

# Horn Detection for Deaf Drivers

Alana Jocelyn Natania Massie  
Vian Sebastian Bromokusumo

22/496239/PA/21331  
22/496698/PA/21355

## Pattern Recognition Course



# Table of contents

01

Background

02

Method

03

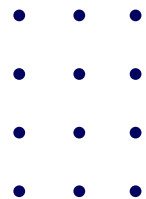
Result &  
Discussion

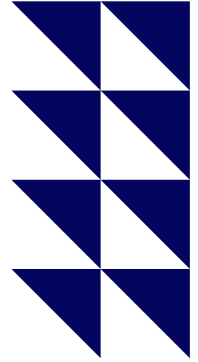
04

Conclusion

05

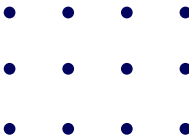
Links &  
References



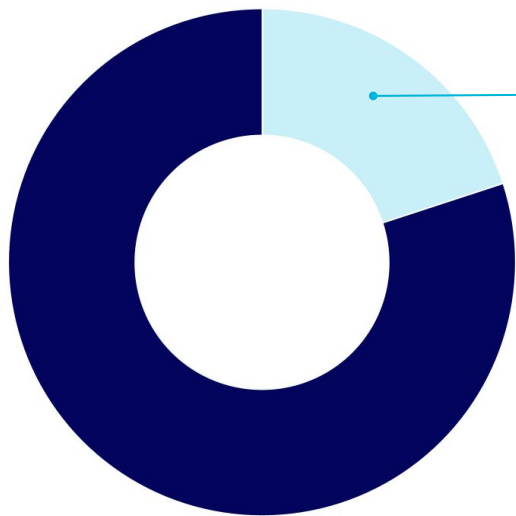


01

# Background



# Background



**20%** of the population has some degree of hearing loss

**1.16 billion** of the 1.50 billion people who have hearing loss have mild severity

Around 70 million people globally have total hearing loss, and this is **projected to double by 2060**

83.3% of deaf drivers face **impaired awareness** during driving, leading to 60% experiencing accident

# Underlying Problems for Deaf Drivers

High interest for IoT devices  
that increase perception and  
driving awareness

Hesitance to acquire  
drivers license due to  
fear of safety

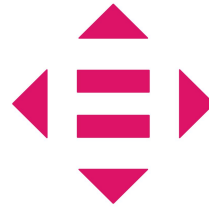
Higher average travel distance  
due to slower routes and  
increased direction confusion

# SDGs

**3** GOOD HEALTH  
AND WELL-BEING

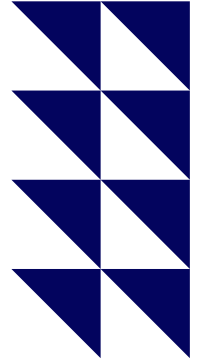


**10** REDUCED  
INEQUALITIES



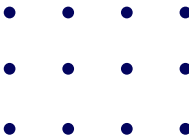
**11** SUSTAINABLE CITIES  
AND COMMUNITIES





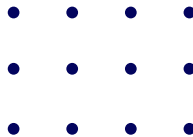
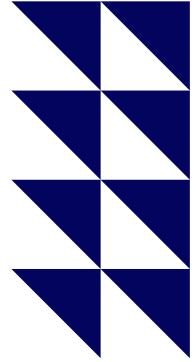
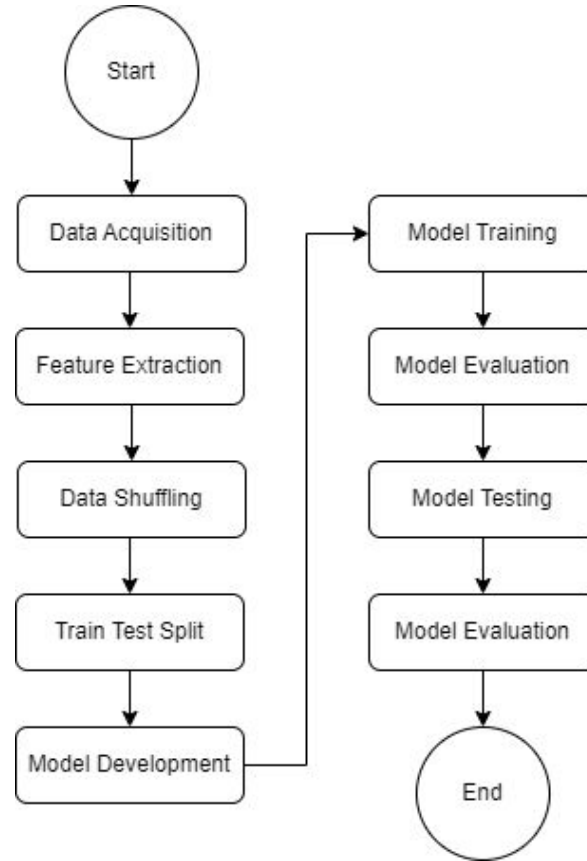
02

