# AI SYSTEM TO PREVENT DISTRACTED AND DROWSY DRIVING

# *INTRODUCTION*

- Emphasized the growing importance of **road safety**, including the influence of distracted and drowsy driving on accident rates.

- Our research makes use of AI-powered technologies, specifically Convolutional Neural Networks (CNNs), to identify driver distraction and weariness in real time.

- The goal is to **identify the state of drivers**, lowering the likelihood of accidents caused by human mistake.

# DATA DESCRIPTION (*Drowsy Driver Detection*)

This dataset (https://www.kaggle.com/datasets/banudeep/nthuddd2)[1] contains images of people driving and includes labels for whether the driver is drowsy or not drowsy. It was collected using a driving simulator and head-mounted cameras. The dataset contains about 66000 images.s

### Data Format

The dataset is organized into two folders:

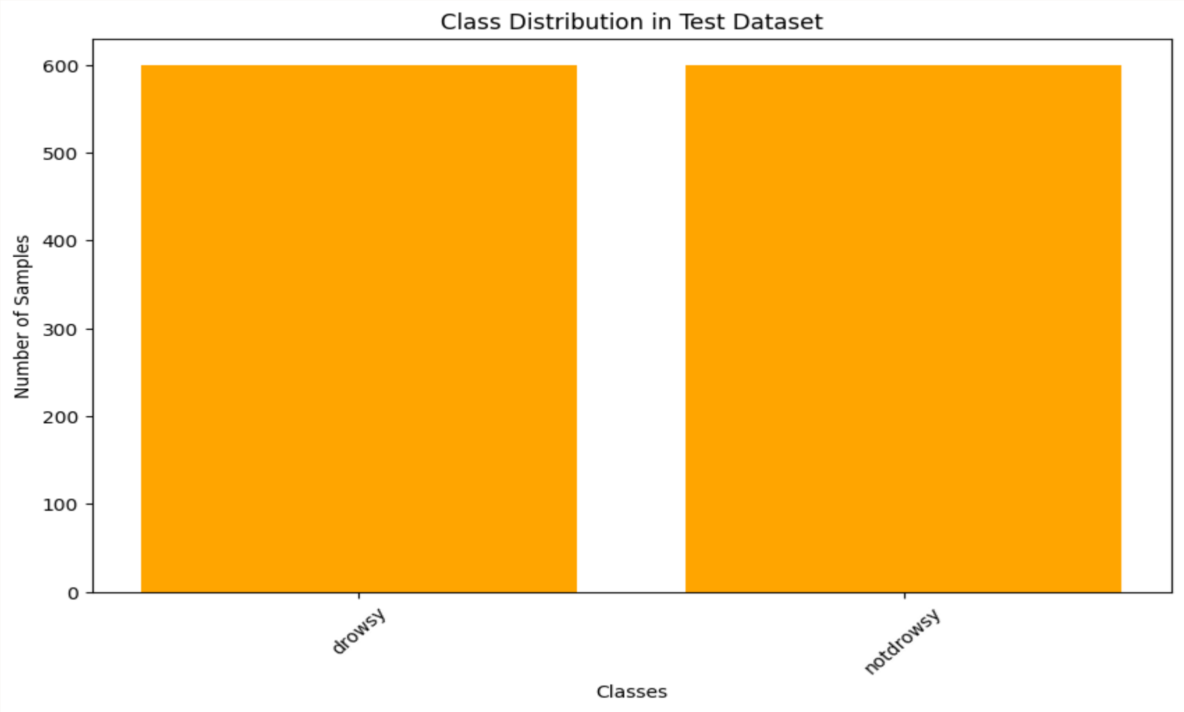
- **train:** This folder contains the training images(2400 for each class).
- **test:** This folder contains the test images(600 for each class).

Each image is a JPEG file with a size of 224x224 pixels. The images are labeled with a binary label: 0 for not drowsy and 1 for drowsy.

