SPEECH LAB EVAL

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Paper Summary :

The paper **"Speech Commands: A Dataset for Fine-Grained Speech Recognition"** presents a dataset with 65,000 one-second recordings of 12 spoken commands, such as "yes," "no," "up," and "down." It aims to advance research in speech recognition by offering a standardized benchmark for fine-grained audio classification, focusing on real-world performance in command recognition.

Google Collab files link :

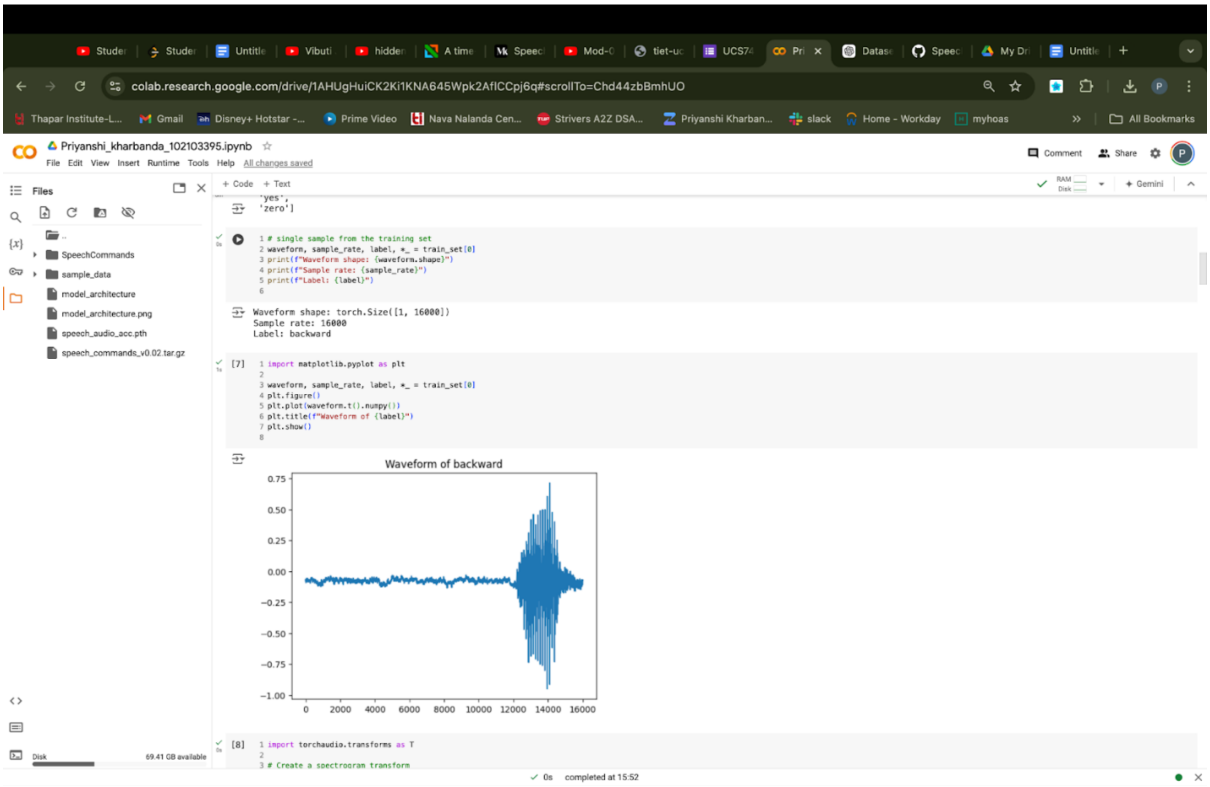
https://colab.research.google.com/drive/1k2v-4TAlplImoT-EbDsSzEr4eQBCU640#scrollTo=SdDDteRj07ft

https://colab.research.google.com/drive/1dcbddNXmg2VLQ_4t2HFQZc86bKP_z6cC

https://colab.research.google.com/drive/1dcbddNXmg2VLQ_4t2HFQZc86bKP_z6cC

Analysis of data

1. A data point in the SPEECHCOMMANDS dataset is a tuple made of a waveform (the audio signal), the sample rate, the utterance (label), the ID of the speaker, the number of the utterance.



```
 'yes',
 'zero']
```

```python
# single sample from the training set
waveform, sample_rate, label, *_ = train_set[0]
print(f"Waveform shape: {waveform.shape}")
print(f"Sample rate: {sample_rate}")
print(f"Label: {label}")
```

