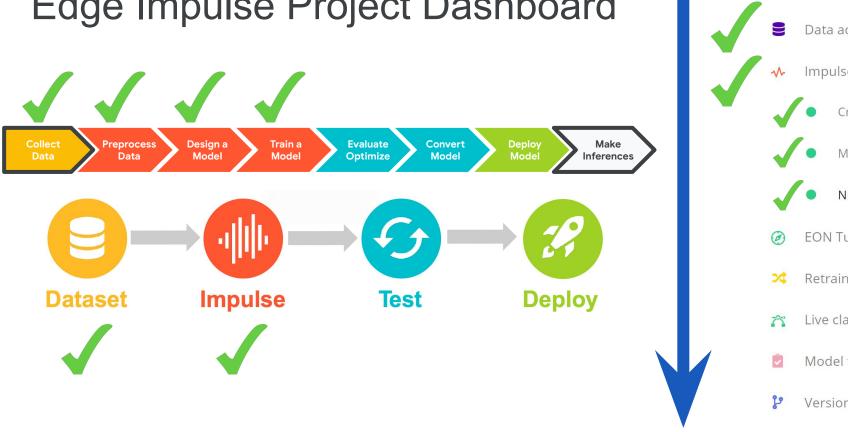
Final Accuracy Accuracy Breakdown Feature Explorer Individual Data Points



Final Accuracy Accuracy Breakdown Feature Explorer Individual Data Points Expected runtime/memory



Edge Impulse Project Dashboard

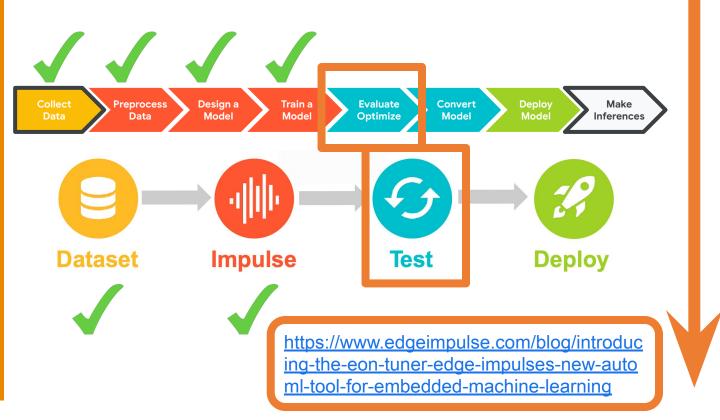


- Dashboard
- Devices
- Data acquisition
- Impulse design
 - Create impulse
 - MFCC
 - **NN Classifier**
 - **EON Tuner**
 - Retrain model
 - Live classification
 - Model testing
 - Versioning
 - Deployment

Today's Agenda

- A Quick Review of What We've Learned
- Data Engineering for KWS
- Hands-on KWS Data Collection with Edge Impulse
- (Hands-on) Data Preprocessing for KWS
- Deploying our Model onto our Arduino
- Summary

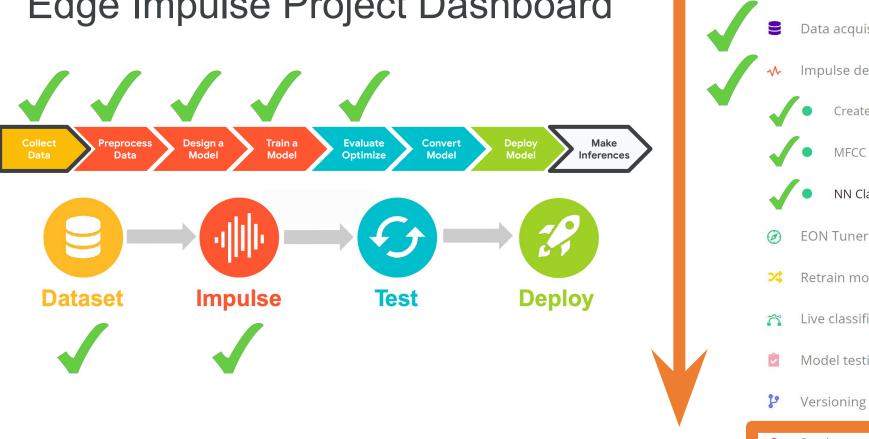
Edge Impulse Project Dashboard



- Dashboard
- Devices
- Data acquisition
- → Impulse design
 - Create impulse
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Edge Impulse Project Dashboard