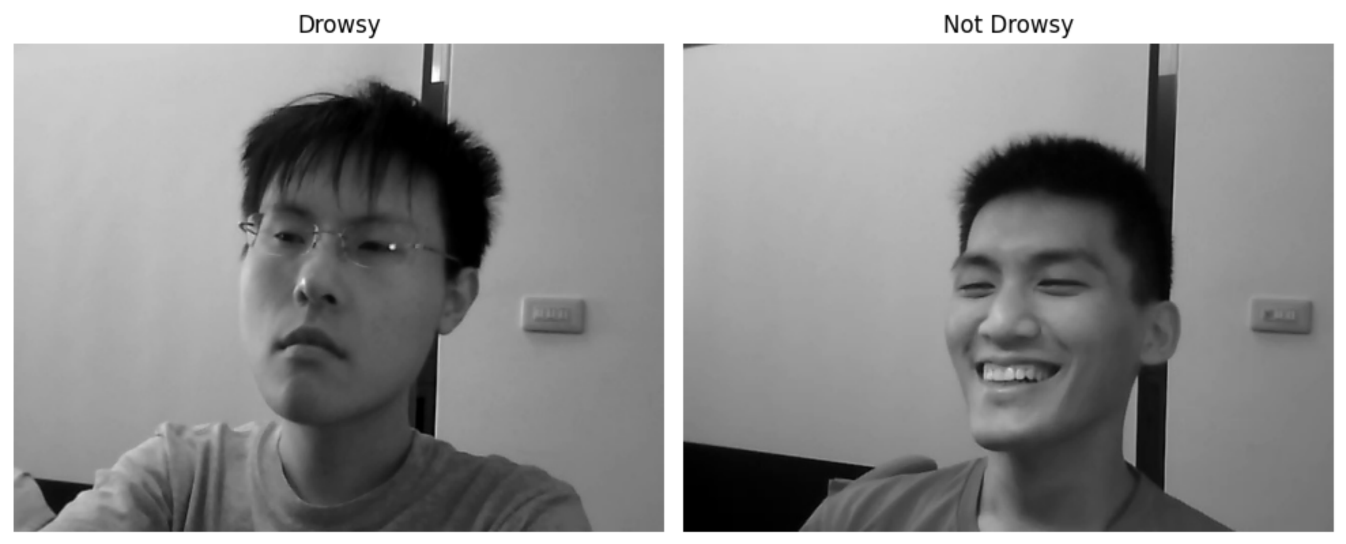
### Data Usage

The dataset is used for training and testing of our model to accurately detect driver drowsiness and ensure reliable real-time predictions.

# DATASET ANALYSIS & VISUALIZATION (Drowsiness)







# METHODOLOGY (Drowsiness)

- Used **Convolutional Neural Networks (CNNs)** for detecting driver drowsiness based on facial features.
- Preprocessed the input data by normalizing the images and applying data augmentation techniques to enhance the model's generalization capabilities.
- **Model Architecture:**
    - Utilized **three convolutional blocks**, each comprising a Convolutional layer, Activation (ReLU), and Max Pooling.
    - Added a Flatten Layer to transform the feature maps into a 1D vector.
    - Included Fully Connected Layers: Dense Layer, Dropout Layer (to prevent overfitting), and Output Layer with a Softmax activation function.
- Compiled the model using the Adam optimizer and sparse categorical crossentropy as the loss function, which is suitable for multi-class classification tasks with integer labels.
- Incorporated callbacks like **ModelCheckpoint** and **EarlyStopping t**o halt training if validation loss plateaus**,** and dynamically adjusts the learning rate.

# *HYPERPARAMETER TUNING & TEST RESULTS (Drowsiness)*

***Train-test data split ratio****:* 80:20

***Learning Rate****:* Set to *0.0001* in the Adam optimizer for gradual, stable convergence.

***Epochs****:* Defined as 10 for the number of training passes. Convolution Filters: Varying numbers (32, 64, 128, 256) capture features at different levels of complexity.

