Utilizing Liquid Neural Network for Efficient Audio Classification

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Presentation Outline

- Motivation
- Project Objectives
- Project Scope
- Project Applications
- Methodology
- Results
- Discussion of Results
- Remaining Tasks
- References

Motivation

- Contemporary models uses millions to billions parameters,
- 19 neurons enough for autonomous driving - Liquid Time Constant (LTC) Neural Network,
- Papers suggest LNN to be efficient for temporal data like Audio.

Project Objectives

- To develop LTC neural network model for audio classification and benchmark against contemporary models,
- To achieve comparable accuracy while using less computational power.

Project Scope

- Classify audio events with Liquid Neural Networks (LNN)
- Achieve high accuracy in real-time sound recognition
- Benchmark performance on multiple audio dataset for optimal results
- Revolutionize speech, environmental sound, and anomaly detection
- Optimize network architecture for diverse audio applications

Project Applications

- Voice Authentication and Security
- Medical Data Analysis
- Abnormality Detection
- Enhanced Music Recommendation Systems
- Audio Content Filtering and Moderation
- Interactive Gaming and Virtual Reality
- Speech Emotion Recognition
- Intelligent Audio Summarization

Liquid Neural Network-[1]
Introduction

- Traditional RNNs, face challenges in adapting to complex time-series dynamics.
- LNNs, still making use of recurrent mechanics, explicitly model time-series dynamics through differential equations that determine neuron states.

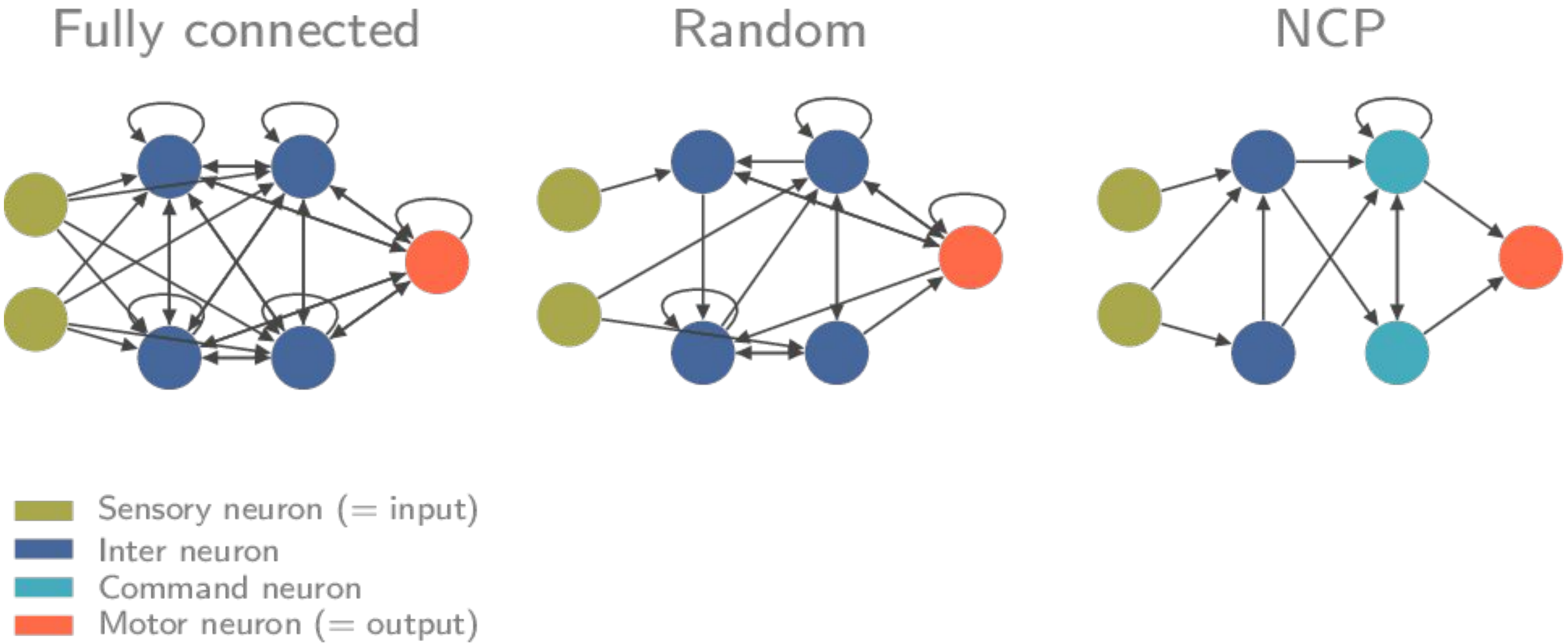
Liquid Neural Network-[2] Mathematical Formulation

- Neuron’s state is the solution to the differential equation

$$\frac{d\mathbf{x}(t)}{dt} = -\left[\frac{1}{\tau} + f(\mathbf{x}(t), \mathbf{I}(t), \boldsymbol{\theta})\right]\mathbf{x}(t) + f(\mathbf{x}(t), \mathbf{I}(t), \boldsymbol{\theta})\mathbf{A} \quad (1)$$

- Where,
  - *x(t)* is the hidden state
  - *I(t)* is the input
  - τ, time constant is a constant that ensures numerical stability

Liquid Neural Network-[3]
Neuron Structure



Liquid Neural Network-[4]
Wiring Configuration

Neuron Model

Liquid time-constant (LTC)

Closed-form continuous-time (CfC)