# Method





# Project Flowchart





# Dataset

## HornBase

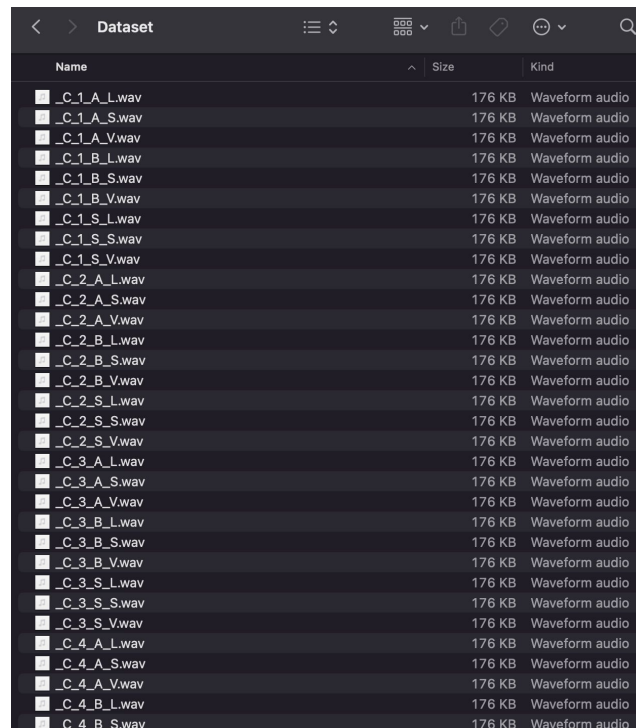
A dataset comprising 1080 audio files of exactly one-second duration each

Classes	Horn	Not Horn
	<ul style="list-style-type: none"><li>– Short honk</li><li>– Long honk</li><li>– Intermittent sequence of three consecutive short honks</li></ul>	<ul style="list-style-type: none"><li>– Road noise</li><li>– Music noise</li><li>– Talking noise</li></ul>

For each possible audio segment, **three temporal windows are cut**, with the first containing the initial half of a horn, the second containing the entire horn, and the third containing the final half of a horn.

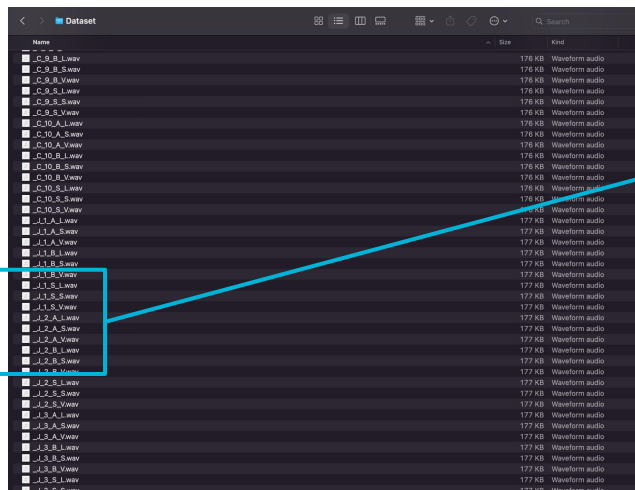
Contributors:

Cleyton Aparecido Dim, Nelson Cruz Sampaio Neto, Jefferson Magalhães de Moraes



Dataset							
Name	Size	Kind					
._C_1_A_L.wav	176 KB	Waveform audio					
._C_1_A_S.wav	176 KB	Waveform audio					
._C_1_A_V.wav	176 KB	Waveform audio					
._C_1_B_L.wav	176 KB	Waveform audio					
._C_1_B_S.wav	176 KB	Waveform audio					
._C_1_B_V.wav	176 KB	Waveform audio					
._C_1_S_L.wav	176 KB	Waveform audio					
._C_1_S_S.wav	176 KB	Waveform audio					
._C_1_S_V.wav	176 KB	Waveform audio					
._C_2_A_L.wav	176 KB	Waveform audio					
._C_2_A_S.wav	176 KB	Waveform audio					
._C_2_A_V.wav	176 KB	Waveform audio					
._C_2_B_L.wav	176 KB	Waveform audio					
._C_2_B_S.wav	176 KB	Waveform audio					
._C_2_B_V.wav	176 KB	Waveform audio					
._C_2_S_L.wav	176 KB	Waveform audio					
._C_2_S_S.wav	176 KB	Waveform audio					
._C_2_S_V.wav	176 KB	Waveform audio					
._C_3_A_L.wav	176 KB	Waveform audio					
._C_3_A_S.wav	176 KB	Waveform audio					
._C_3_A_V.wav	176 KB	Waveform audio					
._C_3_B_L.wav	176 KB	Waveform audio					
._C_3_B_S.wav	176 KB	Waveform audio					
._C_3_B_V.wav	176 KB	Waveform audio					
._C_3_S_L.wav	176 KB	Waveform audio					
._C_3_S_S.wav	176 KB	Waveform audio					
._C_3_S_V.wav	176 KB	Waveform audio					
._C_4_A_L.wav	176 KB	Waveform audio					
._C_4_A_S.wav	176 KB	Waveform audio					
._C_4_B_L.wav	176 KB	Waveform audio					
._C_4_B_S.wav	176 KB	Waveform audio					

# Dataset



## Filename Structure

=HORN CLASS=

C 9 B L .wav

\_\_\_\_\_ present only if is second half horn cut  
\_\_\_\_\_ type of the horn. (S)hort, (L)ong, (V)aried  
\_\_\_\_\_ position of the emitting car. (B)ack, (S)ide, (A)head  
\_\_\_\_\_ scenario identifier. Ranging from 1 to 10  
\_\_\_\_\_ recording smartphone identifier. (C or J)  
\_\_\_\_\_ present only if is first half horn cut

=NOT HORN CLASS=

C 9 B N3.wav

\_\_\_\_\_ range from 1 to 9 to differentiate not-horn cuts  
\_\_\_\_\_ position of the emitting car. (B)ack, (S)ide, (A)head  
\_\_\_\_\_ scenario identifier. Ranging from 1 to 10  
\_\_\_\_\_ recording smartphone identifier. (C or J)



# Dataset Preparation

```
for file in files:
    if os.path.isdir(os.path.join(source_dir, file)):
        continue

    if file.endswith(('S.wav', 'S_.wav', 'V.wav', 'V_.wav', 'L.wav',
        'L_.wav')):
        target_dir = honks_dir
    else:
        target_dir = non_honks_dir

    shutil.move(os.path.join(source_dir, file),
        os.path.join(target_dir, file))

    print('Files in Honks:', os.listdir(honks_dir))
    print('Files in Non-Honks:', os.listdir(non_honks_dir))
```

The code snippet groups the dataset into the correct structure as shown in the figure

## Folder Structure

```
Dataset/
|
| --- Honks/
|
| --- Non-Honks/
```

# Feature Extraction

## What?

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.