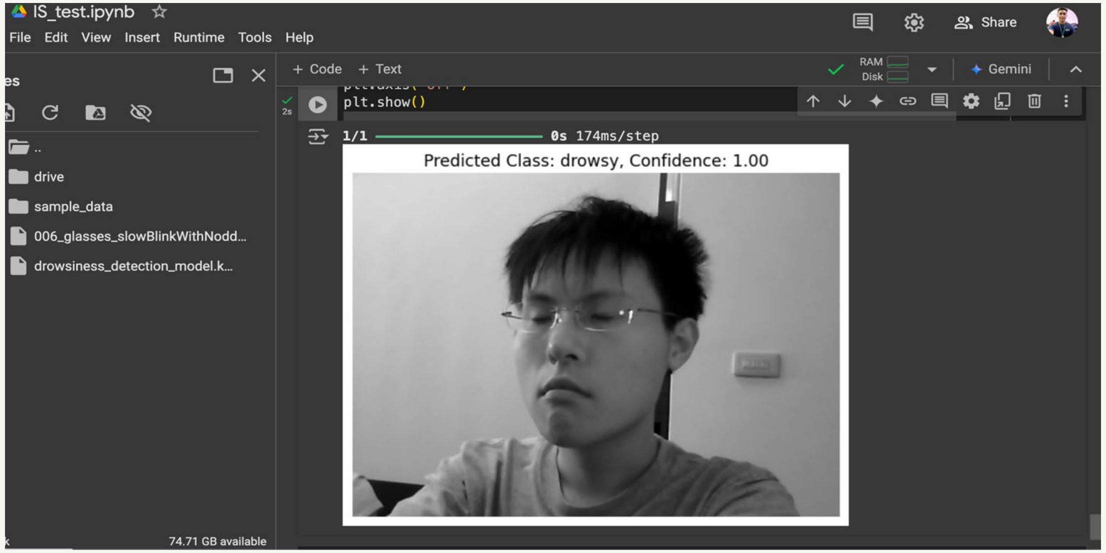
***Kernel Size****: (3, 3)* for detecting fine patterns in data.

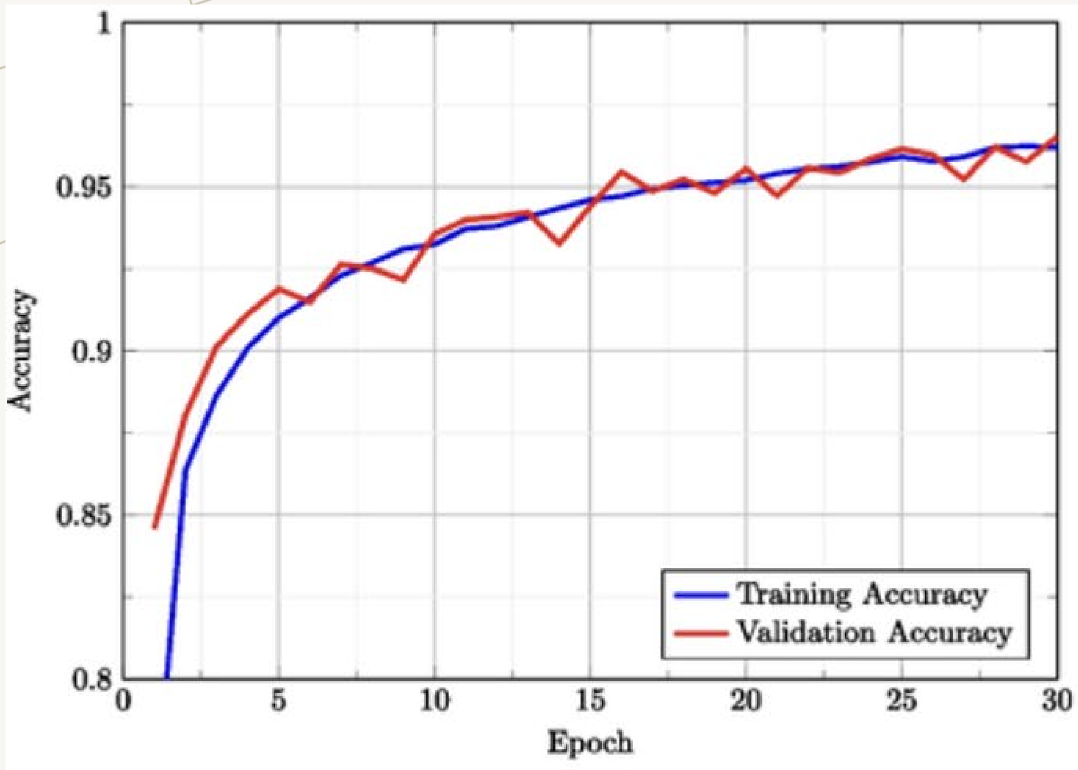
***Callbacks****:* Includes ModelCheckpoint to save the best model and EarlyStopping to halt training if validation loss plateaus.

