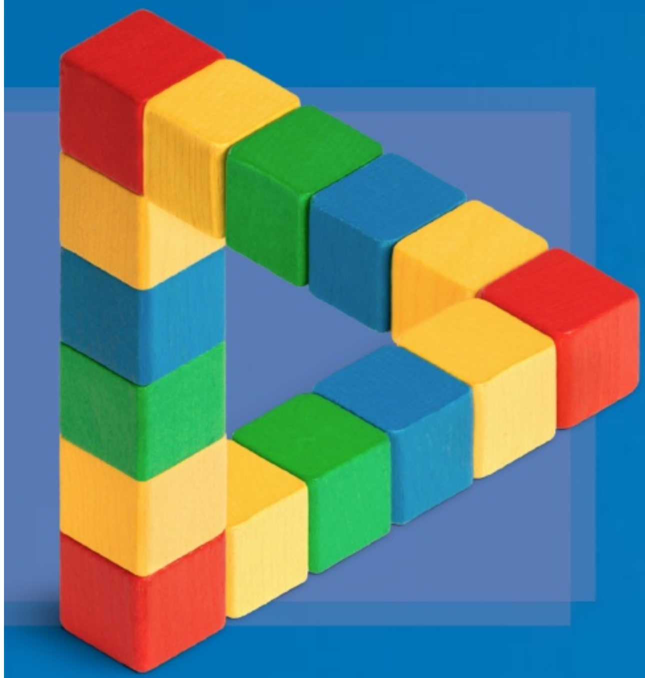

SMART
CITY
Conclusion



Overview

1	**Introduction** Each sub-project introduction & Data
2	**Workflow** The workflow for each project
3	**Results** The outcome of each project
4	**Conclusion** The conclusion


SMART
CITY
Conclusion

Introduction

Vision 2030, Saudi Arabia aims to become a global hub for data and AI.

In order to contribute on 2030 vision, we have created seven sub-projects that accomplish one main idea and show how we can take advantage of deep learning in a smart city.

The primary goal of AI is to improve ways of life by obtaining and analyzing large amounts of data to make more informed decisions.

The following projects aim to achieve the goal of smart cities and contribute to Vision 2030.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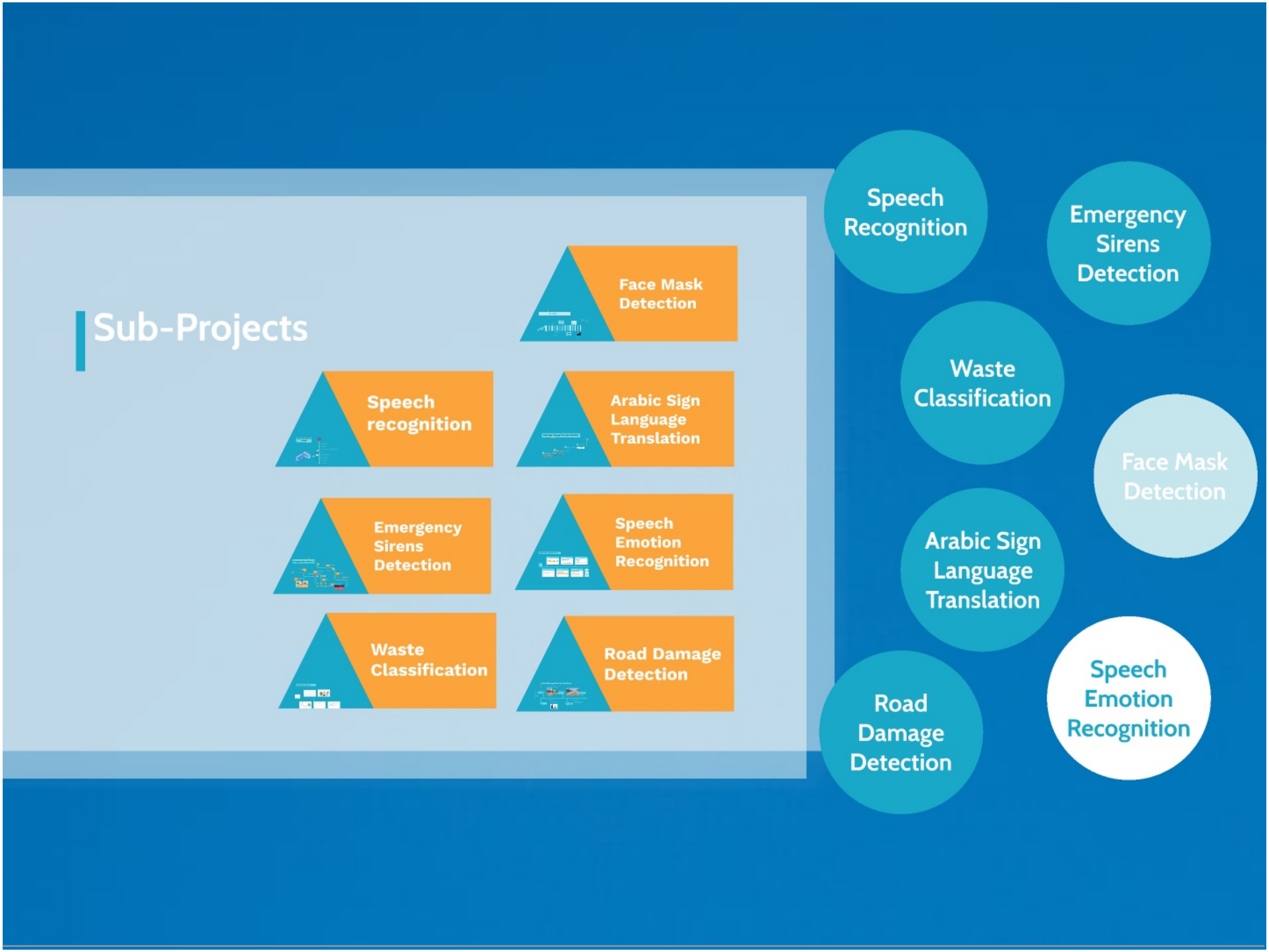
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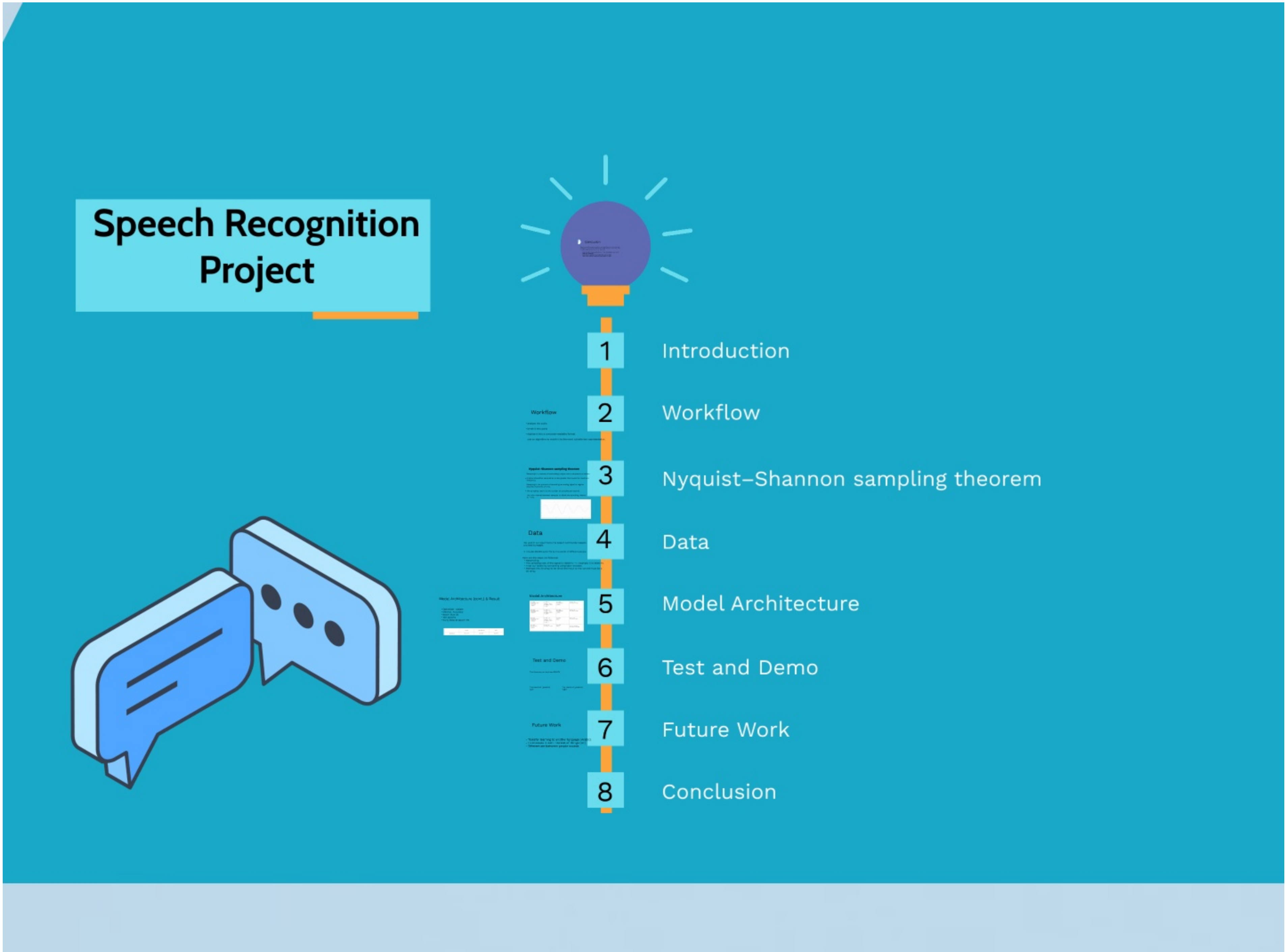

Speech Recognition Project
1 Introduction
2 Workflow
3 Nyquist–Shannon sampling theorem
4 Data
5 Model Architecture
6 Test and Demo
7 Future Work
8 Conclusion

Speech recognition Project introduction

By: Ahmed Almuaybid, Abdulrahman Alrifae, Naif Alzahrani

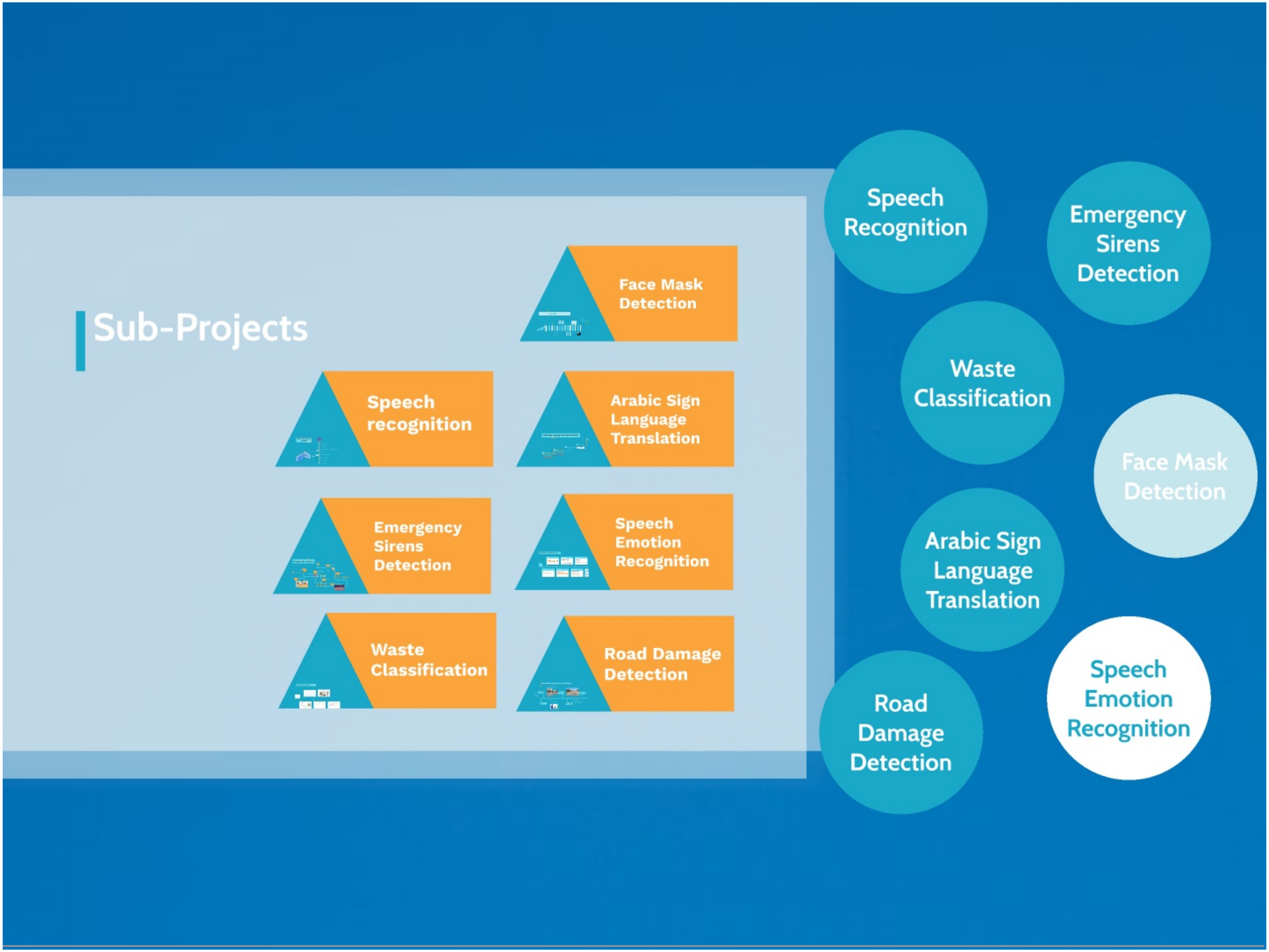
Speech recognition, also known as automatic speech recognition (ASR) or speech-to-text conversion, is the way that we can process human speech and turn it into a written format.

Speech recognition focuses on translating speech from verbal to textual.

Our project is to identify the commands from the user and use it in our daily life.

Smart city use case:

- Internet of Things (Iot)
- Search for reports or documents on your computer
- Medical Field
- Start video conferences
- Print documents on request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Workflow

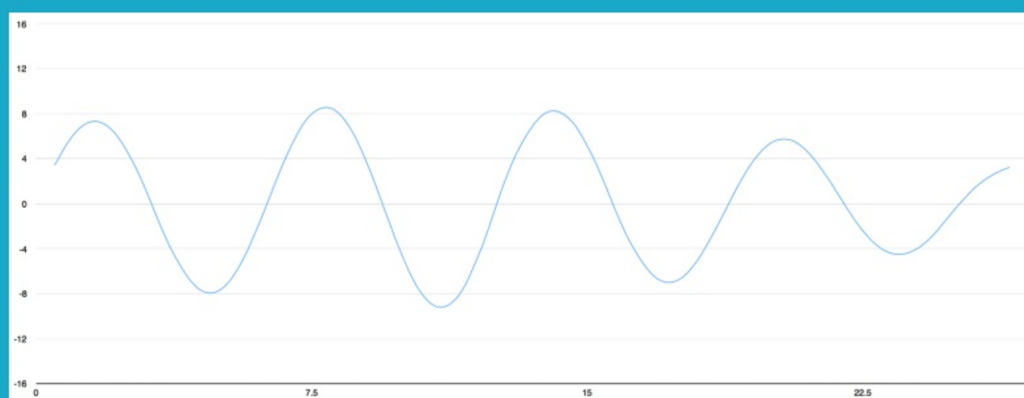
2

- analyze the audio
- break it into parts
- digitize it into a computer-readable format
- use an algorithm to match it to the most suitable text representation.

3

Nyquist–Shannon sampling theorem

- Sampling is a process of converting a signal into a sequence of values.
- A signal should be sampled at a rate greater than twice its maximum frequency.
- Sampling is the process of recording an analog signal at regular discrete moments of time.
- The sampling rate fs is the number of samples per second.
- The time interval between samples is called the sampling interval Ts = 1/fs .



Data

4

We used in our experiments the Speech Commands Datasets provided by Kaggle.

It includes 65,000 audio file by thousands of different people.

Here are the steps we followed:

- Resampling
- The sampling rate of the signal is 16000 hz => resample it to 8000 hz.
- Treat our labels by converting using laber encoder.
- Reshape the 2D array to 3D since the input to the conv1d must be a 3D array.

Model Architecture

1st Layer Convolution Layer MaxPooling Dropout	Filters = 8 Padding = Valid Activation = ReLu Strides = 1	5th Layer Bidirectional(CuDNNGRU)	Units = 128 Activation = TanH
2nd Layer Convolution Layer MaxPooling Dropout	Filters = 16 Padding = Valid Activation = ReLu Strides = 1	6th Layer Bidirectional(CuDNNGRU)	Units = 128 Activation = TanH
3rd Layer Convolution Layer MaxPooling Dropout	Filters = 32 Padding = Valid Activation = ReLu Strides = 1	7th Layer Dense	Units = 256 Activation = ReLu
4th Layer Bidirectional(CuDNNGRU)	Units = 128 Activation = TanH	8th Layer Dense	Units = len(Label) Activation = Softmax

5

Model Architecture (cont.) & Result

- Optimizer nadam
- Metrics Accuracy
- Batch Size 32
- 100 Epochs
- Early Stop at epoch 49

	train	validation	test
Accuracy	95.79 %	90.84%	92.47%

Test and Demo

6

The Accuracy on test was 92.47%

The result of (.predict)
‘yes’

The result of (.predict)
‘right’

Test and Demo

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Future Work

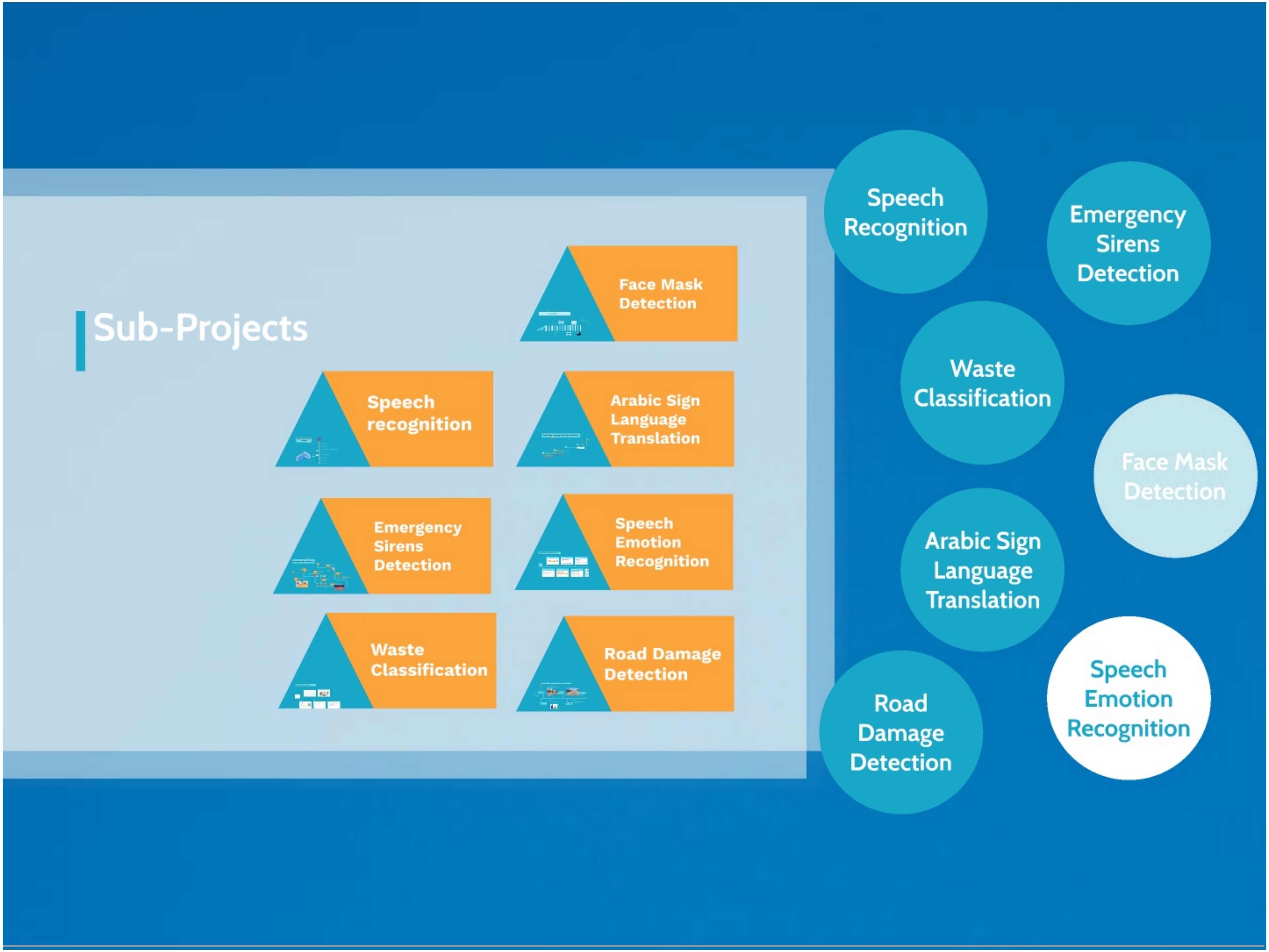
7

- Transfer learning to another language (Arabic)
- Incorporate it with Internet of Things (IoT)
- Differentiate between people sounds

Conclusion

Speech recognition systems that incorporate AI become more effective and easier to use over time. Using this model will help us in smart cities (medical field, banking, and in our daily life)

- It can help to increase productivity in many businesses, such as in healthcare industries.
- It can capture speech much faster than you can type
- Helps those who have problems with speech or sight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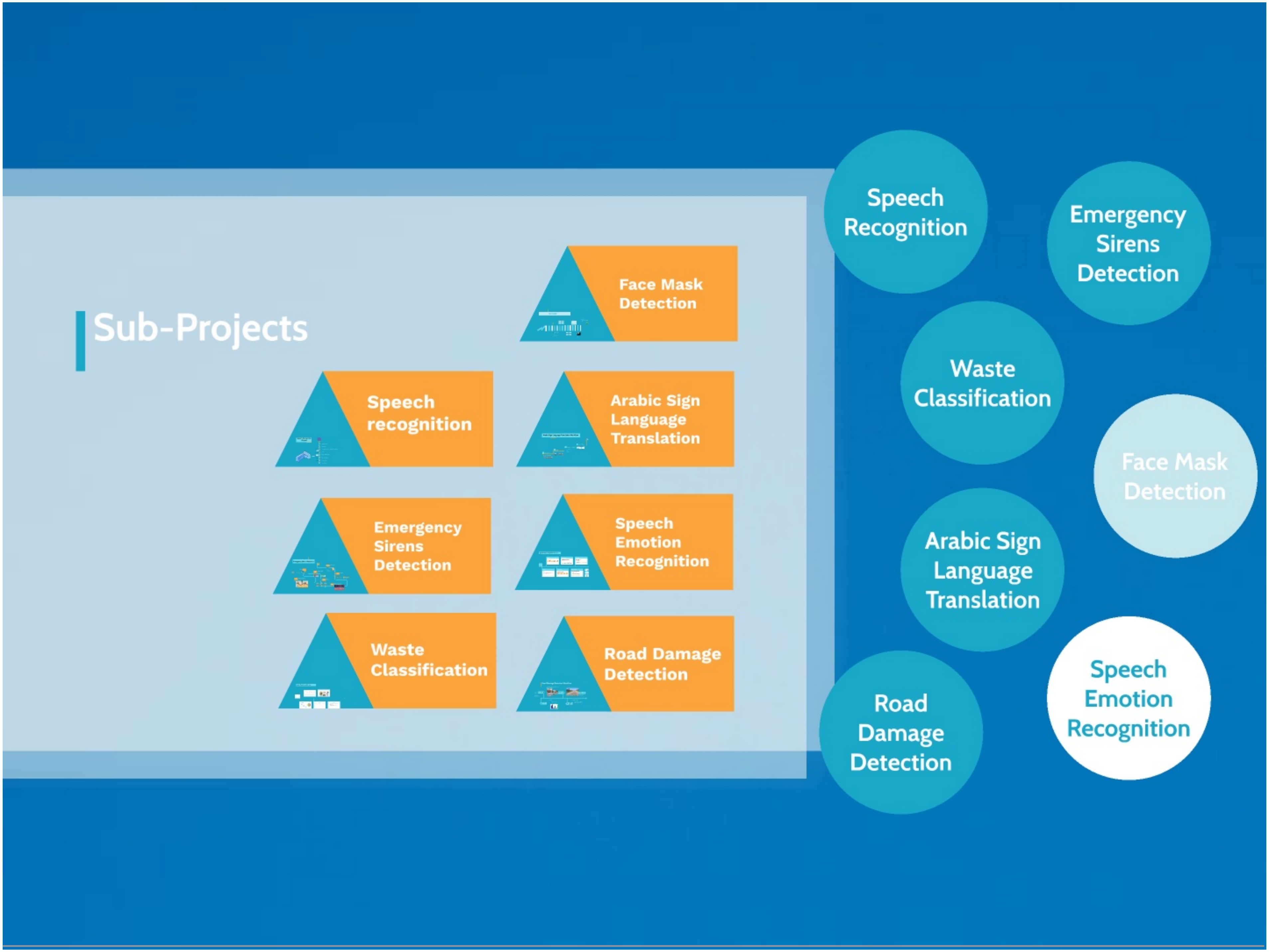
Emergency Sirens Detection

By: Mai Aljuaid & Basma Alduaiji

Introduction

- Due to heavy traffic, emergency vehicles are delayed in responding to an incident.
- This costs people their lives.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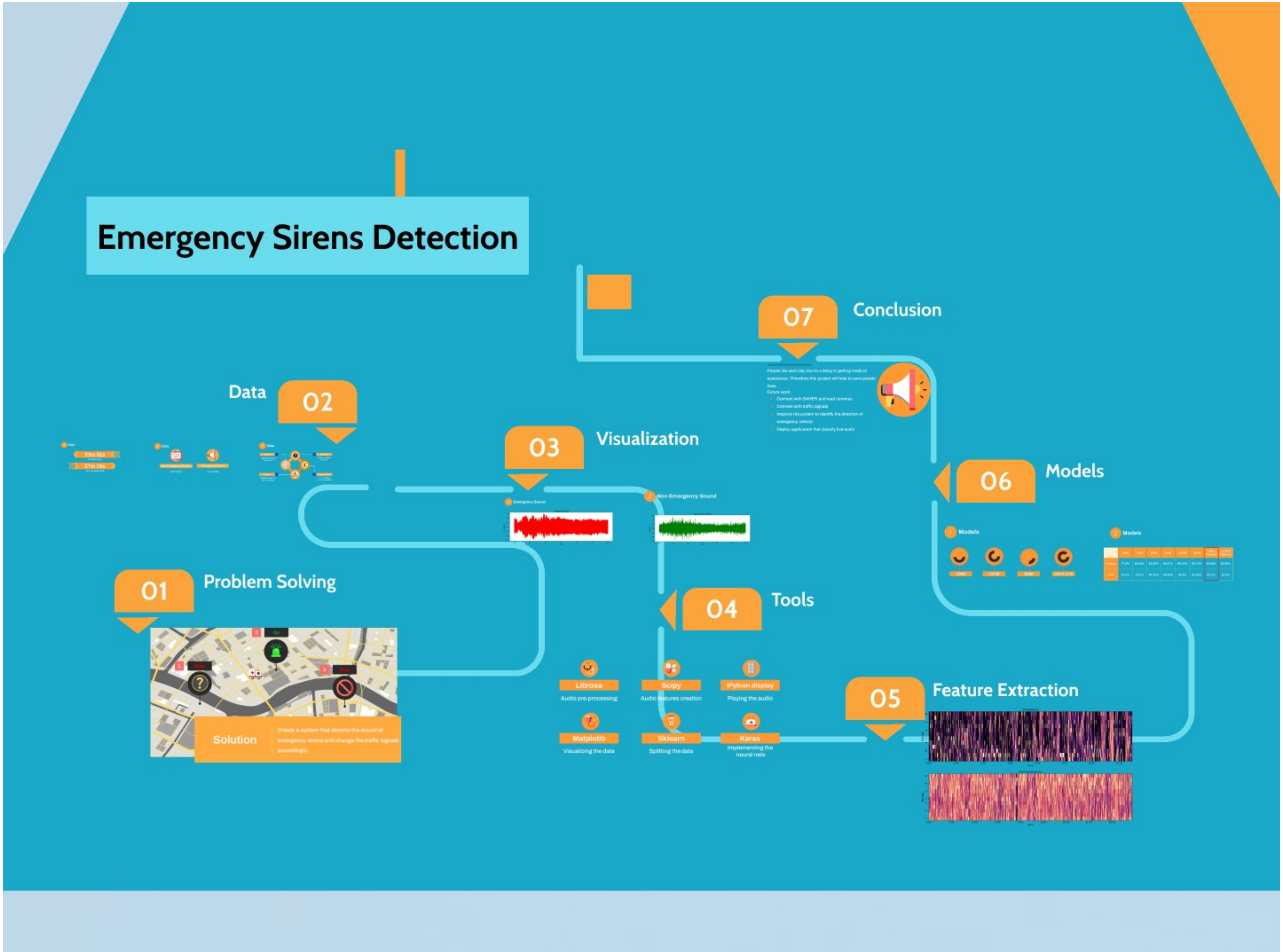
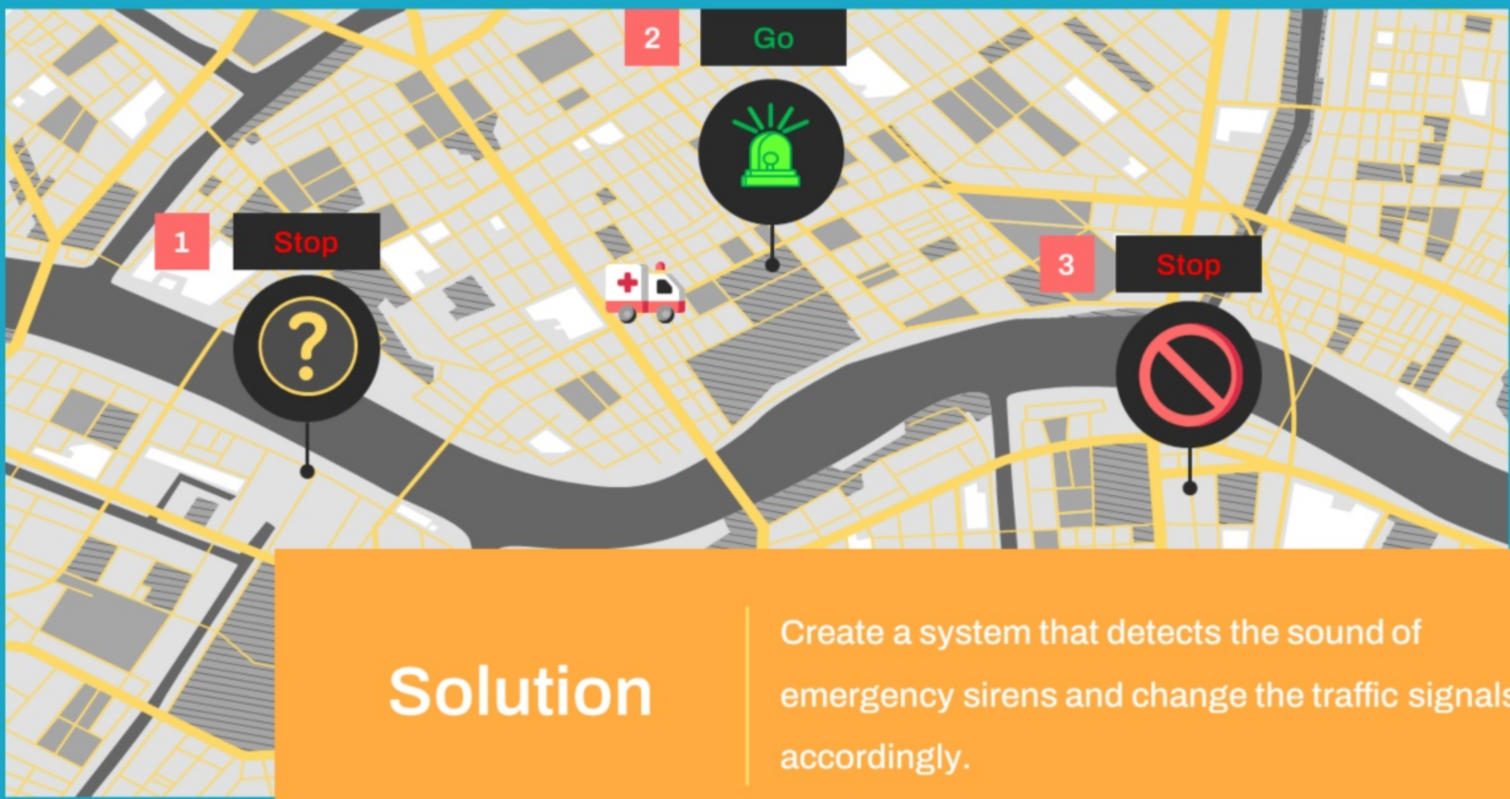

Emergency Sirens Detection
01
Problem Solving
Solution
Create a system that detects the sound of emergency sirens and change the traffic signals accordingly.
02
Data
03
Visualization
04
Tools
Librosa
Audio pre-processing
Scipy
Audio features creation
IPython.display
Playing the audio
Matplotlib
Visualizing the data
Sklearn
Splitting the data
Keras
Implementing the neural nets
05
Feature Extraction
06
Models
07
Conclusion

01 Problem Solving



Solution

Create a system that detects the sound of emergency sirens and change the traffic signals accordingly.

Data

02


1 Data
23m 32s
Emergency clip
27m 16s
Non-Emergency clip


2 Data
Non-Emergency Chunks
1627 chunks
Emergency Chunks
1373 chunks


3 Data
Chunks
1
Split each clip into 3 sec per chunk
Concat
2
Concat emergency & non-emergency
Assign Labels
3
0 -> Emergency
1-> Non-Emergency
Split Data
4
Train, Validation and Test

1 Data

23m 32s

Emergency clip

27m 16s

Non-Emergency clip

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Emergency Chunks

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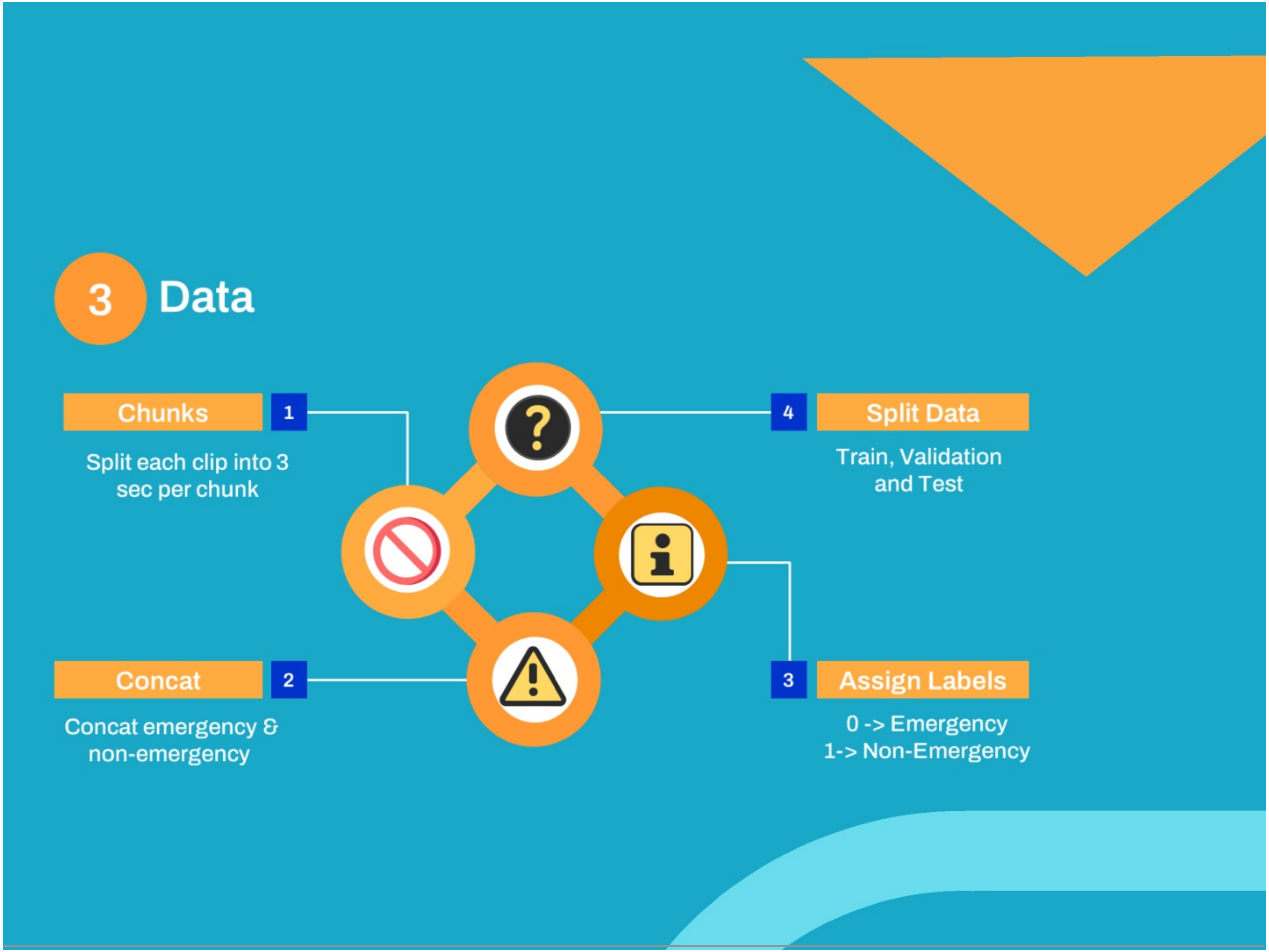
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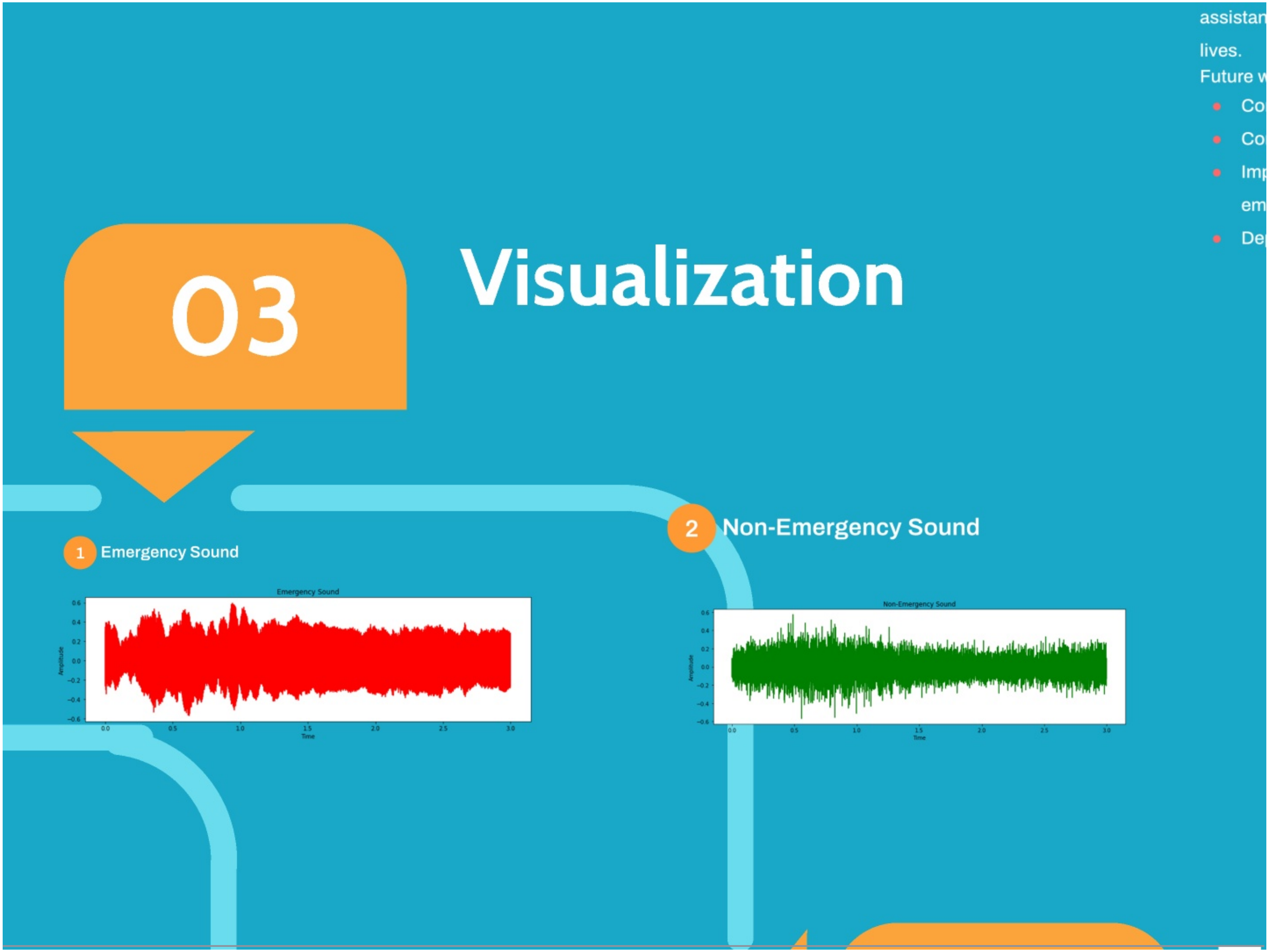
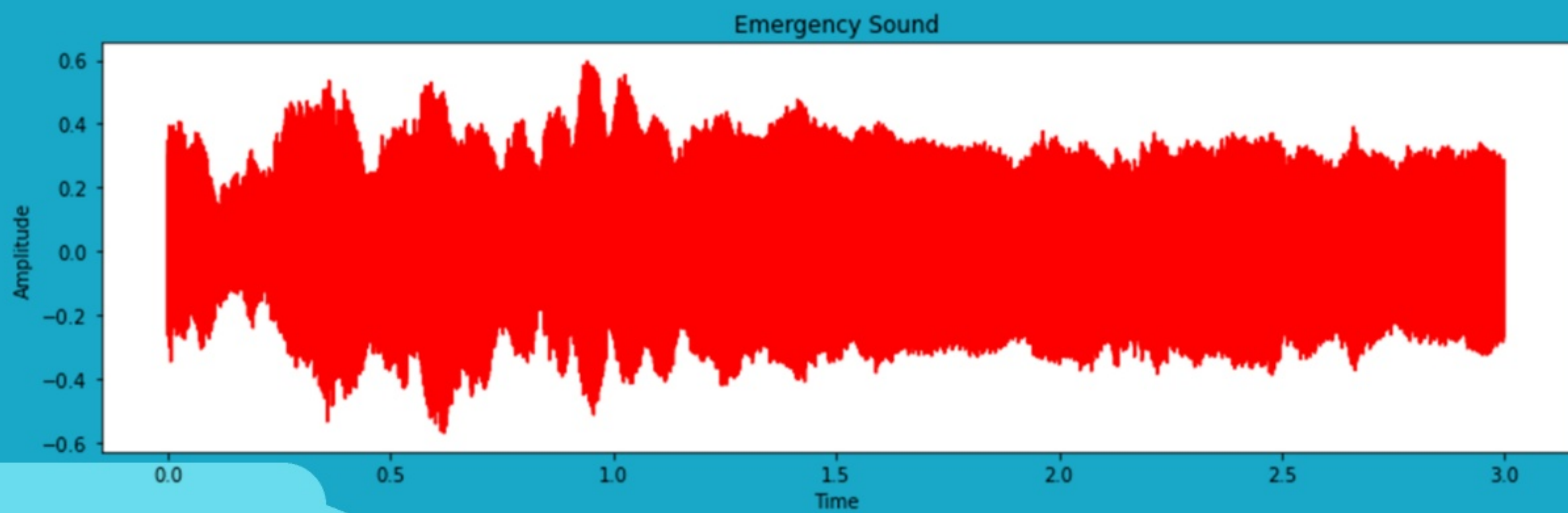
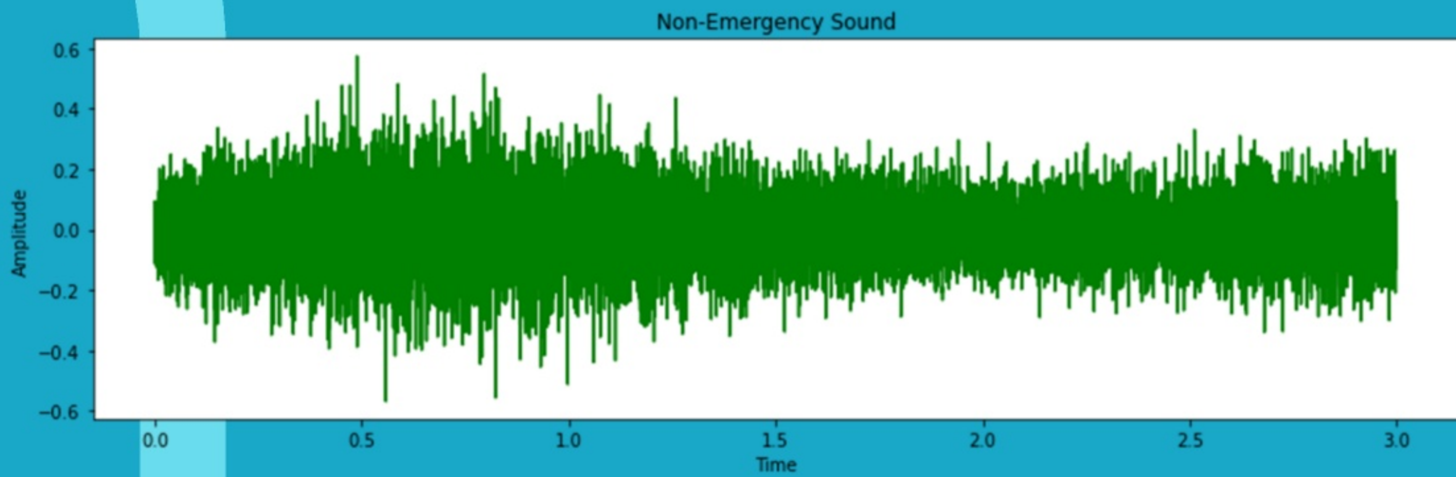

lives.
03
Visualization
1 Emergency Sound
2 Non-Emergency Sound
Emergency Sound
Amplitude
Time
Non-Emergency Sound
Amplitude
Time

1 Emergency Sound



2 Non-Emergency Sound

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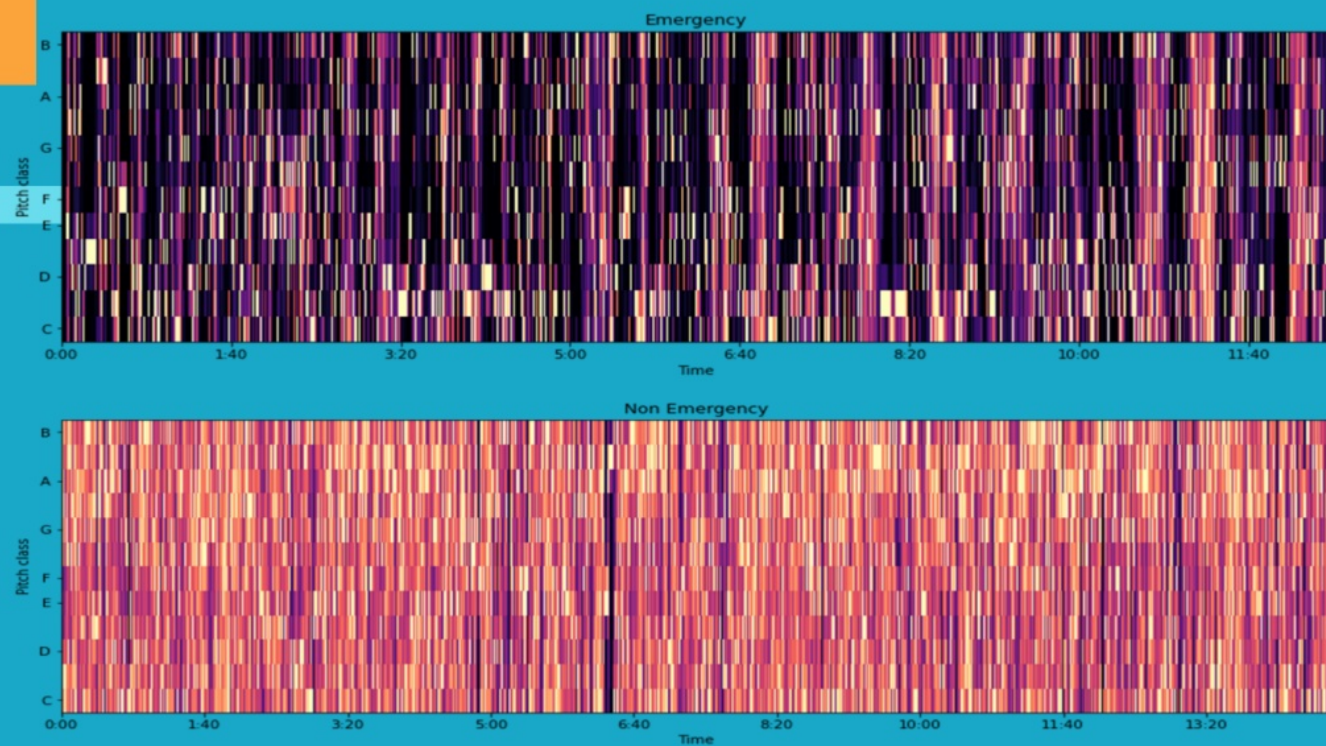
Visualizing the data
Sklearn
Splitting the data
Keras
Implementing the neural nets

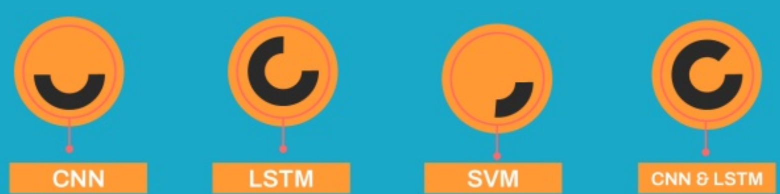
05

Feature Extraction



06 Models

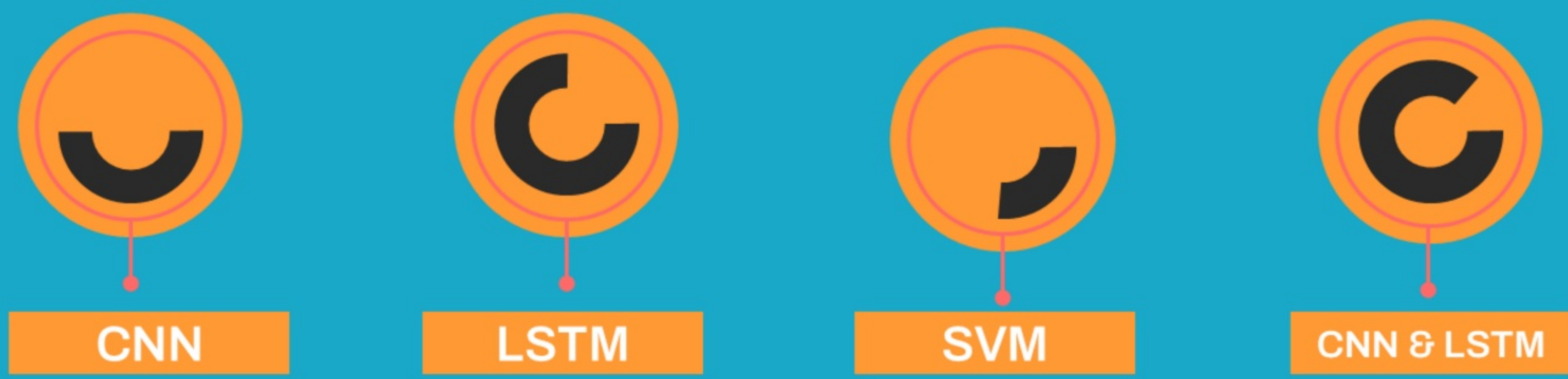
1 Models



2 Models

	CNN	CNN	SVM	SVM	LSTM	LSTM	CNN & Features	LSTM & Features
Traning	77.6%	80.42%	82.23%	99.27%	89.32%	84.74%	98.95%	92.24%
Test	75.0%	78.5%	67.33%	46.83%	80.5%	81.83%	97.5%	91.5%

1 Models



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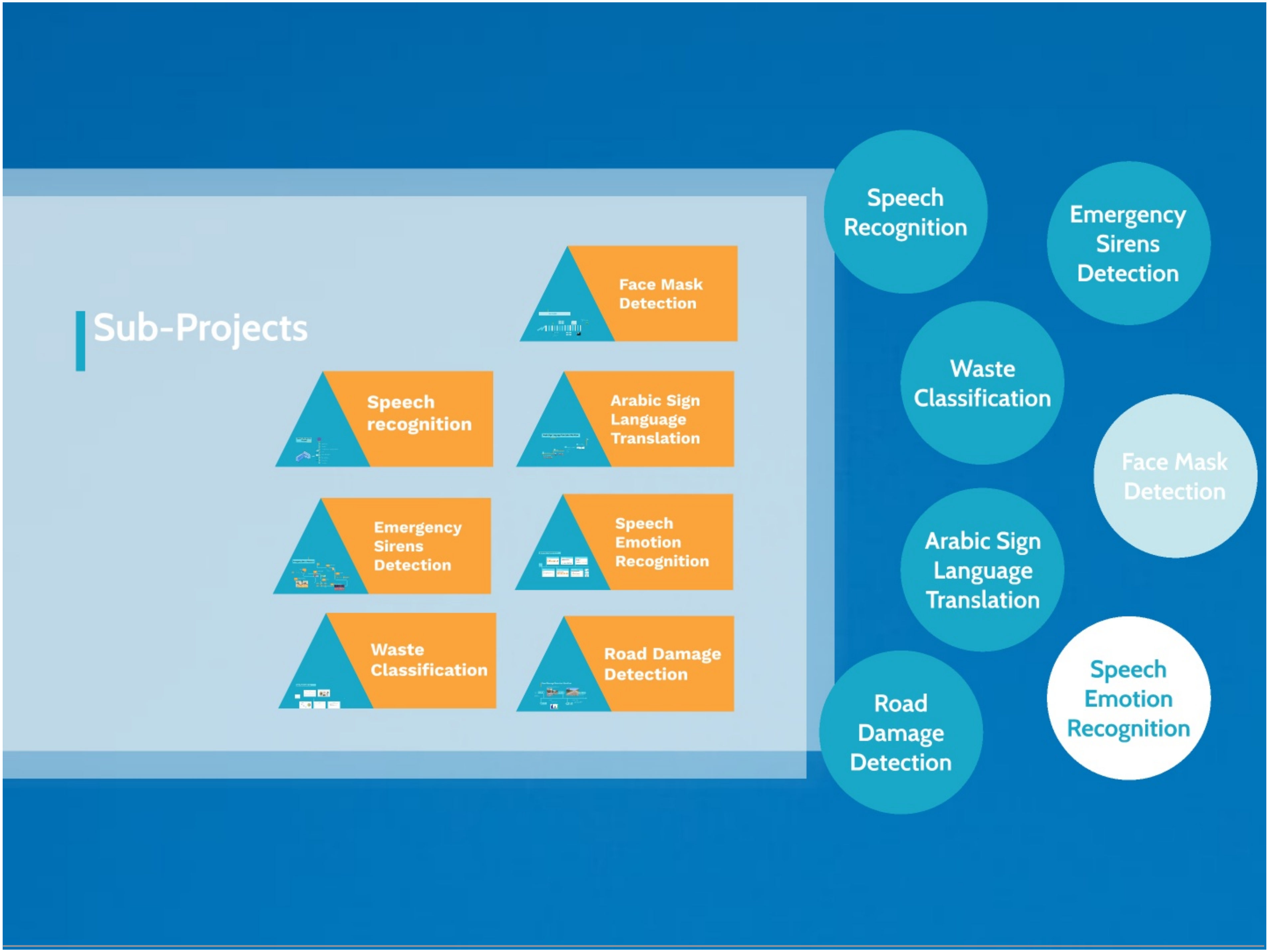
Test	75.0%	78.5%	67.33%	46.83%	80.5%	81.83%	97.5%	91.5%

07 Conclusion

People die each day due to a delay in getting medical assistance. Therefore,this project will help to save people lives.

Future work:

- Connect with SAHER and road cameras
- Connect with traffic signals
- Improve the system to identify the direction of emergency vehicle
- Deploy application that classify live audio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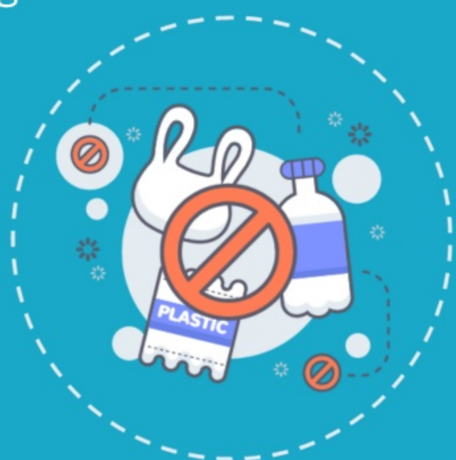
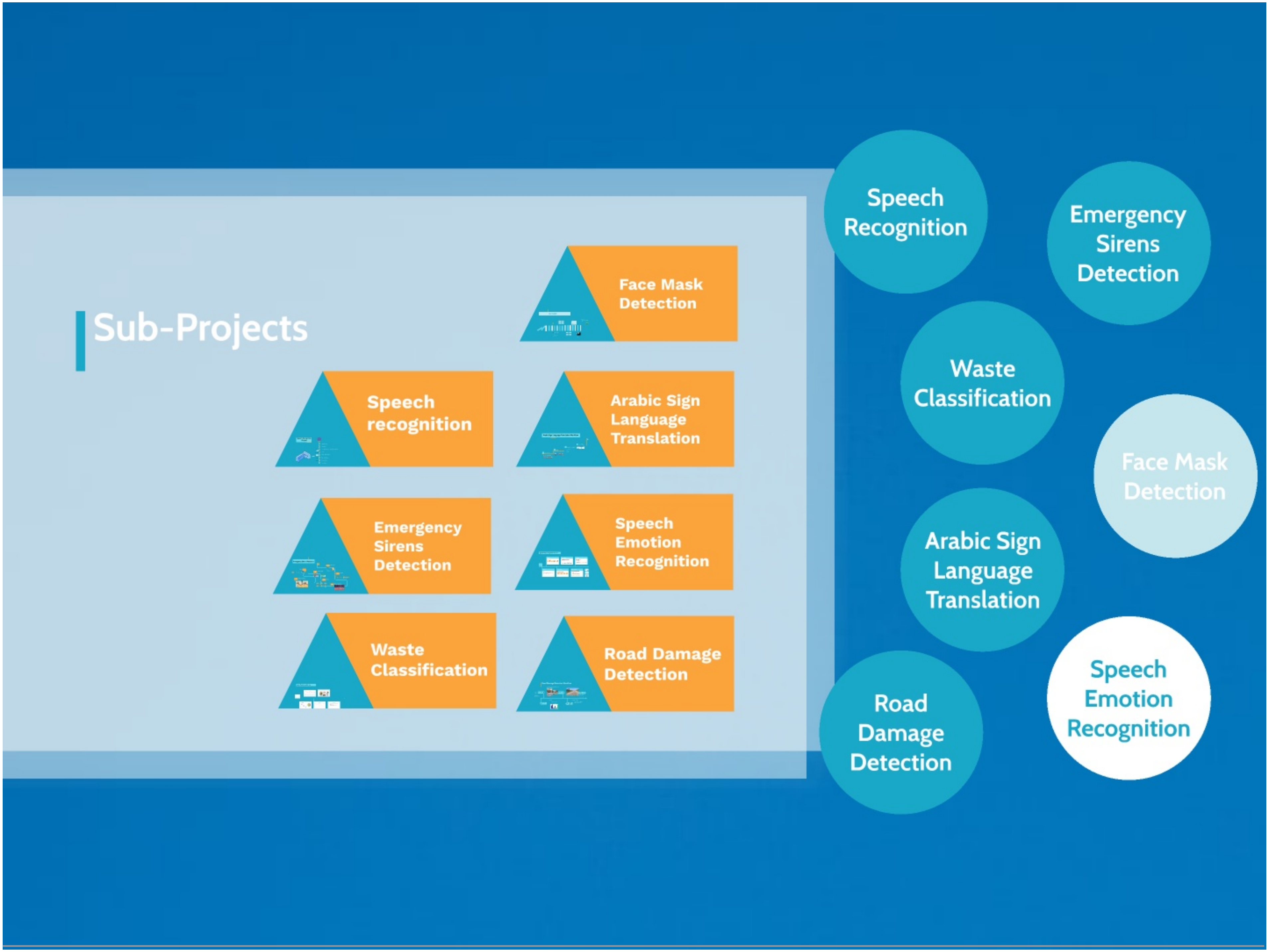
Waste Classification introduction

By: Rahaf Alqahtani

Waste is an important global issue. Increasing amounts of waste are being generated as the world's population and living standards rise. People are increasingly concerned about the production and impact of waste, and are looking for ways to deal with the problem. One of these ways is recycling.

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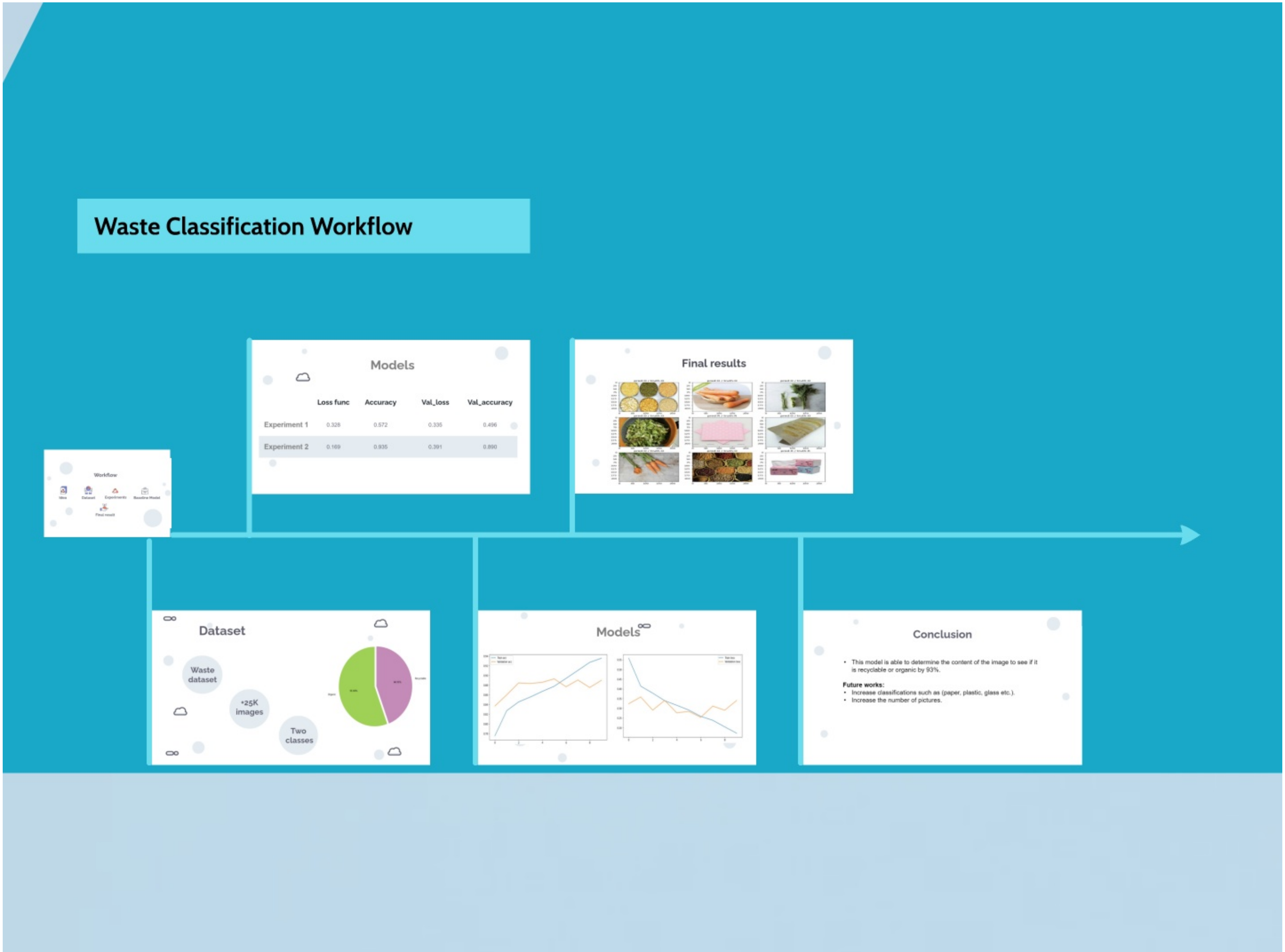


Waste Classification Workflow
Workflow
Models
Loss func
Accuracy
Val_loss
Val_accuracy
Experiment 1
0.328
0.572
0.335
0.496
Experiment 2
0.169
0.935
0.391
0.890
Final results
Dataset
Waste dataset
+25K images
Two classes
Models
Conclusion
This model is able to determine the content of the image to see if it is recyclable or organic by 93%.
Future works:
Increase classifications such as (paper, plastic, glass etc.).
Increase the number of pictures.

Workflow

Idea

Dataset

Experiments

Baseline Model

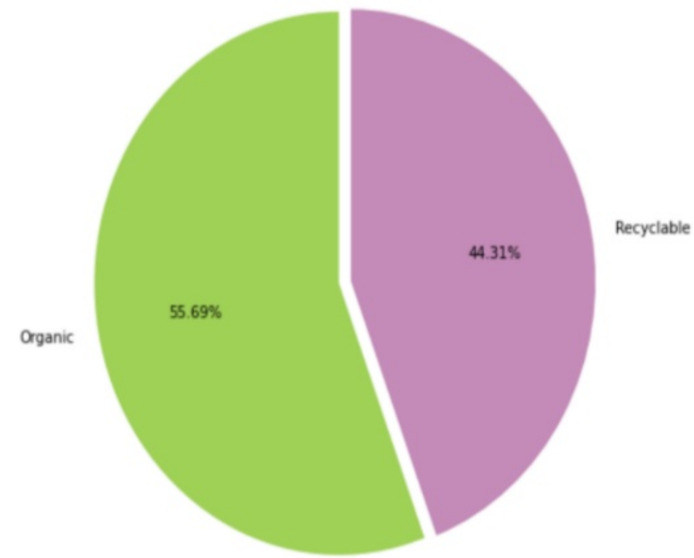
Final result

Dataset

Waste dataset

+25K images

Two classes



Models

	Loss func	Accuracy	Val_loss	Val_accuracy
Experiment 1	0.328	0.572	0.335	0.496
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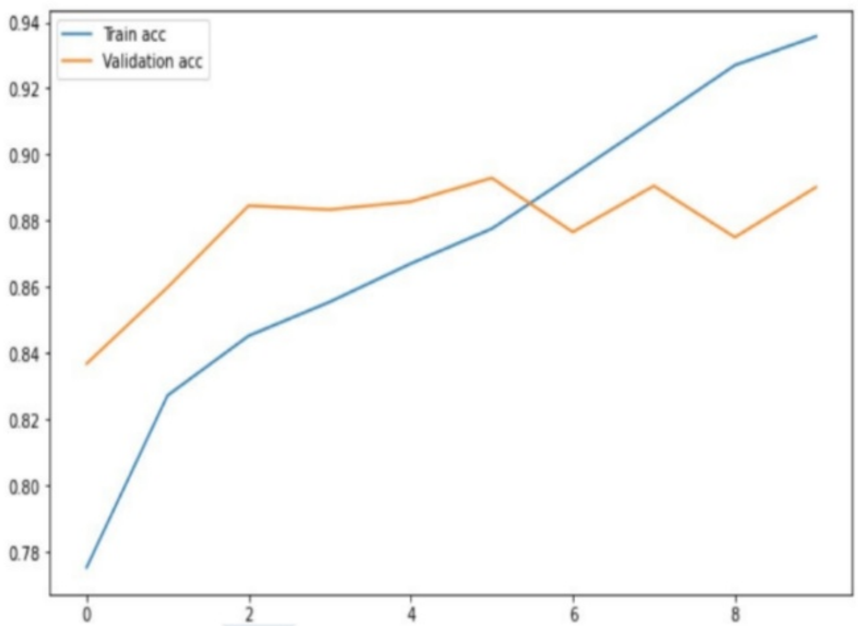
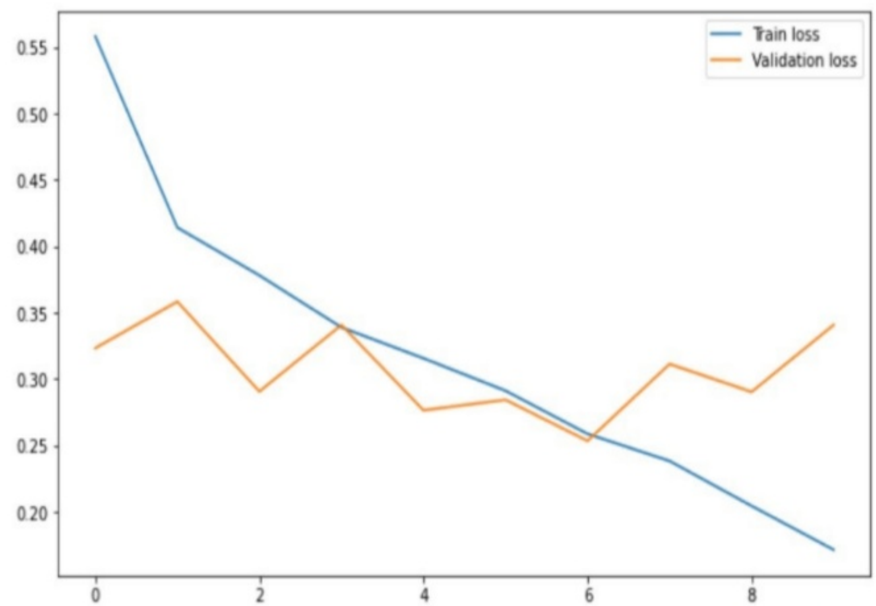
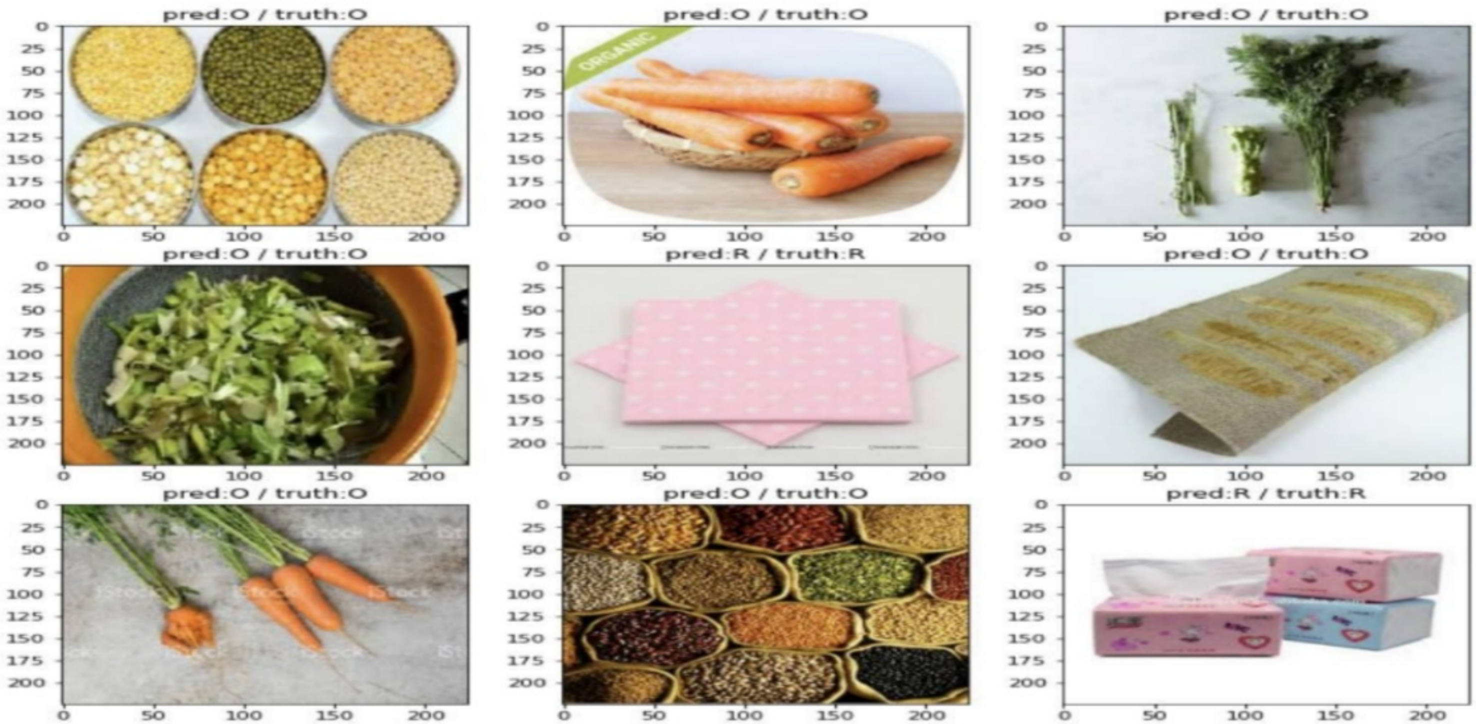
Models





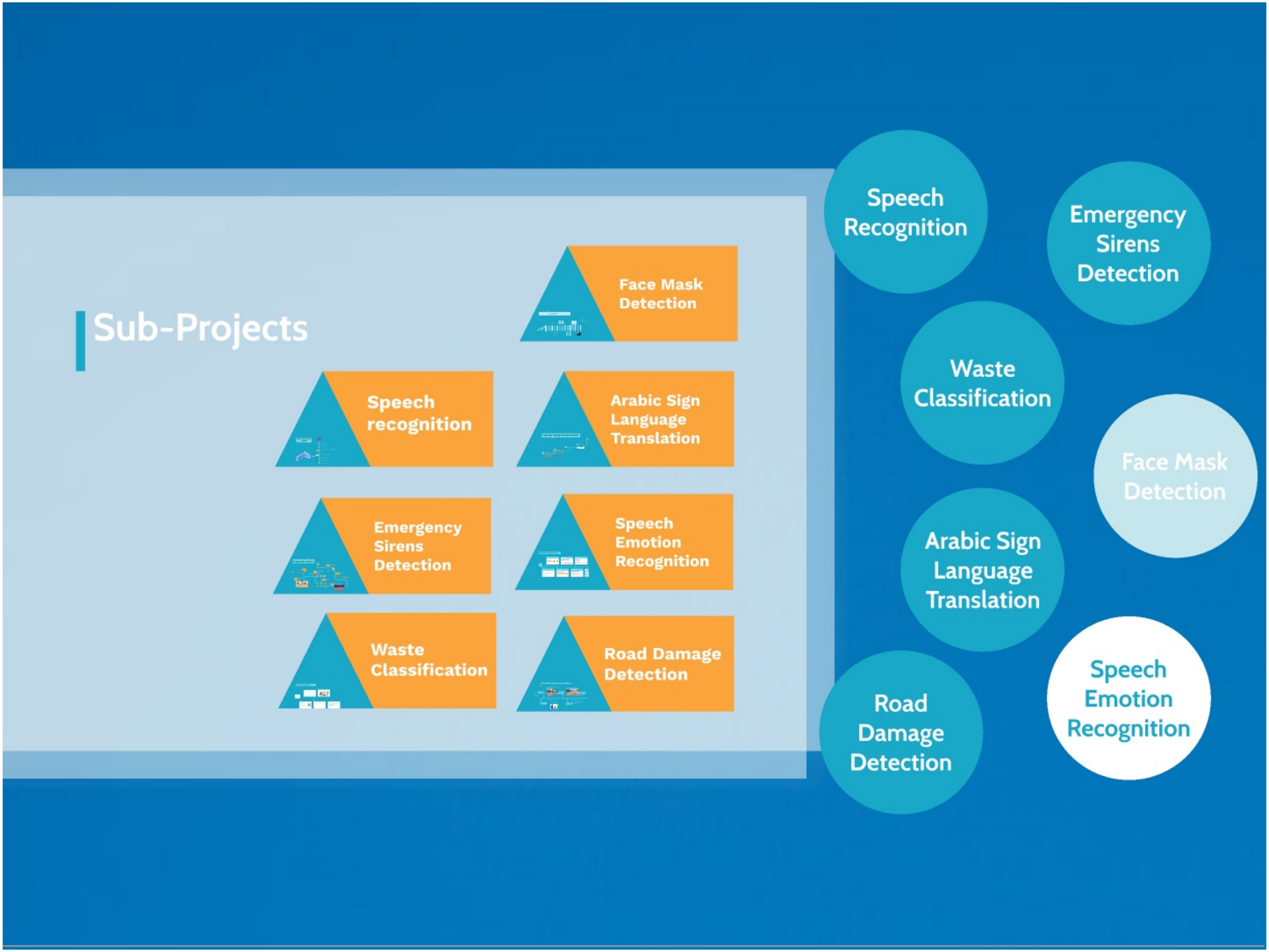
Final results



Conclusion

- This model is able to determine the content of the image to see if it is recyclable or organic by 93%.

Future works:
- Increase classifications such as (paper, plastic, glass etc.).
- Increase the number of pictures.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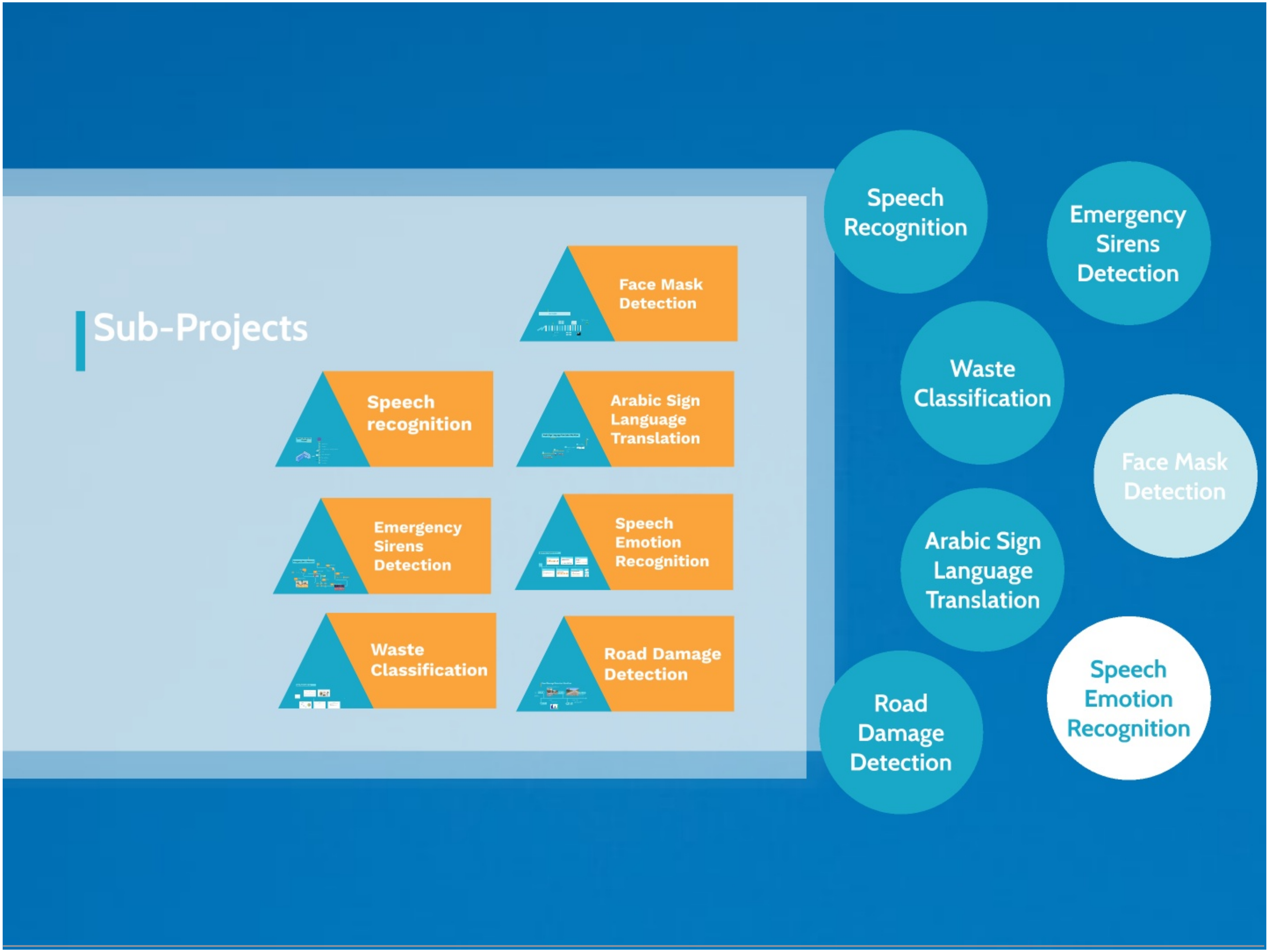
Face Mask Detection

By: Tarfah Alabbad, Muneera Alshunaifi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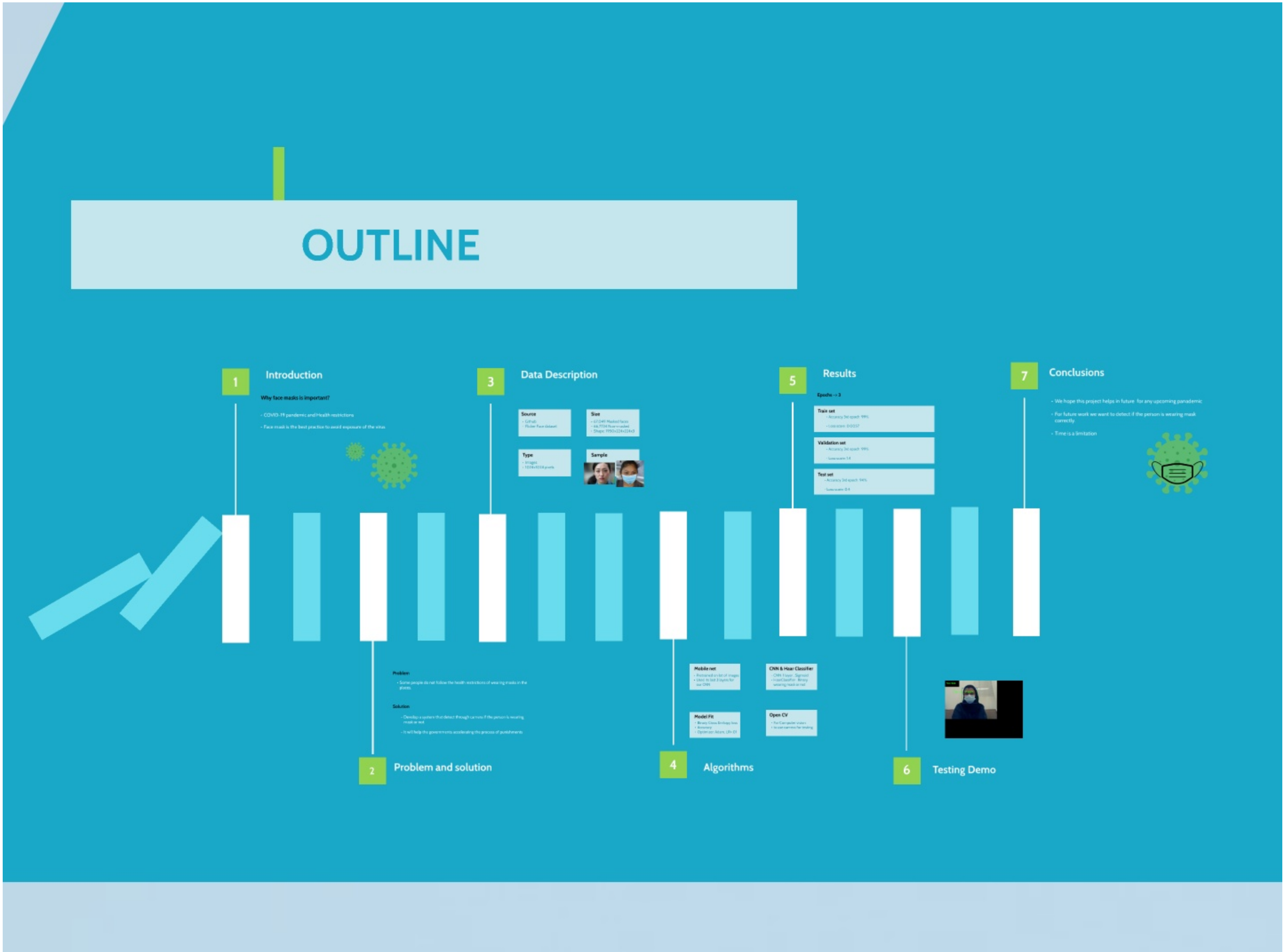
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Problem and solution
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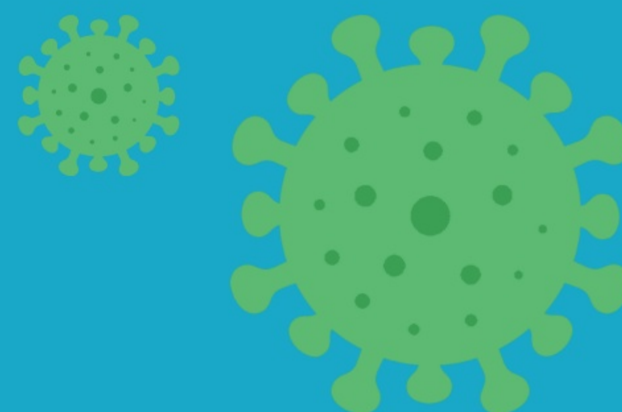
6
Testing Demo

1

Introduction

Why face masks is important?

- COVID-19 pandemic and Health restrictions
- Face mask is the best practice to avoid exposure of the virus



Problem

- Some people do not follow the health restrictions of wearing masks in the places.

Solution

- Develop a system that detect through camera if the person is wearing mask or not.
- It will help the governments accelerating the process of punishments

2

Problem and solution

3

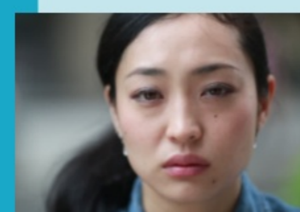
Data Description

Source
- Github
- Flicker Face dataset

Size
- 67,049 Masked faces
- 66,7734 Non-masked
- Shape: 1950x224x224x3

Type
- Images
- 1024x1024 pixels

Sample



Sample

Mobile net

- Pretrained on lot of images
- Used its last 3 layers for our CNN

CNN & Haar Classifier

- CNN: 1 layer , Sigmoid
- HaarClassifier : Binary wearing mask or not

Model Fit

- Binary Cross Enrtopy loss
- Accuracy
- Optimizer: Adam, LR=.01

Open CV

- For Computer vision
- to use camera for testing

4 Algorithms

5

Results

Epochs -> 3

Train set

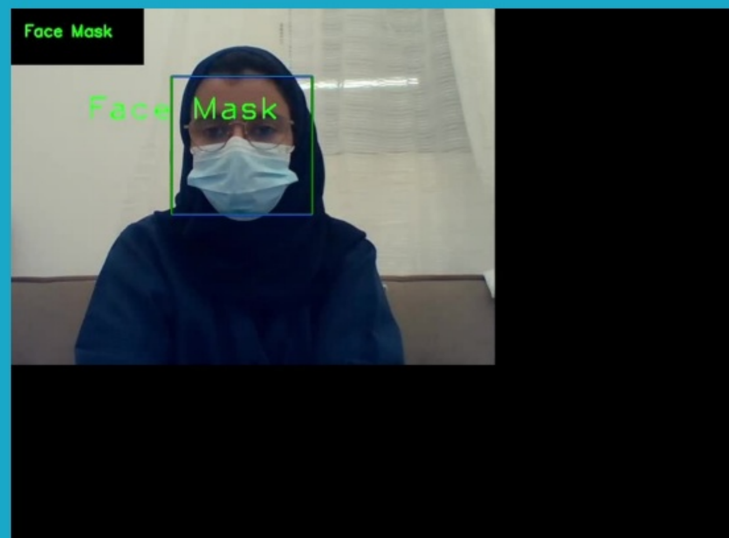
- Accuracy 3rd epoch: 99%
- Loss score: 0.0057

Validation set

- Accuracy 3rd epoch: 99%
- Loss score: 1.4

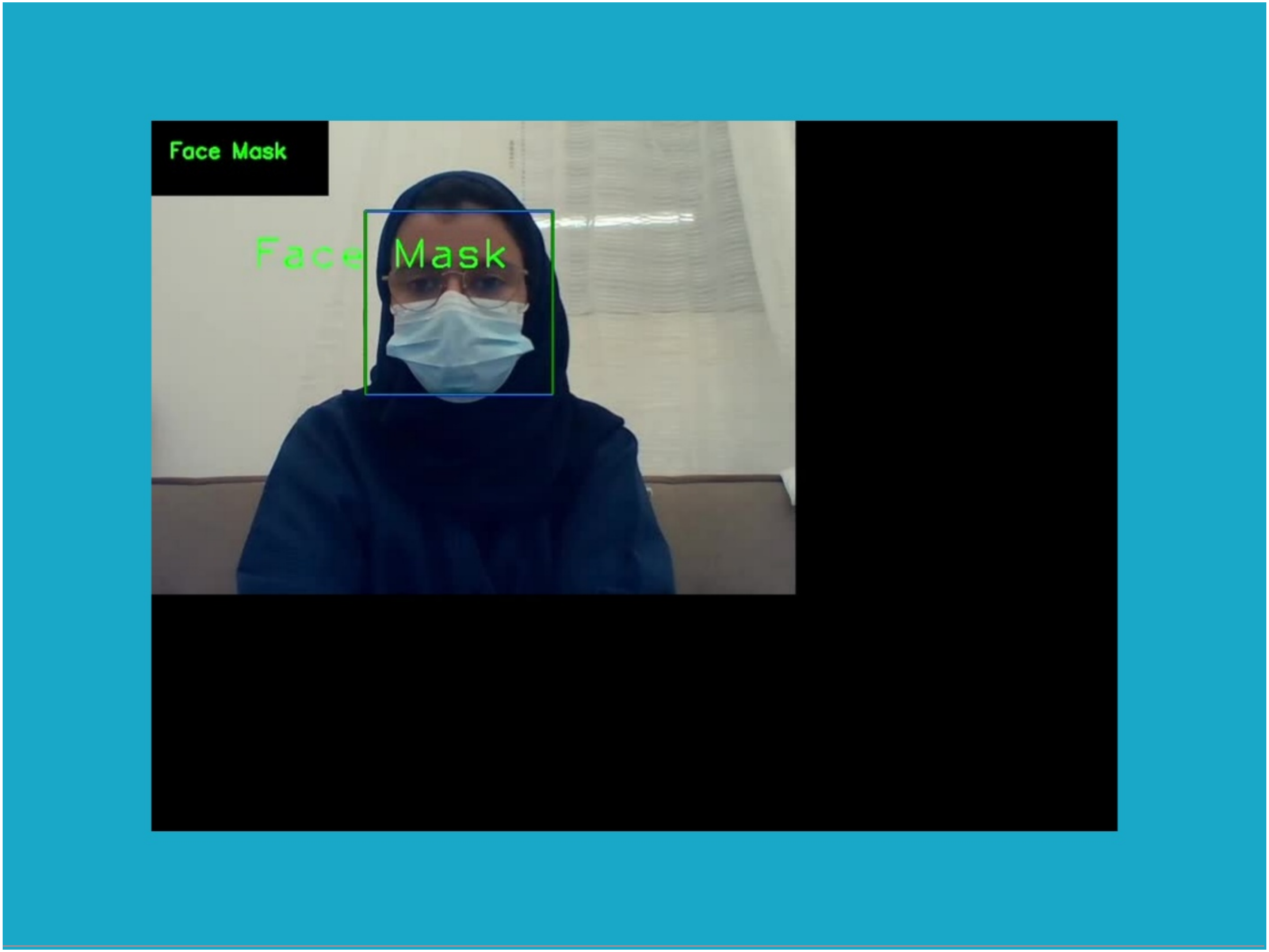
Test set

- Accuracy 3rd epoch: 94%
- Loss score: 0.4



6

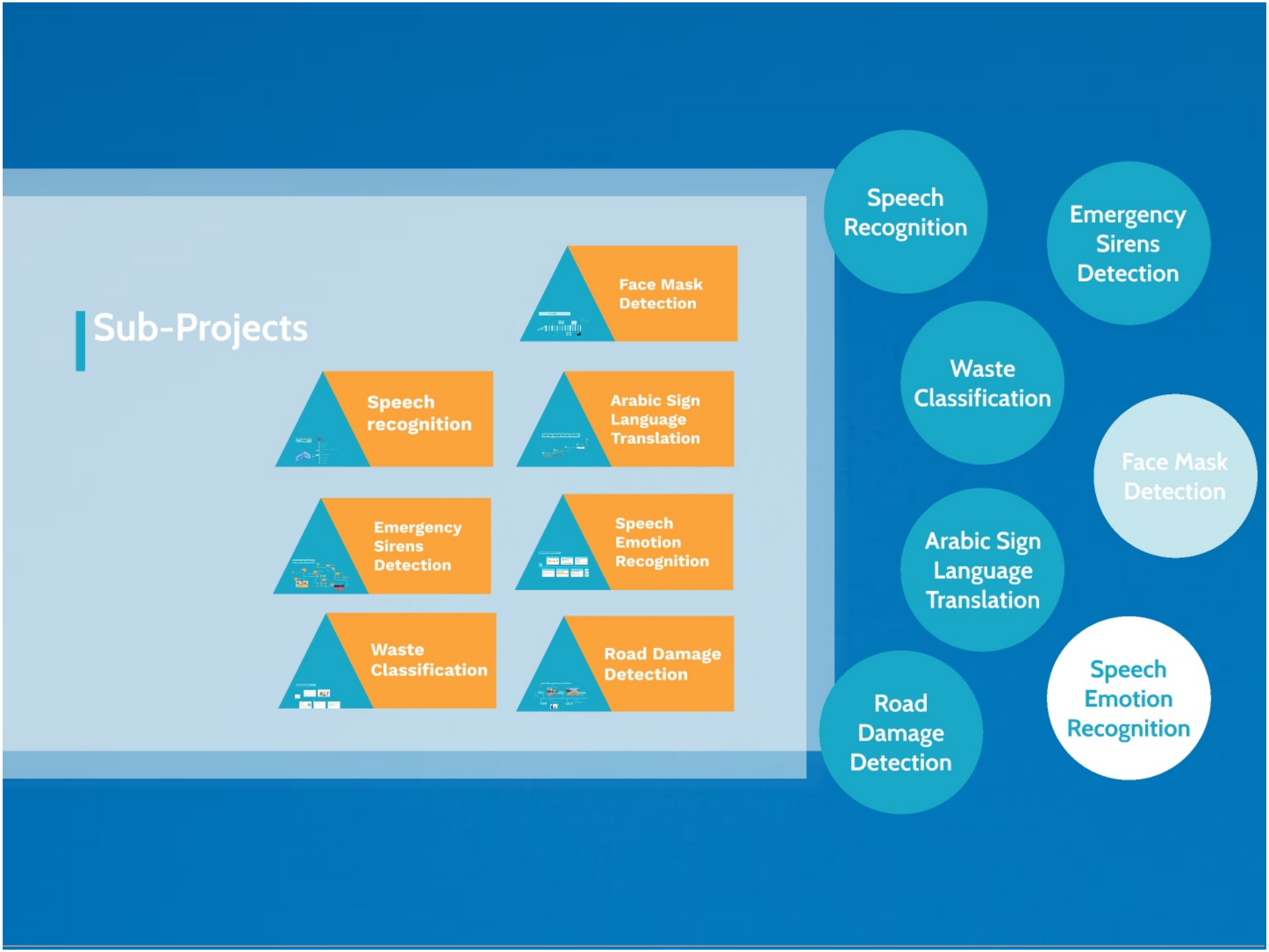
Testing Demo


Face Mask
Face Mask

7

Conclusions

- We hope this project helps in future for any upcoming panademic
- For future work we want to detect if the person is wearing mask correctly.
- Time is a limitation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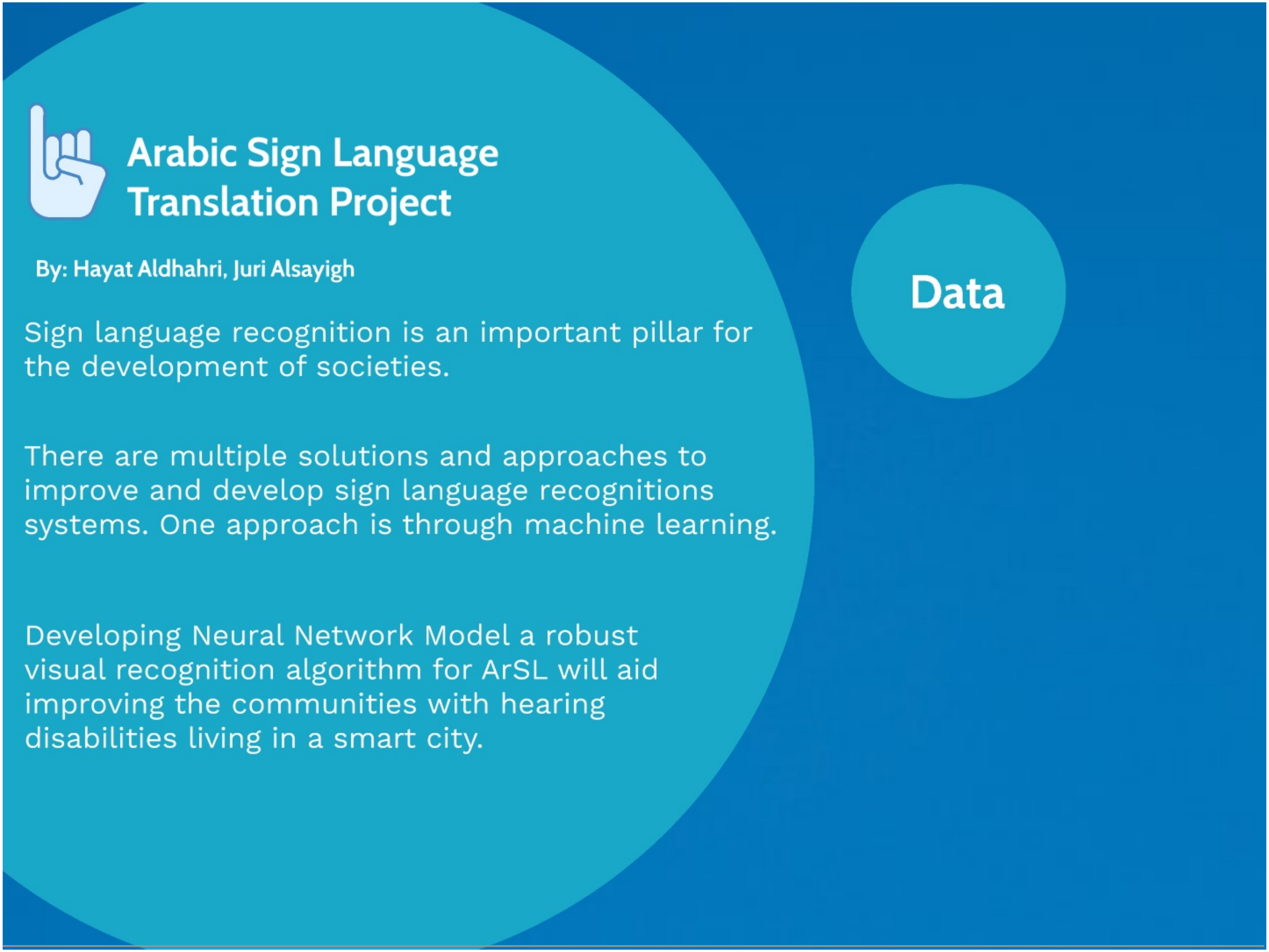
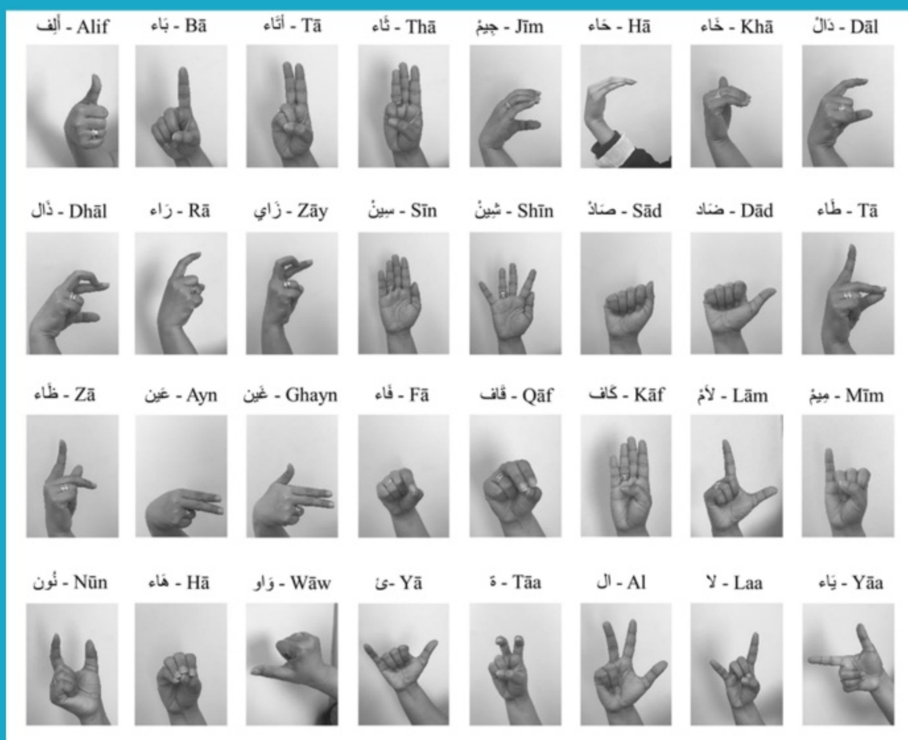
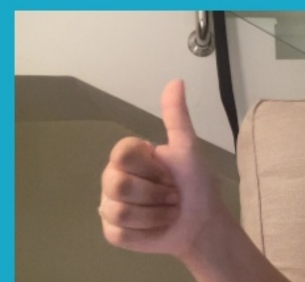
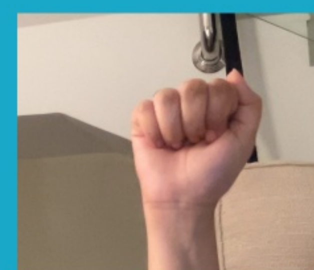

Arabic Sign Language
Translation Project
By: Hayat Aldhahri, Juri Alsayigh
Sign language recognition is an important pillar for the development of societies.
There are multiple solutions and approaches to improve and develop sign language recognitions systems. One approach is through machine learning.
Developing Neural Network Model a robust visual recognition algorithm for ArSL will aid improving the communities with hearing disabilities living in a smart city.
Data

Data Description

The dataset contains 1280 images of Arabic Sign Language alphabets, 40 images for each sign. The images were performed of 32 Arabic signs and alphabets (class). The images were split into 980 training and 240 for test.







Arabic Sign Language Translation Project

By: Hayat Aldhahri, Juri Alsayigh

Data

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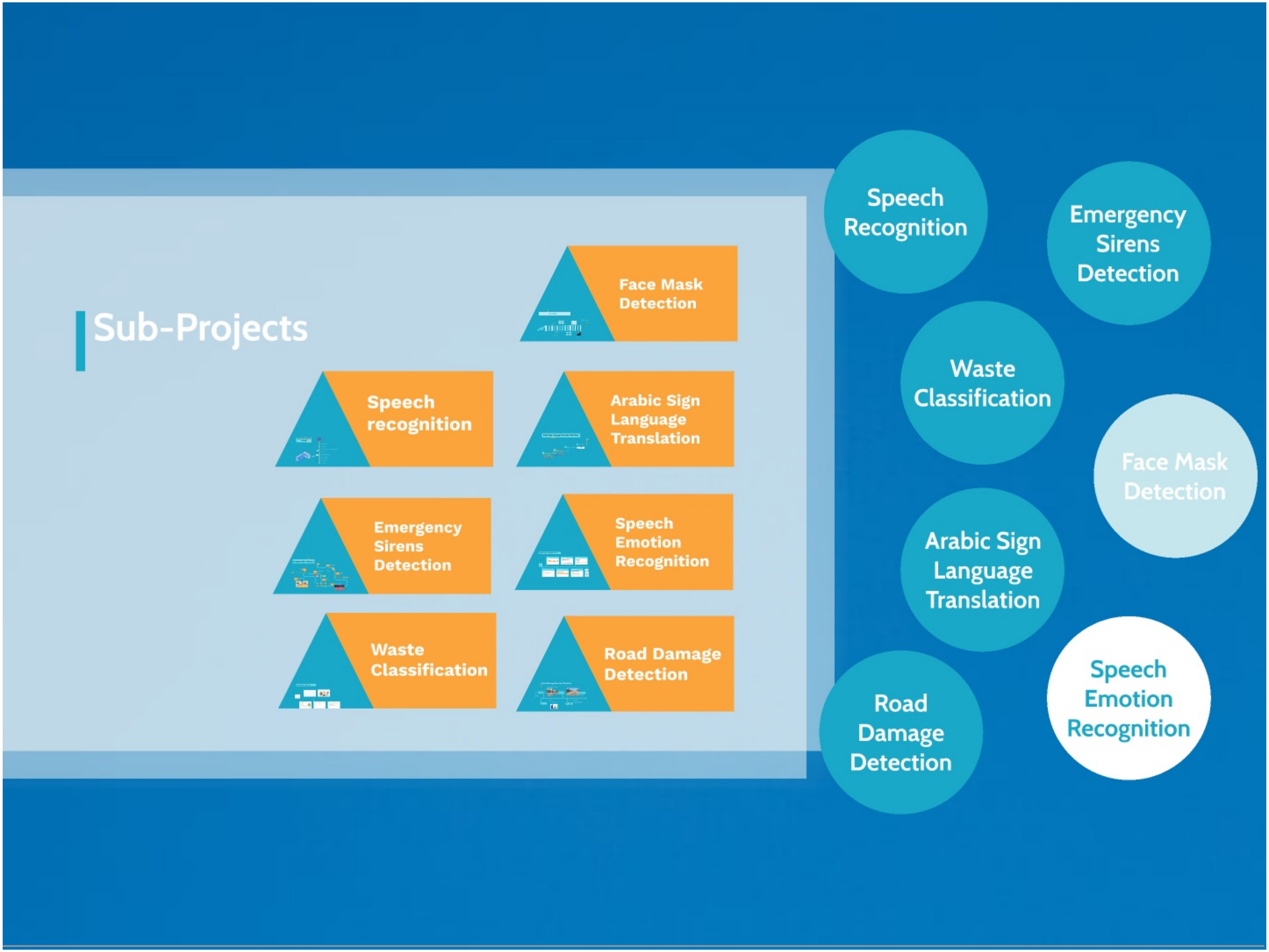
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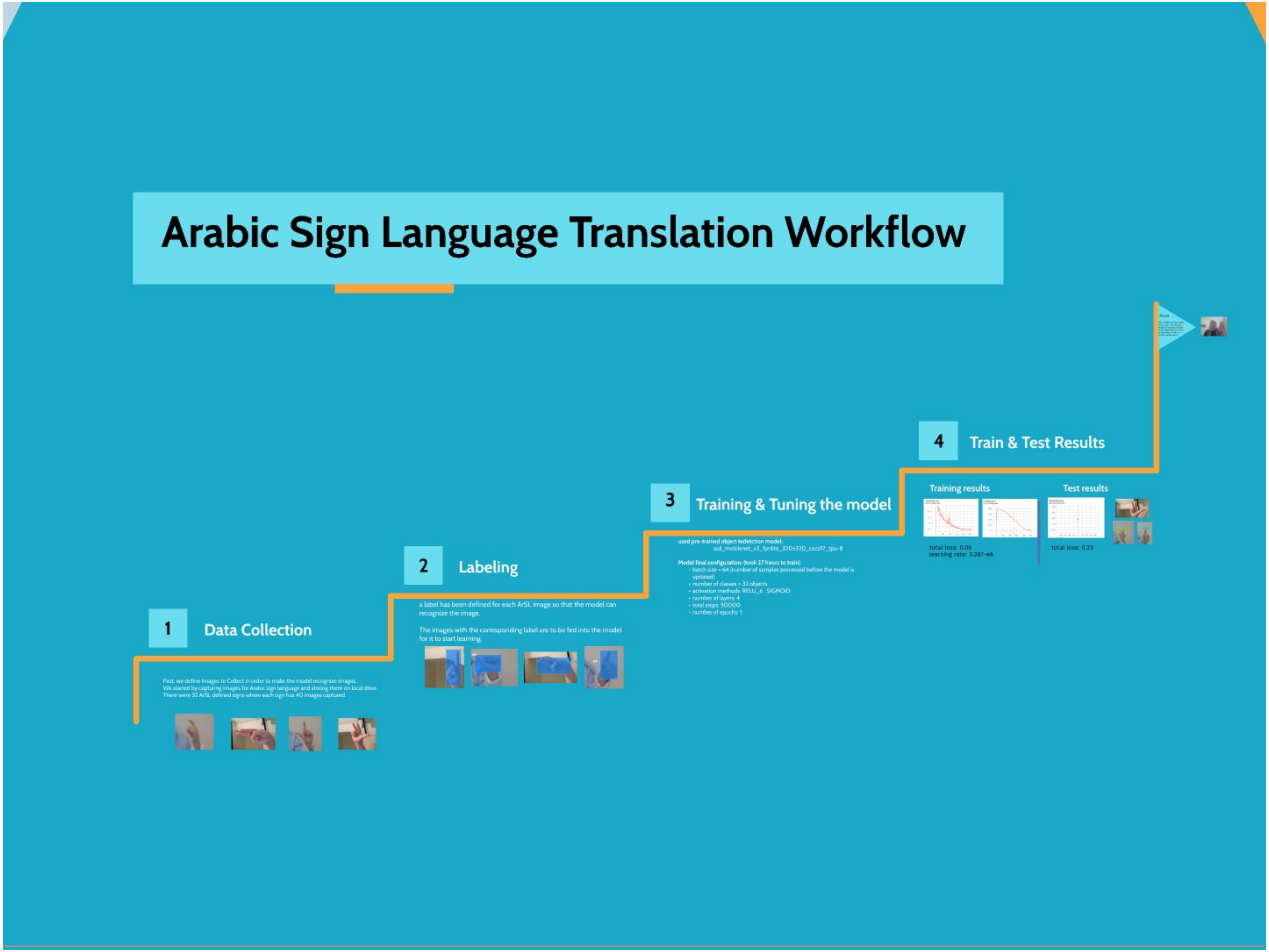
Arabic Sign Language Translation Workflow
1
Data Collection
First, we define Images to Collect in order to make the model recognize images.
We started by capturing images for Arabic sign language and storing them on local drive.
There were 32 ArSL defined signs where each sign has 40 images captured.
2
Labeling
a label has been defined for each ArSL image so that the model can recognize the image.
The images with the corresponding label are to be fed into the model for it to start learning.
3
Training & Tuning the model
used pre-trained object tedetction model:
ssd_mobilenet_v2_fpnlite_320x320_coco17_tpu-8
Model final configuration: (took 27 hours to train)
- batch size = 64 (number of samples processed before the model is updated)
- number of classes = 32 objects
- activation methods: RELU_6 , SIGMOID
- number of layers: 4
- total steps: 50000
- number of epochs: 1
4
Train & Test Results
Training results
total loss: 0.05
learning rate: 3.287-e6
Test results
total loss: 0.23

1

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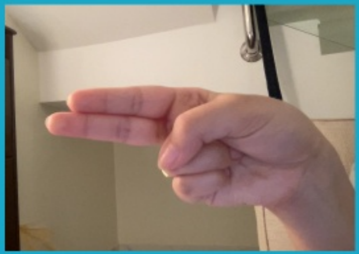

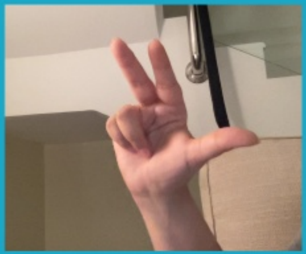

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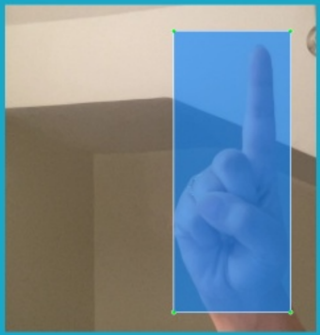
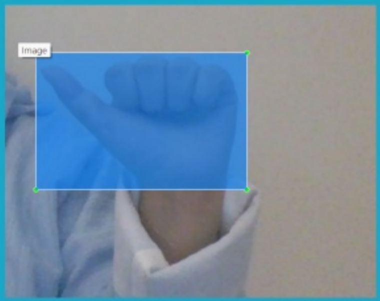
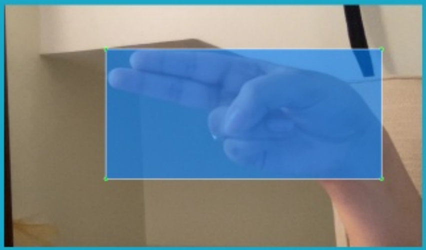
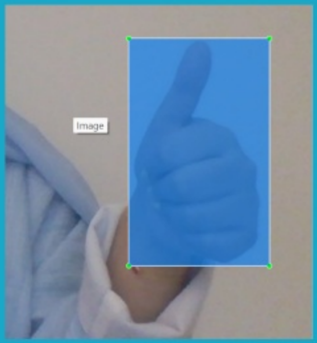

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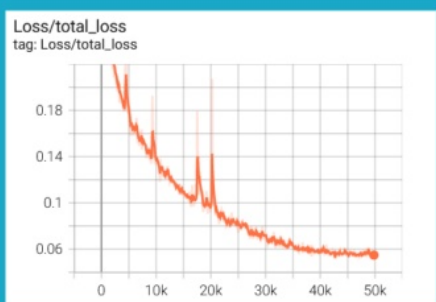
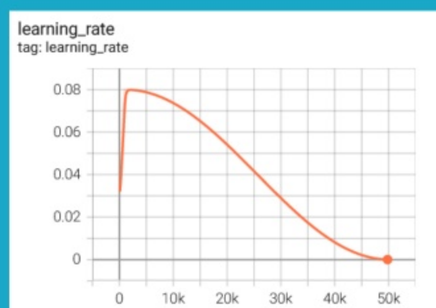
4 Train & Test Results

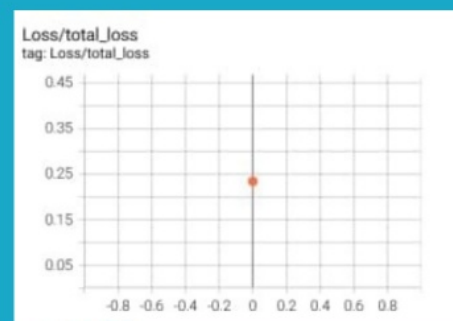
Training results

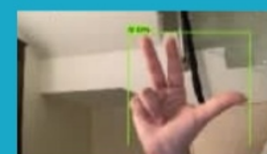


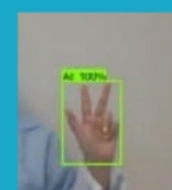


total loss: 0.05
learning rate: 3.287-e6

Test results





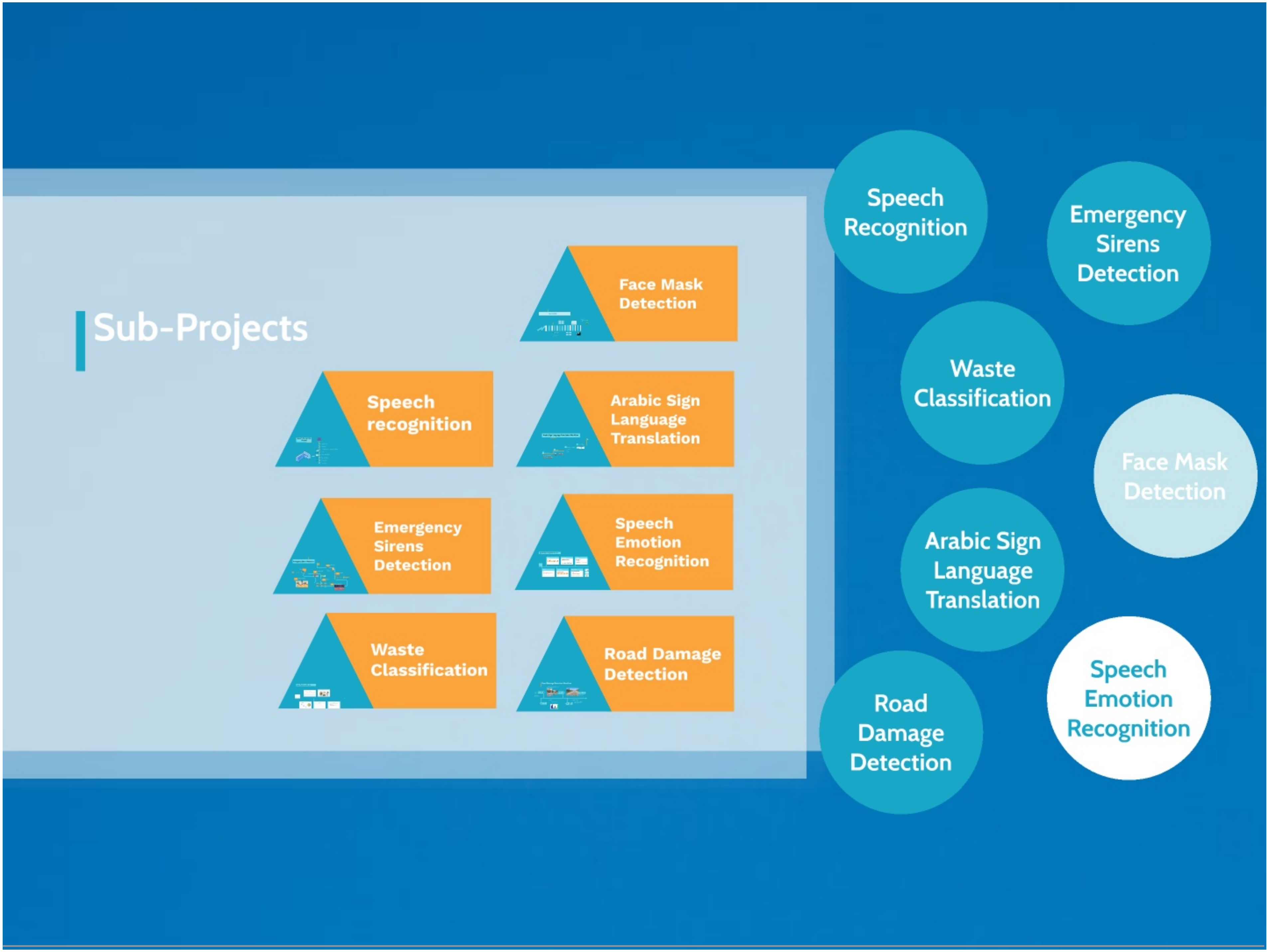


total loss: 0.23

future

the model can be made more user-friendly by Flask or Android Studio to be deployed as tools to develop a web or mobile application.


clideo.com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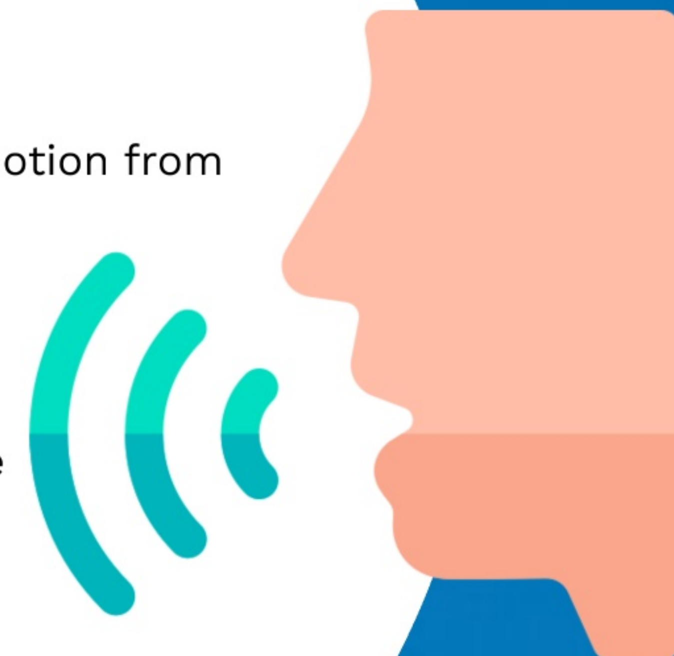
Speech Emotion Recognition (SER)

By: Rawabi Alharbi, Dimah Albunayyih

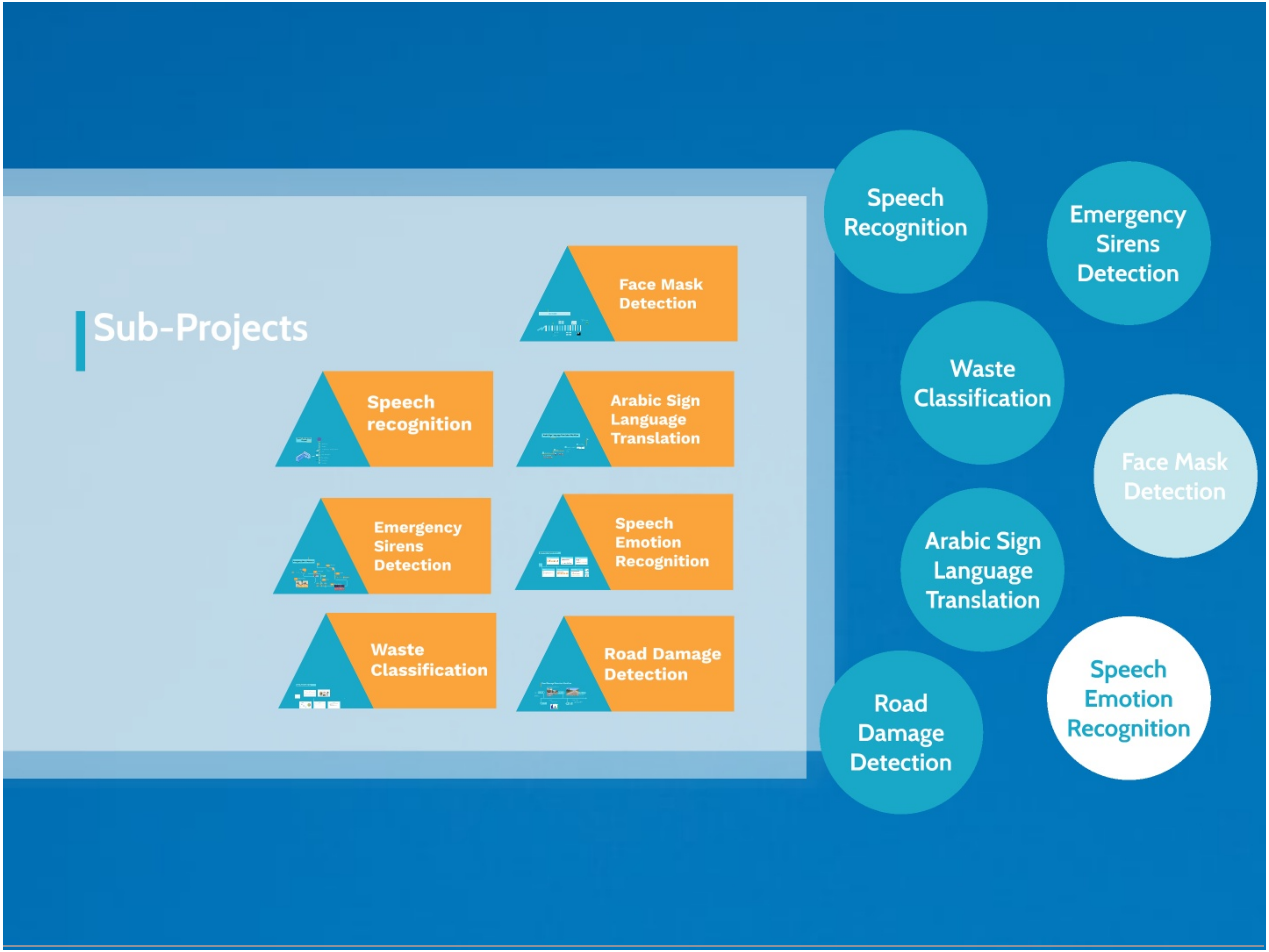
What is SER?

The act of recognizing human emotion from speech



SER Application

- Automated call centers
- Assessing drivers mental state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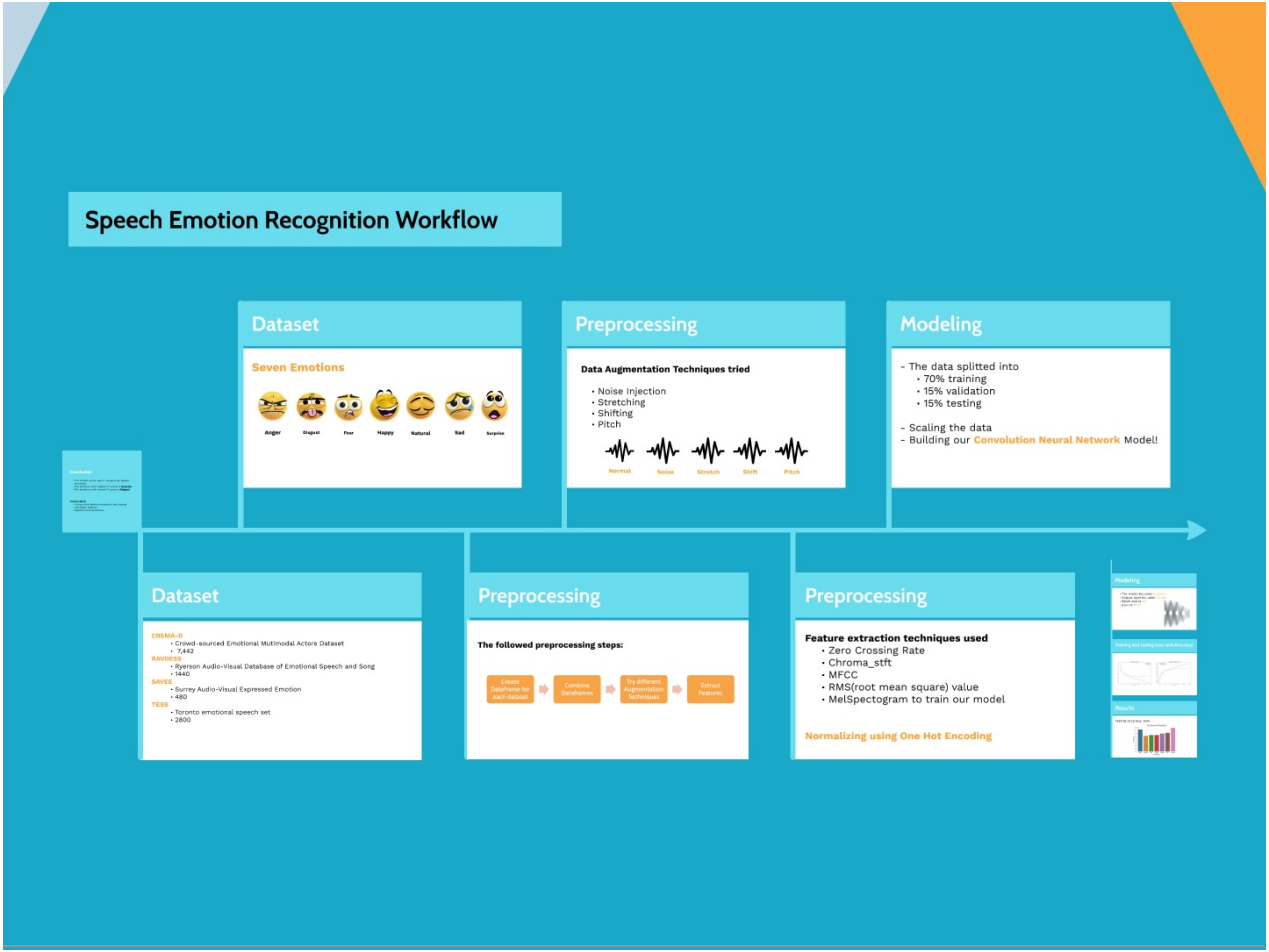
Speech Emotion Recognition Workflow
Dataset
Seven Emotions
Anger
Disgust
Fear
Happy
Natural
Sad
Surprise
Preprocessing
Data Augmentation Techniques tried
• Noise Injection
• Stretching
• Shifting
• Pitch
Normal
Noise
Stretch
Shift
Pitch
Modeling
- The data splitted into
• 70% training
• 15% validation
• 15% testing
- Scaling the data
- Building our Convolution Neural Network Model!
Dataset
CREMA-D
• Crowd-sourced Emotional Mutimodal Actors Dataset
• 7,442
RAVDESS
• Ryerson Audio-Visual Database of Emotional Speech and Song
• 1440
SAVEE
• Surrey Audio-Visual Expressed Emotion
• 480
TESS
• Toronto emotional speech set
• 2800
Preprocessing
The followed preprocessing steps:
Create Dataframe for each dataset
Combine Dataframes
Try different Augmentation Techniques
Extract Features
Preprocessing
Feature extraction techniques used
• Zero Crossing Rate
• Chroma_stft
• MFCC
• RMS(root mean square) value
• MelSpectogram to train our model
Normalizing using One Hot Encoding
Modeling
Results

Dataset

CREMA-D

- Crowd-sourced Emotional Mutimodal Actors Dataset
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Dataset

Seven Emotions

Anger Disgust Fear Happy Natural Sad Surprise

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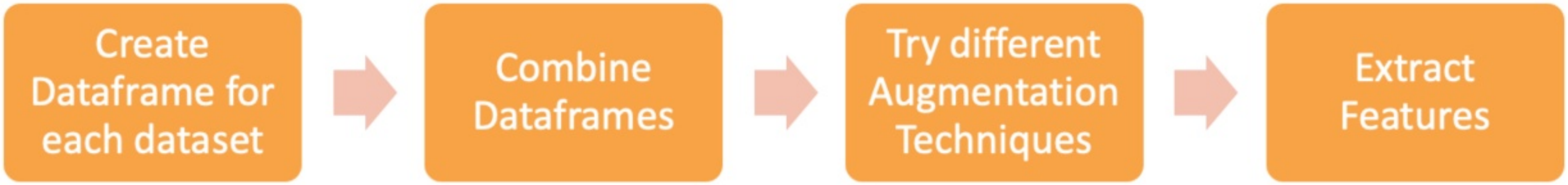

Preprocessing

Data Augmentation Techniques tried

- Noise Injection
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Normal Noise Stretch Shift Pitch

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Feature extraction techniques used

- Zero Crossing Rate
- Chroma_stft
- MFCC
- RMS(root mean square) value
- MelSpectogram to train our model

Normalizing using One Hot Encoding

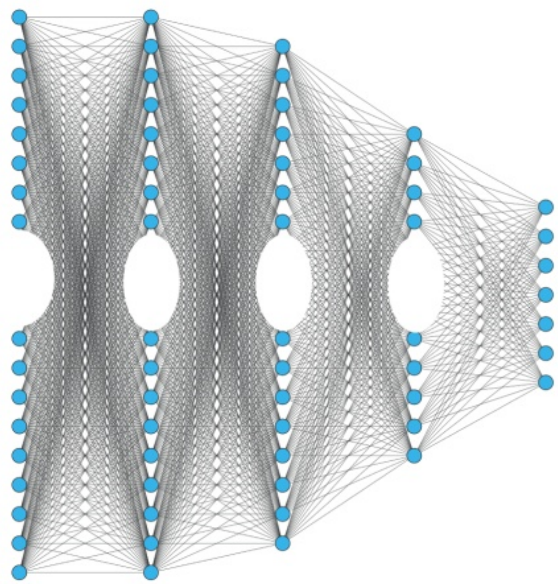
Modeling

- The data splitted into
  - 70% training
  - 15% validation
  - 15% testing

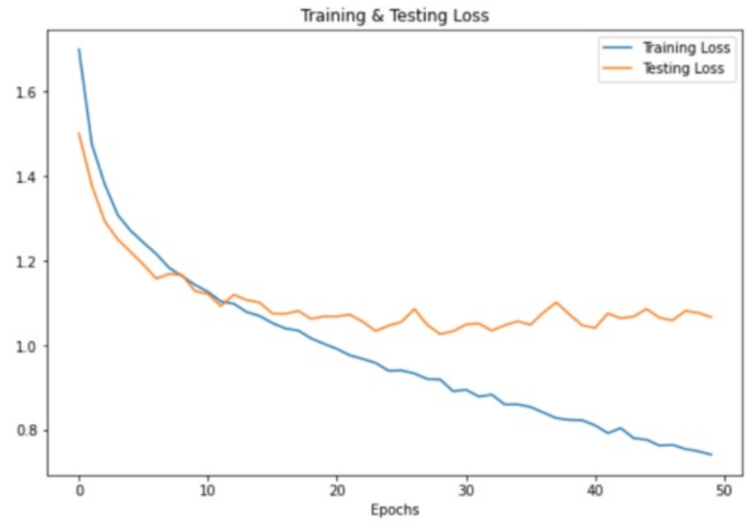
- Scaling the data
- Building our **Convolution Neural Network** Model!

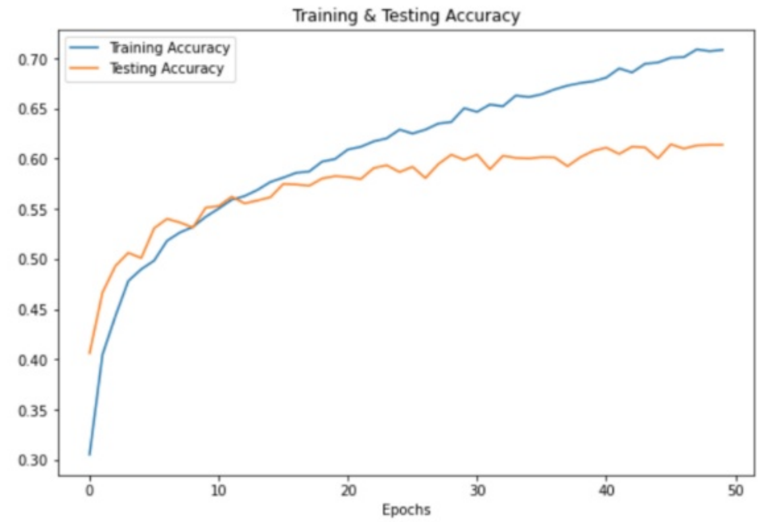
Modeling

- The model includes 5 layers
- Output layer includes 7 units
- Batch size is 64
- epochs = 50



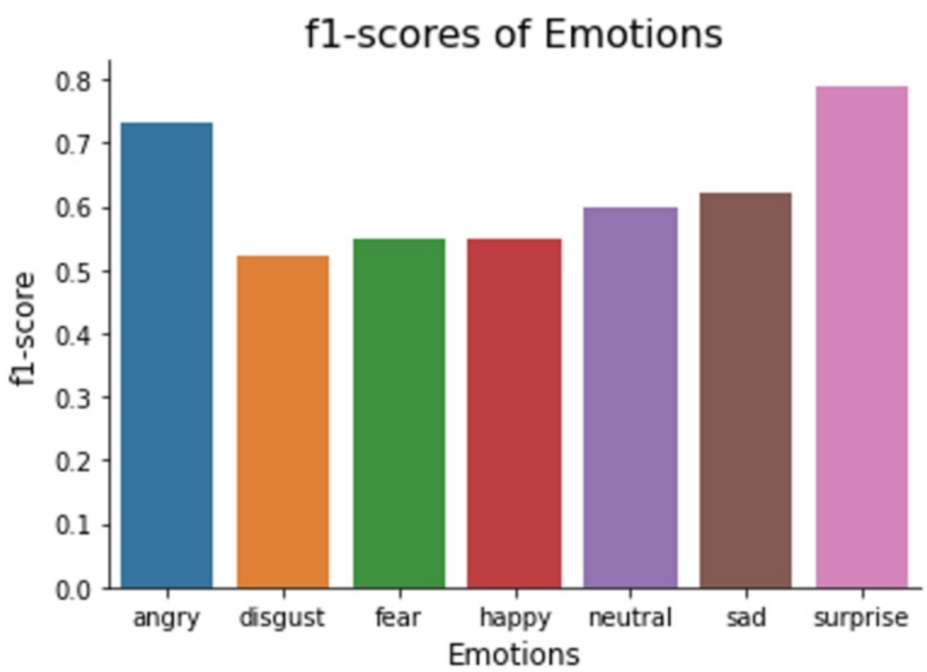
Training and testing (Loss and Accuracy)





Results

Testing Accuracy: 63%

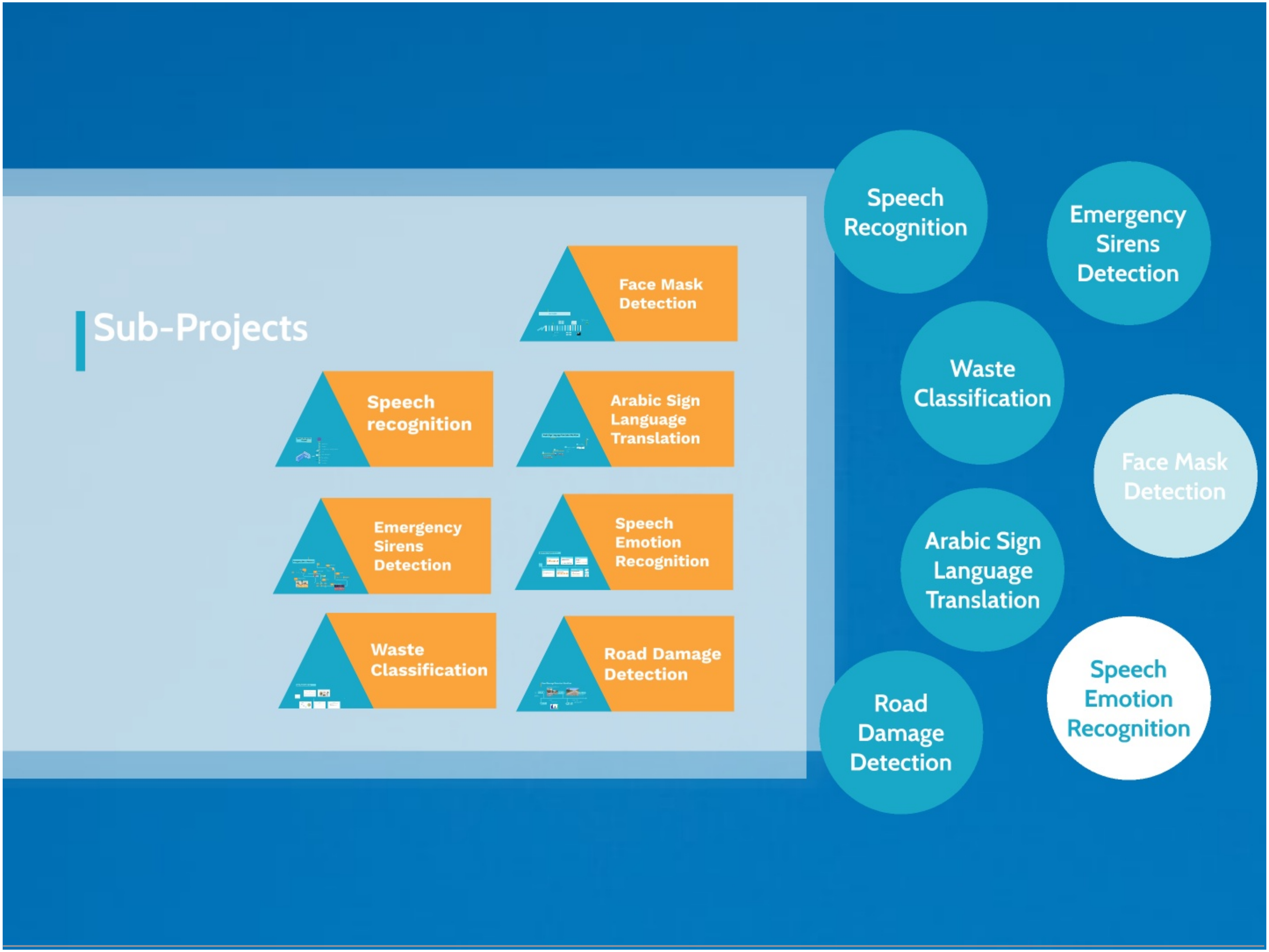


Conclusion

- The model works well in recognizing speech emotions
- The emotion with highest F1 score is **Surprise**
- The emotion with lowest F1 score is **Disgust**

Future Work

- Trying more feature extraction techniques
- Use larger dataset
- Explore more emotions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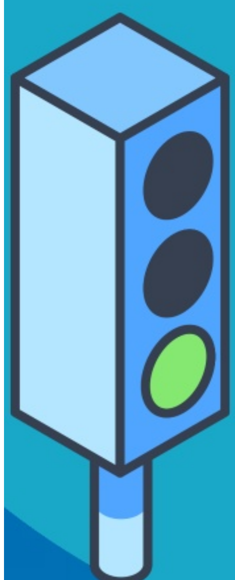
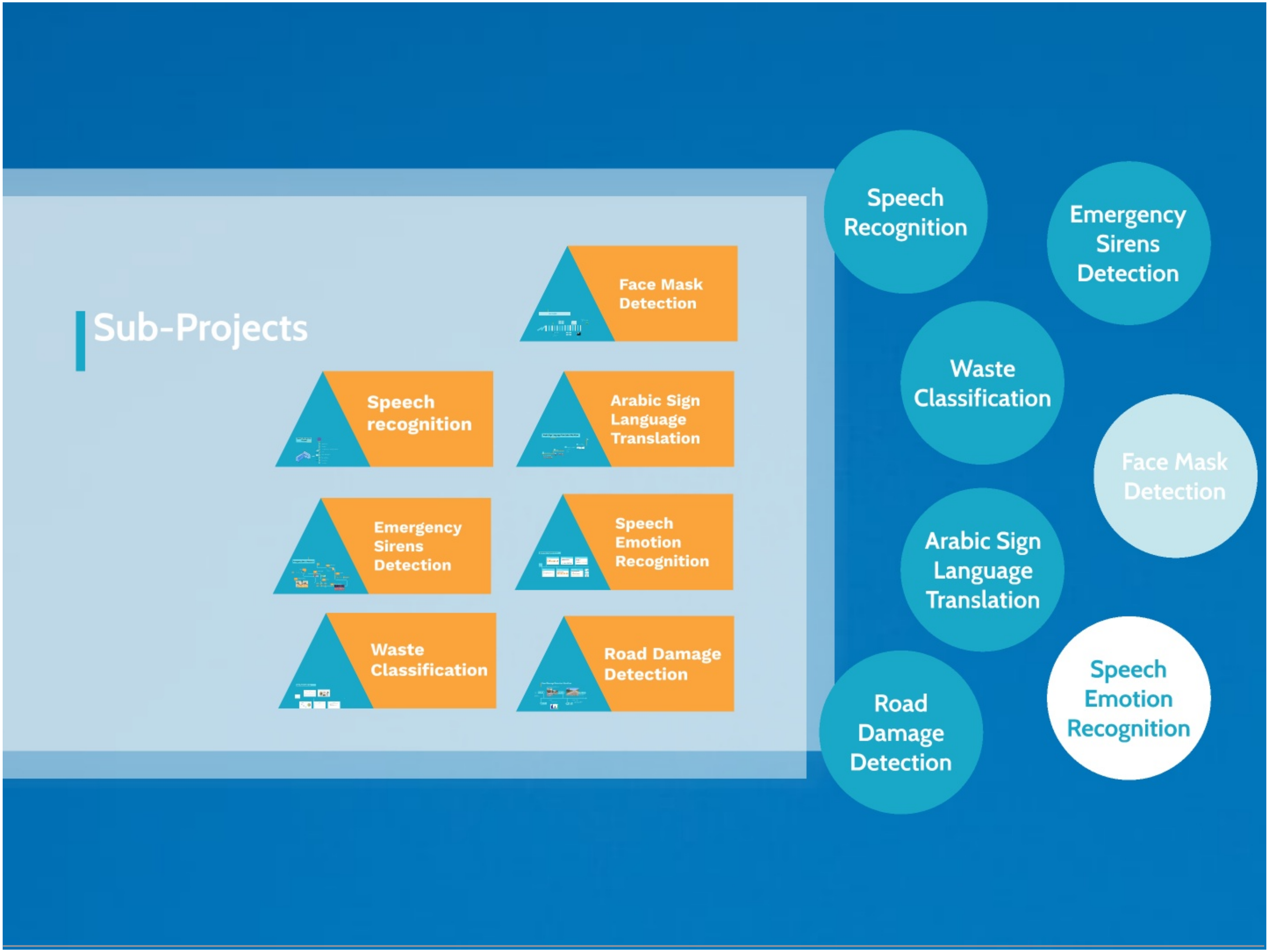
Road Damage Detection

By: Waleed Aldalham, Abdulaziz Wali

In a real-world scenario, when the road managers from a governing body need to repair such damage, they need to clearly understand the type of damage in order to take effective action.



So, using deep neural networks with images captured, road damage will be detected and fixed by the governing body or whom are responsible.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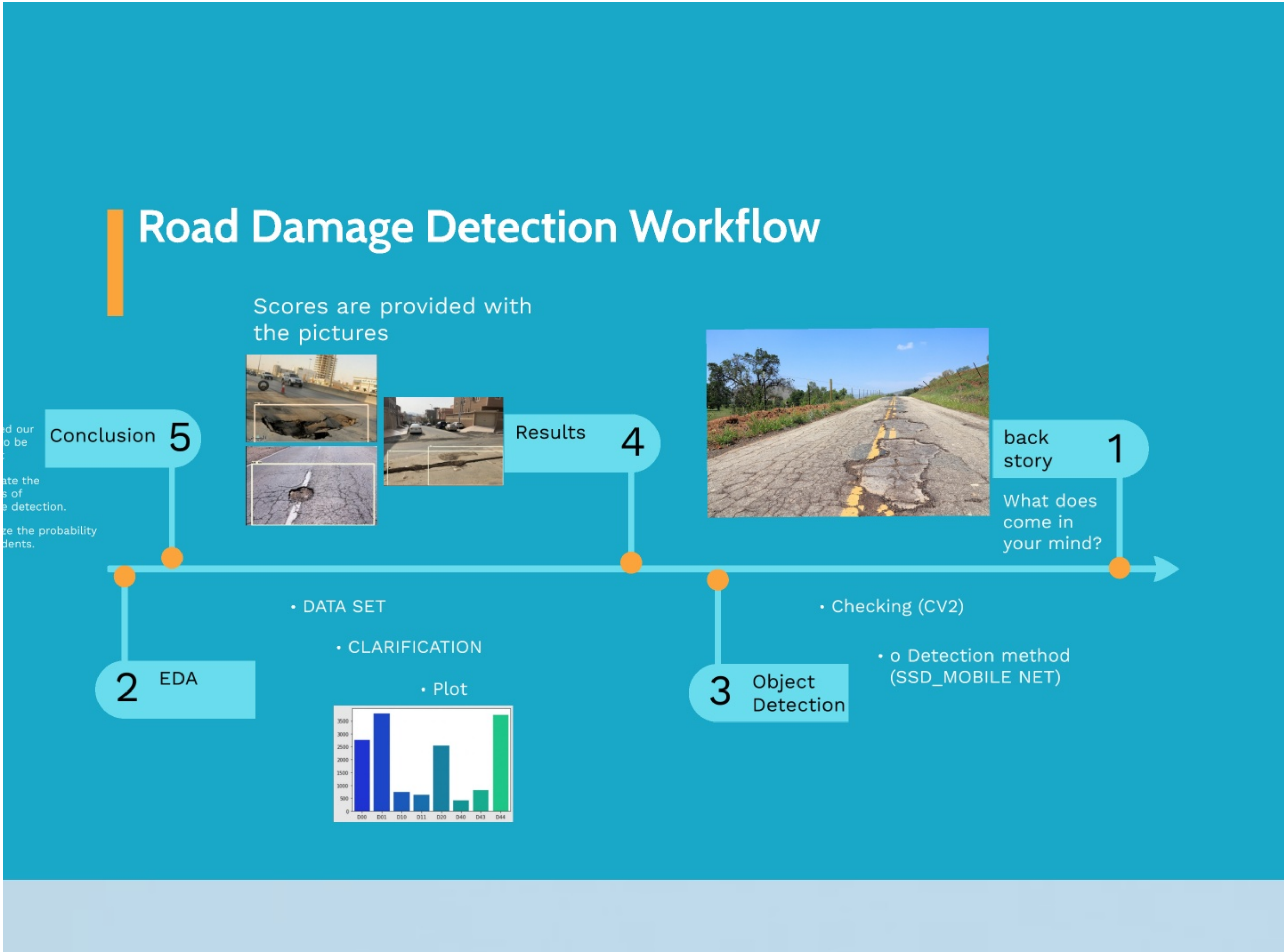
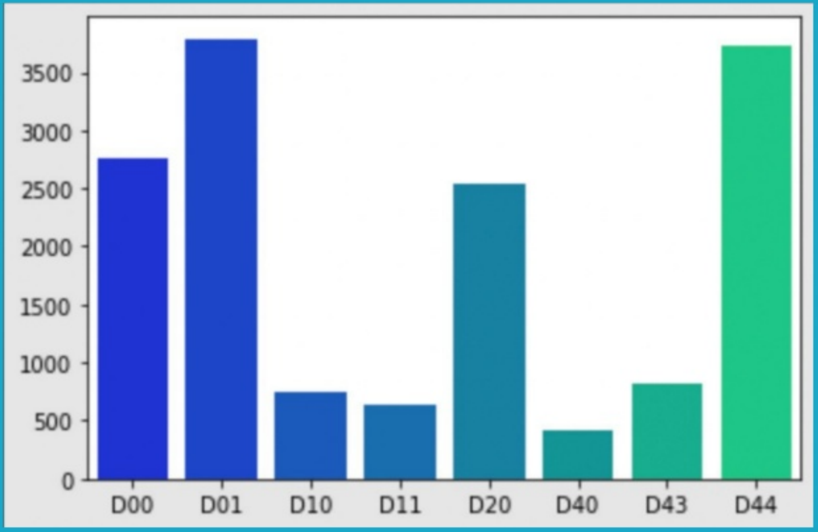

Road Damage Detection Workflow
Scores are provided with the pictures
Conclusion 5
Results 4
back story 1
What does come in your mind?
2 EDA
• DATA SET
• CLARIFICATION
• Plot
3 Object Detection
• Checking (CV2)
• o Detection method (SSD_MOBILE NET)

back
story

What does
come in
your mind?

EDA

- DATA SET
  - CLARIFICATION
    - Plot



your mind?

Object Detection

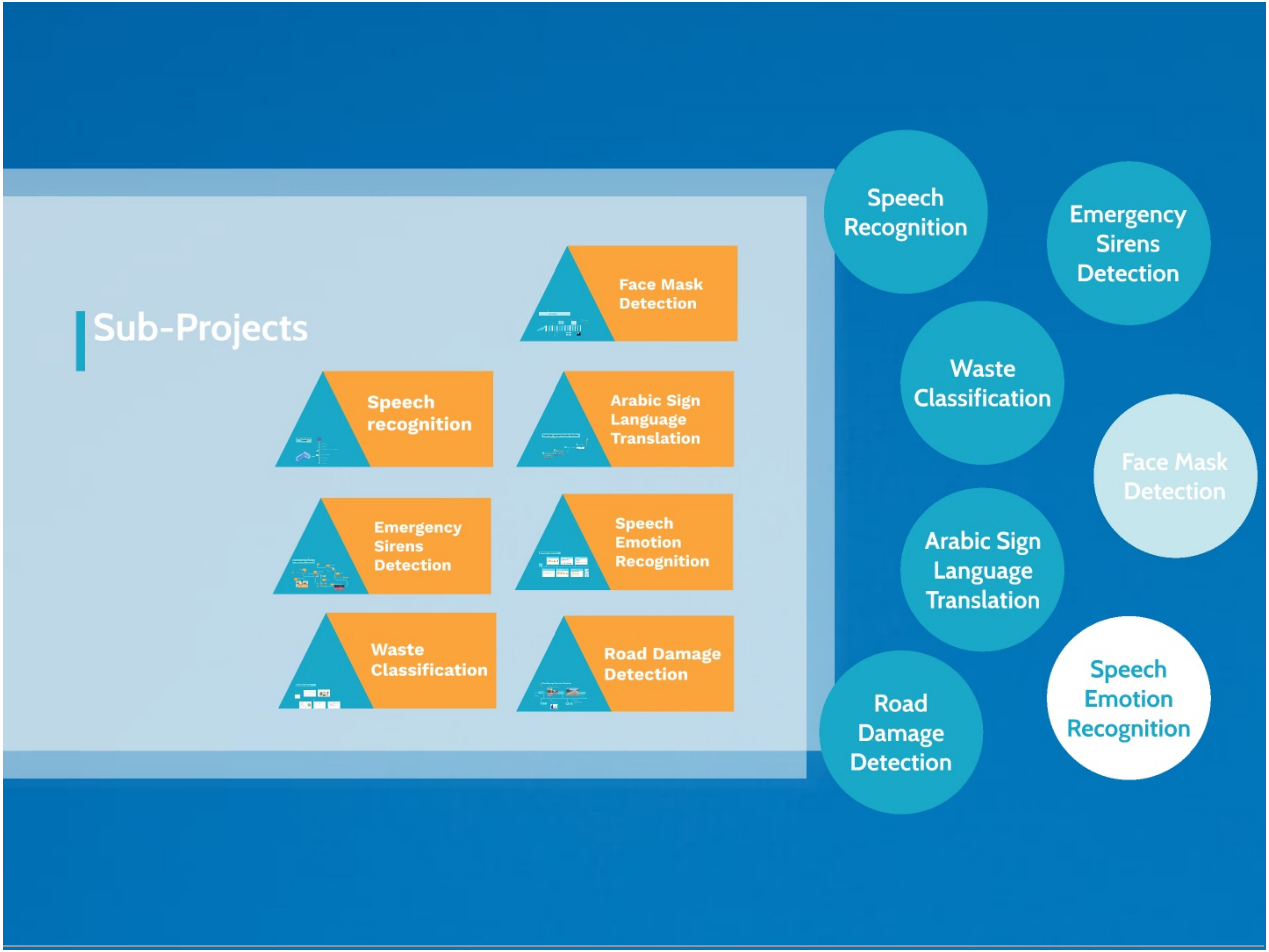
- Checking (CV2)
- o Detection method (SSD_MOBILE NET)

Scores are provided with the pictures

Results

Conclusion

- We need our roads to be perfect
- Automate the process of damage detection.
- Minimize the probability of accidents.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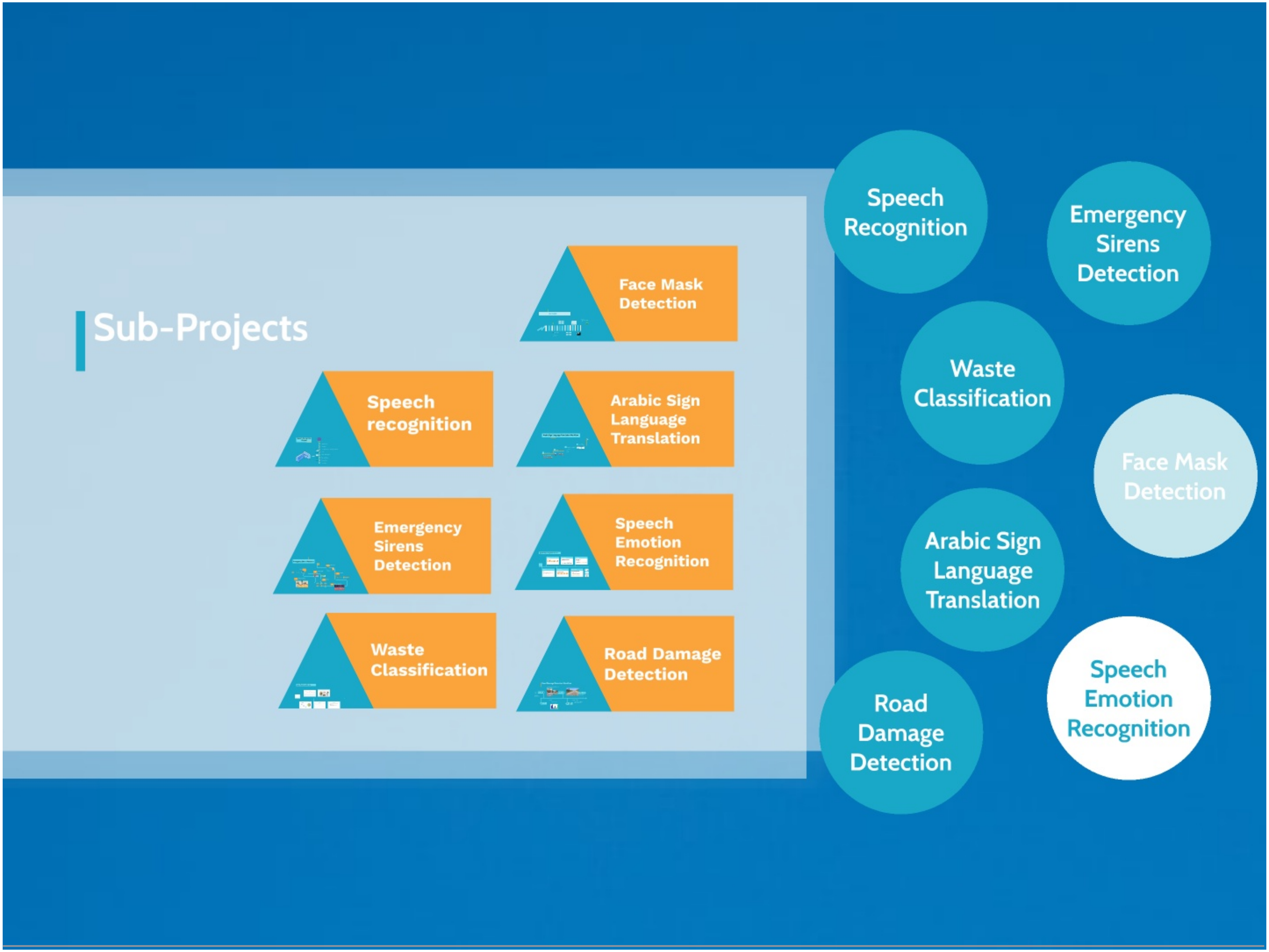
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SMART
CITY
Conclusion

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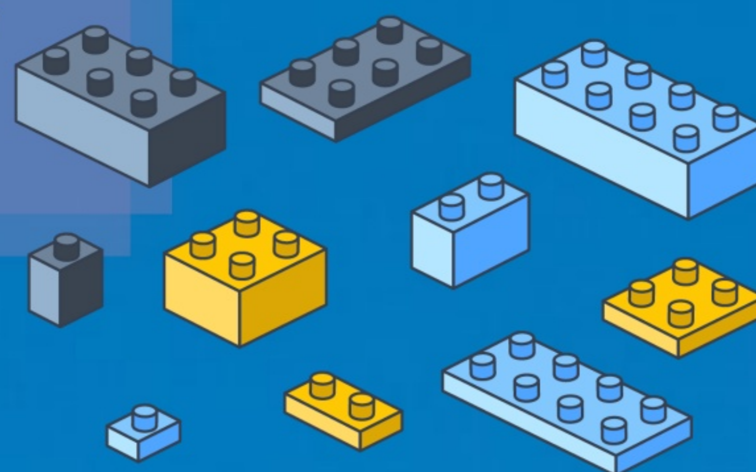
The sub projects can be used by Saudi government to contribute 2030 vision in AI field

Providing Arabic and specifically data related to Saudi will be helpful

For Future work we want to Utilize IoT technologies with deep learning for a smarter city

Thank You



Thank you

- Naif Alzahrani
- Mai Aljuaid
- Hayat Aldhahri
- Juri Alsayigh
- Waleed Aldalham
- Ahmed Almuaybid
- Tarfah Alabbad
- Abdulaziz Wali
- Abdulrahman Alrifae
- Basma Alduaiji
- Dimah Albunayyih
- Rahaf Alqahtani
- Rawabi Alkhalaf
- Muneera Alshunaifi

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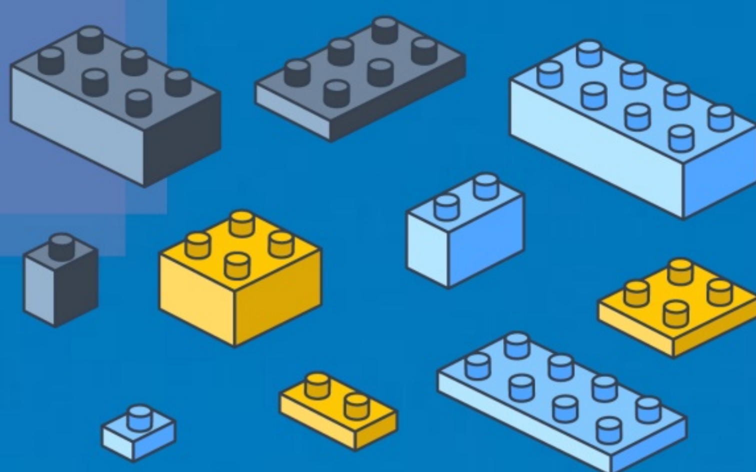


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