Dashboard Devices Data acquisition Impulse design Create impulse MFCC **NN Classifier EON Tuner** Retrain model Live classification Model testing



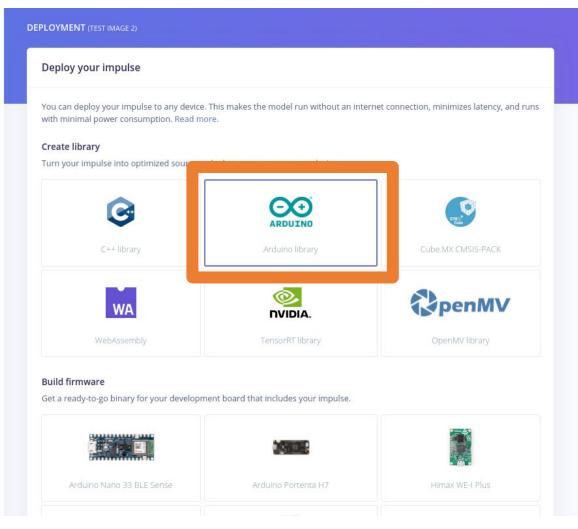


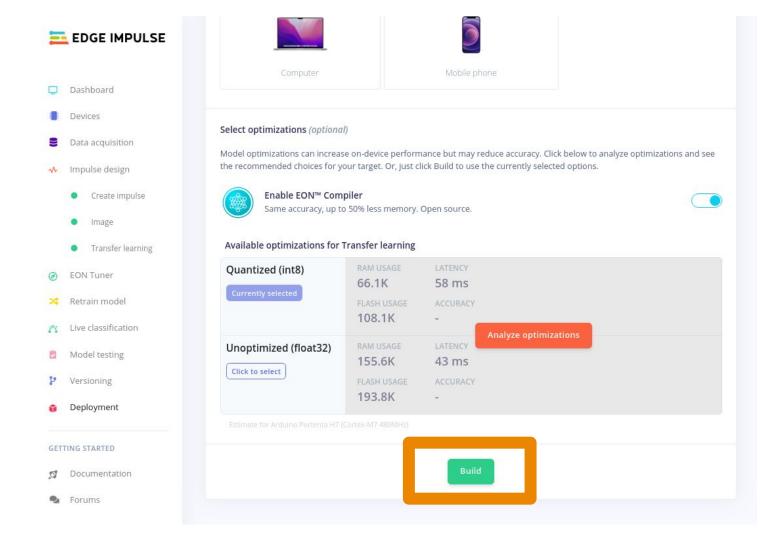


- Dashboard
- Devices
- B Data acquisition
- √ Impulse design
 - Create impulse
 - Image
 - Transfer learning
- EON Tuner
- Retrain model
- Live classification
- Model testing
- Deployment