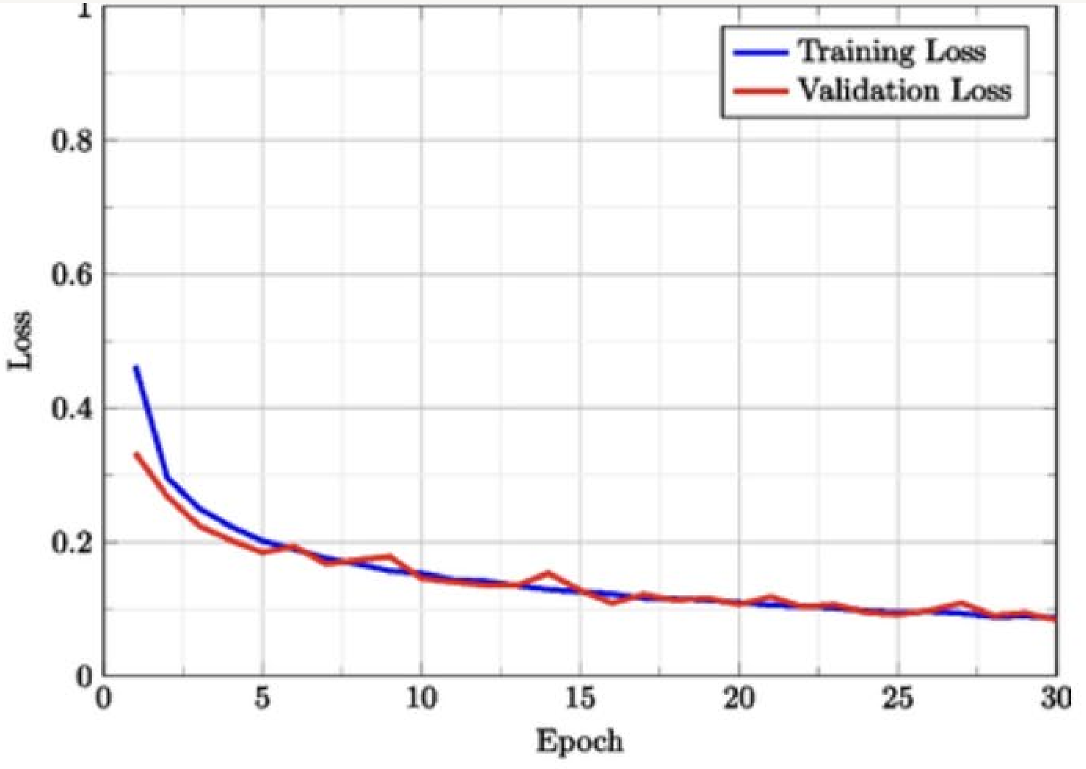
***Dropout Rate****: 0.5* in fully connected layers to prevent overfitting.

