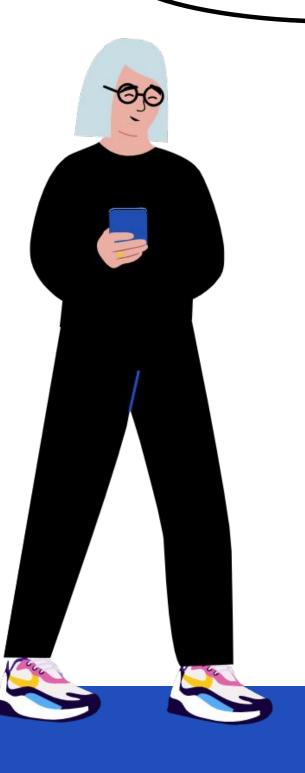
# AUTO COM "YOUR GUARDIAN ON THE ROAD"



## PROBLEM STATEMENT

Distracted Driving Is A Significant Contributor To Road Accidents, Leading To Injuries And Fatalities Worldwide.



The Challenge Is To Develop An Accurate And Reliable Machine Learning Model That Can Detect And Classify Various Types Of Driver Distractions From Images.

•The Goal Is To Classify Images Into One Of Ten Categories Representing Different Driver Behaviors, Such As Safe Driving, Texting, Talking On The Phone, Eating, And More.

### MEET OUR TEAM!



Kumaran Hariharan

Frontend And Integration



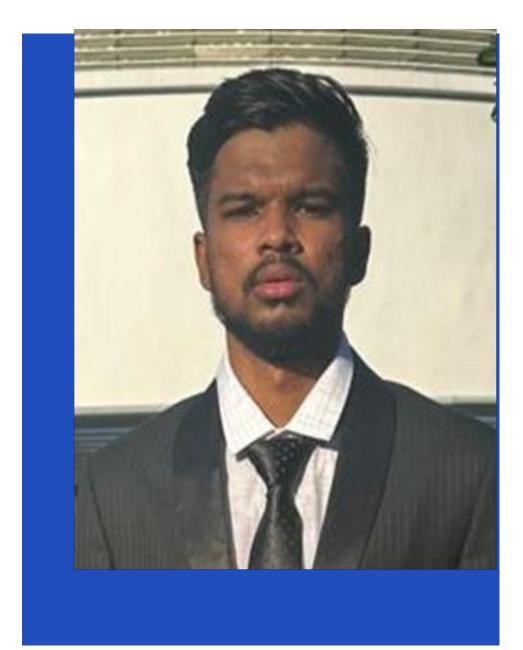
Roshan Rajendran

Model Design And Training



Tejaswini Swaroop

Model Building



**Pradhap Rane** 

Model Training



**Farhad Khan** 

Data Evaluation
And Training

## **ABSTRACT**

- Distracted Driving Poses A Significant Risk To Road Safety, Leading To Numerous Accidents.
- The Aim Of This Project Is To Develop An Advanced Machine Learning Model Capable Of Detecting Various Forms Of Driver Distractions From Images.
- The Project Involves Applying Image Processing Techniques And Deep Learning Algorithms To Identify And Categorize Driver Behaviors Into Distinct Classes Such As Texting, Eating, Talking On The Phone, And Others.
- Providing Real-Time Alerts By Text To Speech Mechanism.
- The Research Integrates
  - 1.Data Collection
  - 2.Model Training
  - 3. Performance Evaluation High Accuracy



## IMPORTANT USE CASE

- Drive Safe, Even When No Ones Watching
- Ola, Uber, Safe Driving, Cab
- Driving Schools, Post In Person Lectures Driver Monitor System.
- Cargo Safety, Ensure Goods Are Safe
- TARGET AUDIENCE :-
  - **1.Cab Service Providers**
  - 2.Car Rental Service Providers
  - 3. Driving School.
  - 4.Insurance Providers.
- Logistic Service Providers Insurance Service Providers Law Enforcement



## CONCEPTS USED

#### Streamlit

Frontend: Interactive web application

#### **COMPUTER VISION**

Image Classification: Predicting driver action
Preprocessing: Resizing and data augumentation