Wiring

Fully Connected

```
from ncps.torch import LTC
input_size = 20
units = 50
rnn = LTC(input_size, units)
```

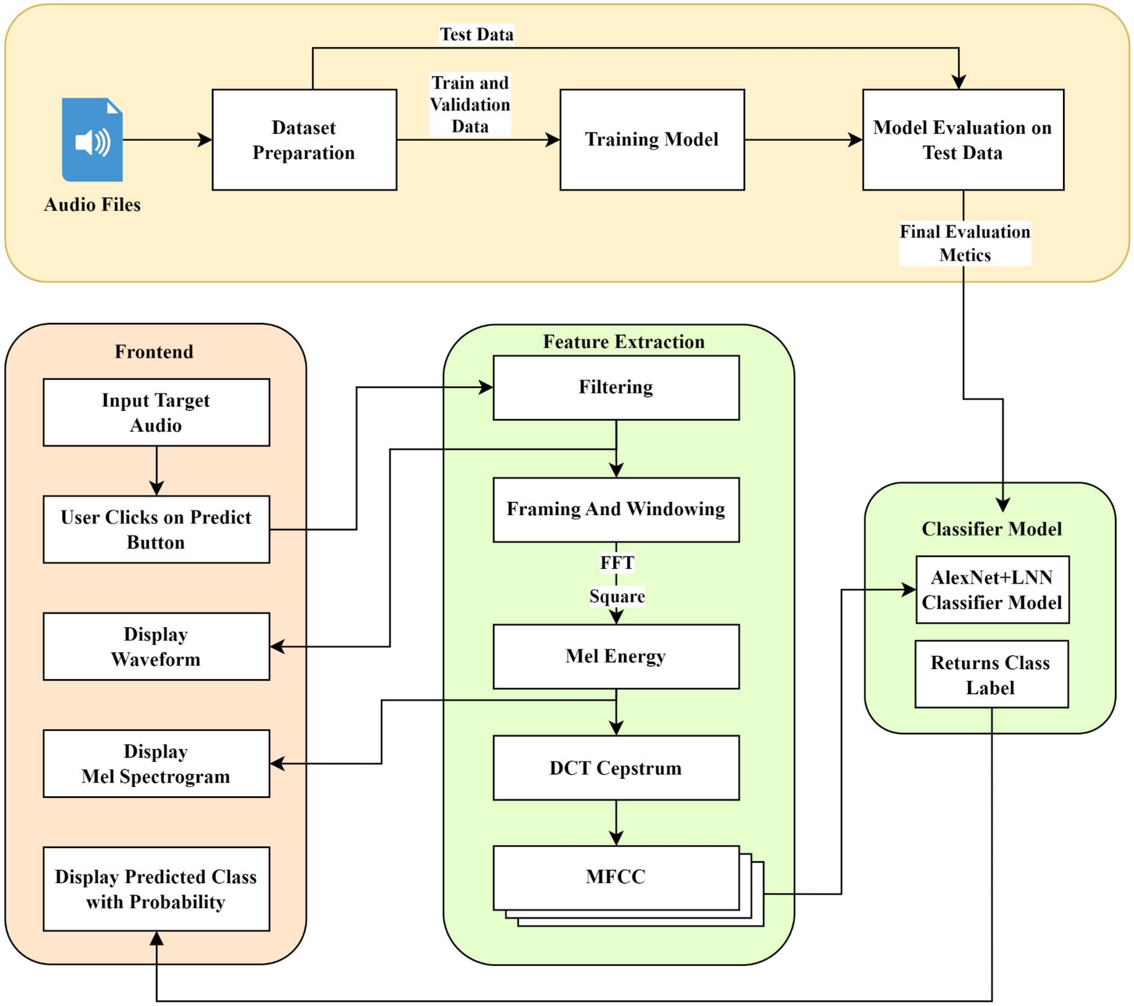
```
from ncps.torch import CfC
input_size = 20
units = 50
rnn = CfC(input_size, units)
```

Neural Circuit Policy (NCP)

```
from ncps.torch import LTC
from ncps.wirings import AutoNCP
input_size = 20
units = 50
output_size = 10
rnn = LTC(input_size,
    AutoNCP(units,output_size))
```

```
from ncps.torch import CfC
from ncps.wirings import AutoNCP
input_size = 20
units = 50
output_size = 10
rnn = CfC(input_size,
    AutoNCP(units, output_size))
```

Methodology-[1]
System Architecture



Methodology-[2]
Dataset Exploration

1. **VGG (Visual Geometry Group)**

- Audio-visual dataset with 210,000 data with 310 audio classes,
- Classes like wind noise, sliding door, car, train, etc.
- 10-second audio clips,
- Roughly 200 audio per each class,
- Used by Mirasol3B has 69.8% accuracy on this dataset.