Test Loss: 0.04243792966008186
Test Accuracy: 0.9825000166893005

# Visualizations for Drowsiness Detection



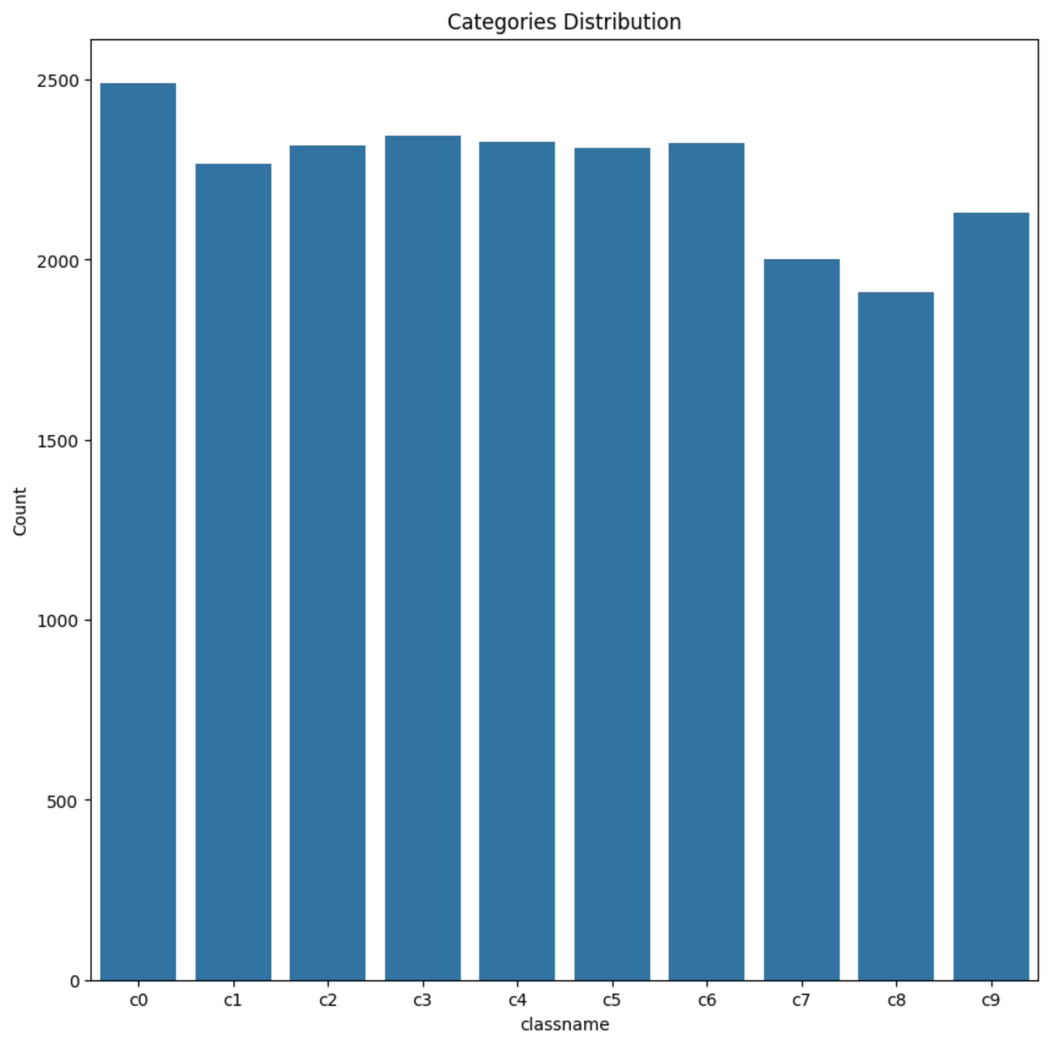



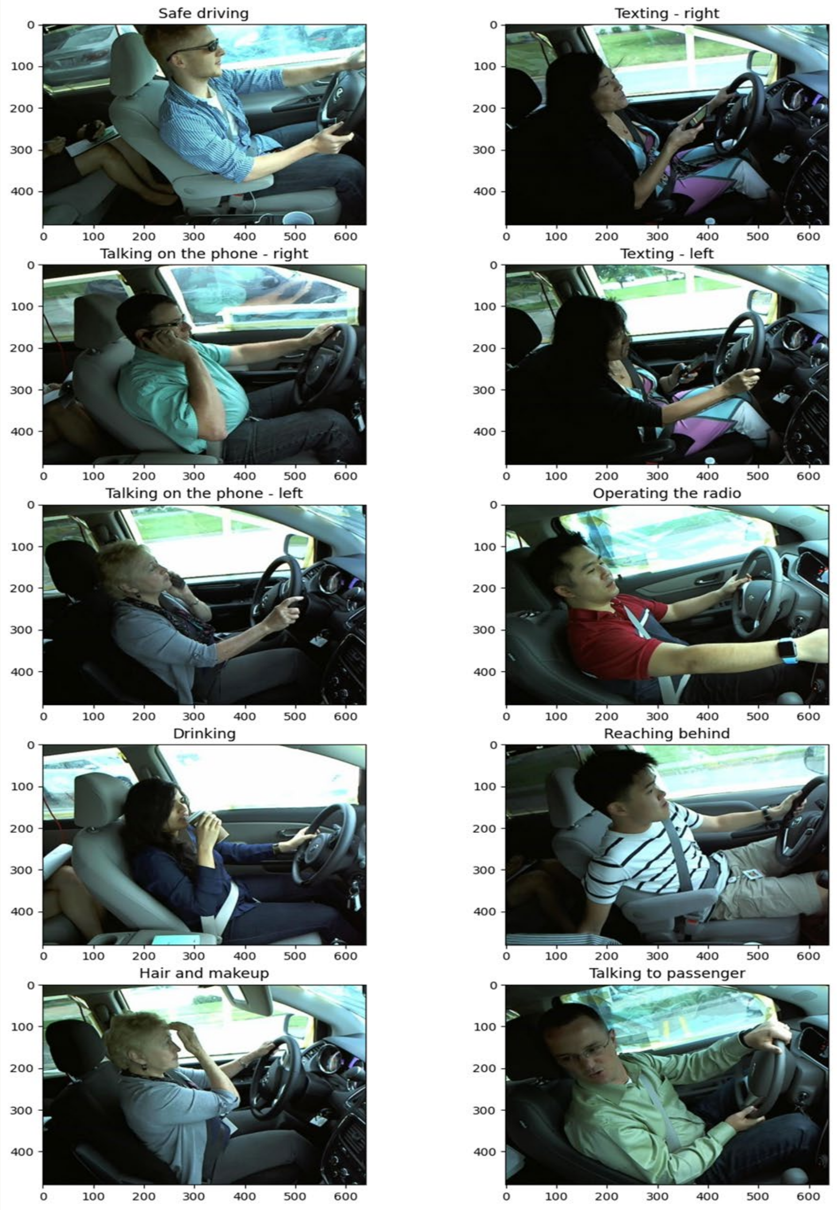



# *DATA DESCRIPTION (DISTRACTED DRIVER DETECTION)*

- State Farm Distracted Driver Detection Dataset (https://www.kaggle.com/competitions/state-farm-distracted-driver-detection/data) [2] consists of labelled photos of drivers taken inside the car.
- These graphics depict ten different types of driver behaviours, including safe driving and various forms of distracted driving. These graphics depict ten different types of driver behaviours, including safe driving and various forms of distracted driving, such as texting, chatting on the phone, eating, and reaching behind.
- Format: RGB photos in ‘jpg’ format, with uniform image dimensions.
- Dataset Content : Over 22,000 labelled photos divided into ten categories.
- Goal: Use the dataset to classify driver behaviors using supervised and deep learning methods in order to prevent distracted driving incidents

# *DATASET ANALYSIS & VISUALIZATION (Distracted)*



# *METHODOLOGY (Distracted)*

- Used *Convolutional Neural Networks (CNNs)* for distracted driver image classification.
- Normalized the images for stabilizing and accelerating the training process of the neural network.
- Model Architecture
  - Four convolutional blocks each consisting of Convolutional layer, Batch normalization, and Max pooling layer.
  - Flatten Layer to convert the 2D feature maps into a 1D array.
  - Fully Connected Layers: Dense layer, Dropout layer and Output layer.
- Compiled the model with the *Adam* optimizer, used categorical crossentropy as the loss function, suitable for multi-class classification tasks.