## How?

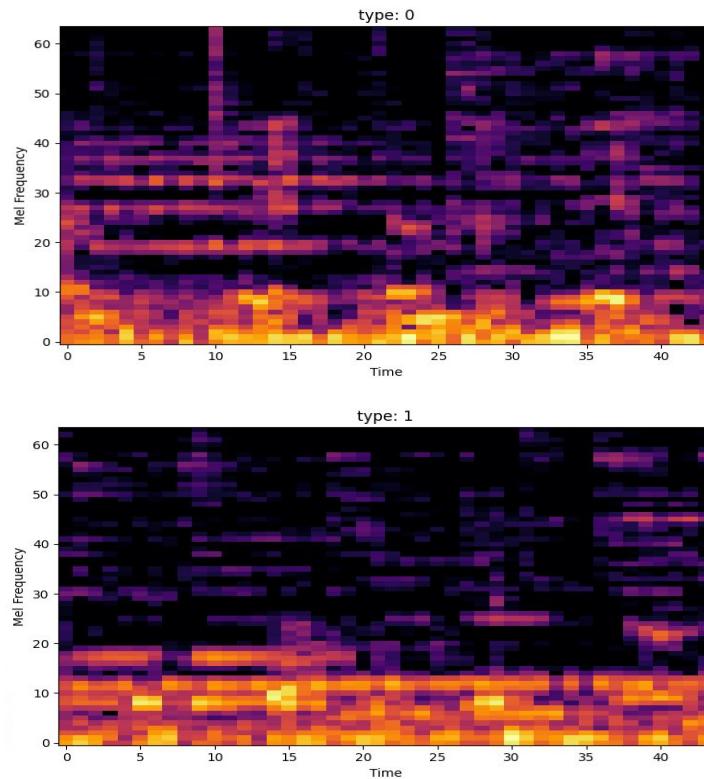
The main feature we extracted from the audio files are the spectrograms, the sample of each class can be seen in the next slide.

The type 0 will be the Horns, and the type 1 will be the Non-Horns.

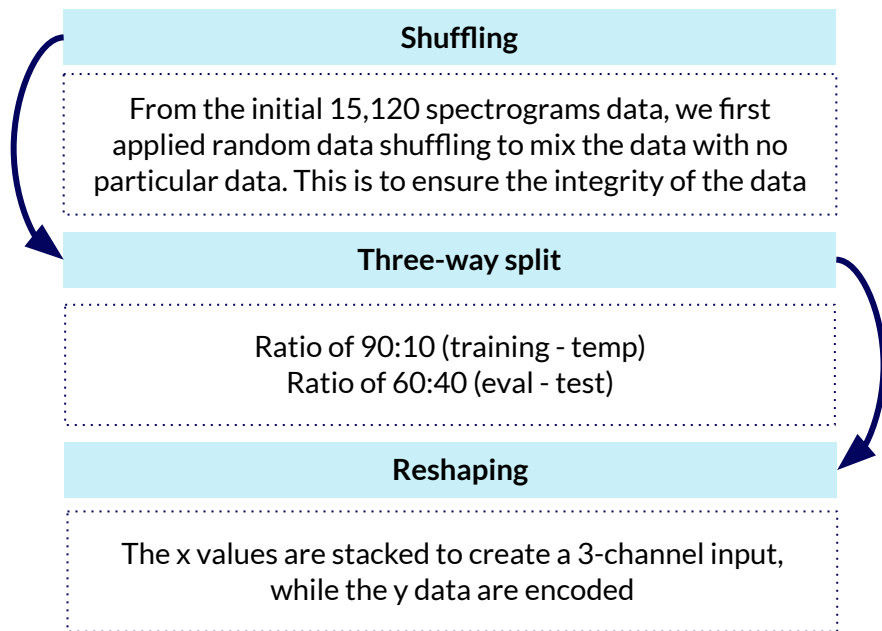


# Feature Extraction

```
for genre, genre_number in genres.items():
    directory = os.path.join(base_dir, genre)
    genre_data = []
    for filename in os.listdir(directory):
        files = os.path.join(directory, filename)
        for index in range(14):
            y, sr = librosa.load(files, mono=True, duration=2)
            ps = librosa.feature.melspectrogram(y=y, sr=sr,
            hop_length=512, n_fft=512, n_mels=64)
            ps = librosa.power_to_db(ps**2)
            genre_data.append(['spectrogram': ps, 'type':
            genre_number])
    genre_df = pd.DataFrame(genre_data)
    dfs.append(genre_df)
```