Methodology-[3]
Dataset Exploration

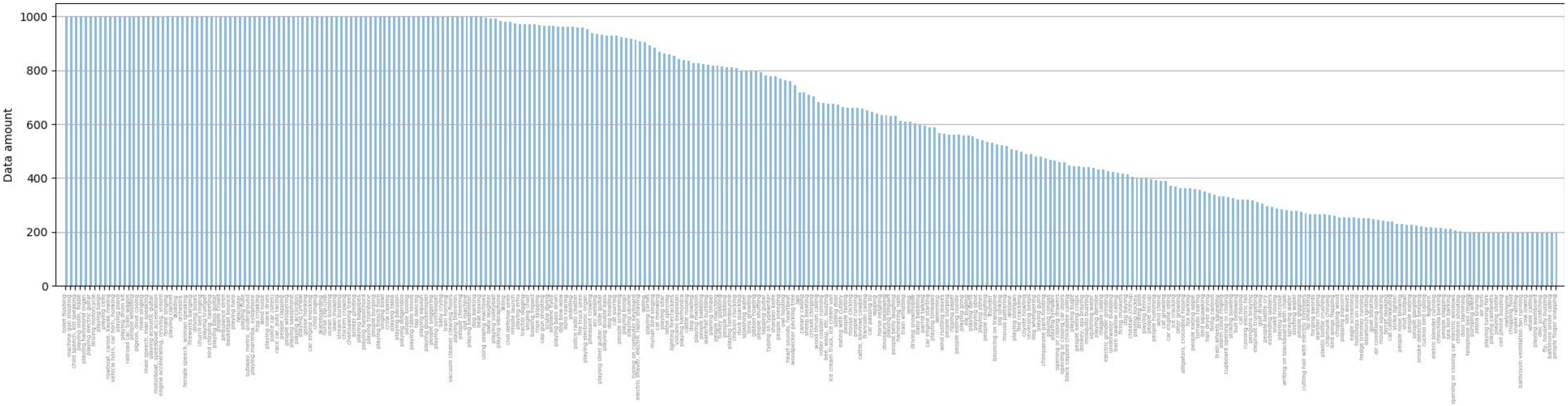


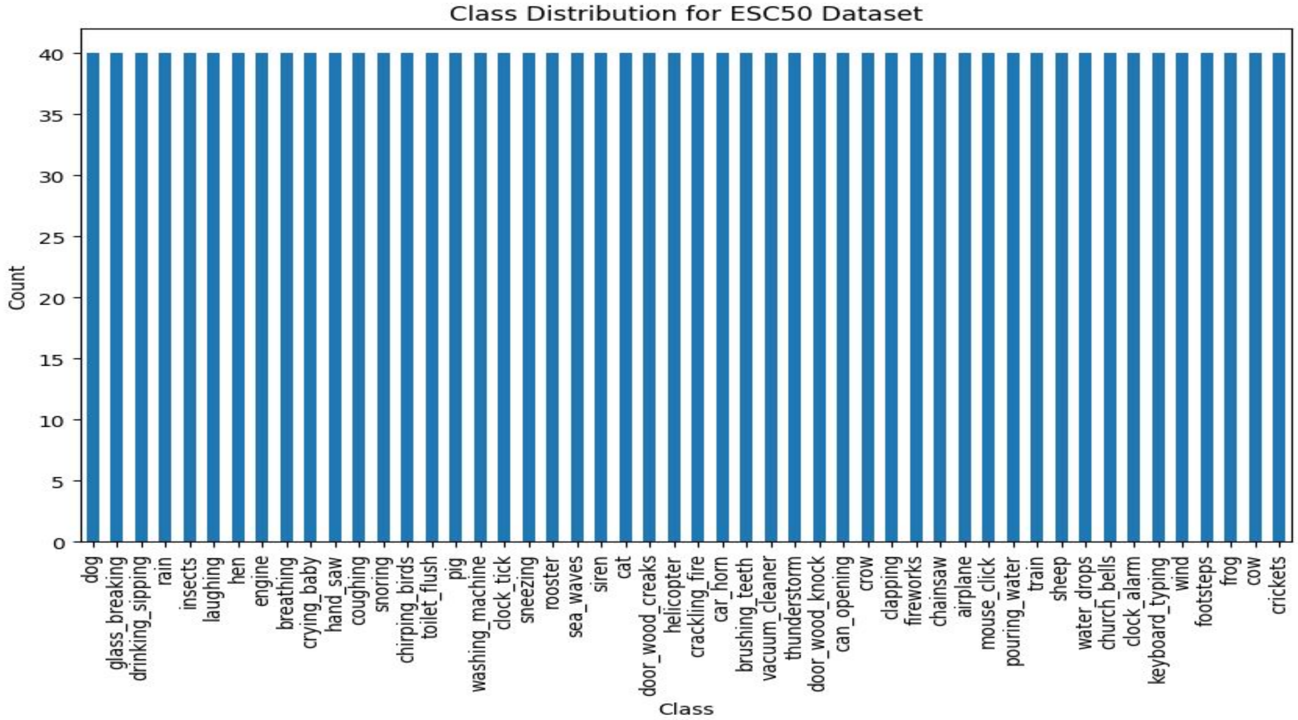
Fig: Dataset distribution for VGG Dataset

Methodology-[4]
Dataset Exploration

2. ESC-50

- 2000 labelled environmental audio recordings,
- Each clip of 5 seconds, covering 50 distinct classes,
- Includes classes like animals, water sound, natural soundscapes, etc.
- Pre-arranged in 5-folds,
- Used by OmniVec-2 Model with 99.1% accuracy.