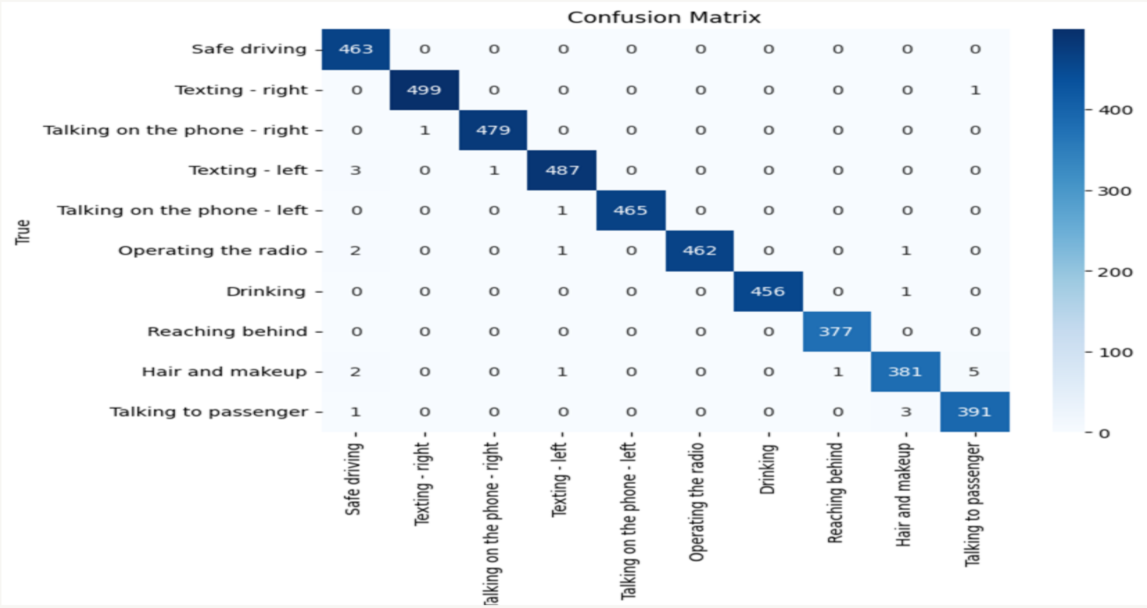
# *HYPERPARAMETER TUNING (Distracted)*

- *Learning Rate:* Set to 0.0001 in the Adam optimizer for gradual, stable convergence.
- *Batch Size*: Fixed at 32 to balance memory use and training efficiency.
- *Epochs:* Defined as 30 for the number of training passes.
- *Convolution Filters*: Varying numbers (32, 64, 128, 256) capture features at different levels of complexity.
- *Kernel Size:* (3, 3) for detecting fine patterns in data.
- *Dropout Rate:* 0.5 in fully connected layers to prevent overfitting.
- *K-Fold Cross-Validation:* Set to 5 for robust performance evaluation($4/5$ th data for training,$1/5$ th data for testing)
- *Callbacks:* Includes ModelCheckpoint to save the best model and EarlyStopping to halt training if validation loss remain unchanged.

# *RESULTS (Distracted)*

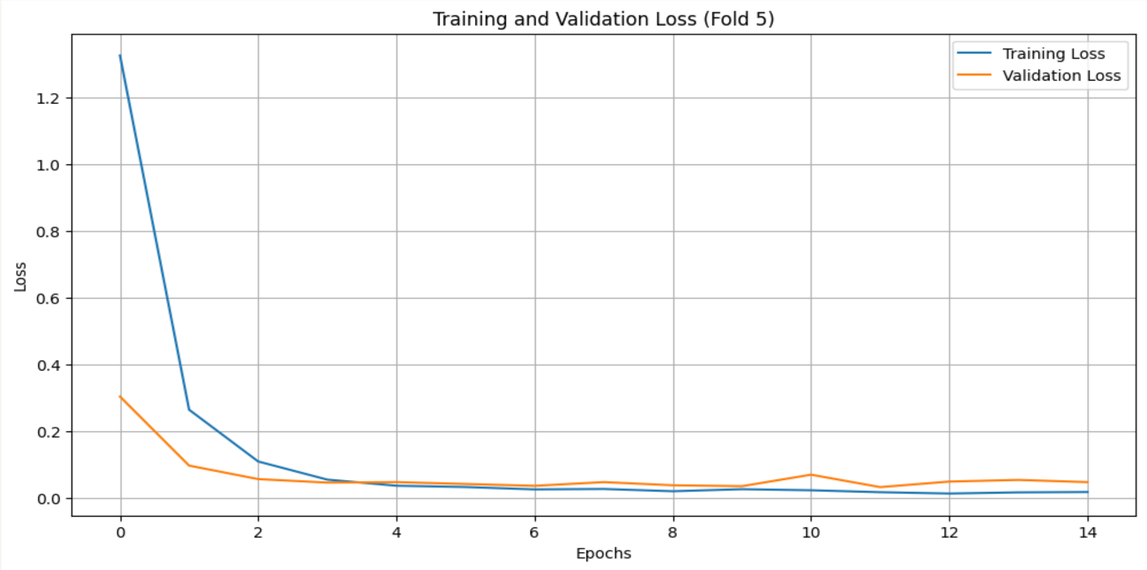
- *Confusion Matrix:* Shows the model's performance across ten classes. High diagonal values indicate correct predictions, such as 499 for "Texting - right" and 463 for "Safe driving". Minimal misclassifications indicate the model's robustness.
- *Evaluation Metrics Table:* Displays the accuracy, precision, recall, and F1 score for each cross-validation fold. Metrics are constantly high (e.g., accuracy varies from *98.9% to 99.3%*), indicating consistent performance across folds.
- *Training and Validation Accuracy Graphs:* The training and validation accuracy curves converge and stabilize, showing no overfitting.
- Validation accuracy remained somewhat higher than training accuracy, at about *99.3%.*
- *Training and Validation Loss Graphs:* Loss decreases quickly in the early epochs and stabilizes, indicating effective learning.
- Both training and validation losses remain low, indicating a well-generalized model.