# Train Test Split



```
shuffled_df = df.sample(frac = 1, random_state = 42)
shuffled_df
```

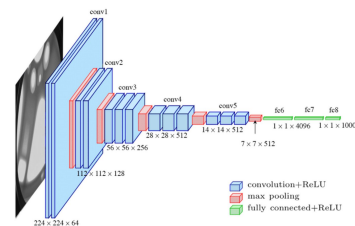
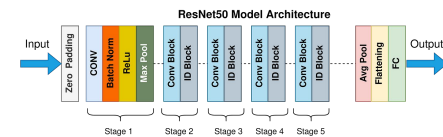
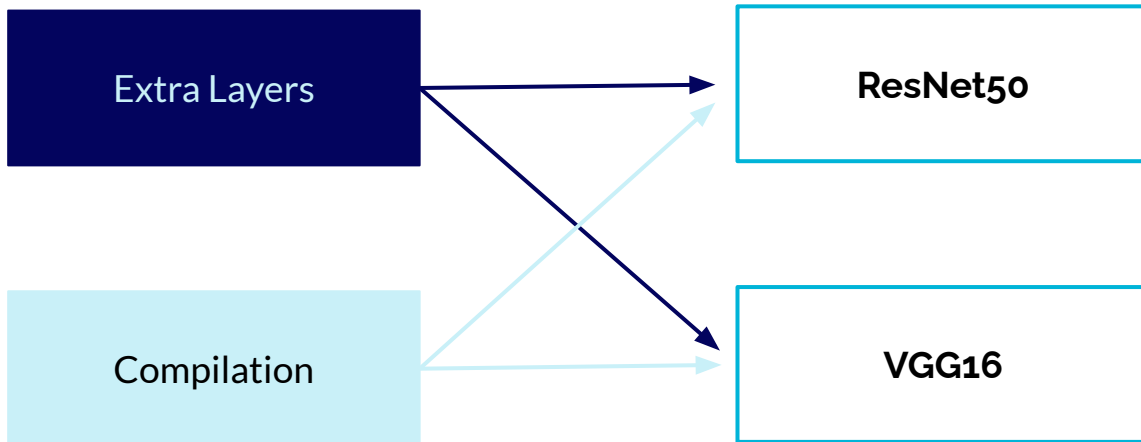
```
x_train, x_temp, y_train, y_temp = train_test_split(x, y,
test_size = 0.1, random_state = 123)
x_val, x_test, y_val, y_test = train_test_split(x_temp,
y_temp, test_size = 0.4, random_state = 123)
```

```
x_train = np.repeat(x_train, 3, axis=-1)
x_val = np.repeat(x_val, 3, axis=-1)
x_test = np.repeat(x_test, 3, axis=-1)
```

```
y_train = tf.keras.utils.to_categorical(y_train,
num_classes=2)
y_val = tf.keras.utils.to_categorical(y_val, num_classes=2)
y_test = tf.keras.utils.to_categorical(y_test, num_classes=2)
```



# Model Development



# Model Development

**VGG16**



VGG-16 is a deep learning network consisting of 16 weight layers: 13 convolutional layers and 3 fully connected layers. The network uses small 3x3 filters in all convolutional layers and max-pooling layers to reduce dimensionality.

**ResNet50**



ResNet50 is a 50 layer deep learning network consisting of convolutional layers, identity mappings, and pooling layers. Key advantage of the ResNet network is the presence of residual blocks that effectively mitigates the vanishing gradient problem.

**Extra Layers**



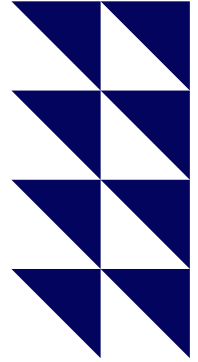
Batch Normalization, Dropout, and two Dense layers for dataset customization.

**Compilation**



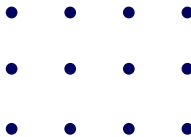
Categorical Crossentropy, Adam optimizer, and accuracy metric.