#### **DEEP LEARNING**

CNNs: For image data processing Transfer Learning: Fine-tuning MobileNetV2

#### **MOBILE NET V2**

Pretrained Model: Lightweight CNN Custom Layers: For classification

## Data Augmentation:

TENSERFLOW/KERAS

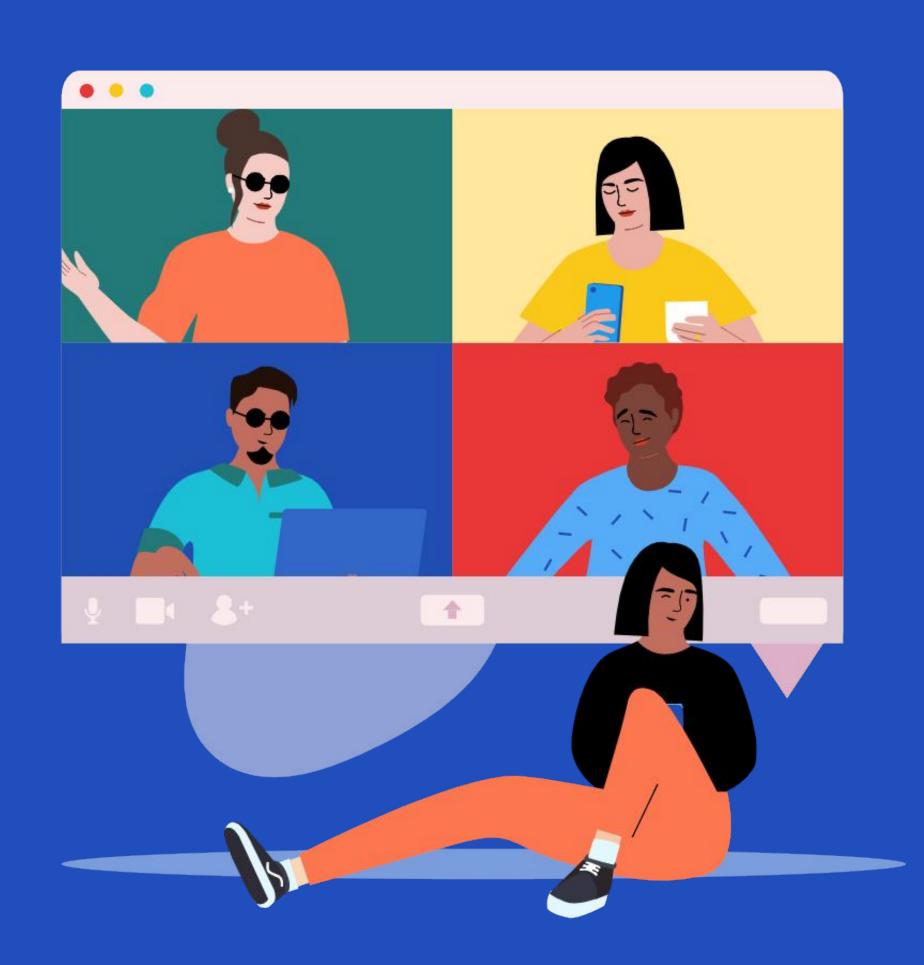
Frameworks: For neural network training

Training: Compiling, evaluating.

Enhancements: Improving model performance.

#### **Model Evaluation:**

Metrics: Accuracy and loss monitoring



## Data Used!

Driver Images, Each Taken In A Car With A Driver Doing Something Unsafe In The Car (Texting, Eating, Talking On The Phone, Makeup, Reaching Behind, Etc) Organized Into 10 Classes.

The 10 Classes To Predict Are:

Co: Safe Driving

C1: Texting-Right

C2: Talking On The Phone - Right

C3: Texting-Left

C4: Talking On The Phone – Left

**C5: Operating The Radio** 

C6: Drinking

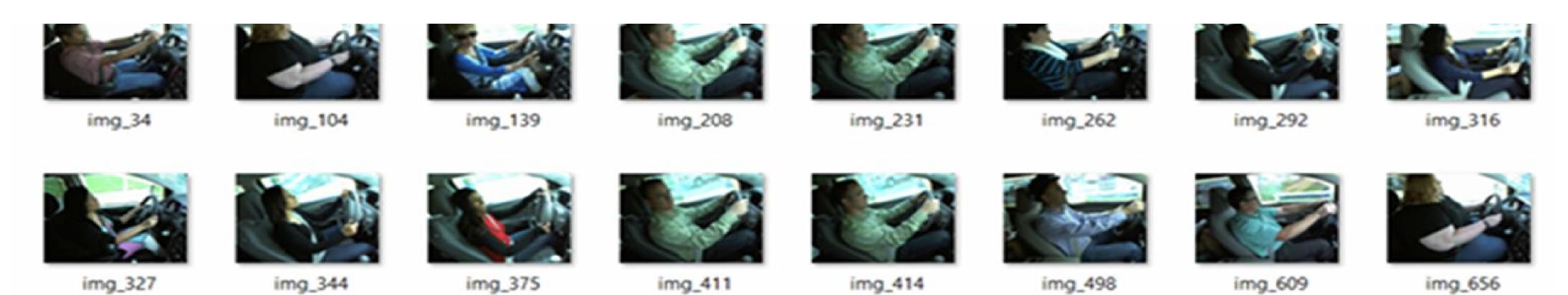
**C7: Reaching Behind** 

**C8: Hair And Makeup** 

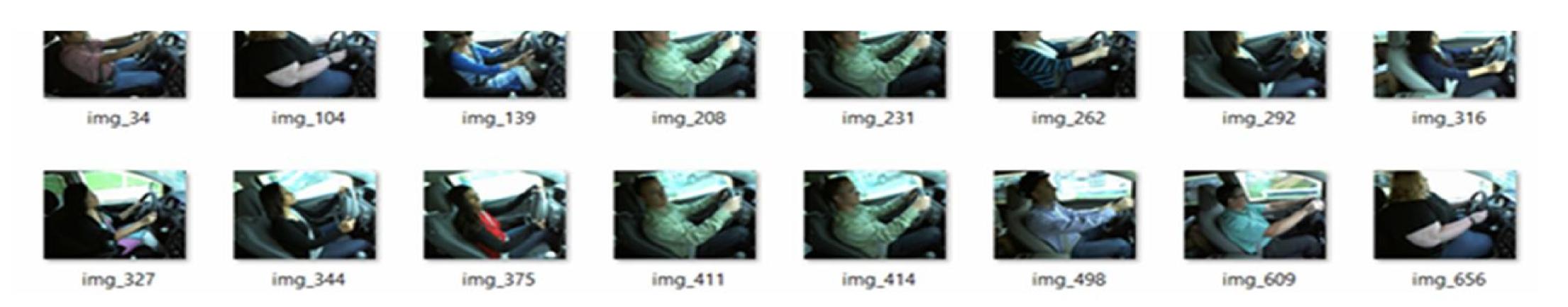
**C9: Talking To Passenger** 

### GLIMPSE OF THE DATASET!

#### **C0:Safe State**

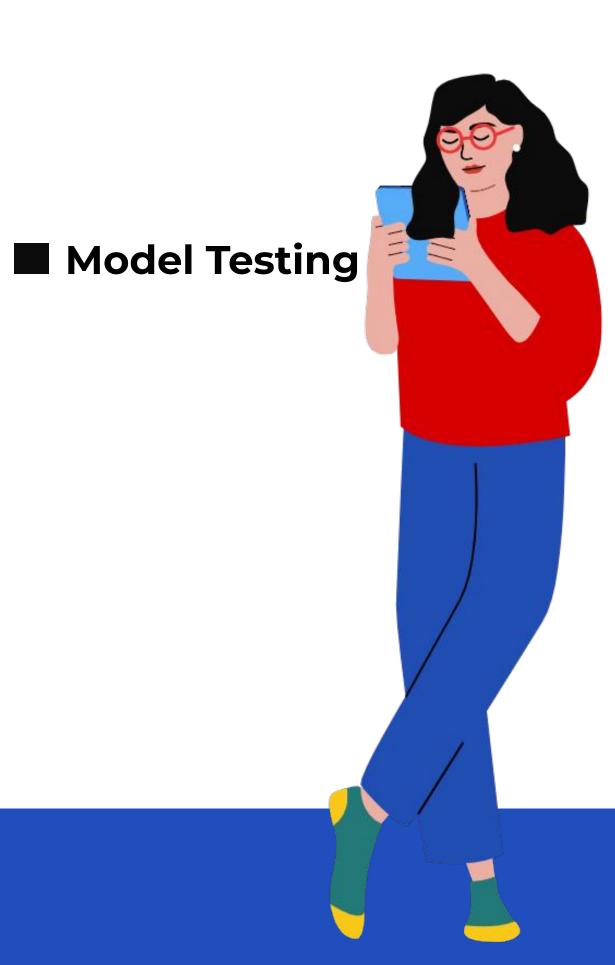


#### **C8:Unsafe State(Hair And Makeup)**



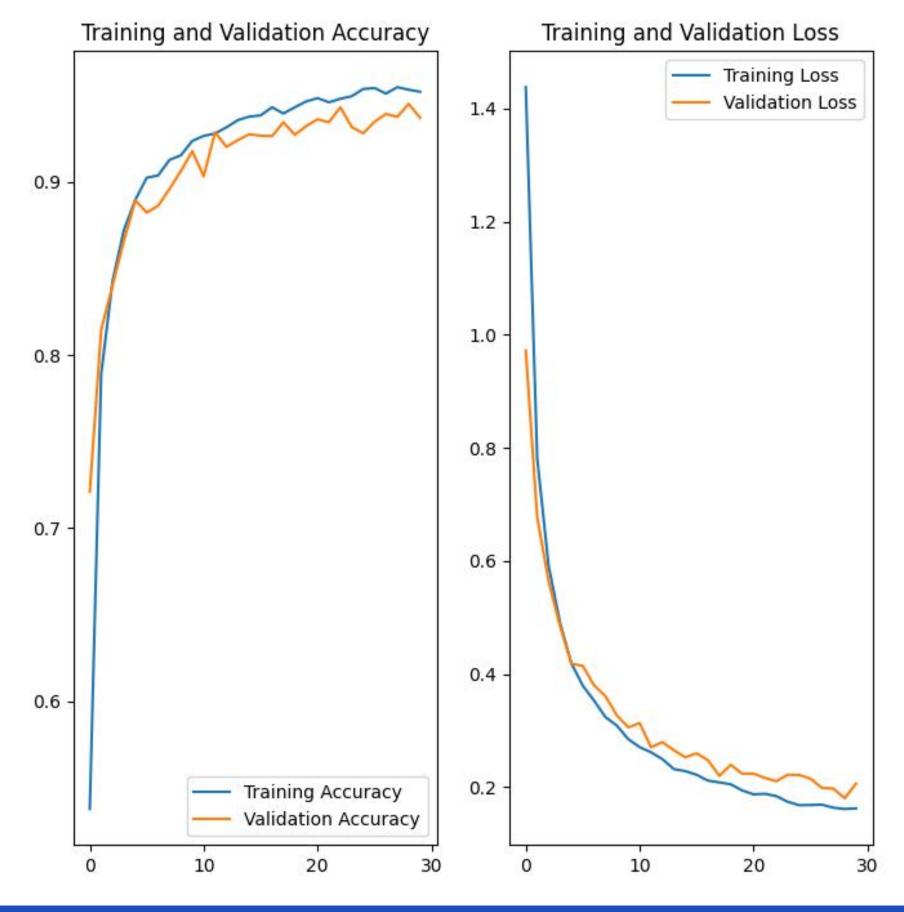
# MODEL TESTING AND CELL OUTPUT

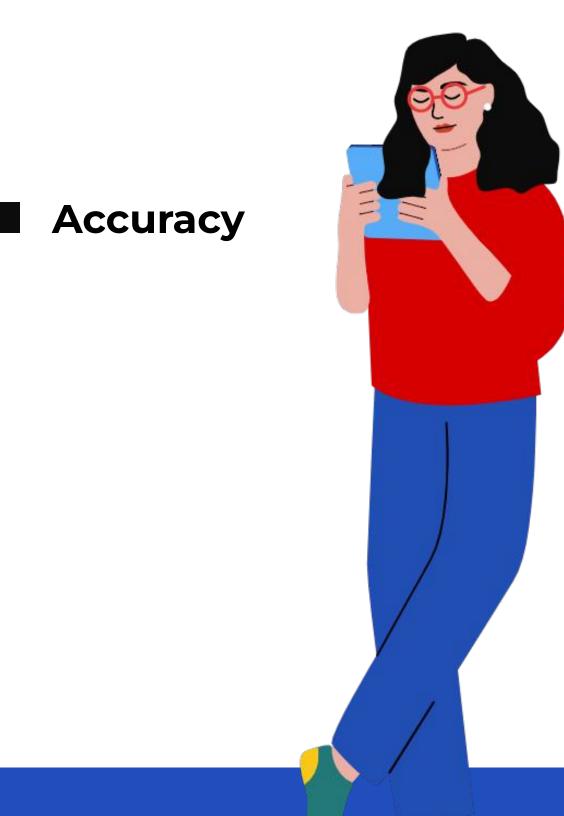
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                                                   model_final_30_epoch[1].h5
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           self. warn if super not called()
                                                              128s 550ms/step - accuracy: 0.3629 - loss: 1.8475 - val_accuracy: 0.7210 - val_loss: 0.9720
         Epoch 2/30
         225/225
                                                              165s 724ms/step - accuracy: 0.7669 - loss: 0.8532 - val_accuracy: 0.8145 - val_loss: 0.6777
         Epoch 3/30
         225/225
                                                              187s 818ms/step - accuracy: 0.8299 - loss: 0.6279 - val_accuracy: 0.8401 - val_loss: 0.5644
