# Distracted Driver APP

FLAT IRON MORINGA SCHOOL

GROUP 4 CAPSTONE PROJECT

# Topic Outline

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# Problem Statement

Among the primary contributors to road accidents are speeding, drunk driving, and distracted driving. While measures such as speed guns, speed governors, and speed limits address speeding, and tools like alco-blow combat drunk driving, there remains a notable gap in addressing distracted driving effectively.

Distracted driving poses significant risks, including accidents, injuries, and fatalities. Identifying and mitigating instances of distraction while driving is crucial to reducing road accidents.

The ballooning of car insurance claims led Directline Insurance, Kenya, to engage us in this project, with a vision to lower the rising claims from their customers.

# Business Understanding

The increase in population and depletion of resources has led to the need for humans to move about frequently.Unfortunately, accident rates has been increasing by about 2% yearly.

Road fatalities affect both the developed and developing countries alike.

Our analysis has shown that about 8% of these road traffic accidents are caused by drivers being distracted.This leads to delayed response time and increased possibility of accidents.

We sought to find out the influence of distracted driving on road crashes.Unfortunately, we could not find realibale data about the causes of road accidents in Kenya from the NTSA (National Transport and Safety Authority) or any other credible source.The data runs from 2017 to 2021 and we will use it to find out the influence and the trend of road crashes caused by distracted driving.

# Objectives

**Main Objective**

Create a robust system for real-time detection of distracted drivers using computer vision.

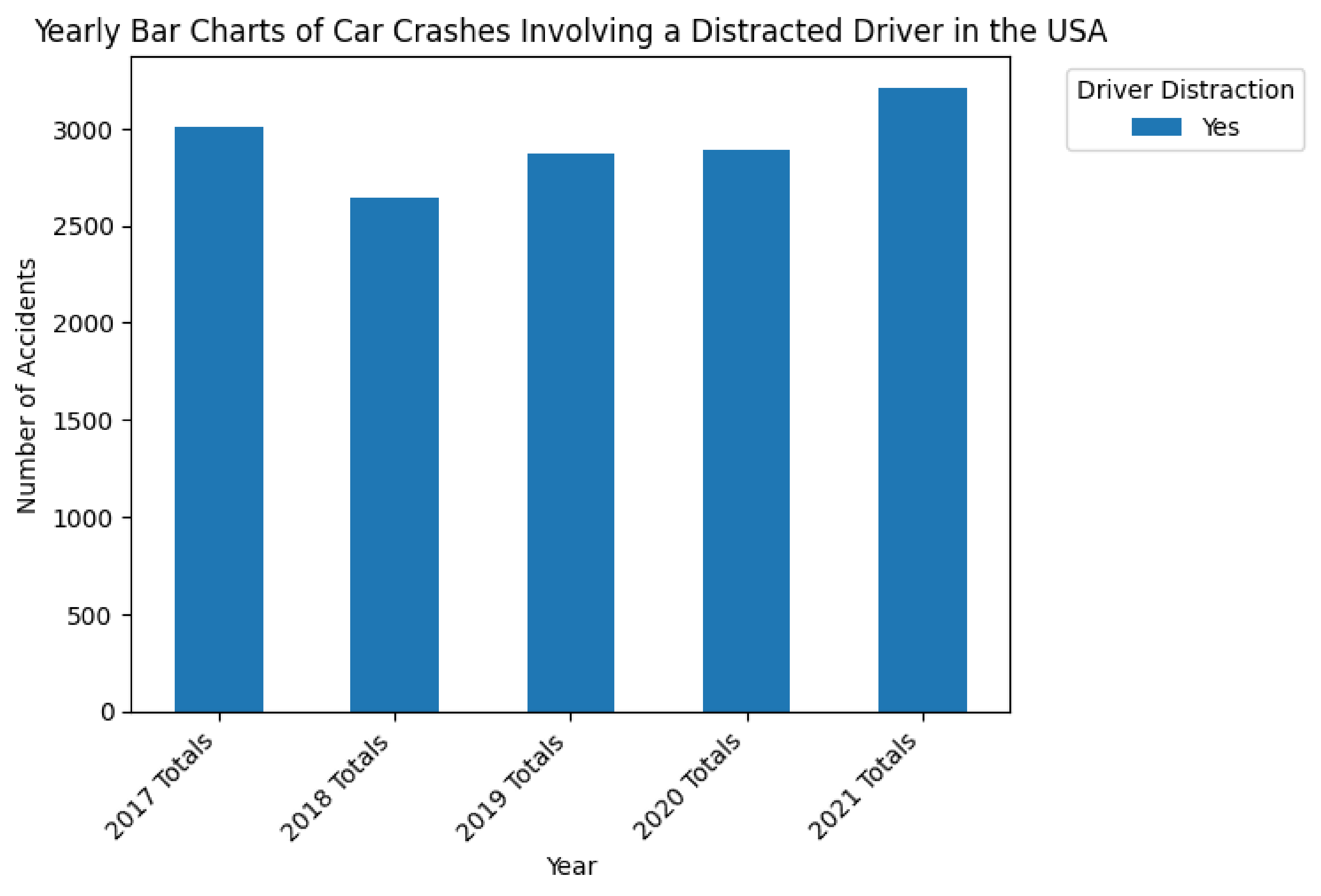
**Specific Objectives:**

i.) **Dataset Acquisition**: Source a credible dataset comprising images of drivers exhibiting various forms of distraction (e.g., phone usage, eating, grooming).

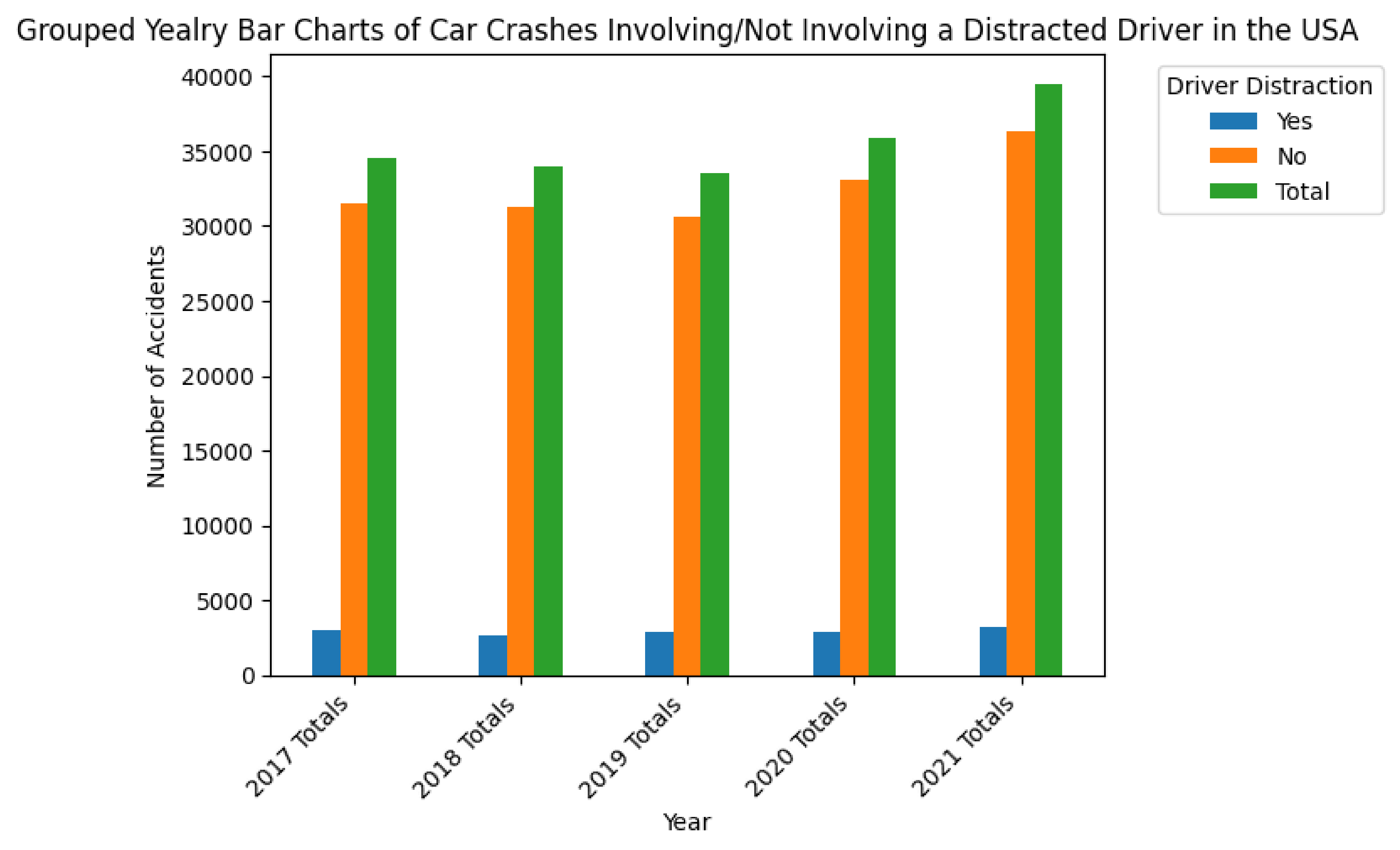
ii.) **Model Development**: Utilize computer vision techniques to build a deep learning model capable of accurately identifying distracted driver behaviors from visual cues.

iii.) **Real-Time Implementation**: Deploy a feedback system that alerts the driver when they're being distracted by integrating auditory alerts or haptic feedback.

# Number of Accidents per Year.



# Causes of Accidents per year.

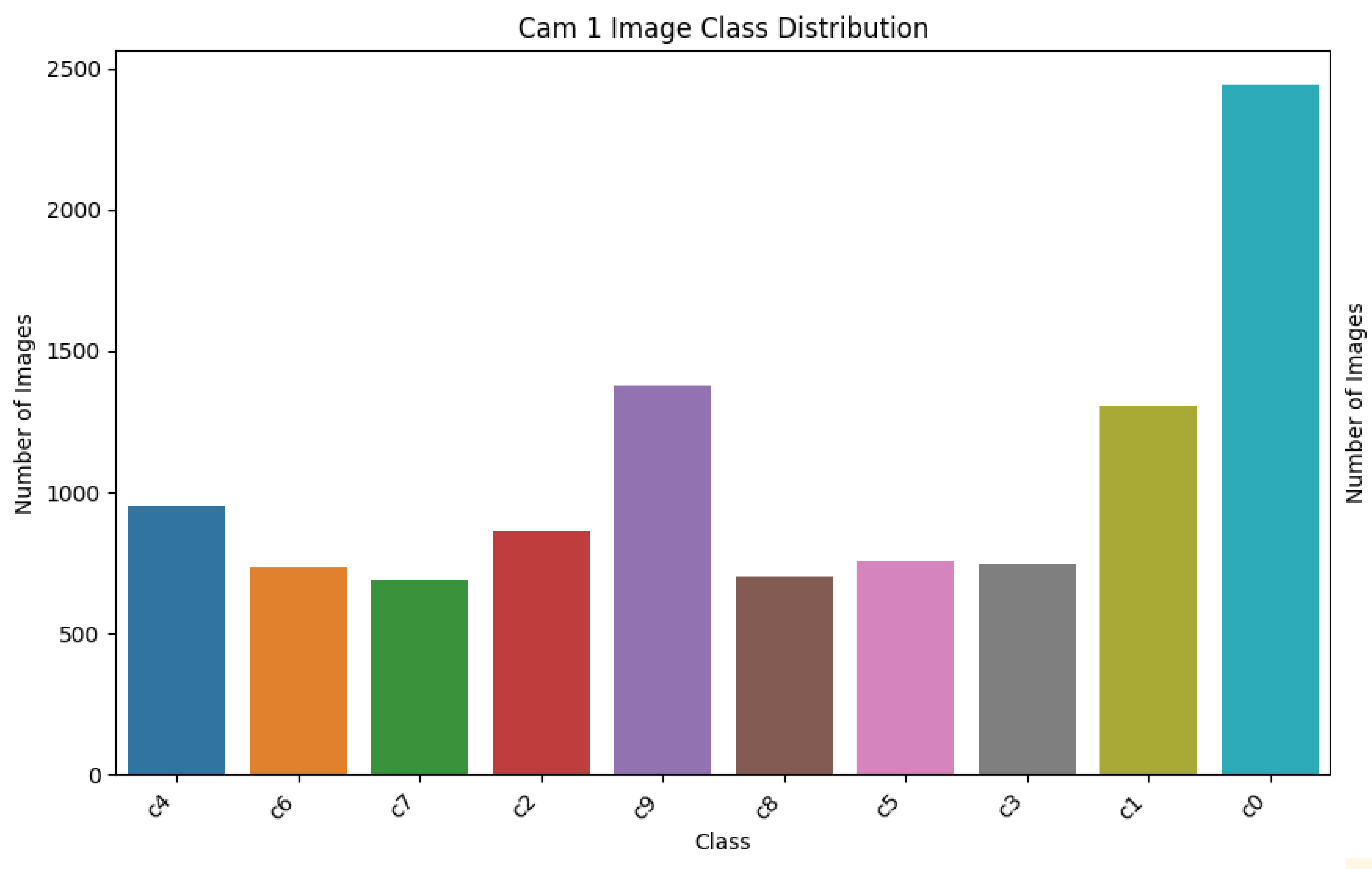


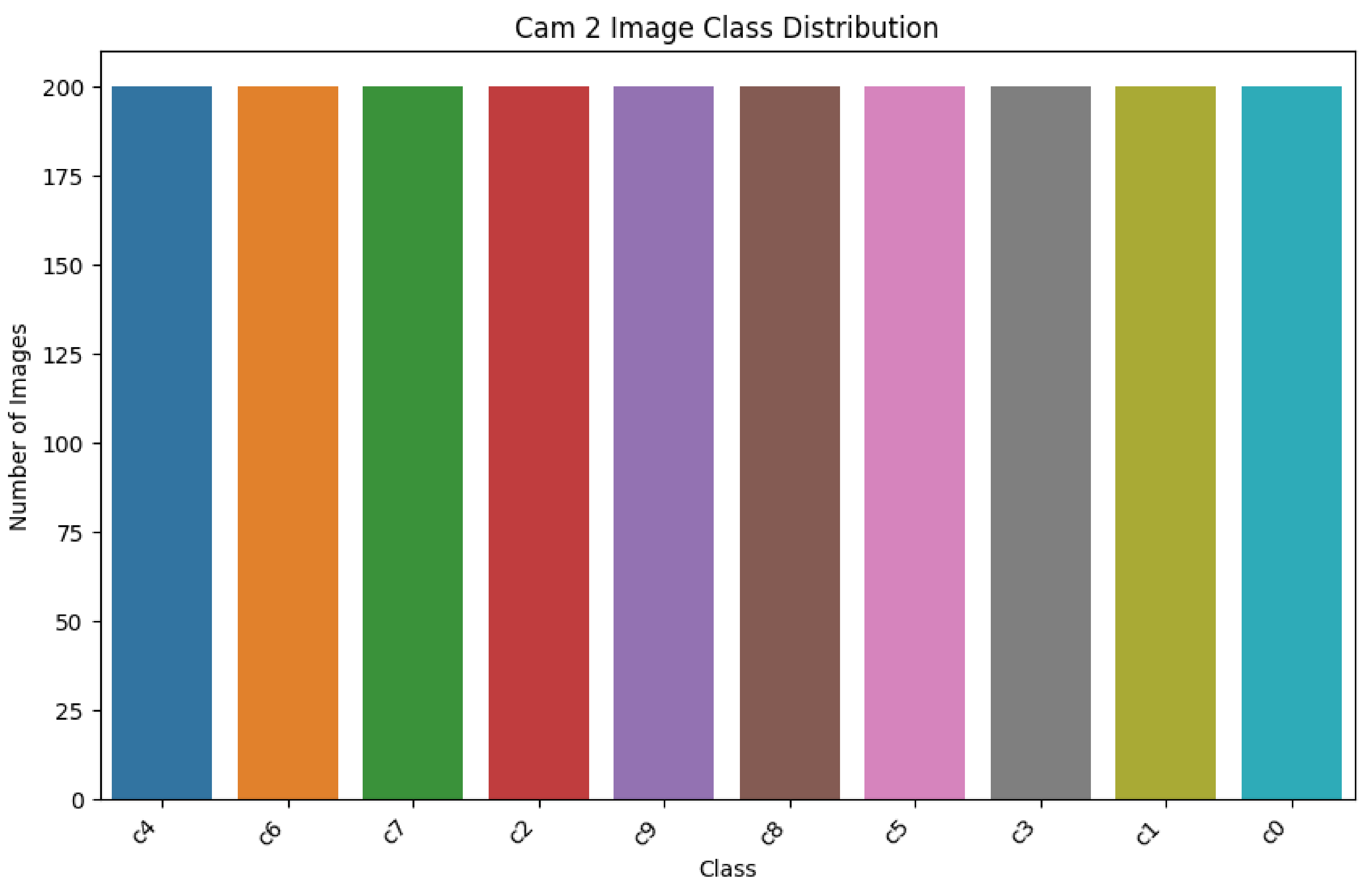
# Image Understanding

Here we have a sample of the photos from the American University of Cairo

# Image Distribution

Here we see the distribution of photos in the different categories from the 2 different camera angles.



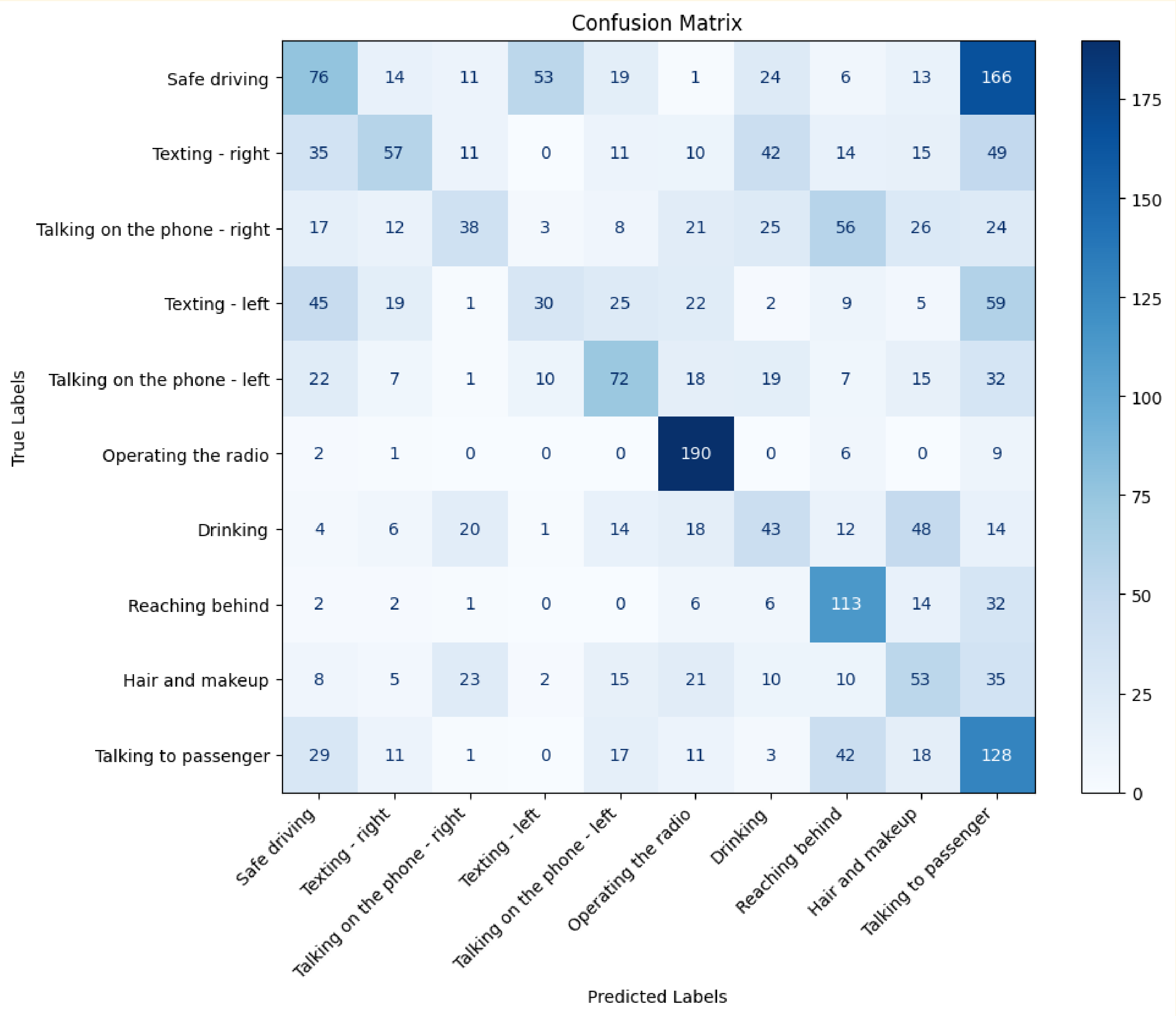
# Model Performance

- This is a summary of how the models performed. They generally had low accuracy due to the quality of the data.
- GoogleNet Inception was our best performing model.

| | Model | Test_Accuracy |
|---|---|---|
| 0 | Vanilla CNN Target Size (64x64) | 0.088042 |
| 1 | Vanilla CNN Target Size (224x224) | 0.078785 |
| 2 | Pretrained VGG16 | 0.286027 |
| 3 | Pretrained VGG19 | 0.225580 |
| 4 | EfficientNetB0 | 0.090670 |
| 5 | EfficientNetB3 | 0.087604 |
| 6 | GoogLeNet_Inception_(2Inception_Modules) | 0.332457 |
| 7 | GoogLeNet_Inception_(3Inception_Modules) | 0.350416 |

# Confusion on best model

- Here we have a confusion matrix for our best performing model.
- The model has the highest likelihood of a True Positive in the 'radio' category, that is, the rate of classifying someone as operating the radio when the person is operating the radio is 0.91.
- The next easiest category to classify is 'reaching behind' with a recall of 0.64 and a precision of 0.41.



# Deployment

- We were able to deploy our app via streamlit. Below is a link to the website.
- https://distracteddriverdetection.streamlit.app/

# Challenges

**1. Data Limitations:**

The lack of data on the causes of road accidents in Kenya posed a significant challenge in understanding local driving behaviors and distractions.

The limited availability of images of Kenyan drivers necessitated training and testing models on images of Egyptians, potentially impacting model generalization in our nation.

**2. Classification Complexity:**

Models were trained to classify single actions, lacking the ability to identify multiple simultaneous actions, such as tuning the radio and talking on the phone. Challenges with blurred images, overlapping hand and body movements, and cropped targets hindered accurate classification of distracting actions.

**To tackle some of these challenges, we implemented blur detection and augmentation algorithms to address issues with image quality, resulting in a test accuracy improvement from approximately 25% to over 35%.**

# Recomendations & Next Steps

**Localized Data Collection:**
Collaborate with local authorities and organizations to gather data specific to Kenyan driving behaviors and distractions, enhancing model accuracy and relevance.
**Video training:**
Train models using not just photos but also video footage.
**Enhanced Model Architecture:**
Explore more sophisticated architectures and techniques, such as object detection and instance segmentation, to improve the identification of complex and overlapping distracting actions.
**Real-Time Feedback Refinement:**
Further refine the feedback system to minimize False Positive errors, ensuring accurate detection and timely alerts for distracted driving instances.
**Continuous Improvement:**
Continuously evaluate and iterate upon model performance and data augmentation strategies to adapt to evolving driving behaviors and environmental conditions.
**Hardware improvements:**
Increase accessibility of the team to top-tier graphics cards to make work easier for all members.

# Conclusion

In conclusion, to enhance the effectiveness of distracted driving detection systems, it is imperative to **refine model architectures**, **employ techniques like ensemble learning**, and **diversify datasets to achieve a target accuracy threshold of 0.9.**

Real-time performance can be optimized through model inference optimizations and hardware acceleration, facilitating seamless integration with in-vehicle systems and minimizing latency.

Continuous validation across diverse driving scenarios ensures robustness and reliability, while iterative refinement of feedback mechanisms based on user input enhances effectiveness and user acceptance of distraction alerts. Implementing these recommendations will lead to the development of more robust systems, thereby contributing significantly to road safety and accident prevention efforts.

# Meet the Team

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