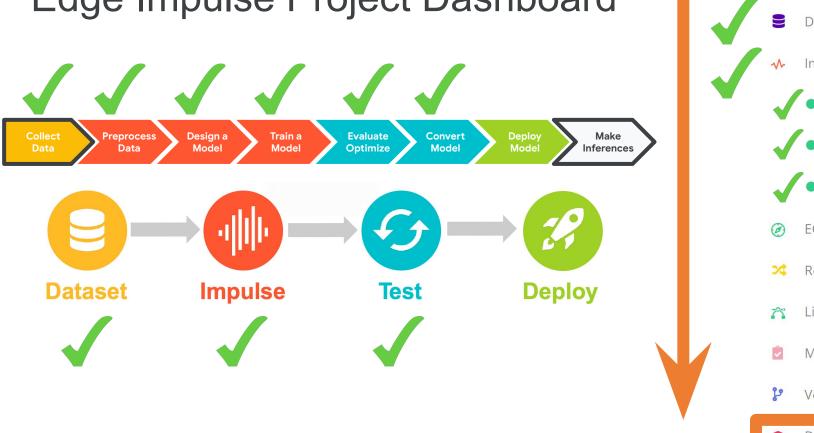
GETTING STARTED

- Documentation
- Forums



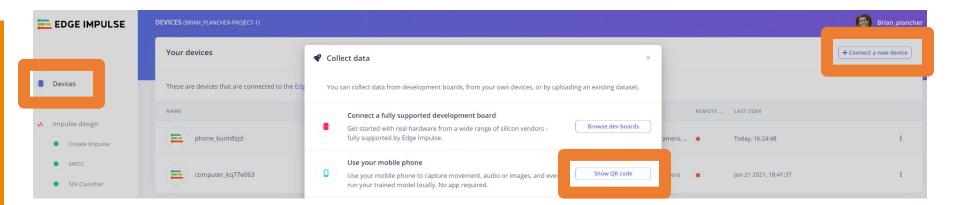


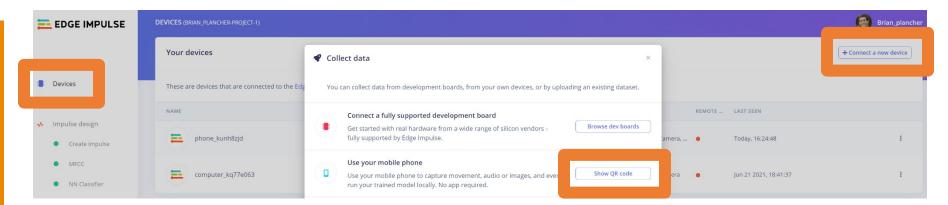
Edge Impulse Project Dashboard

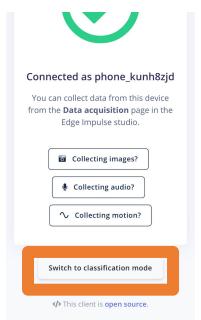


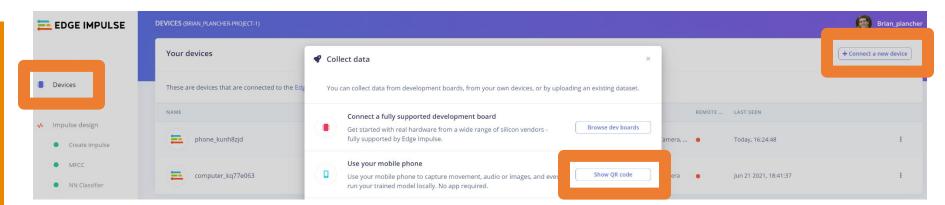
- Dashboard

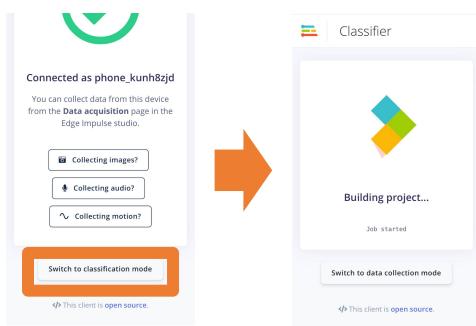
 Devices
- Data acquisition
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- NN Classifier
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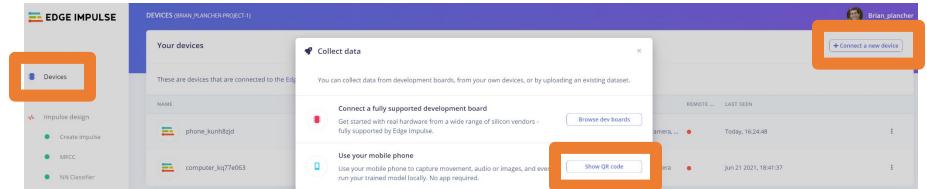