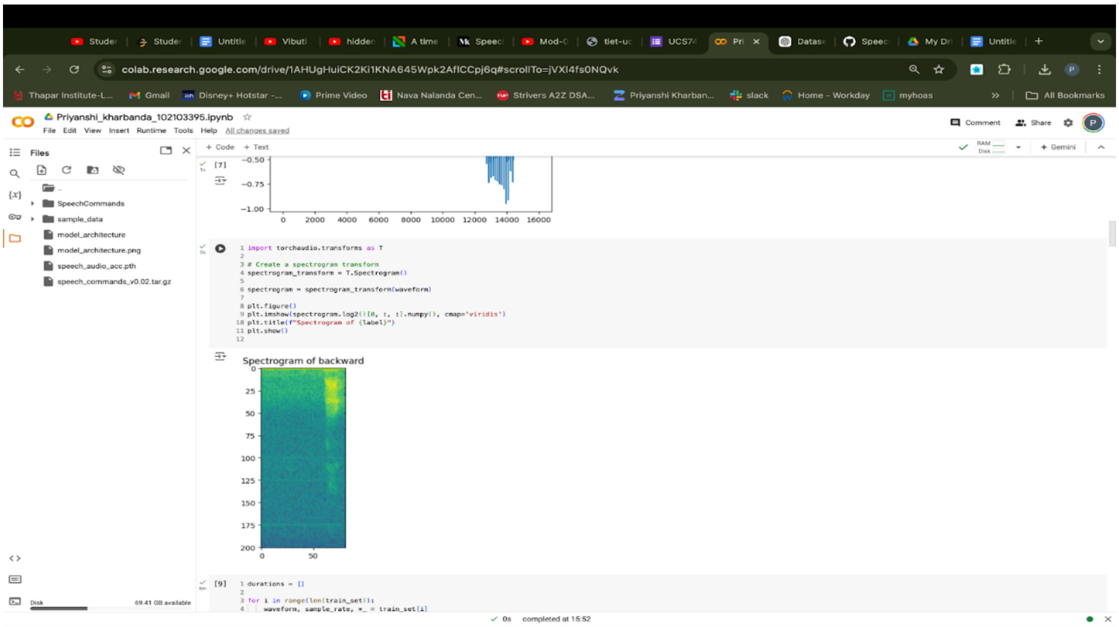
```
Waveform shape: torch.Size([1, 16000])
Sample rate: 16000
Label: backward
```

```python
[7]
import matplotlib.pyplot as plt

waveform, sample_rate, label, *_ = train_set[0]
plt.figure()
plt.plot(waveform.t().numpy())
plt.title(f"Waveform of {label}")
plt.show()
```

```python
[8]
import torchaudio.transforms as T

# Create a spectrogram transform
```

