AI Hardware, Fall 2024
ECE 4501

Shaz *Animal*

Bioacoustic Animal Identifier

Project Group #2
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Project Motivation

Have you ever heard an animal sound and wondered what made it?

- Demonstrate the ***feasibility of deployed bioacoustic ID tools***
    - Automated, seamless, and accessible classification
- Leverage ***TinyML*** for efficient processing
    - Powerful machine learning in resource-constrained environments
    - Enables on-site application of audio recognition algorithms
- ***Variety of applications*** for system usage
    - Educational tool to teach children elementary concepts
    - Sustainable & practical method for ecologist wildlife monitoring

Objectives

1. Develop a machine learning algorithm capable of processing and identifying the animal responsible for a given audio input
2. Train the model such that it is capable of classifying the sounds of **4 common animals** with at least **80% accuracy**

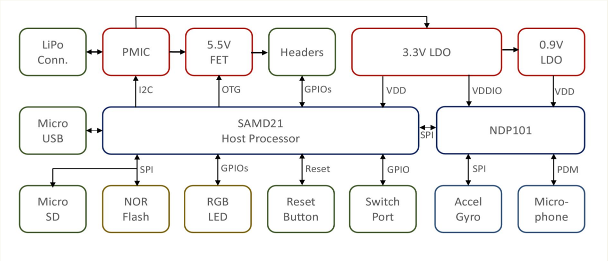



3. Integrate the program with the Syntiant TinyML board, utilizing the built-in microphone, so the system can be used on-site

Technology Stack

Hardware

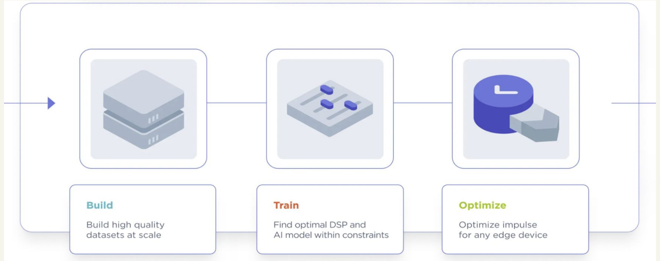
- Syntiant TinyML Board
  - NDP101
  - ARM Cortex-M4
- Linux-enabled device



Syntiant TinyML Board block diagram

Software

- Code and package tools
  - git
  - edge-impulse-cli, arduino-cli
- Edge Impulse Studio



Edge-Impulse modeling process

Syntiant NDP101

Neural Decision Processor

- Compute-in-memory for high parallelism and efficiency
- Memory for 589k parameters
- Low power consumption and fast inferences on 5mmx5mm chip, perfect for resource- constrained edge AI applications

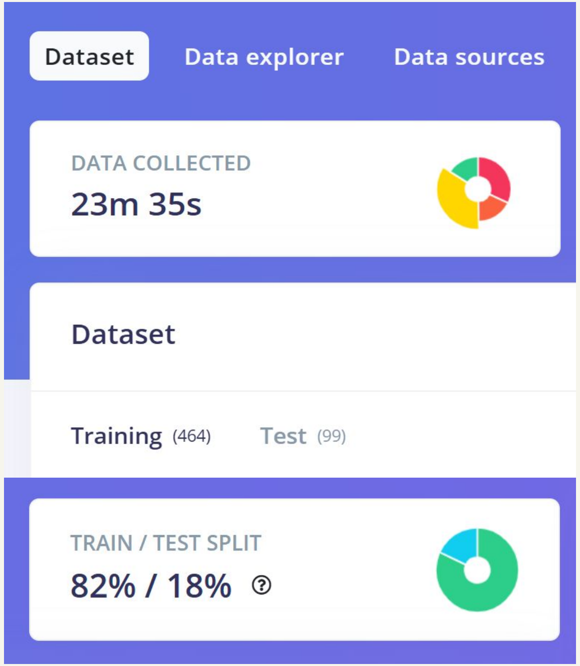
Methodology

- **Step 1** Data Acquisition & Research
- **Step 2** Model Design Using Edge Impulse
- **Step 3** Model Training & Report
- **Step 4** Finalized Performance & Results
- **Step 5** Integration of Systems
- **Step 6** Final Iteration & Live Demo