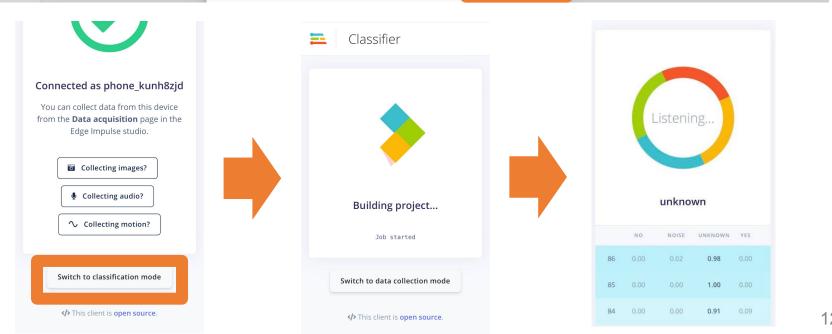






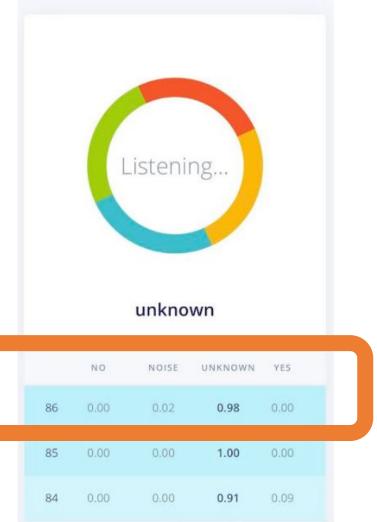


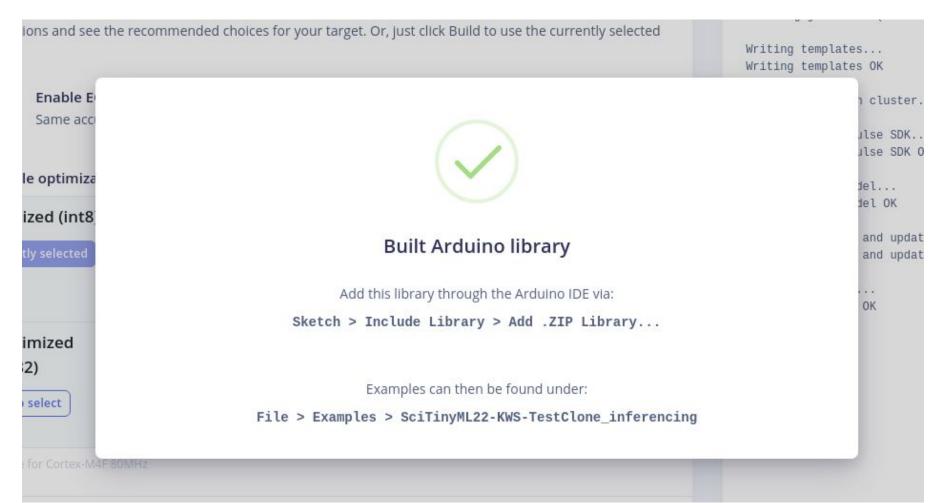


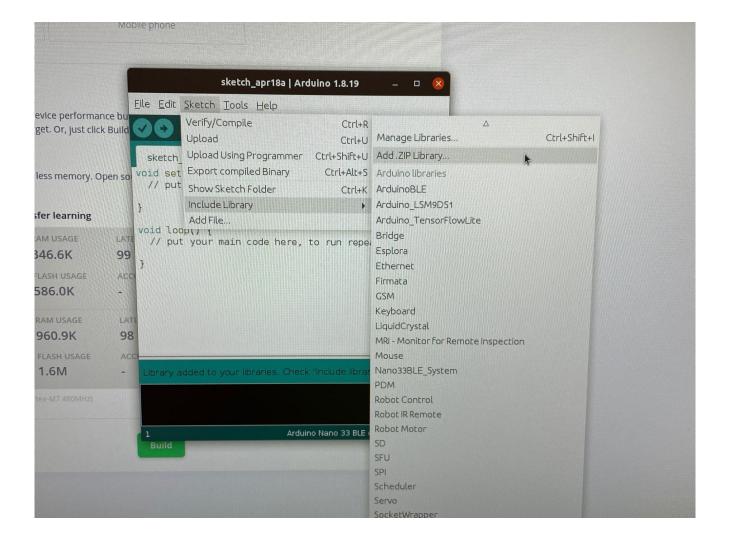


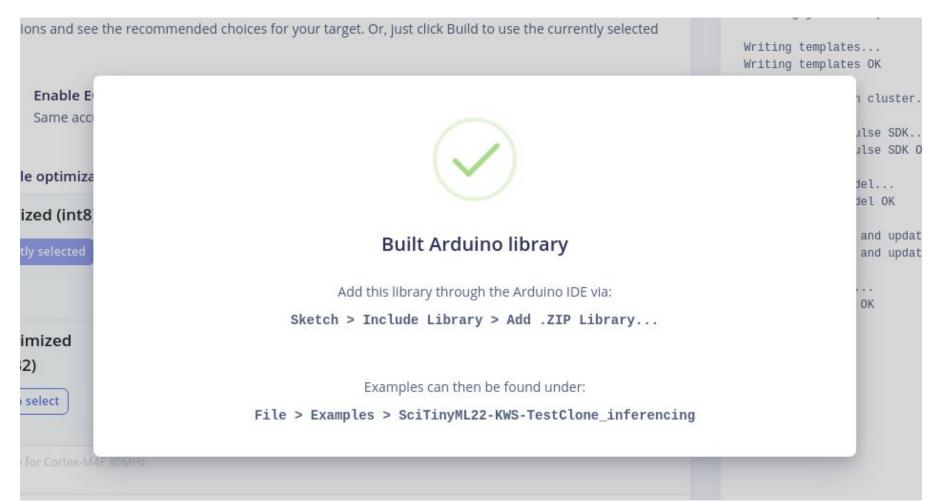