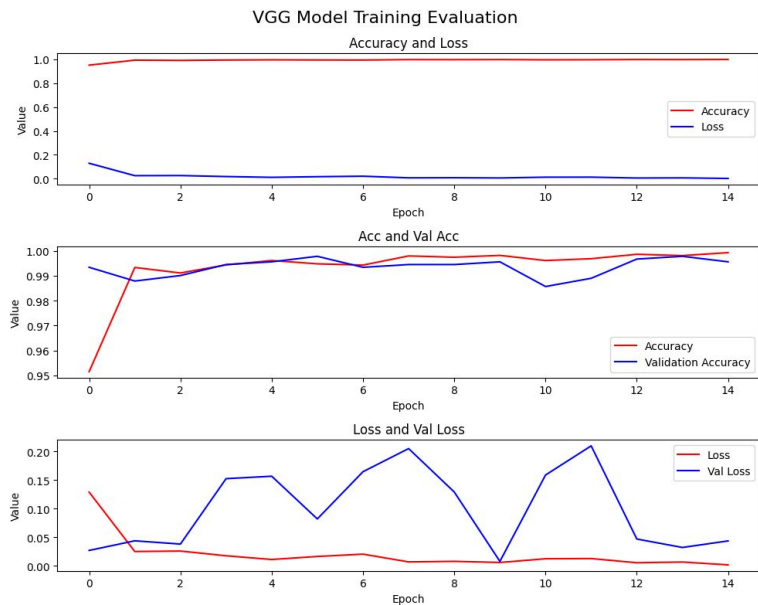


03

# Results & Discussion

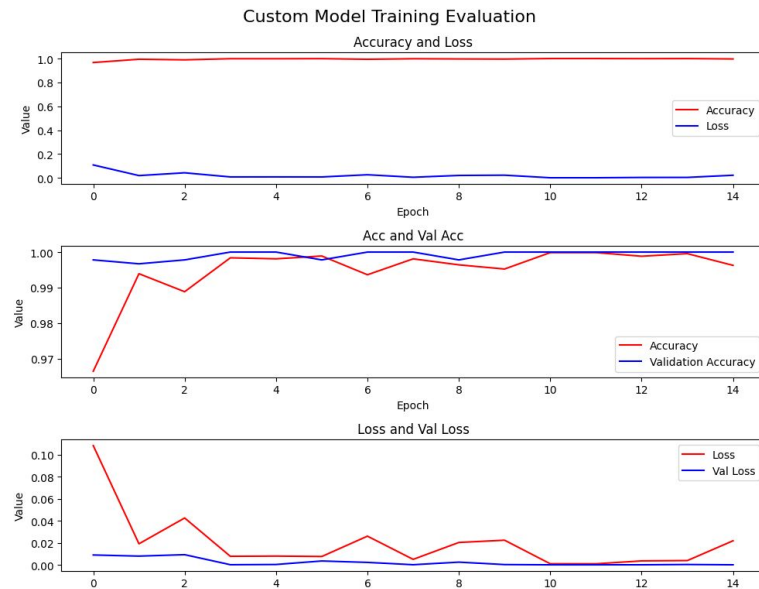


# VGG16 Training Result

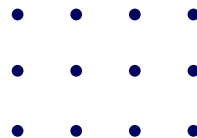


Highest recorded Accuracy: 0.9993  
Highest recorded Val Accuracy: 0.9978

# ResNet 50 Training Result



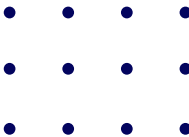
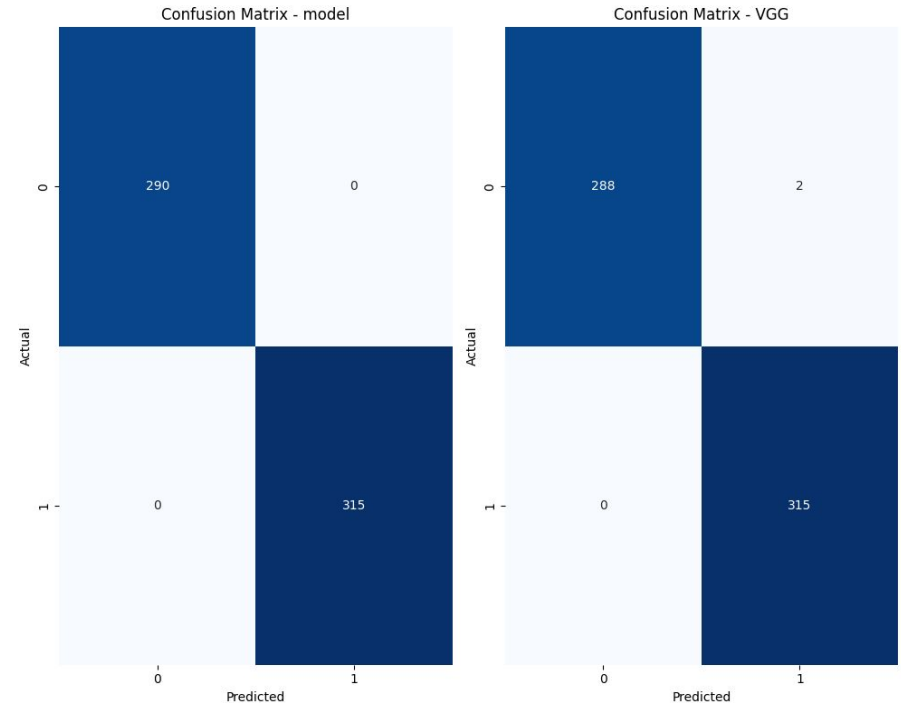
Highest recorded Accuracy: 0.9999  
Highest recorded Val Accuracy: 1.000