Step 1

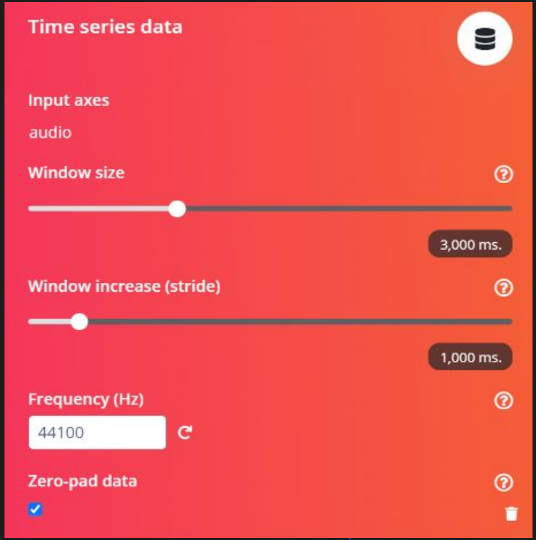
Data Acquisition & Research

- Collected 563 total audio files from online audio libraries
  - Cat: 185 audio files
  - Cow: 84 audio files
  - Dog: 128 audio files
  - Frog: 67 audio files
- Data loaded into Edge-Impulse with an **82% / 18%** Train/Test split
  - Training: 464 audio files
  - Testing: 99 audio files