Deploy and Test your Model

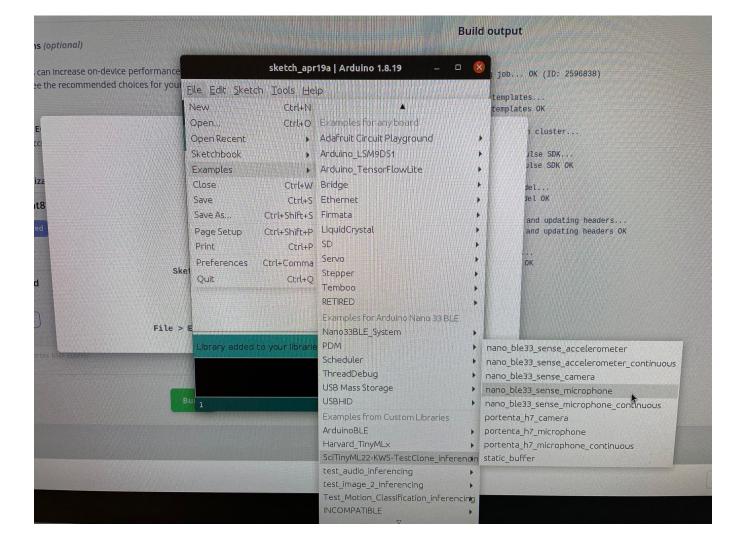
Shows the score for (confidence that the current sounds is) each of the various keywords and unknown and bolds the highest score.