Methodology-[5]
Dataset Exploration

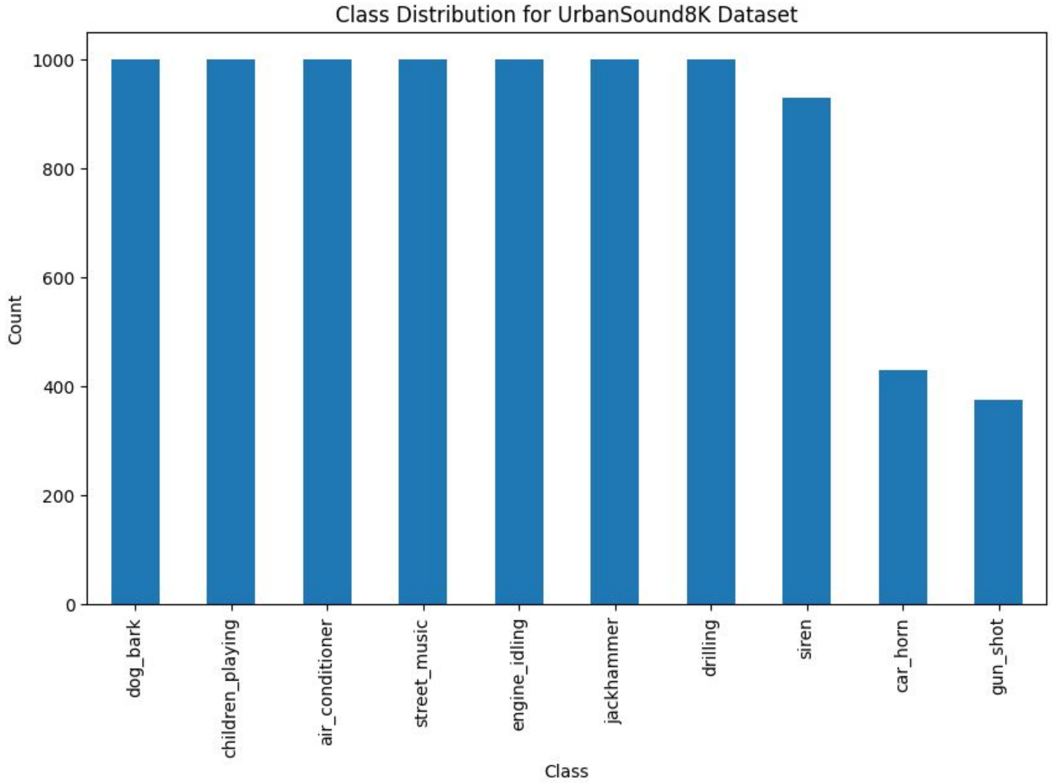


Methodology-[6]
Dataset Exploration

3. UrbanSound8K

- Comprising 8,732 labelled sound excerpts,
- Each clip of 4 seconds, with total 27 hours of audio,
- Includes classes like air conditioner, car horn, children playing, dog bark, etc,
- Used by ASM-RH-I with 97.96% accuracy (10-fold).