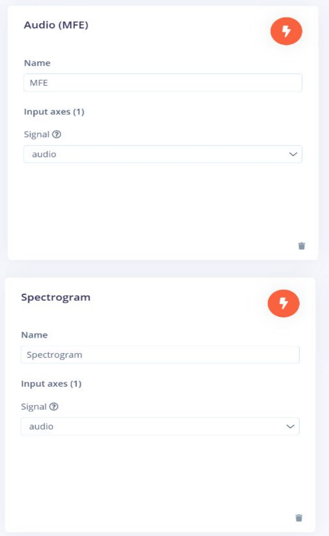


Step 2
Model Design

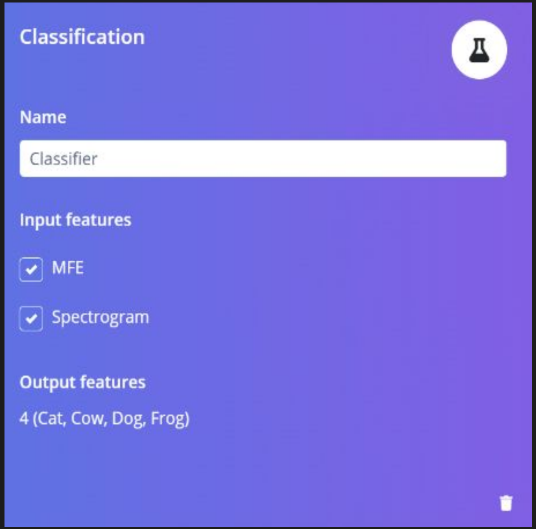
Step 2.1
Model Input



Step 2.2
Processing Blocks



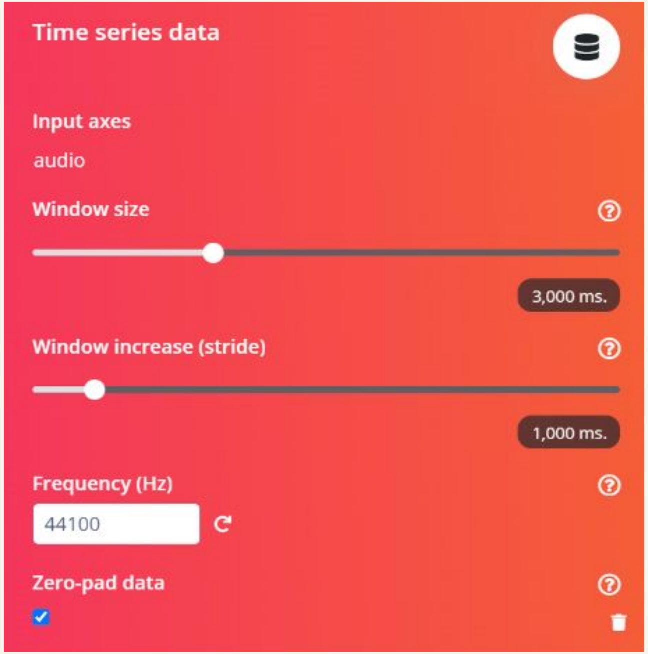
Step 2.3
Learning Block



Step 2.1

Definition of Model Input

- Audio files varied in length, generally ranging between 2 to 5 seconds
- Analyzed a 3 second (3000 ms) window of each file
    - Widow stride of 1 second (1000ms), for files longer than the window
- Nominal sampling frequency common for digital audio



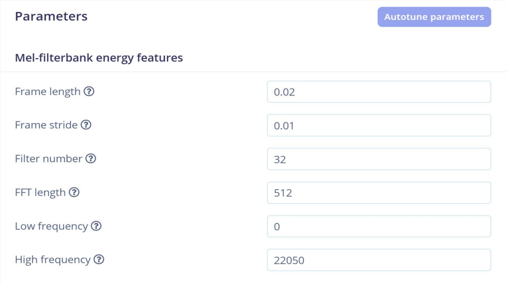
Step 2.2

Design of Processing Blocks

Used 2 processing blocks to analyze the audio data:

Block 1: Mel Frequency Energy (MFE)

- Extracts audio signal features
- Emphasizes frequencies important for audio classification



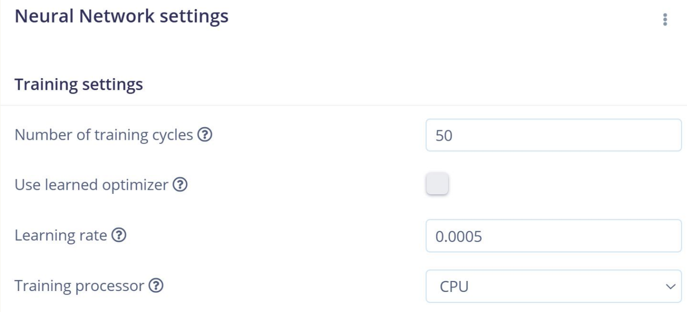
Block 2: Spectrogram

- Visualizes the audio frequencies over time
- Detailed representation for training and testing

Step 2.3

Design of Learning Block

- Chose a **Classification** learning block
  - Trains the model to distinguish and classify the different sounds



Input: *Processed features (48,139) from the MFE and Spectrogram*

Output: *Classification of each of the audio files (563) into one of the 4 animals*

Step 3

Model Training

- Conducted 3 training iterations
- Model trained for 50 epochs
  - Saved best model results for later usage
- Reported training **accuracy of 86.4%** and a **loss of 0.48**
  - Surpasses our targeted model training accuracy of 80%
  - Ready for hardware integration

Training output (0)

```
p
Epoch 47/50
15/15 - 0s - loss: 0.3563 - accuracy: 0.8792 - val_loss: 0.4802 - val_accuracy: 0.8644 - 352ms/epoch - 23ms/ste
p
Epoch 48/50
15/15 - 0s - loss: 0.3606 - accuracy: 0.8750 - val_loss: 0.6769 - val_accuracy: 0.7288 - 377ms/epoch - 25ms/ste
p
Epoch 49/50
15/15 - 0s - loss: 0.3760 - accuracy: 0.8369 - val_loss: 0.5295 - val_accuracy: 0.7966 - 399ms/epoch - 27ms/ste
p
Epoch 50/50
15/15 - 0s - loss: 0.3266 - accuracy: 0.8771 - val_loss: 0.5547 - val_accuracy: 0.8220 - 394ms/epoch - 26ms/ste
p
Finished training

Saving best performing model... (based on validation loss)
```

Model — Model version: Quantized (int8)

Last training performance (validation set)

ACCURACY 86.4%

LOSS 0.48

Confusion matrix (validation set)

	CAT	COW	DOG	FROG
CAT	87.9%	3.0%	6.1%	3.0%
COW	4.8%	76.2%	19.0%	0%
DOG	0%	6.8%	93.2%	0%
FROG	0%	5%	15%	80%
F1 SCORE	0.92	0.76	0.87	0.86