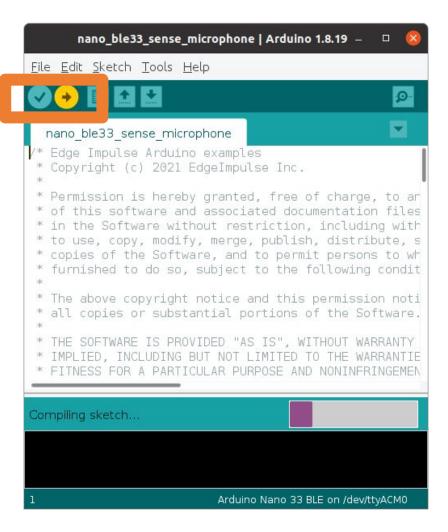












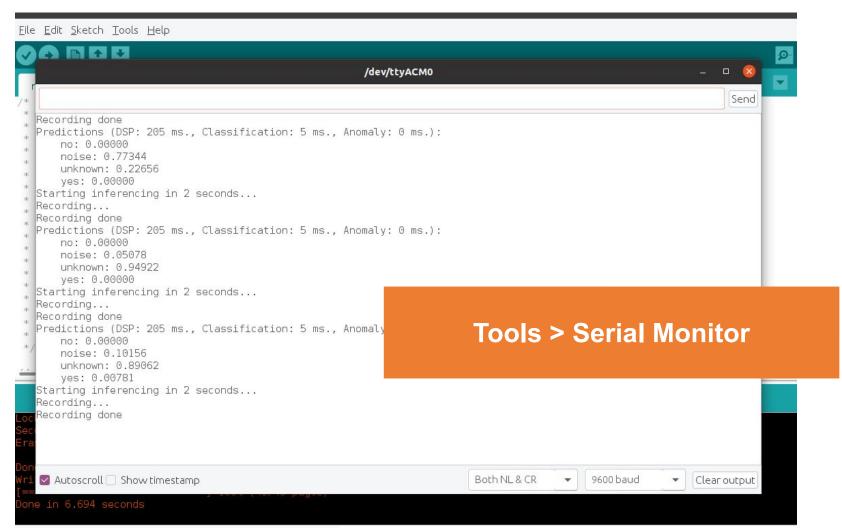


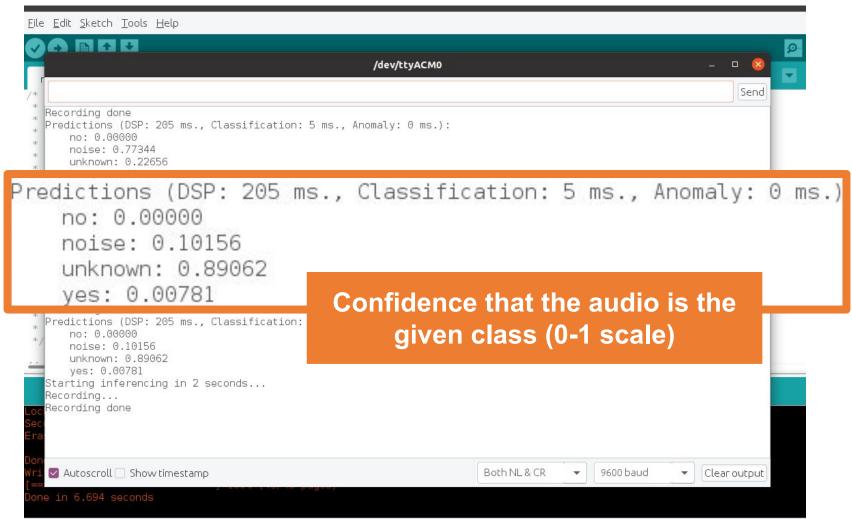
```
An error occurred while uploading the sketch
```

Sketch uses 224024 bytes (22%) of program storage space. Maximum is 983040 bytes. Global variables use 58672 bytes (22%) of dynamic memory, leaving 203472 bytes for local variables. Maximum is 262144 bytes. An error occurred while uploading the sketch

Device unsupported

Double Tap Reset for Bootloader Mode!