Methodology-[7]
Dataset Exploration

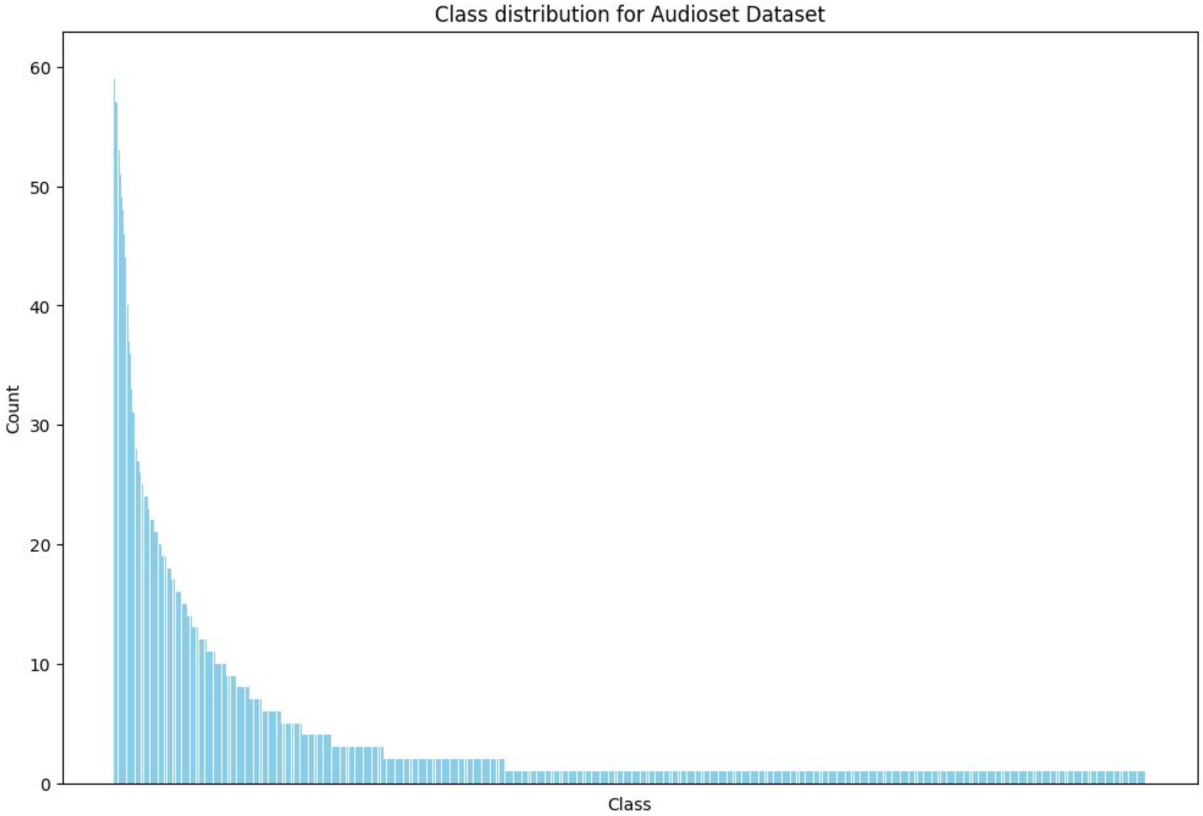


Methodology-[8]
Dataset Exploration

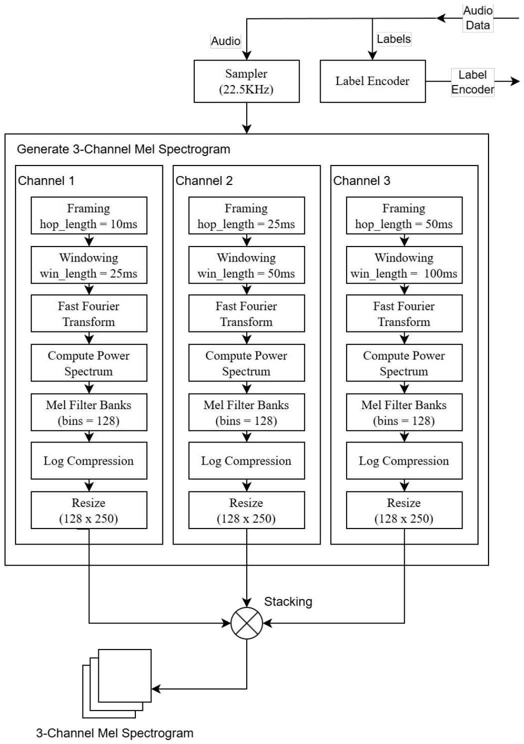
4. AudioSet

- 2,084,320 YouTube videos containing 527 labels,
- 10-second sound clips sourced from YouTube videos and labelled by humans,
- Includes classes like music, speech, vehicle, car, etc.,
- Used by OmniVec with 0.548 mAP.