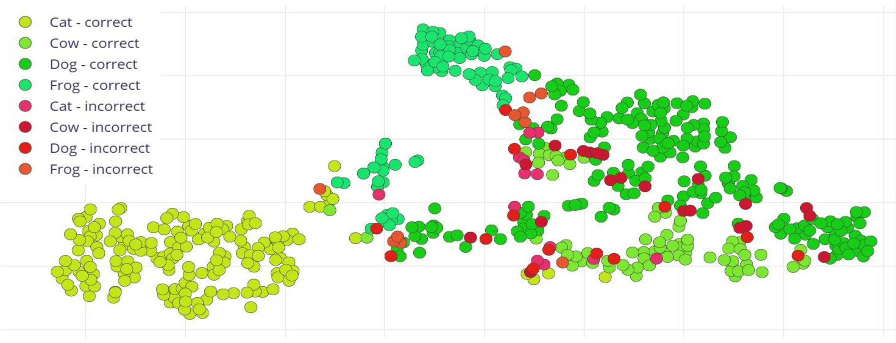
Step 4

Model Performance & Results

Metrics (validation set)

METRIC	VALUE
Area under ROC Curve	0.96
Weighted average Precision	0.87
Weighted average Recall	0.86
Weighted average F1 score	0.86

Data explorer (full training set)



Accuracy = 86.4%, Loss = 0.48

- Accurate classifications for the majority of data
- Some errors depicted within class clusters
  - Limited training data
  - Lack of preprocessing

On-device performance

Engine: EON™ Compiler

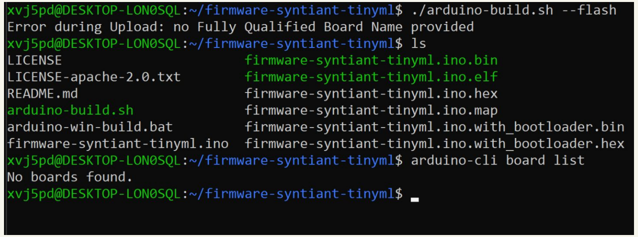
INFERENCING TIME	PEAK RAM USAGE	FLASH USAGE
19 ms.	48.4K	955.5K

Step 5

Integration with Hardware

Current status:

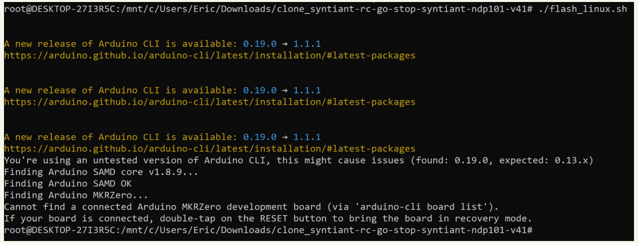
- Now necessary to ***flash*** the system to the Syntiant board
- Experiencing difficulties in establishing communication



Connection with board error

Next steps:

- Ensure relevant tool files are accessible in Ubuntu
  - Reconfigure Syntiant link
- Explore device workarounds



Project flash error

Step 6

Final Iteration & Live Demo

- Once hardware connection is established, the serial output will be used for real-time classification results
- Digital playback will be used so sufficient trials can be manually executed to calculate accuracy of on-board model
- Expect similar (slightly worse?) performance compared to test results, as speaker/microphone noise may reduce audio clarity

Final Thoughts

Lessons learned:

- Processing blocks greatly affect the accuracy of the model
  - Spectrogram processing alone does not accurately classify audio
- Necessary to implement a robust dataset for both testing and training processes

Conclusions:

- System successfully designed and capable of classifying animal calls
  - Classes defined and tested
  - Accuracy greater than 80% with minimal loss
- On track to successful integration using the Syntiant TinyML Hardware

Expansion & Improvements

- Possible to increase the accuracy of the model by acquiring additional audio files per animal *(e.g. 500/animal)*
    - Larger dataset, more robust training capabilities
- Add additional classifiers to expand beyond current scope
    - Requires a search for additional audio files
    - More realistic on-site system implementation
- Include another processing block to streamline identification
- Integrate a visual aid component for better user accessibility

Thank you!