Number of training samples: 84843
Number of testing samples: 11005

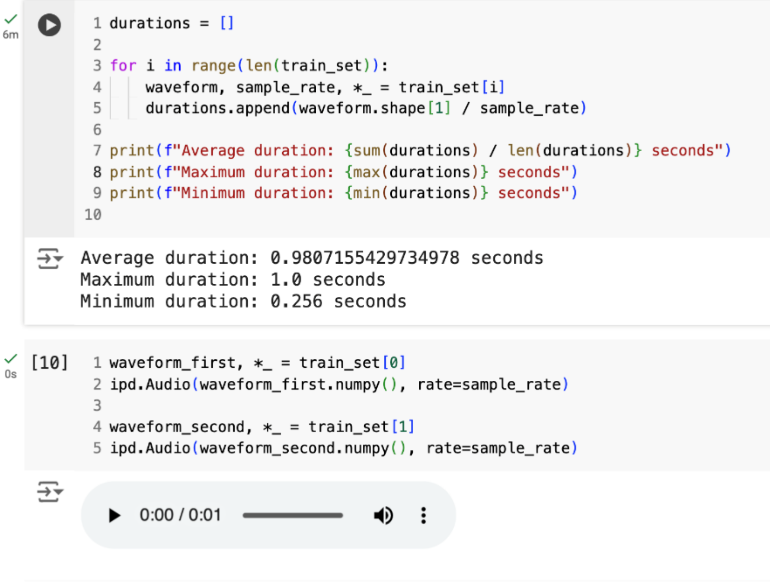
2. After applying fourier transformation, here is what a pectrogram of label backward looks like



```
import torchaudio.transforms as T

# Create a spectrogram transform
spectrogram_transform = T.Spectrogram()

spectrogram = spectrogram_transform(waveform)

plt.figure()
plt.imshow(spectrogram.log2()[0, :, :].numpy(), cmap='viridis')
plt.title(f"Spectrogram of {label}")
plt.show()

```

```
durations = []

for i in range(len(train_set)):
    waveform, sample_rate, *_ = train_set[i]
```