## Testing Results

	ResNet	VGG
Acc	1.0	0.9966
Prec	1.0	0.9967
Rec	1.0	0.9966
F1	1.0	0.9966

Highest recorded Accuracy: 0.9993  
Highest recorded Val Accuracy: 0.9978

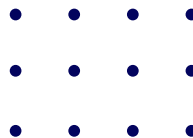


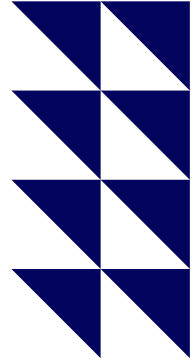
## Discussion

	ResNet50	VGG16
Acc	1.0	0.9966
Prec	1.0	0.9967
Rec	1.0	0.9966
F1	1.0	0.9966

	ResNet50	VGG16
Size	98 MB	528 MB
Params	98.6 M	138.4 M
Trainable Params	4 MB	1 MB
Inference time	4.6 ms	4.2 ms

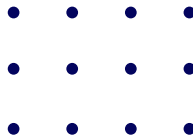
From this project, it is undisputed that the **ResNet50 model performed better, with less space complexity**, making it a better suit in the ideally proposed solution in deploying the model to a mobile environment. Although, it is worth mentioning that both these models are very sophisticated deep learning models, which might be an overkill.

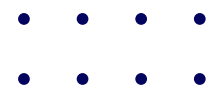




04

# Conclusion



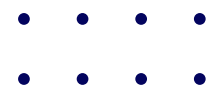


# Conclusion

Considering the accuracy, size, and many other factors, both ResNet50 and VGG16 output outstanding results in classifying and detecting horn sounds from other noises. ResNet50 performed better and is significantly more space-efficient, with a smaller model size and fewer parameters. Although ResNet50's inference time is marginally longer, its overall performance and lower space complexity make it better suited for deployment.

It can be concluded that this project effectively created a horn detection system with the aim to help deaf drivers in the driving environment.





# Future Recommendations

## Real-world testing

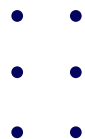
Have deaf drivers test the models to evaluate efficiency in practical scenarios and gather feedback for improvements.

## Hybrid Architectures

Explore combining VGG16 and ResNet50 features or using newer architectures like EfficientNet or Vision Transformers.