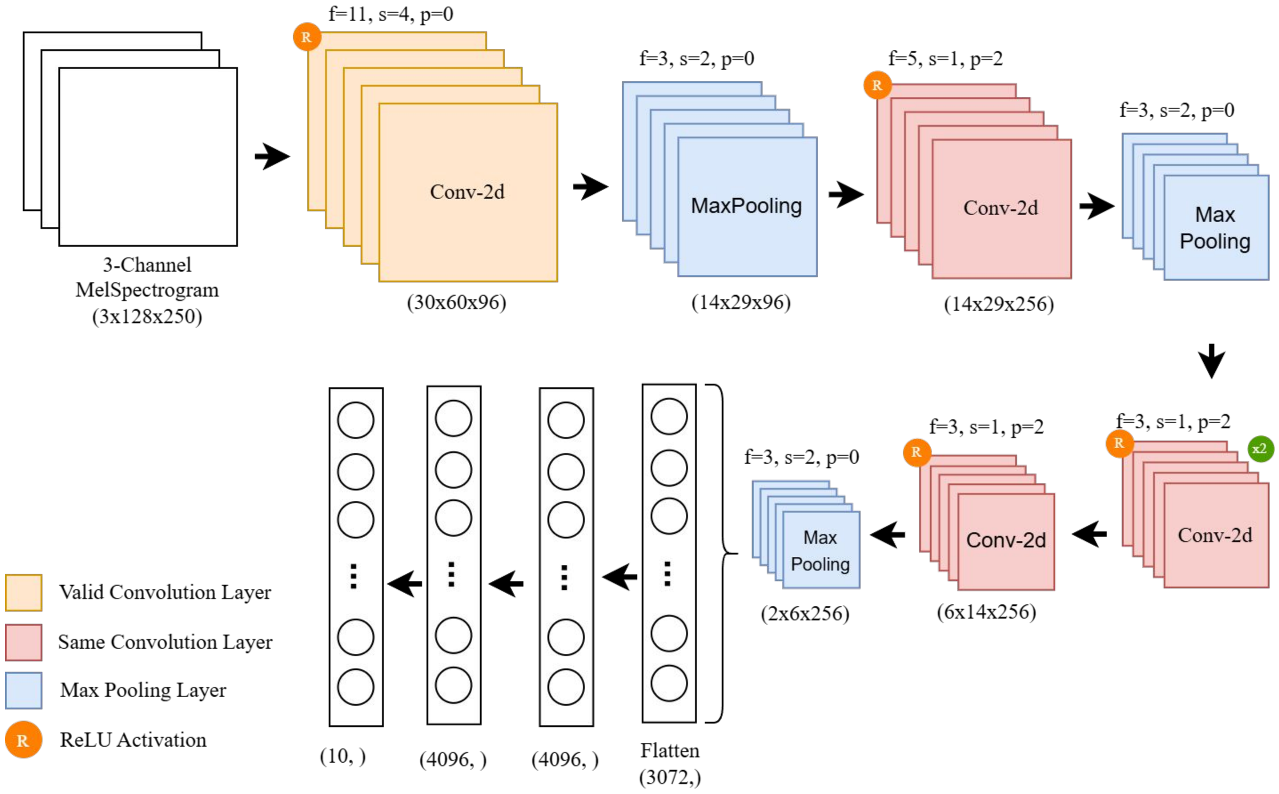
Methodology-[9]
Dataset Exploration



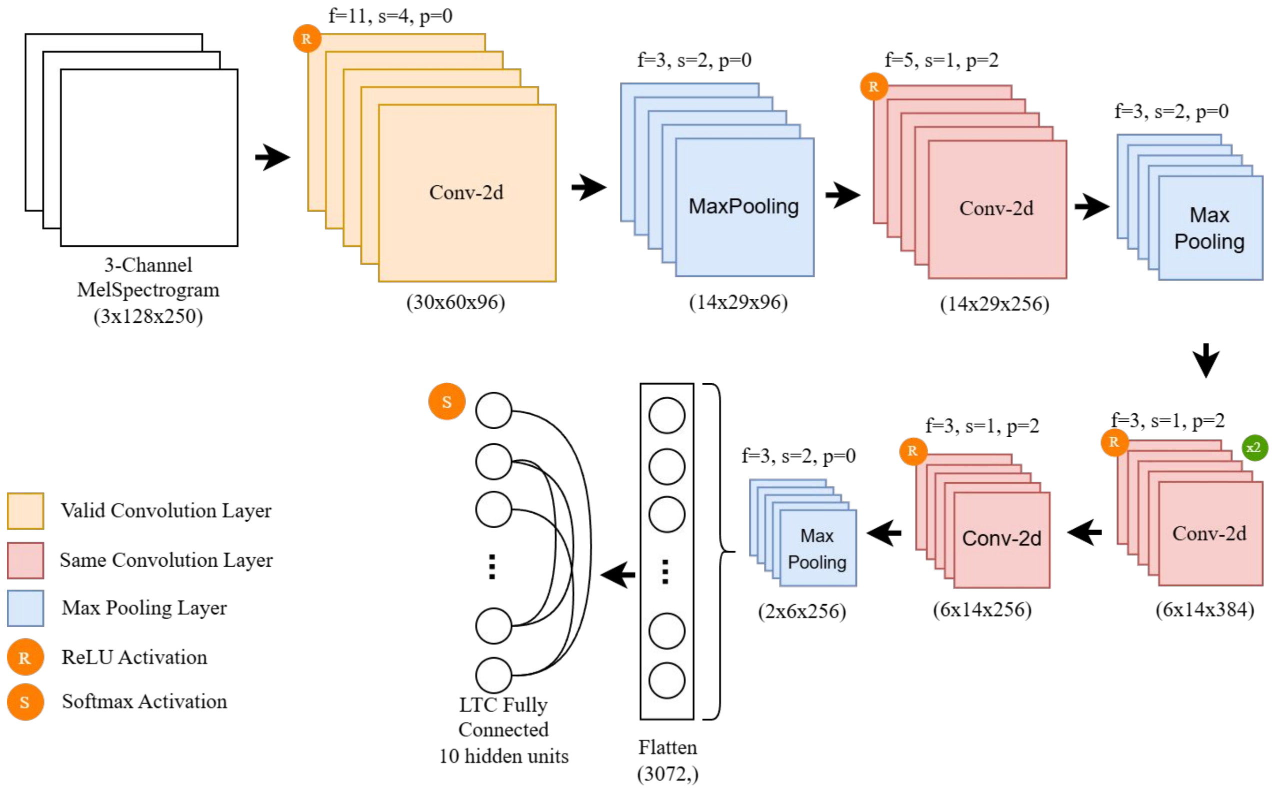
Methodology-[10]
Data PreProcessing



Methodology-[11]
Baseline Model (CNN)



Methodology-[12]
Our Model (CNN + LTC)



Methodology-[13]
Evaluation Metrics

- **F1-Score**

- Used when the class distribution is imbalanced,
- Provides a single measure that balances both the false positives and false negatives.
- **Precision** is the ratio of true positive detections to the total number of positive detections,
- **Recall** is the ratio of true positive detections to the total number of actual positives.

Methodology-[14]
Evaluation Metrics

- **F1-Score**

- Harmonic mean of precision and recall.

$$F1Score = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision}$$

Methodology-[15]
Evaluation Metrics

- **Mean Average Precision (mAP)**

- **Average Precision** is the area under the precision-recall curve for a single query or class.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i$$

Methodology-[16]
Evaluation Metrics

- **Accuracy**

- measures the proportion of correct predictions made by the model out of all predictions.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{All Predictions}}$$

Methodology-[17]
Instrumentation

1. **Kaggle Notebook**

- Kaggle Notebooks are essentially Jupyter Notebooks hosted on the cloud
- Provides 4 CPU cores, 20GB of RAM, and 1 x Nvidia Tesla P100 GPU with 4 cores and 29 GB of RAM,
- GPU can be used for 30 hours a week and 9 hours per session.

Methodology-[18]
Instrumentation

2. Google Colaboratory

- Provides an Intel Xeon CPU with 2 vCPUs (virtual CPUs) and 13 GB of RAM,
- NVIDIA Tesla K80 with 12GB of VRAM (Video Random-Access Memory)

Methodology-[19]
Instrumentation

3. Librosa

- Python package for music and audio analysis,
- Calculation of time domain features like Zero-crossing rate,
- Calculation of frequency domain features.

Methodology-[20]
Instrumentation

4. Pytorch

- Open-source deep learning framework developed by Facebook's AI Research lab,
- Uses Dynamic Computation Graph,
- Rich ecosystem and community support.

Results - [1]

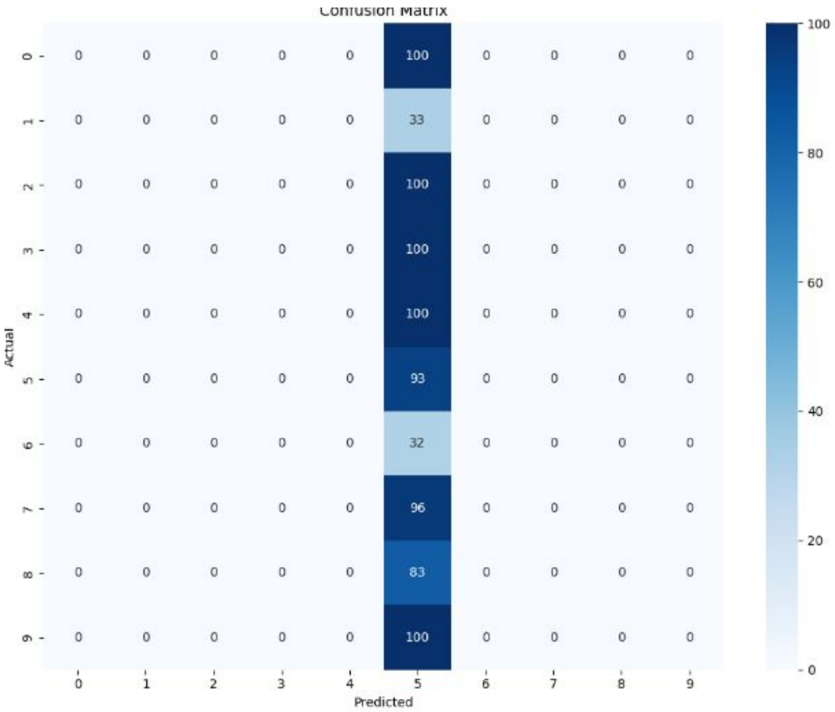


Fig: Confusion Matrix

Results - [2]

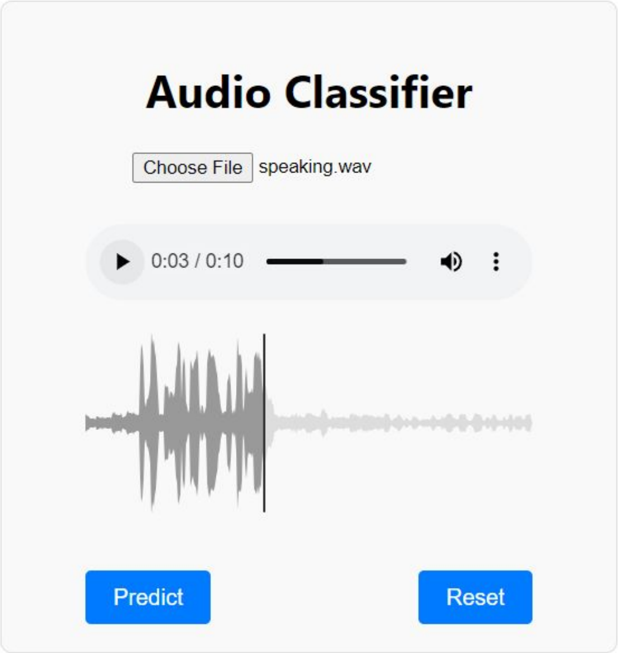


Fig: Web application interface

Results - [3]

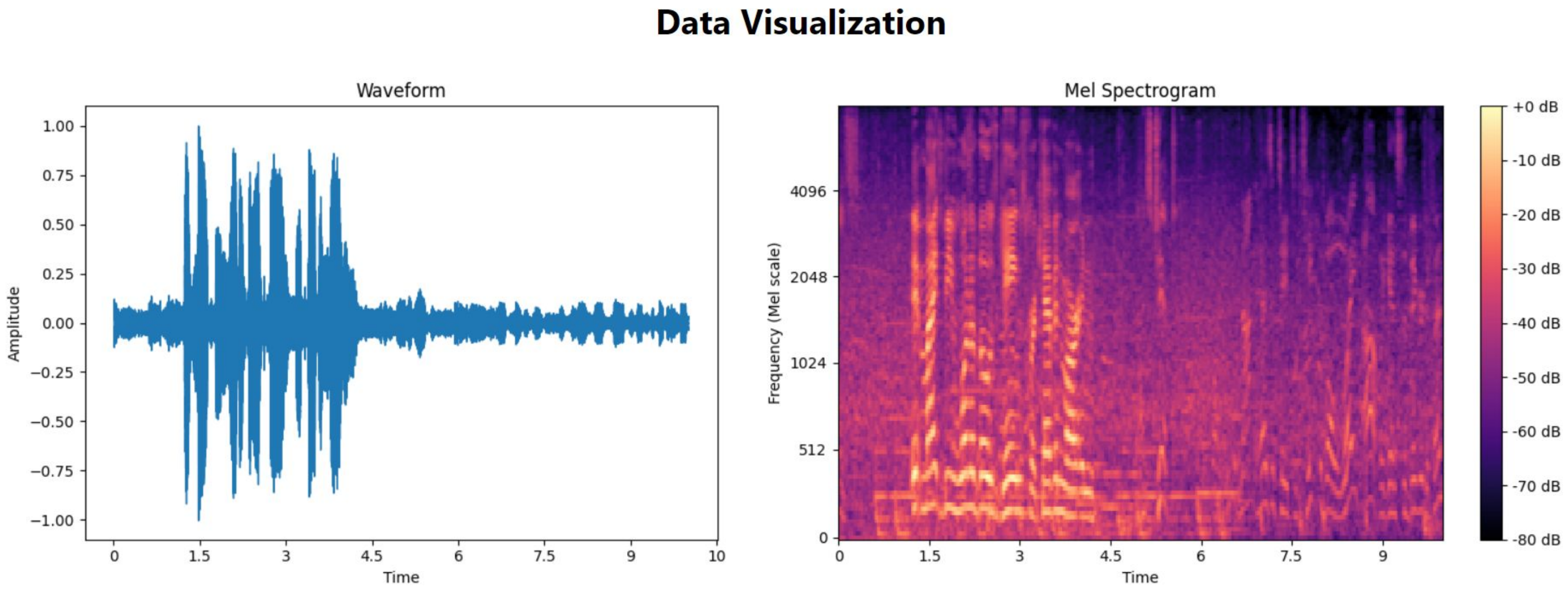


Fig: Web application interface

Results - [4]

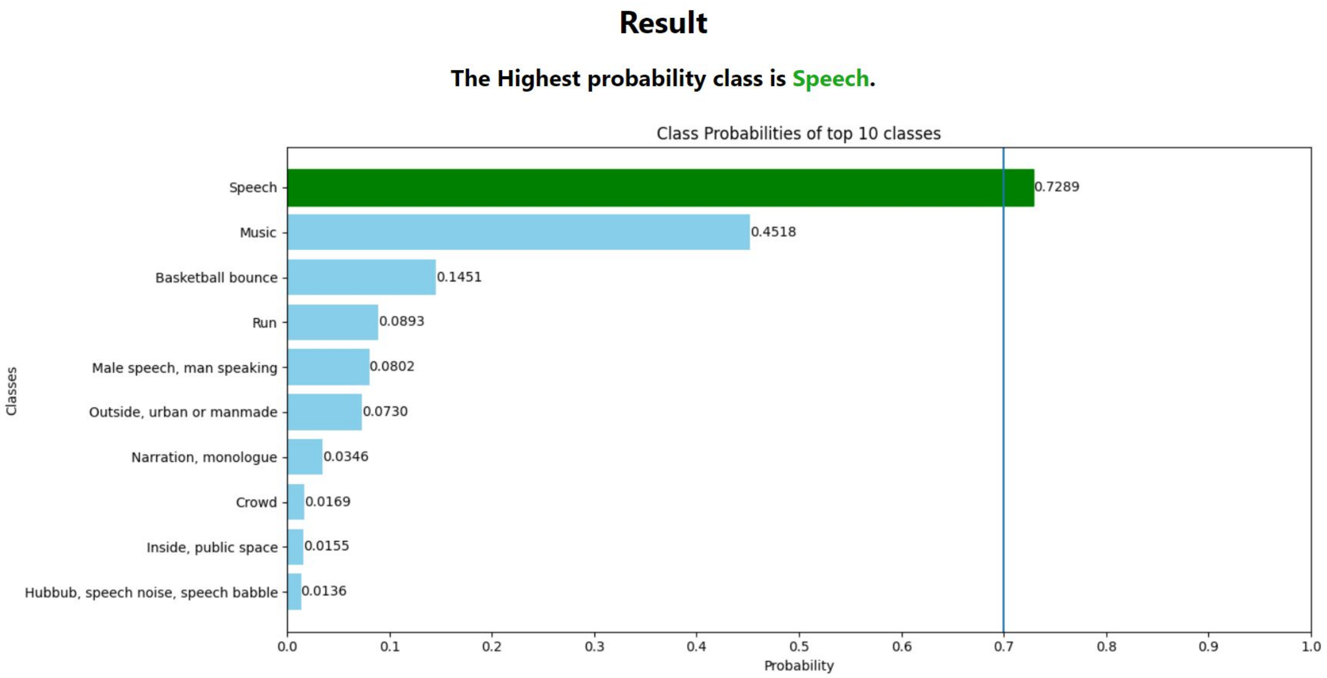


Fig: Web application interface

Discussion of Results - [1]

Frontend:

- User-Friendly Interface for Seamless Audio Interaction
- Upload .wav or .mp3 Files for Instant Audio Spectrograms
- Predict Top 10 Audio Classes Quickly and Accurately
- Single File Upload with Cancel Option for Flexibility

Discussion of Results - [2]

Backend:

- **Model Integration:** Uses a LNN with CNN architecture for audio classification.
- **Feature Extraction:** Extracts and normalizes features like mel-spectrograms from uploaded audio.
- **Visualization:** Generates and serves waveform plots, bar plots and mel-spectrograms.
- **Error Handling:** Manages file upload errors and provides user-friendly error messages.
- **Adaptive Precision and Hardware Utilization:** Uses Automatic Mixed Precision (AMP) for faster computation on GPUs, and switches to CPU if a GPU is unavailable.

Remaining Tasks

- The models need to be tuned and modified for better accuracy,
- Different configuration of LTCs is to be tried,
- Methods like knowledge distillations are needed to be explored for decreasing model size.

Reference - [1]

[1] R. Hasani, M. Lechner, A. Amini, D. Rus, and R. Grosu, “Liquid time-constant networks,” Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 9, 7657–7666, May 2021. DOI: 10.1609/aaai.v35i9.16936. https://ojs.aaai. org/index.php/AAAI/article/view/16936.

[2] S. Srivastava and G. Sharma, Omnivec: Learning robust representations with cross modal sharing, 2023. arXiv: 2311.05709 [cs.CV].

Reference - [2]

[3] M. Chahine, R. Hasani, P. Kao, et al., “Robust flight navigation out of distri bution with liquid neural networks,” Science Robotics, vol. 8, no. 77, eadc8892, 2023, Published online 2023 Apr 19, ISSN: 2470-9476.

[4] H. Ju, J.-X. Xu, and A. M. VanDongen, “Classification of musical styles using liquid state machines,” in The 2010 International Joint Conference on Neural Networks (IJCNN), 2010, 1–7.