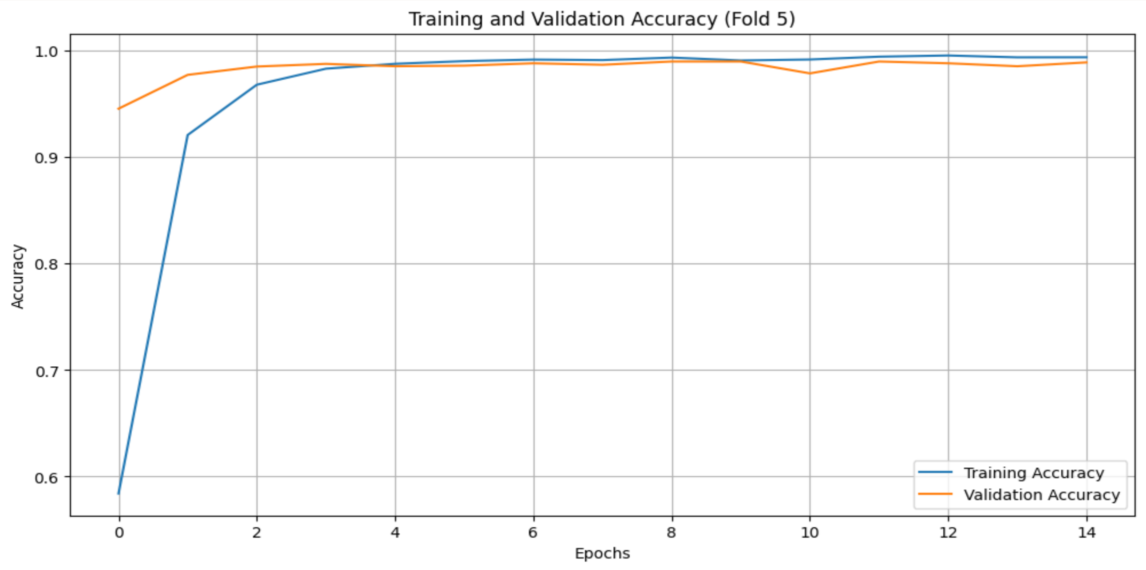
# RESULTS - VISUALIZATION (Distracted)




Evaluation Metrics Table for Each Fold:

| Fold | Accuracy | Precision | Recall |
|---|---|---|---|
| 1 | 0.9904 | 0.9906 | 0.9904 |
| 2 | 0.9940 | 0.9940 | 0.9940 |
| 3 | 0.9924 | 0.9925 | 0.9924 |
| 4 | 0.9920 | 0.9920 | 0.9920 |



# ***CONCLUSION***

- This project developed AI models to detect drowsy and distracted drivers using facial features and driver image data.
- The models achieved excellent accuracy in identifying unsafe driving behaviors, making a significant contribution to road safety.
- ***Challenges Faced:*** One challenge faced was handling large amounts of data, but through effective data preprocessing and optimization techniques, we were able to overcome this and achieve high accuracy and reliability in real-world scenarios.
- ***Future Scope:*** The future scope of this project includes integrating additional sensors and advanced algorithms to enhance accuracy and adaptability for diverse real-world driving conditions.

# REFERENCES

[1] Chen, C.-Y., Wang, C.-C., & Chen, Y.-C. (2019). A drowsiness detection dataset based on driving simulators. IEEE Access, 7, 10322-10330.

[2] M. S. H. S. Bahari and L. Mazalan. "Distracted Driver Detection Using Deep Learning". 2022 IEEE 18th International Colloquium on Signal Processing & Applications (CSPA), Selangor, Malaysia, May 12, 2022.