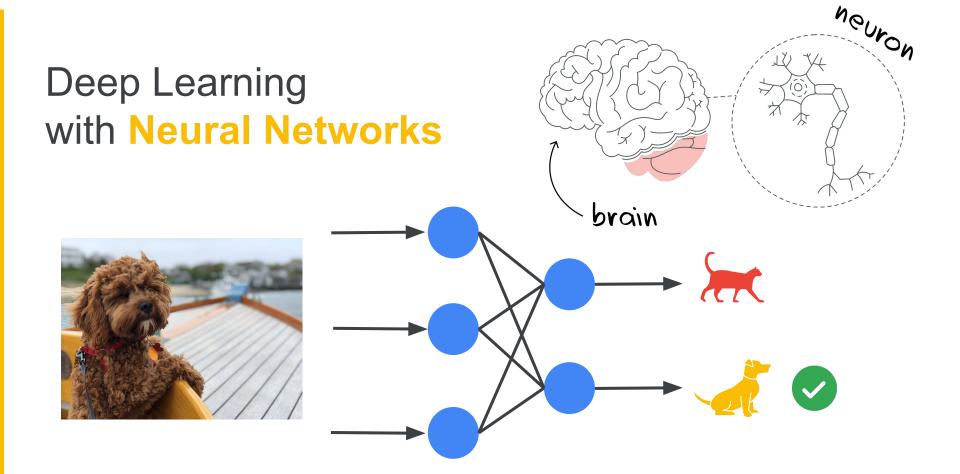




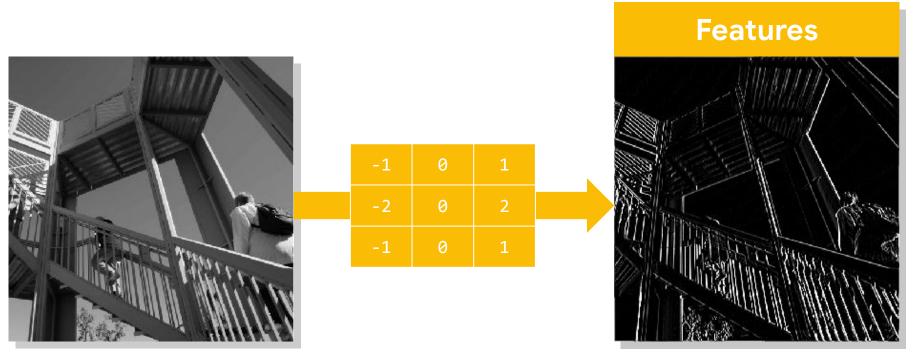
Today's Agenda

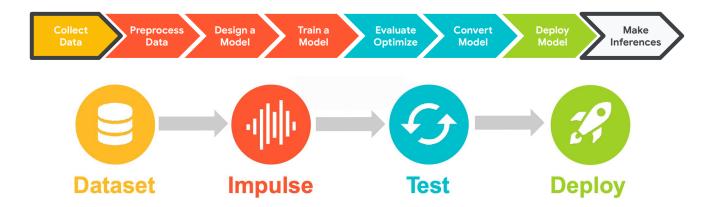
- A Quick Review of What We've Learned
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Features can be found with Convolutions







Who will use your ML model?