3. Analysis done of duration of samples in our speechcommand dataset.

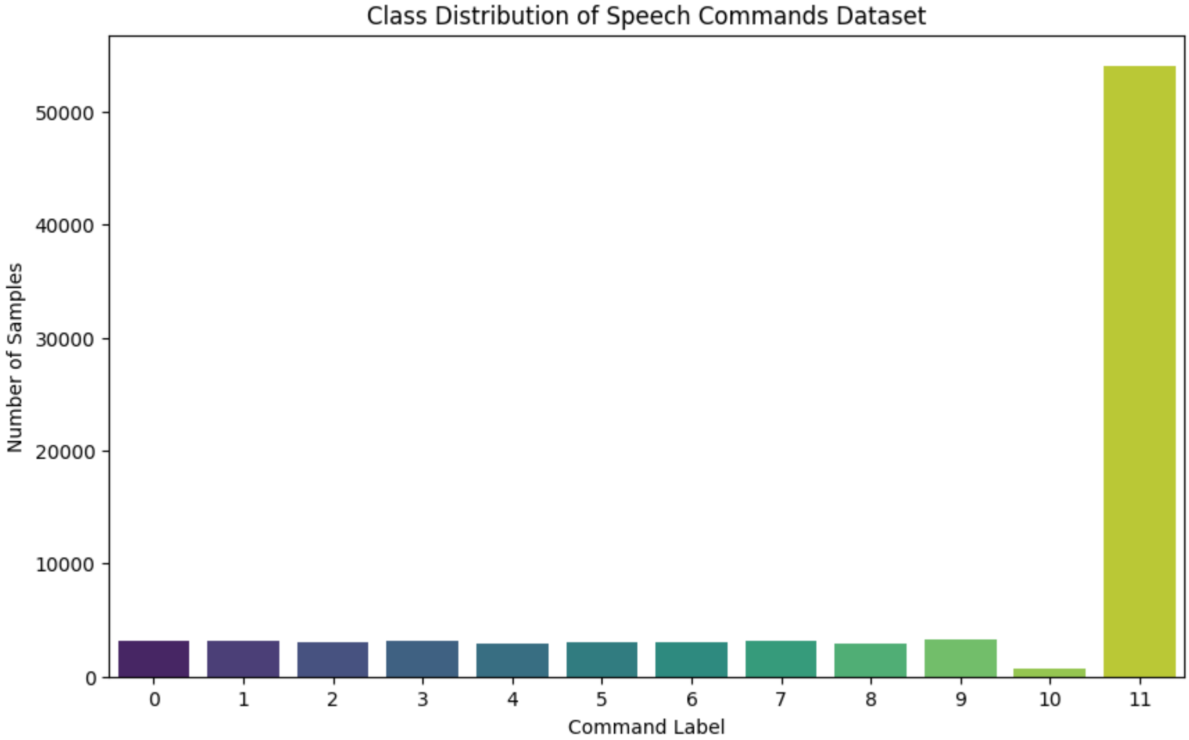


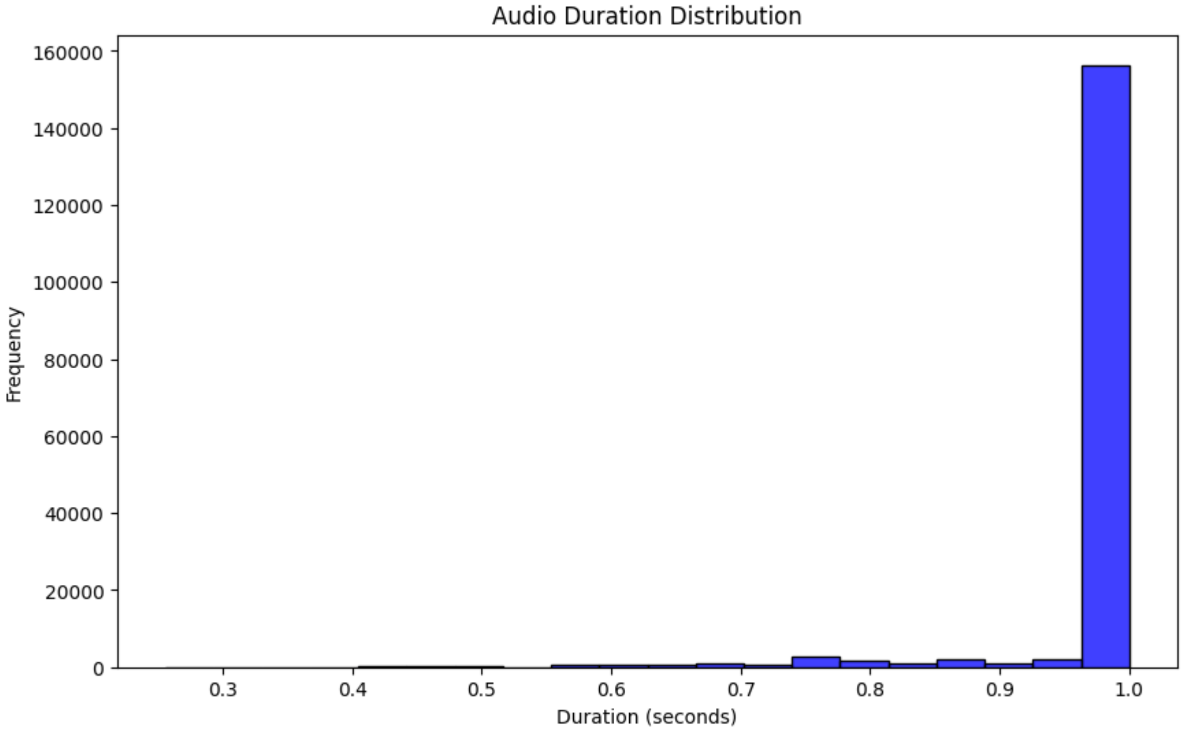
```
durations = []

for i in range(len(train_set)):
    waveform, sample_rate, *_ = train_set[i]
    durations.append(waveform.shape[1] / sample_rate)

print(f"Average duration: {sum(durations) / len(durations)} seconds")
print(f"Maximum duration: {max(durations)} seconds")
print(f"Minimum duration: {min(durations)} seconds")

```

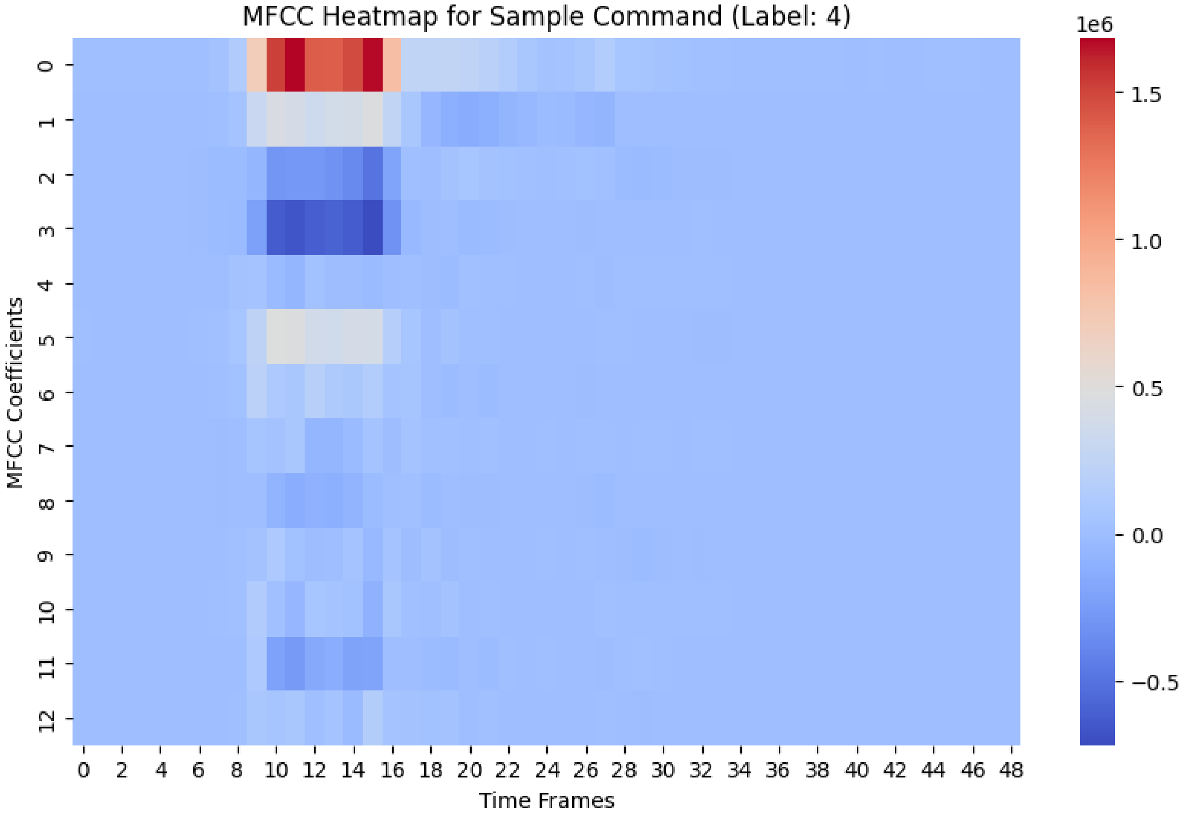
```
Average duration: 0.9807155429734978 seconds
Maximum duration: 1.0 seconds
Minimum duration: 0.256 seconds
```

```
[10]
waveform_first, *_ = train_set[0]
ipd.Audio(waveform_first.numpy(), rate=sample_rate)

waveform_second, *_ = train_set[1]
ipd.Audio(waveform_second.numpy(), rate=sample_rate)
```

Some snippets of analysis :




Audio Duration Distribution
Frequency
0
20000
40000
60000
80000
100000
120000
140000
160000
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Duration (seconds)


MFCC Heatmap for Sample Command (Label: 4)
MFCC Coefficients
0
1
2
3
4
5
6
7
8
9
10
11
12
0
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
34
36
38
40
42
44
46
48
Time Frames
1e6
1.5
1.0
0.5
0.0
−0.5

Steps considered while setting up data loading and batching for training and testing a model using the SPEECHCOMMANDS dataset with PyTorch.

2. **Padding Sequences (pad_sequence function)**

- **Purpose**: Ensures all tensors in a batch are the same length by padding with zeros.
- **Details**:
    - Transposes each tensor in the batch.
    - Uses torch.nn.utils.rnn.pad_sequence to pad tensors to the same length.
    - Permutes the dimensions of the padded tensor to match the expected input shape for your model (usually (batch_size, channels, sequence_length)).

3. **Collate Function (collate_fn function)**

- **Purpose**: Defines how to collate (combine) individual data samples into a batch.
- **Details**:
    - Extracts waveforms and labels from each sample in the batch.
    - Applies pad_sequence to ensure waveforms in the batch have the same length.
    - Converts labels to indices using label_to_index and stacks them into a tensor.

4. **DataLoader Configuration**

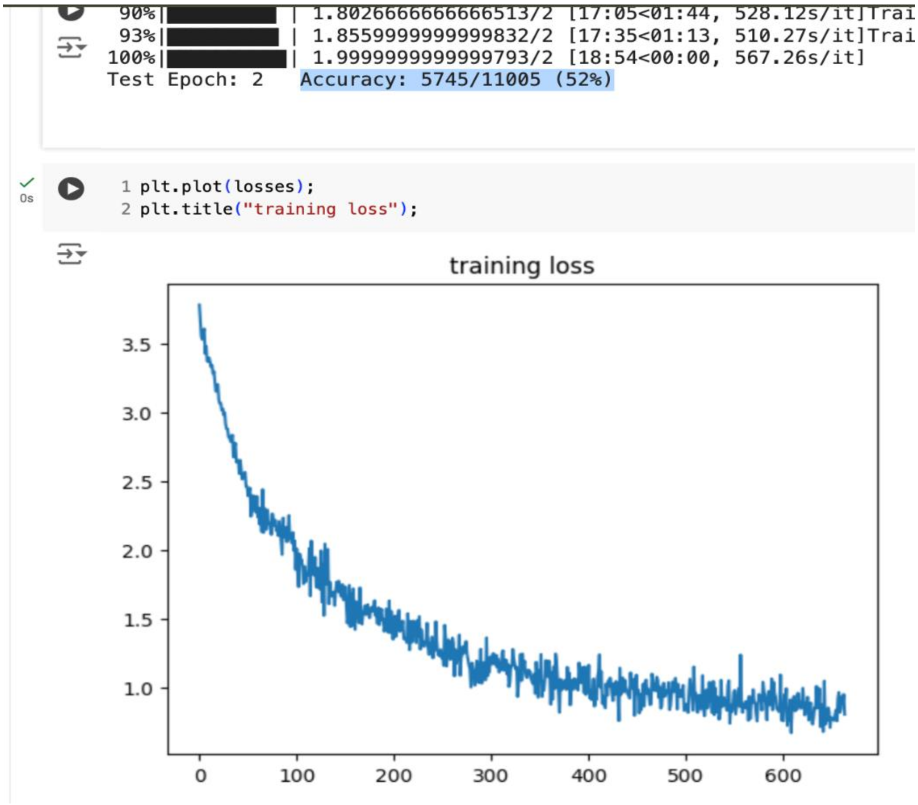
- **Purpose**: Creates DataLoader instances for the training and test datasets.
- **Details**:
    - **train_loader**: Loads training data with batching, shuffling, and custom collate function.
        - batch_size=256
        - shuffle=True: Shuffles data at each epoch.
        - num_workers and pin_memory are set based on whether a GPU (cuda) or CPU is used.
    - **test_loader**: Loads test data with batching and custom collate function.
        - batch_size=256
        - shuffle=False: No shuffling for test data.
        - drop_last=False: Keeps the last batch even if it’s smaller than the batch size.

Model Used (M5 Class)

Purpose: Defines a CNN model for classification.
Components:

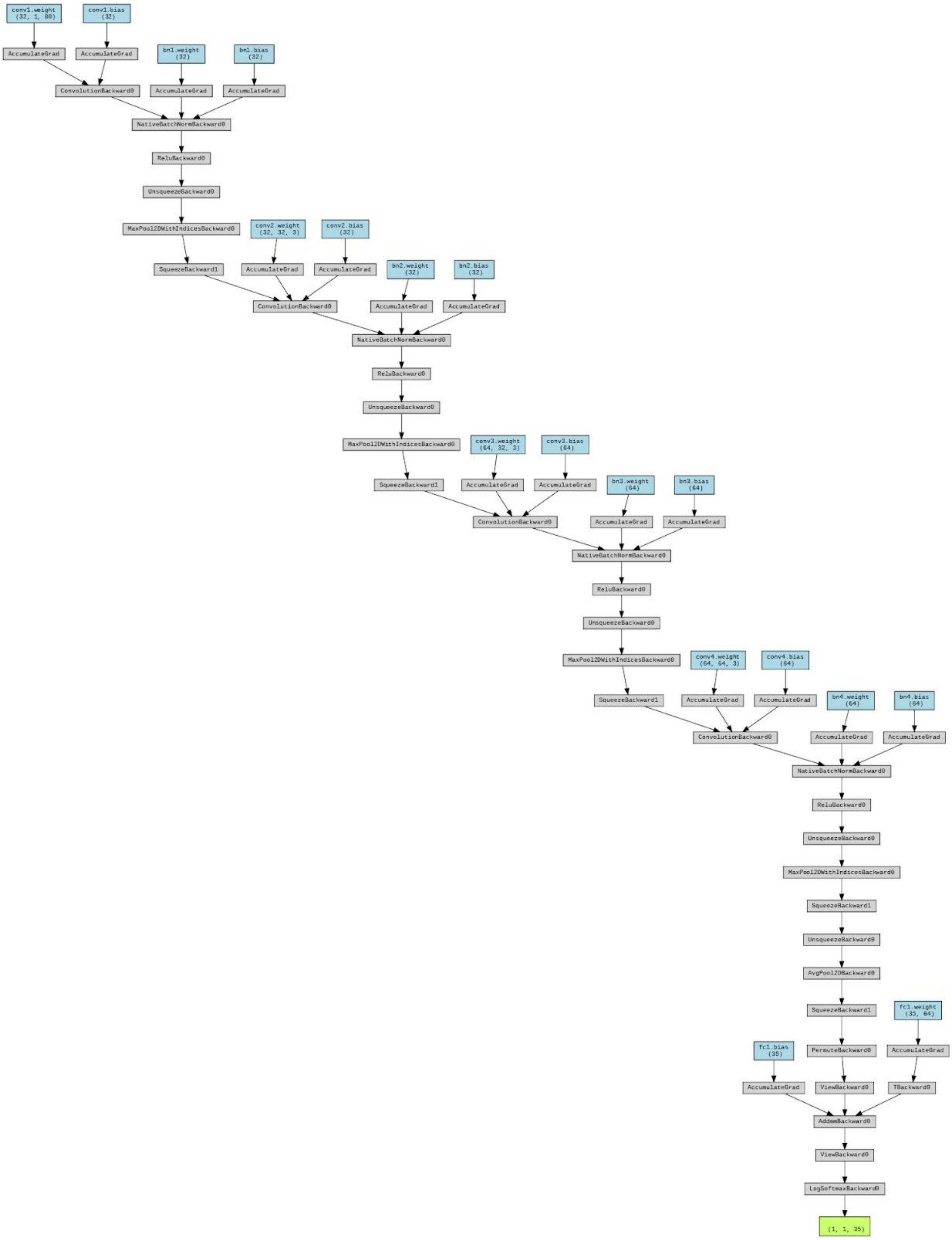
- **Convolutional Layers**:
    - conv1: 1D convolution with kernel size 80, stride 16.
    - conv2: 1D convolution with kernel size 3.
    - conv3: 1D convolution with kernel size 3, output channels doubled.
    - conv4: 1D convolution with kernel size 3, output channels doubled.
- **Batch Normalization**:
    - bn1, bn2, bn3, bn4: Normalize outputs of respective convolutional layers.
- **Pooling Layers**:
    - pool1, pool2, pool3, pool4: Max pooling with kernel size 4.
- **Fully Connected Layer**:
    - fc1: Linear layer that maps from the output channels to the number of classes.

- **Forward Pass**:
    - Applies convolutions, batch normalization, ReLU activation, pooling, and average pooling.
    - Reshapes and passes through a fully connected layer followed by log_softmax for classification.



```
 90%|█████████ | 1.8026666666666513/2 [17:05<01:44, 528.12s/it]Trai
 93%|█████████▎| 1.8559999999999832/2 [17:35<01:13, 510.27s/it]Trai
100%|██████████| 1.9999999999999793/2 [18:54<00:00, 567.26s/it]
Test Epoch: 2   Accuracy: 5745/11005 (52%)
```

```
plt.plot(losses);
plt.title("training loss");
```



Model M5 Architecture

Results – 72.53 % Accuracy