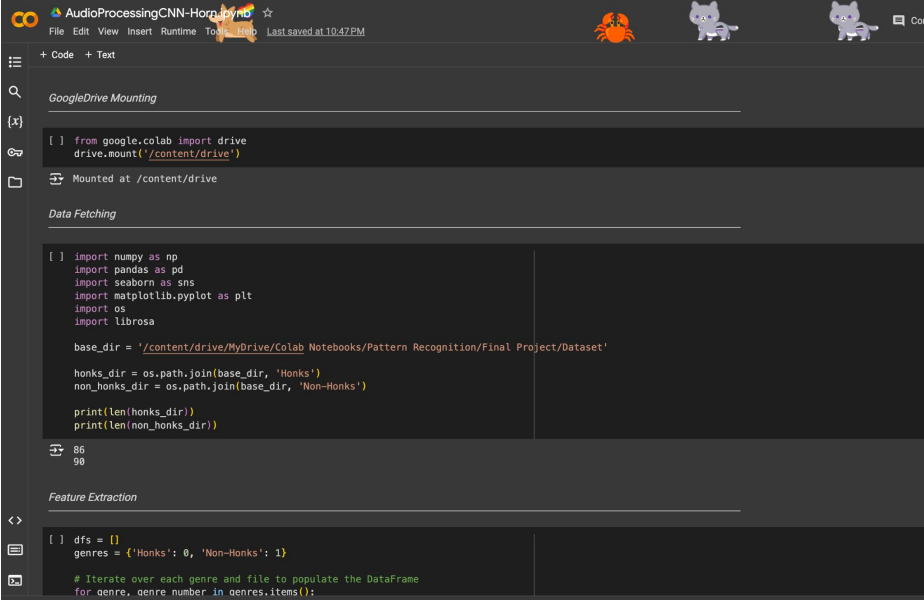
## Dataset Augmentation

Find more extensive and diverse datasets and apply data augmentation techniques for better generalization.



# Project Link

[https://colab.research.google.com/drive/1W\\_0KWlmaiSbr5\\_QPc3mA-vhig83r2YYF?usp=sharing](https://colab.research.google.com/drive/1W_0KWlmaiSbr5_QPc3mA-vhig83r2YYF?usp=sharing)



The screenshot shows a Google Colab notebook interface. The title bar indicates the notebook is named 'AudioProcessingCNN-Honk.ipynb' and was last saved at 10:47 PM. The notebook is divided into sections: 'GoogleDrive Mounting', 'Data Fetching', and 'Feature Extraction'. The 'GoogleDrive Mounting' section contains a code cell that mounts the drive at '/content/drive'. The 'Data Fetching' section contains a code cell that imports various libraries (numpy, pandas, seaborn, matplotlib, os, librosa) and defines paths for 'honks\_dir' and 'non\_honks\_dir'. The 'Feature Extraction' section contains a code cell that initializes a dictionary 'genres' and starts a loop to iterate over each genre and file to populate a DataFrame.

```
[ ] from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

Data Fetching

```
[ ] import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
import librosa

base_dir = '/content/drive/MyDrive/Colab Notebooks/Pattern Recognition/Final Project/Dataset'

honks_dir = os.path.join(base_dir, 'Honks')
non_honks_dir = os.path.join(base_dir, 'Non-Honks')

print(len(honks_dir))
print(len(non_honks_dir))
```

86  
90

Feature Extraction

```
[ ] dfs = []
genres = {'Honks': 0, 'Non-Honks': 1}

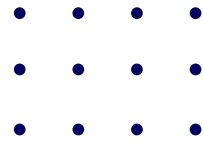
# Iterate over each genre and file to populate the DataFrame
for genre, genre_number in genres.items():
```





# Dataset Link

<https://drive.google.com/drive/folders/1c2L7efiMOzDqa98EVINGwKulZoAFUJP1?usp=sharing>



Name    ↑



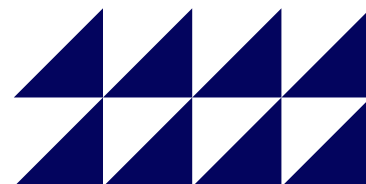
Honks

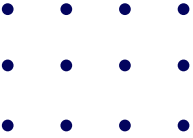


Non-Honks



audio\_data.csv    👤

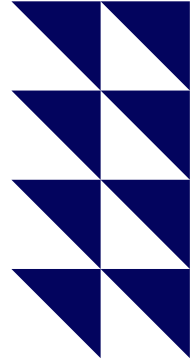




# References

1. Dim, Cleyton Aparecido; Neto, Nelson Cruz Sampaio; de Moraes, Jefferson Magalhães (2024), "HornBase - A Car Horns Dataset", Mendeley Data, V2, doi: 10.17632/y5stjsnp8s.2
2. MathWorks. (n.d.). What is feature extraction? MathWorks. Retrieved June 11, 2024, from <https://www.mathworks.com/discovery/feature-extraction.html>
3. Mascarenhas, S., & Agarwal, M. (2021). A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification. In 2021 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON-2021) IEEE.  
<https://doi.org/10.1109/CENTCON52345.2021.0017>





# Thank You

Any questions?