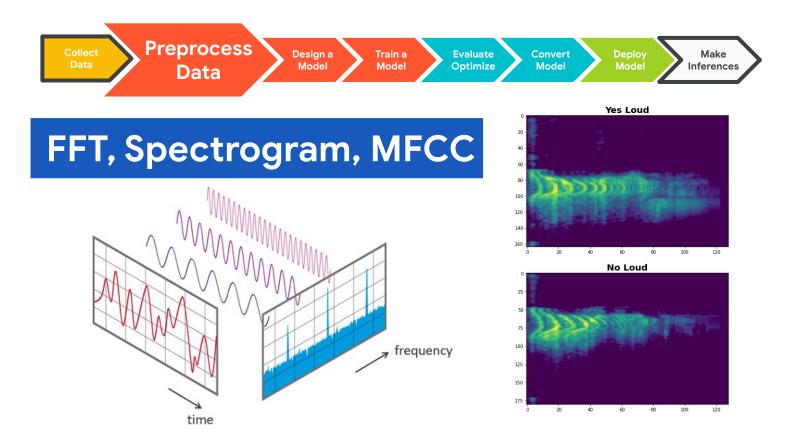
Where will your ML model be used?

Why will your ML model be used? Why those Keywords?

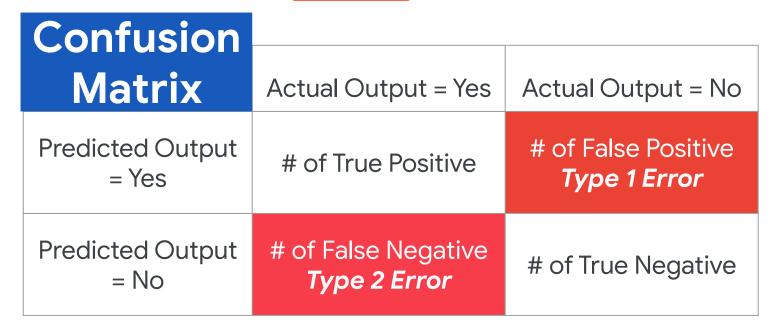
Training Set

Validation Set

Test Set





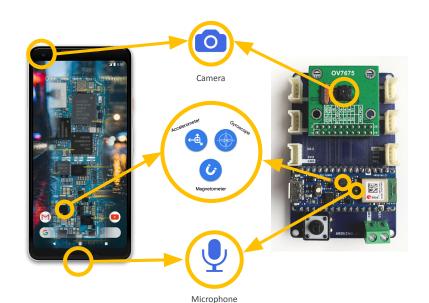




Reduces the precision of numbers used in a model which results in:

- smaller model size
- faster computation





Edge Impulse Simplifies Deployment

Better Data = Better Models!



Data Pre-Processing for Hands-on Keyword Spotting

Brian Plancher
Harvard John A. Paulson School of Engineering and Applied Sciences
Barnard College, Columbia University
brianplancher.com



Edge Impulse CLI Notes:

- 1. Install the Arduino CLI
 - a. On linux:

```
curl -fsSL https://raw.githubusercontent.com/arduino/arduino-cli/master/install.sh | sh
```

b. On mac:

```
brew update
brew install arduino-cli
```

- c. Or view the link for binaries
- 2. Add to your .bashrc:

```
# Arduino (CLI)
export PATH="ARDUINO_INSTALL_LOCATION/bin:$PATH"
```

Where ARDUINO_INSTALL_LOCATION is e.g.,: \$HOME/Documents/arduino-1.8.19

Edge Impulse CLI Notes:

- 1. Install the Edge Impulse CLI
 - a. Install Node.js by following the link or on Linux:

```
curl -sL https://deb.nodesource.com/setup_14.x | sudo -E bash -
sudo apt-get install -y nodejs
```

- b. Run: npm install -g edge-impulse-cli --force
- c. Add to your .bashrc:

```
# EI (CLI)
export PATH="$HOME/.npm-global/bin:$PATH"
```

2. Run edge-impulse-daemon --clean to start the daemon and then follow the instructions in the terminal to add it to your current project using your edge impulse account!

Edge Impulse CLI Notes:

