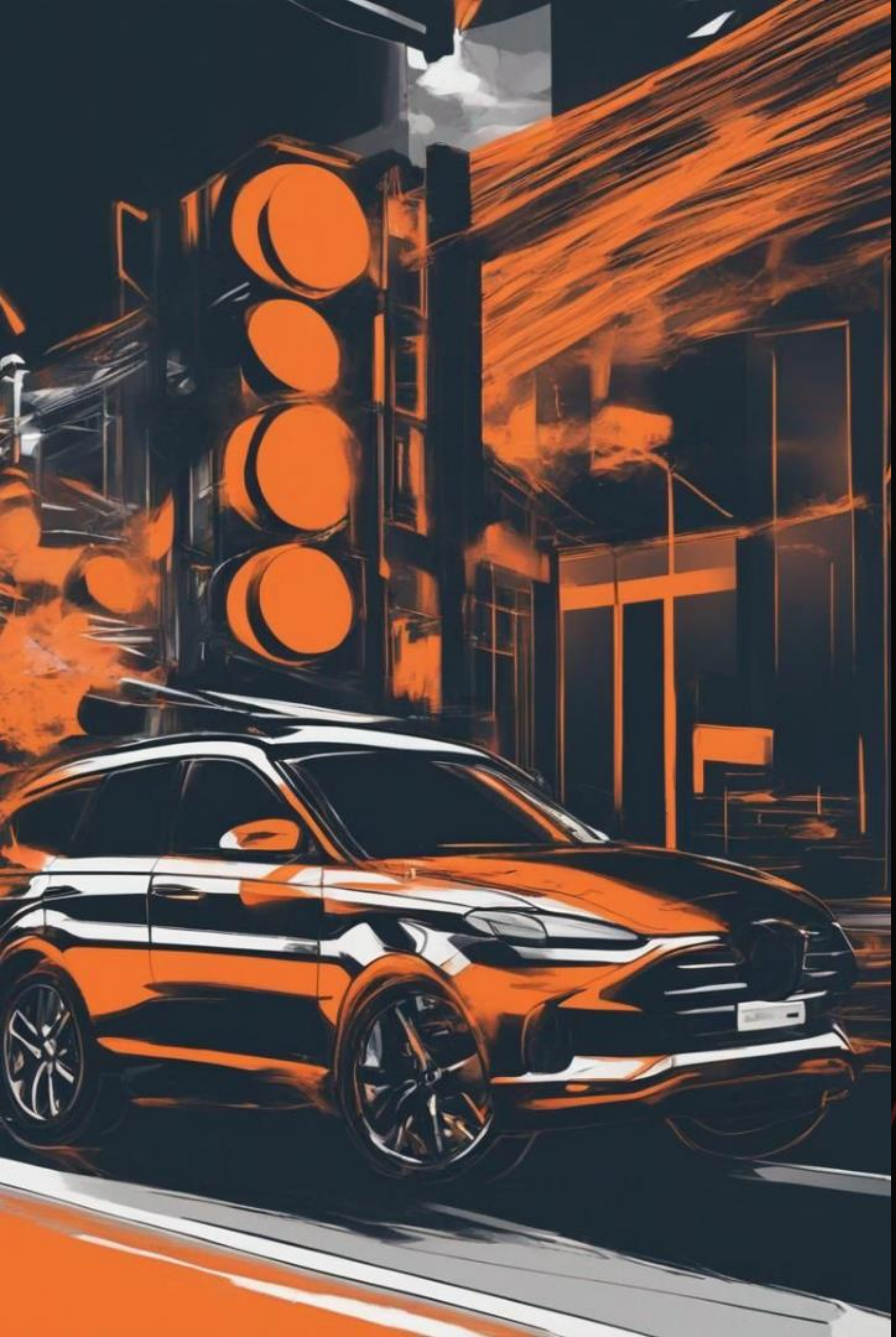

Understanding and Mitigating Distracted Driving: Informative Overview

Distracted driving is a critical concern for road safety, leading to an alarming increase in accidents and fatalities. This report delves into the Distracted Driver Project, focusing on its objectives, research findings, and strategies to enhance road safety.

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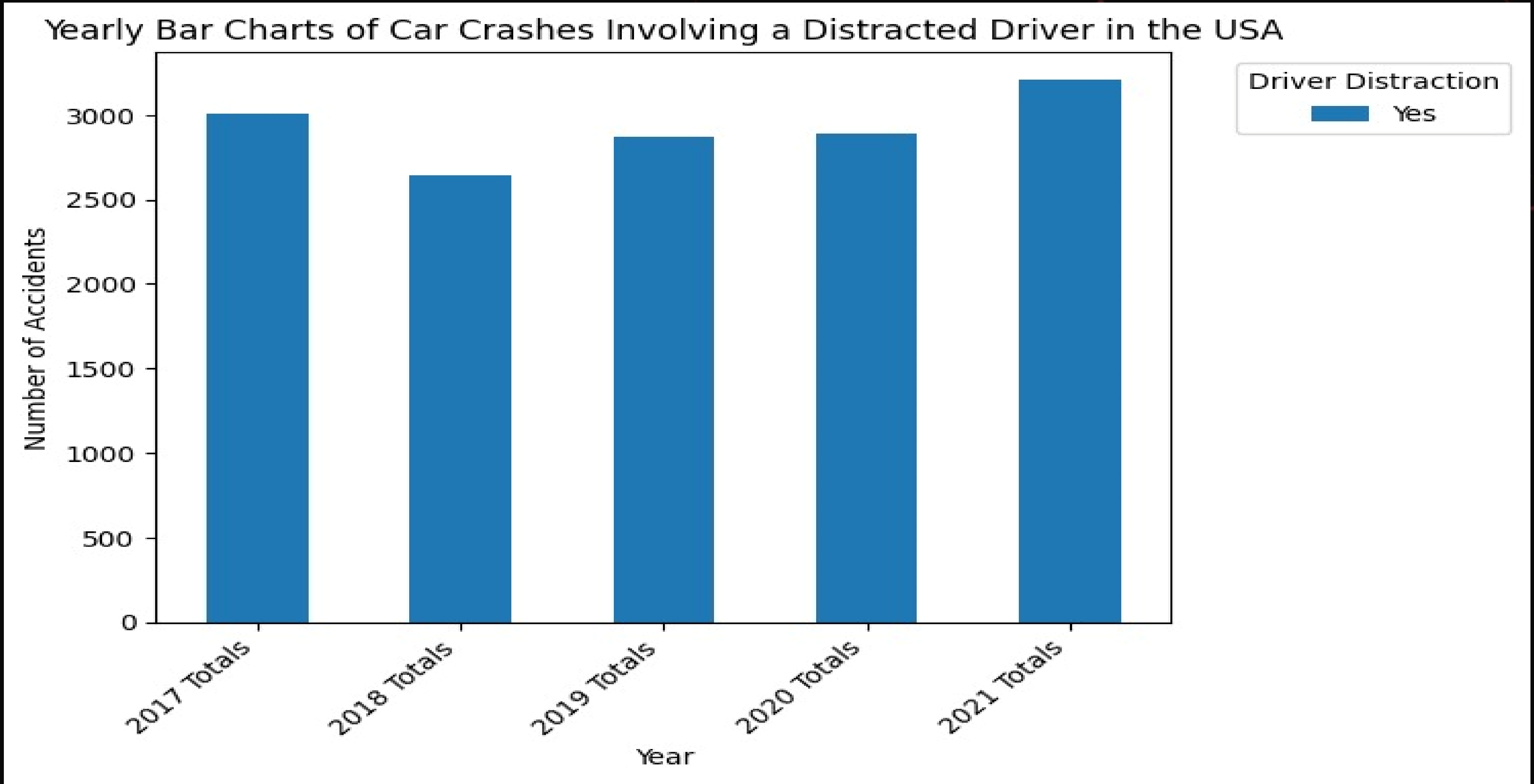
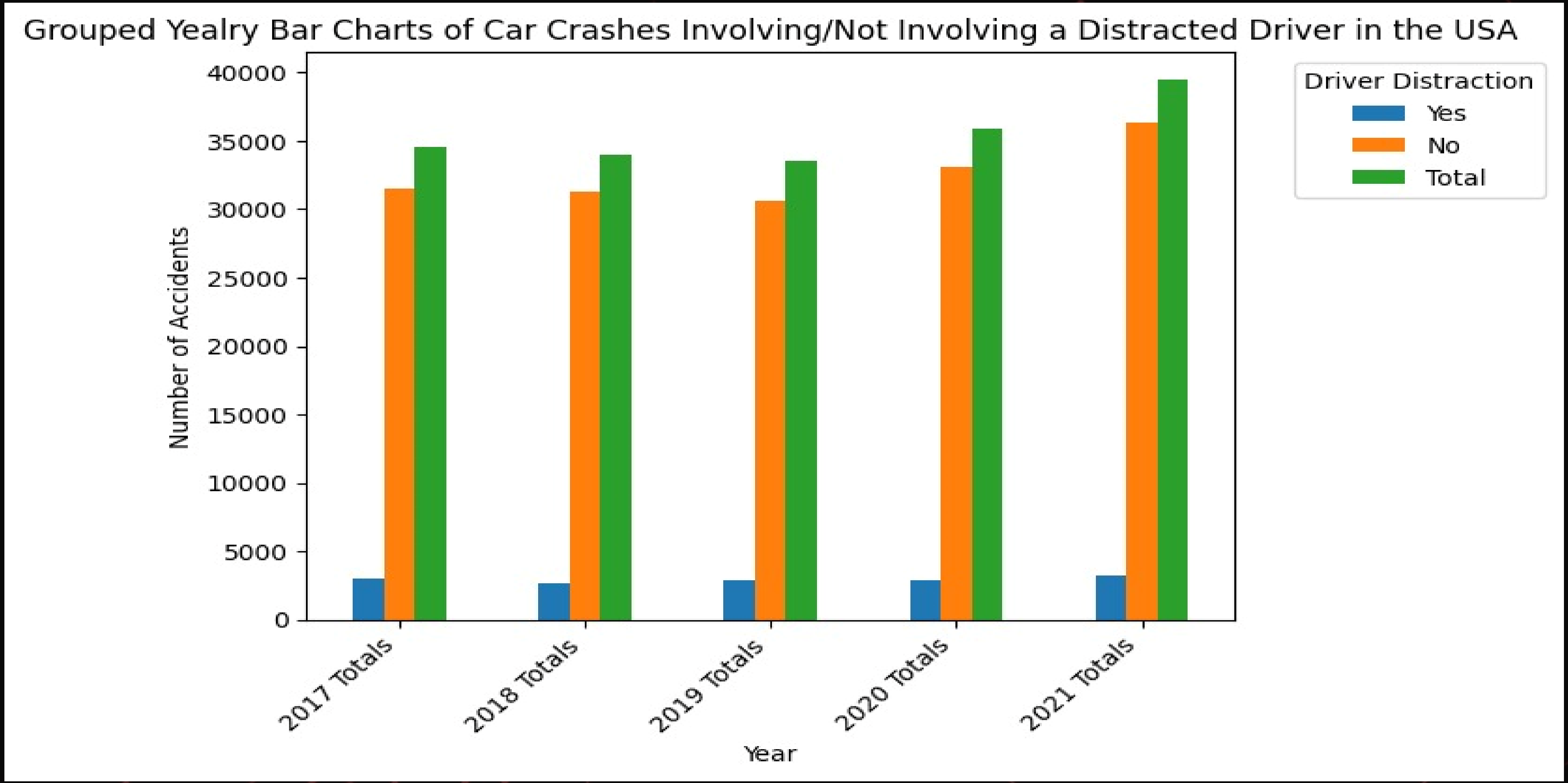
Yearly crashes involving distracted driver



crashes involving/not involving distracted driver



Problem statement and Business Understanding

BUSINESS UNDERSTANDING

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.

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 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 distracted drivers

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

iii.) Real-Time Implementation: Deploy a feedback system that alerts the driver when they're get distracted.

Success/Performance Criteria:

i.) Accuracy: Measure the model's ability to correctly identify instances of driver distraction against a labeled dataset. we're aiming for a minimum test accuracy of 0.9.

ii.) Real-Time Performance: Assess the system's efficiency in processing and detecting distractions within an acceptable time frame (e.g., milliseconds).

iii.) Successful haptic or audio feedback on detecting distraction.

iv.) Robustness: Test the model's performance across diverse environmental conditions, varying lighting, and different types of distractions to ensure consistent and reliable detection.

Research Findings

1 Common Causes

Mobile phone use (texting and calling).

In-car entertainment systems.

External distractions (advertisements, fellow passengers).

2 Data Analysis Highlights

Correlation between mobile phone use and accident rates.

Increased risk during peak traffic hours and in urban areas.

Age-related patterns, with younger drivers more prone to distractions.

Image Data Understanding

Dataset Details

Source: American University in Cairo

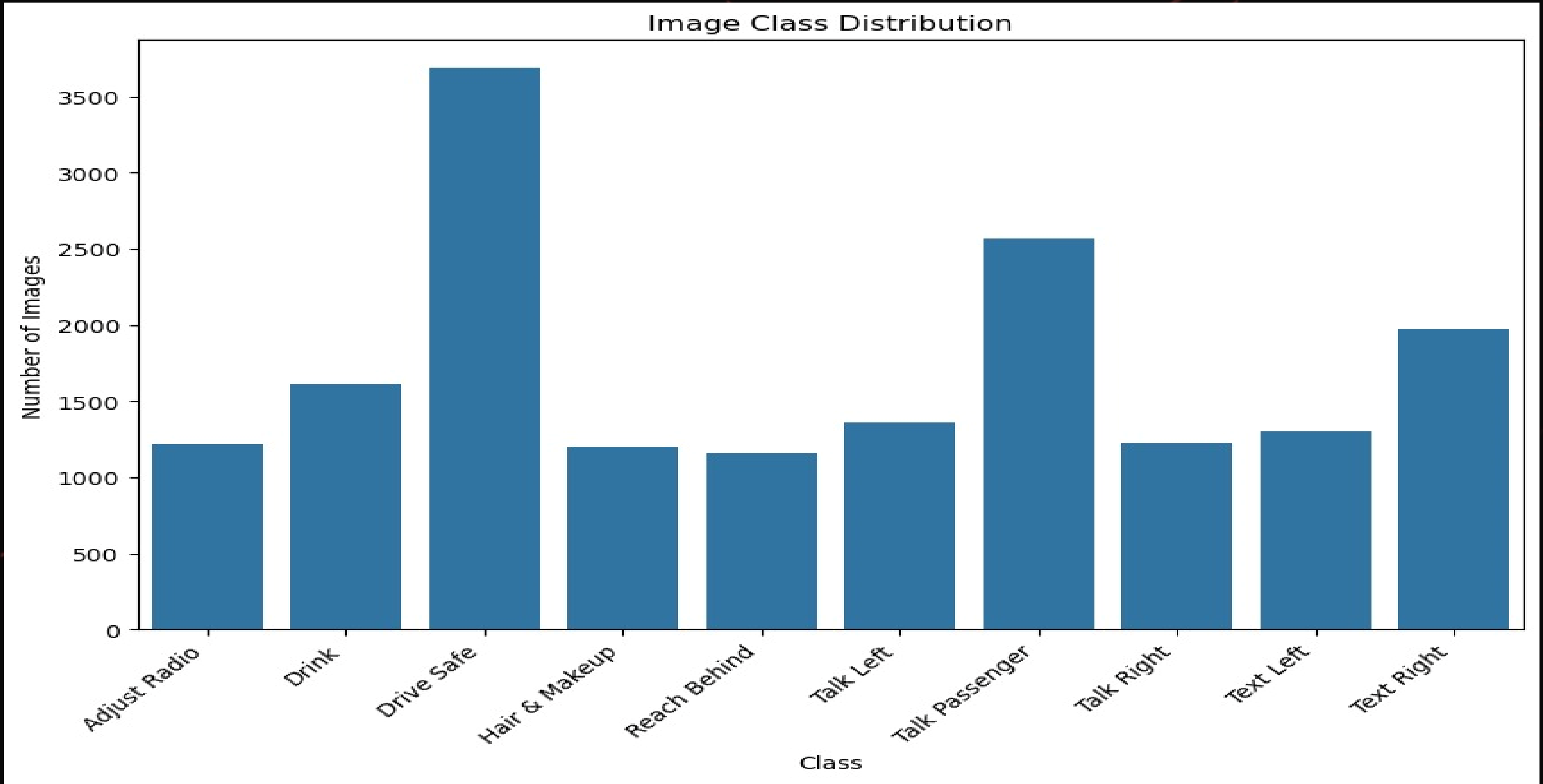
Size: 14,478 images

Classes: 10 categories representing different driving behaviors.

Significance of Image Data

Incorporating image data allows for a nuanced analysis, training machine learning models to improve predictions and gain insights into the visual cues associated with distracted driving.

Image Class Distribution



Sample Photo Images

Machine Learning Models

Baseline CNN

Baseline CNN

Initial model used for comparison.

VGG16

VGG16

Deep learning model known for its accuracy.

VGG19

VGG19

Similar to VGG16 but with more layers.

EfficientNetB0

EfficientNetB0

Efficient model architecture for mobile devices.

Challenges and Considerations

Improved Image Quality

Integration of a deblurring algorithm to counter reflections and shades.

Augmentation algorithm focusing on contrast restoration, flipping, and rotation.

Enhanced Feature Visibility

Preprocessing steps, including contrast adjustments and brightness level tuning.

Corrective measures to mitigate the impact of cropping.

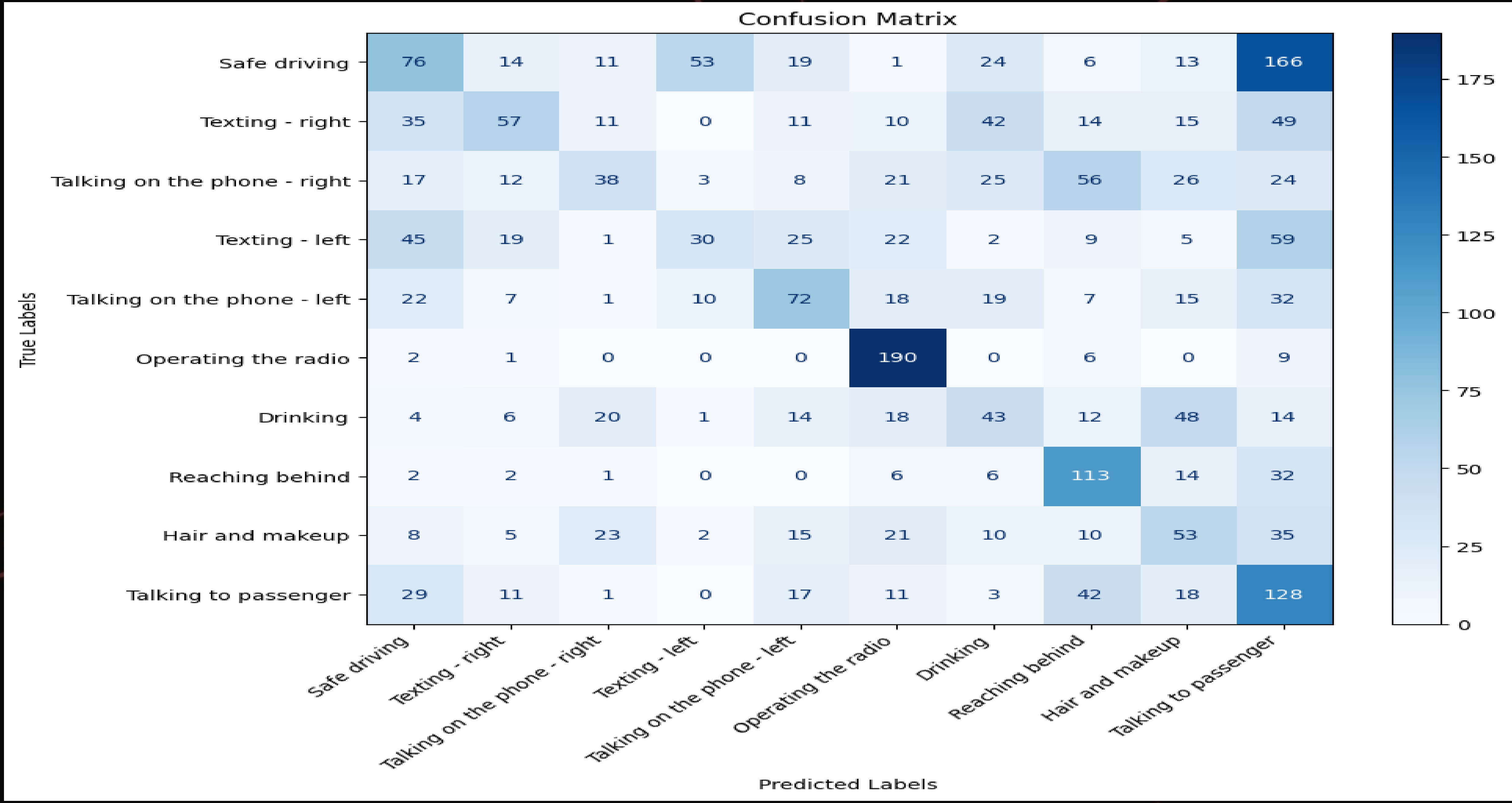
Model Performance

Model Performance Comparison

	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

GoogleNet_Inception recorded the best performance

Confusion matrix



Classification Report

Classification Report

	precision	recall	f1-score	support
Drinking	0.25	0.24	0.24	180
Hair and makeup	0.26	0.29	0.27	182
Operating the radio	0.60	0.91	0.72	208
Reaching behind	0.41	0.64	0.50	176
Safe driving	0.32	0.20	0.24	383
Talking on the phone - left	0.40	0.35	0.38	203
Talking on the phone - right	0.36	0.17	0.23	230
Talking to passenger	0.23	0.49	0.32	260
Texting - left	0.30	0.14	0.19	217
Texting - right	0.43	0.23	0.30	244
accuracy			0.35	2283
macro avg	0.35	0.37	0.34	2283
weighted avg	0.35	0.35	0.33	2283

Observations

- The model has the highest likelihood of a True Positive in the 'operating the radio class', that is, classifying someone as operating the radio when the person is actually operating the radio.
- For a person who is safely driving, there is the highest likelihood of a False Positive, that is, classifying him or her as talking to a passenger while they're actually driving safely.

Observations

Model Evaluation

1.Model Variants:

•Vanilla CNN, VGG16, and VGG19 models on larger image sizes yielded low accuracy results.

•Pretrained models on augmented images did not substantially improve accuracy.

2.Training Approaches:

•Training on camera 1 images versus the combined dataset did not significantly affect model accuracies.

•Dropout regularization and learning rate adjustments had minimal impact.

Observations

Recommendations for Future Work

1.Localized Data Collection:

Collaborate with local authorities and organizations to gather data specific to Kenyan driving behaviors and distractions, enhancing model accuracy and relevance.

2.Video training:

Train models using not just photos but also video footage.

3.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.

4.Real-Time Feedback Refinement:

Further refine the feedback system to minimize False Positive errors, ensuring accurate detection and timely alerts for distracted driving instances.

5.Continuous Improvement:

Continuously evaluate and iterate upon model performance and data augmentation strategies to adapt to evolving driving behaviors and environmental conditions.

6.Hardware improvements:

Increase accessibility of the team to top-tier graphics cards to make work easier for all member

Thank you