         Epoch 4/30
                                                              199s 876ms/step - accuracy: 0.8679 - loss: 0.5057 - val accuracy: 0.8661 - val loss: 0.4852
         225/225
         Epoch 5/30
         225/225
                                                              207s 910ms/step - accuracy: 0.8899 - loss: 0.4247 - val_accuracy: 0.8892 - val_loss: 0.4184
         Epoch 6/30
                                                              204s 897ms/step - accuracy: 0.8966 - loss: 0.3900 - val_accuracy: 0.8823 - val_loss: 0.4144
         225/225
         Epoch 7/30
                                                             226s 993ms/step - accuracy: 0.9043 - loss: 0.3593 - val_accuracy: 0.8862 - val_loss: 0.3800
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         Epoch 8/30
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                                                            • 237s 1s/step - accuracy: 0.9144 - loss: 0.3306 - val accuracy: 0.8959 - val loss: 0.3607
         Epoch 9/30
         225/225 -
                                                              242s 1s/step - accuracy: 0.9160 - loss: 0.3078 - val_accuracy: 0.9062 - val_loss: 0.3268
         Epoch 10/30
         225/225 -
                                                              235s 1s/step - accuracy: 0.9210 - loss: 0.2936 - val accuracy: 0.9177 - val loss: 0.3057
         Epoch 11/30
         225/225
                                                              228s 999ms/step - accuracy: 0.9236 - loss: 0.2740 - val_accuracy: 0.9032 - val_loss: 0.3132
         Epoch 12/30
         225/225
                                                             • 213s 937ms/step - accuracy: 0.9281 - loss: 0.2583 - val accuracy: 0.9286 - val loss: 0.2704
         Epoch 13/30
                                                              216s 950ms/step - accuracy: 0.9292 - loss: 0.2506 - val accuracy: 0.9202 - val loss: 0.2796
         225/225
         Epoch 29/30
                                                              202s 890ms/step - accuracy: 0.9526 - loss: 0.1623 - val_accuracy: 0.9450 - val_loss: 0.1804
         225/225 -
         Epoch 30/30
                                                             203s 891ms/step - accuracy: 0.9530 - loss: 0.1591 - val accuracy: 0.9369 - val loss: 0.2064
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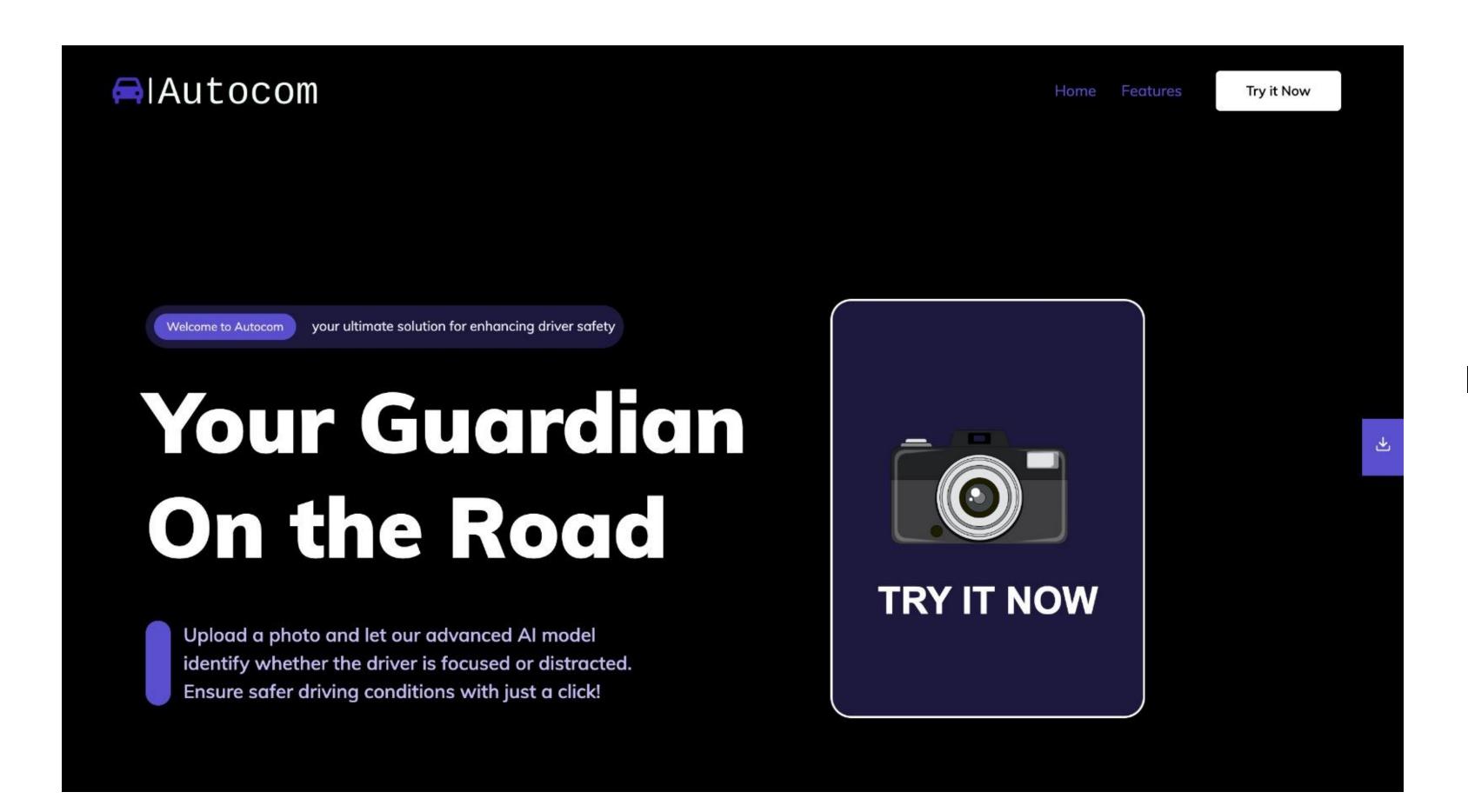
# Model Testing And Accuracy





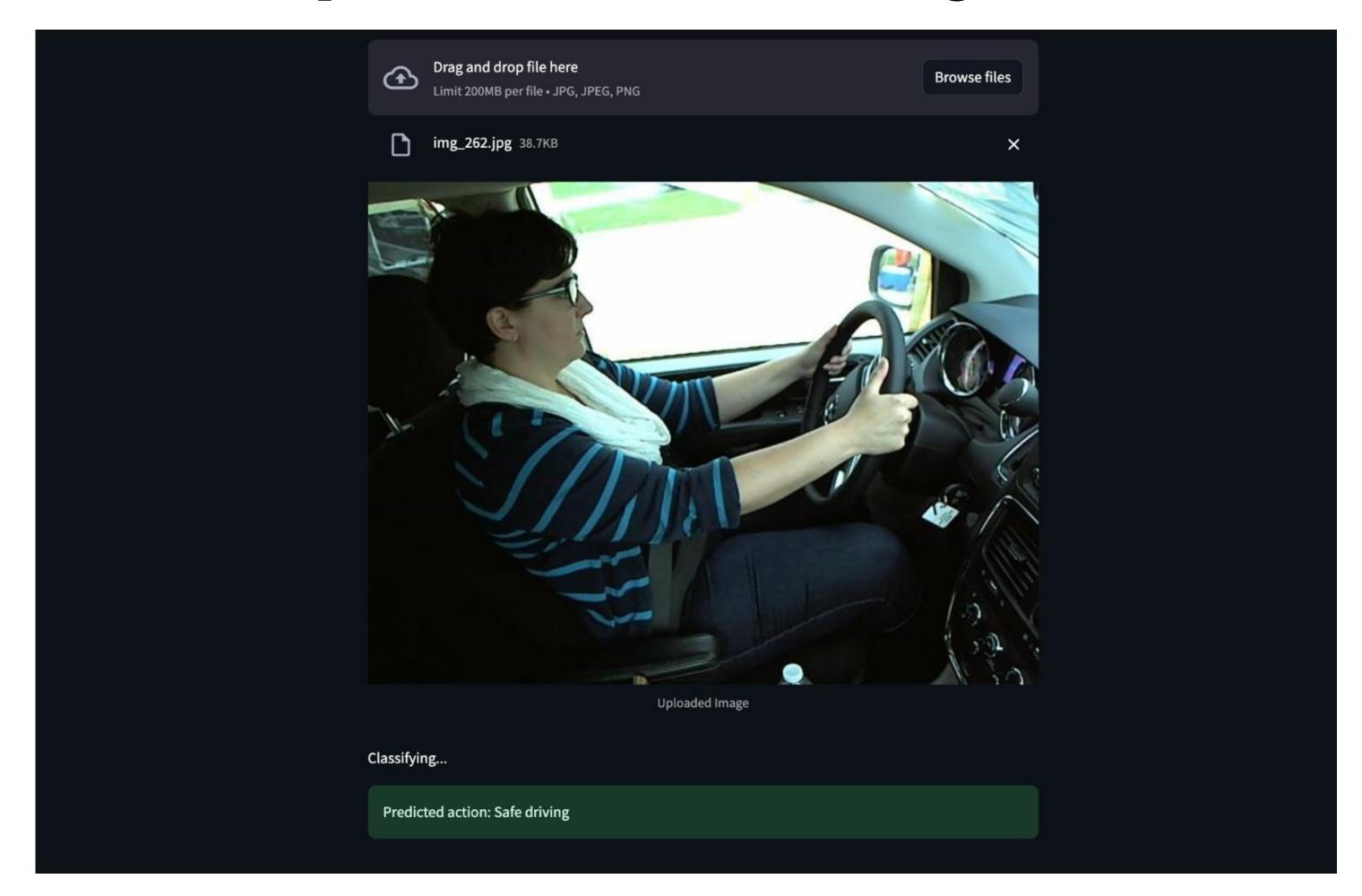


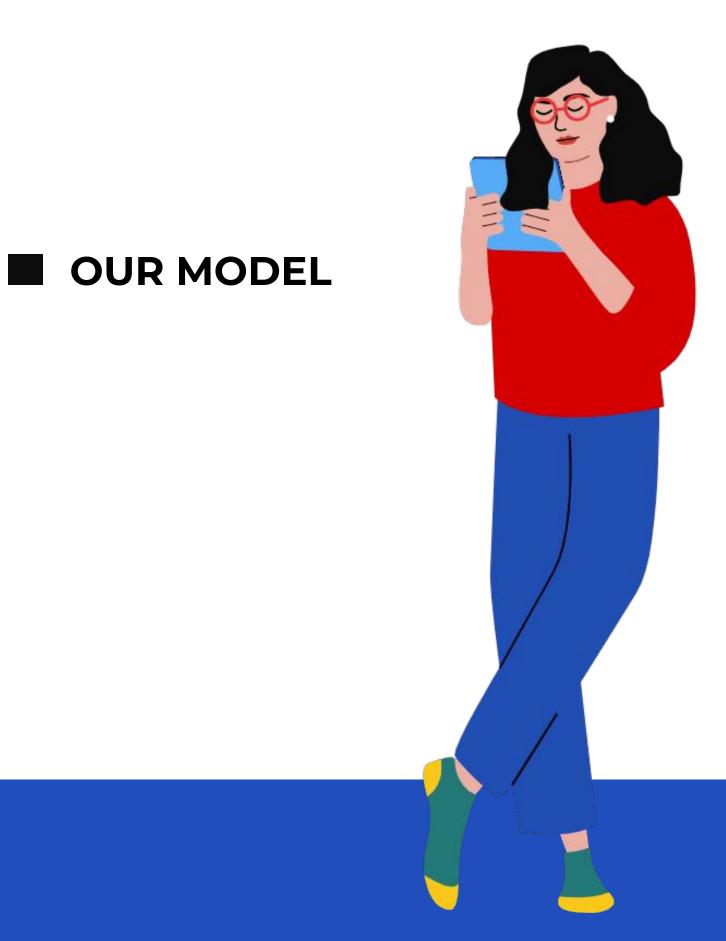
## Glimpse Of The Project!



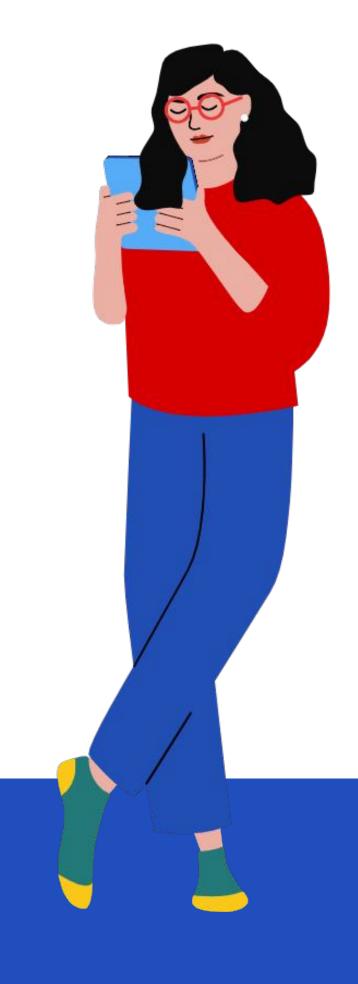


## Glimpse Of The Project!





# LET'S CHECK OUT THE PROTOTYPE!!!



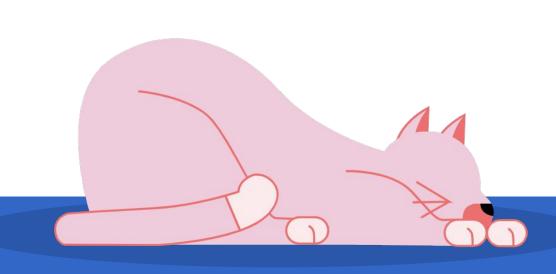
# MOBILE NET V2 ARCHITECTURE

Type: Convolutional Neural Network (CNN)

#### **Key Features:**

- Depthwise Separable Convolutions: Reduces Computational Cost By Factorizing A Standardconvolution Into A Depthwise Convolution Followed By A Pointwise Convolution.
- Inverted Residuals And Linear Bottlenecks: Improves Model Performance By Optimizing The Flow Of Information Through The Network.





## WE LEARNT!

**Deep Learning Implementation** 

Data Augmentation

**Model Training and Evaluation** 

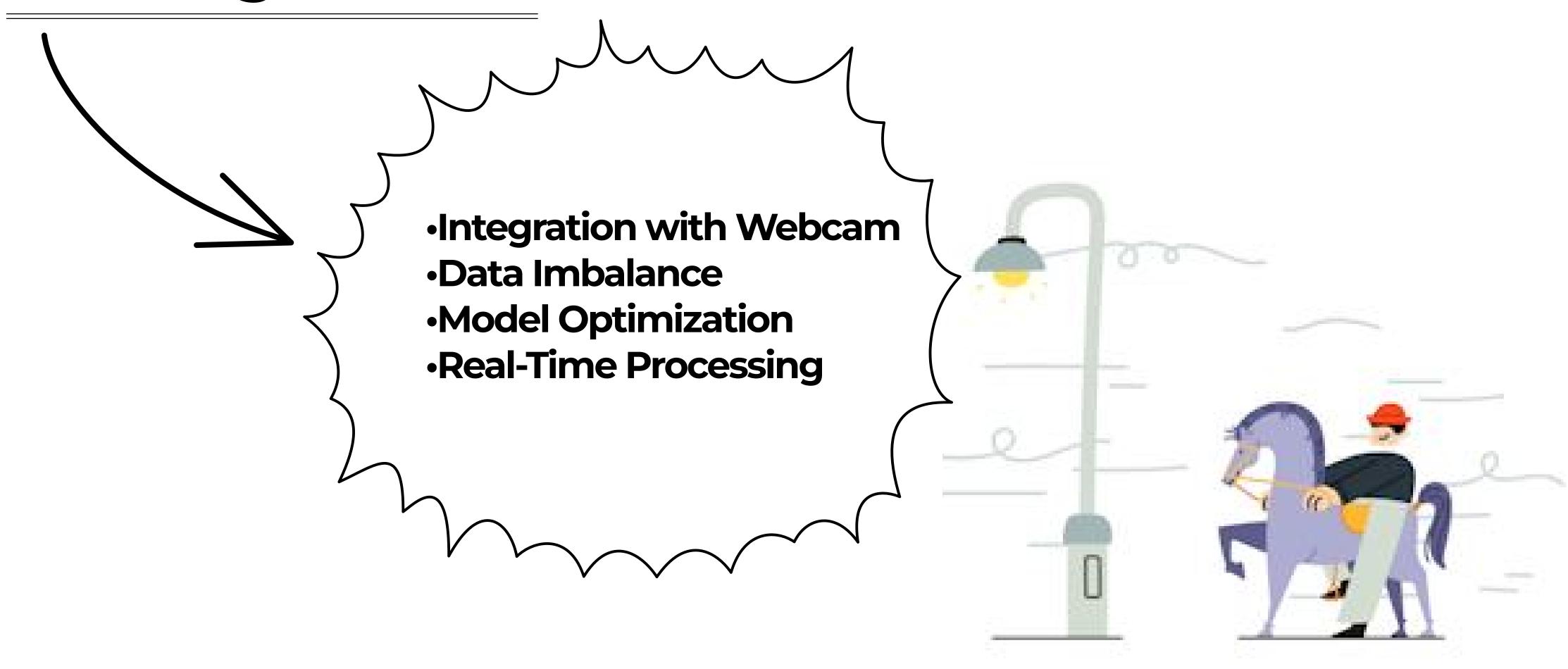
Image processing

Deployment with streamlit

**TensorFlow lite** 



## Challenges faced



## Future Enhancement

#### 1.Real-Time Alerts:

•Integrate Audio And Visual Alerts For Detected Risky Behaviors.

#### 2.Extended Dataset:

•Incorporate Additional Driver Behaviors And Larger Datasets For Improved Accuracy.

#### 3. Multimodal Inputs:

•Combine Image Data With Sensor Data (E.G., Speed, GPS) For Comprehensive Analysis.

#### 4.Edge Deployment:

•Optimize The Model For Deployment On Edge Devices Like Raspberry Pi For In-Car Implementation.

#### **5.Behavior Trends:**

•Analyze And Visualize Driver Behavior Trends Over Time For Individual Drivers.

#### **6.Custom Alerts:**

•Allow Users To Set Custom Alerts For Specific Behaviors.



### CONCLUSION

- This project demonstrates the potential of machine learning and computer vision techniques in enhancing road safety by detecting and classifying distracted driving behaviors.
- By accurately identifying various types of distractions from driver images, the developed model can be integrated into advanced driver assistance systems to provide real-time alerts, helping to mitigate the risks associated with distracted driving.

