IN CAB DRIVER DISTRACTION DETECTION

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Abstract

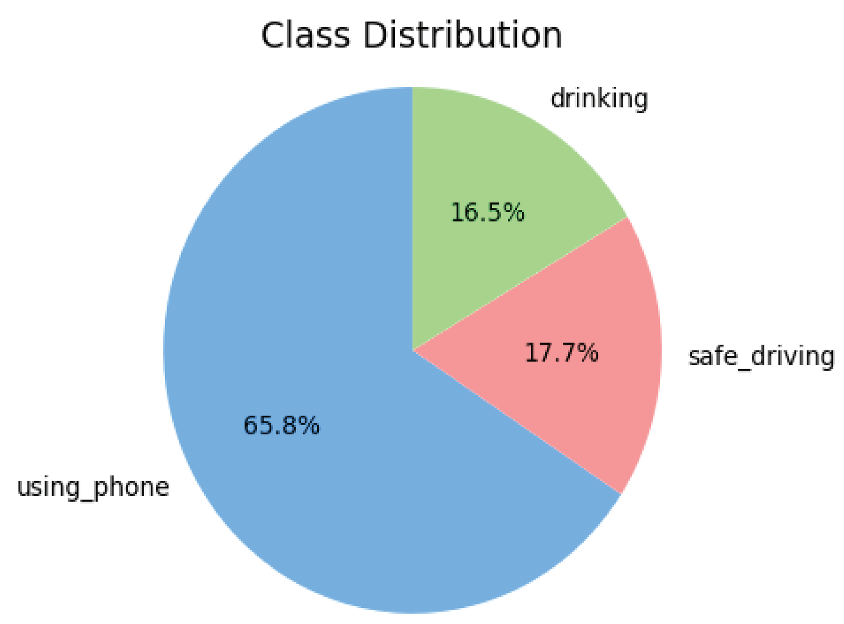
This project addresses the growing issue of **in-cabin driver distractions** by developing a deep learning-based image classification system to identify **unsafe driving behaviours**. Using a curated subset of the **State Farm Distracted Driver Detection dataset**, we focused on three key classes: **safe driving**, **using phone**, and **drinking**. A baseline Convolutional Neural Network was implemented and enhanced with a **custom CNN model** using dropout regularization and class balancing, achieving over **95% test accuracy** with balanced precision and recall. To extend its applicability, we built a **video-to-image inference pipeline** that flags and annotates distracted behaviour in uploaded driving videos, highlighting the potential of computer vision for improving road safety.

Motivation

Distracted driving is a leading cause of **road accidents** worldwide, responsible for millions of crashes and preventable deaths each year. Actions like **using a phone**, **drinking**, or adjusting in-car controls reduce driver focus and raise accident risk. The **World Health Organization** reports over **1.19 million** road traffic deaths annually, with distraction as a major factor. In Ireland, the **Road Safety Authority** links **20–30%** of collisions to distraction, causing over **1,400** serious or fatal crashes yearly. Our project addresses this issue by using deep learning and computer vision to analyse in-cabin driving videos, automatically flagging distracted behaviour to help reviewers identify risks and take preventive action.

Dataset Used

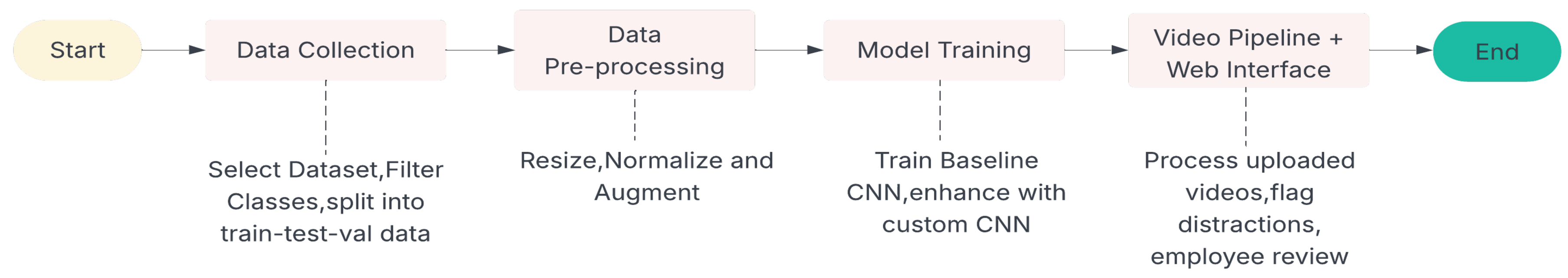
Our project uses the **State Farm Distracted Driver Detection** dataset, focusing on three key safety behaviours: **safe driving**, **using a phone** (merged from multiple phone-related categories), and **drinking**. We worked with about **14,000 images**, splitting them into training, validation, and testing sets, each with metadata for quick access. The classes are imbalanced, with using a phone being the most common and drinking the least, which we kept in mind during model development.



Video Interface + Webpage

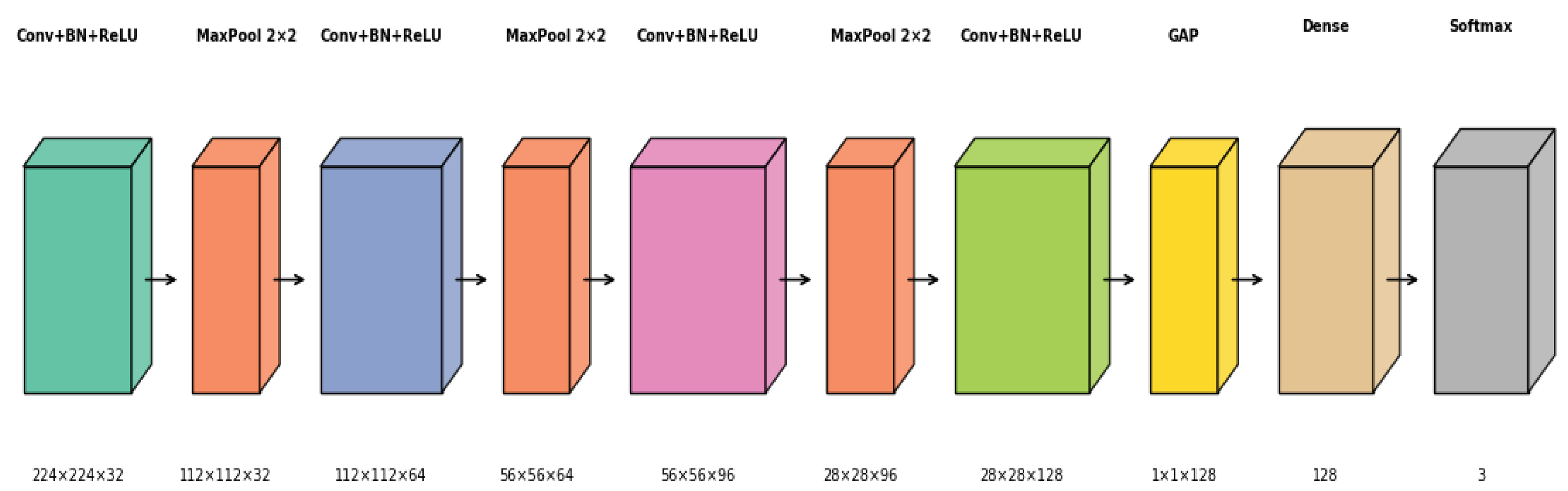
Methodology

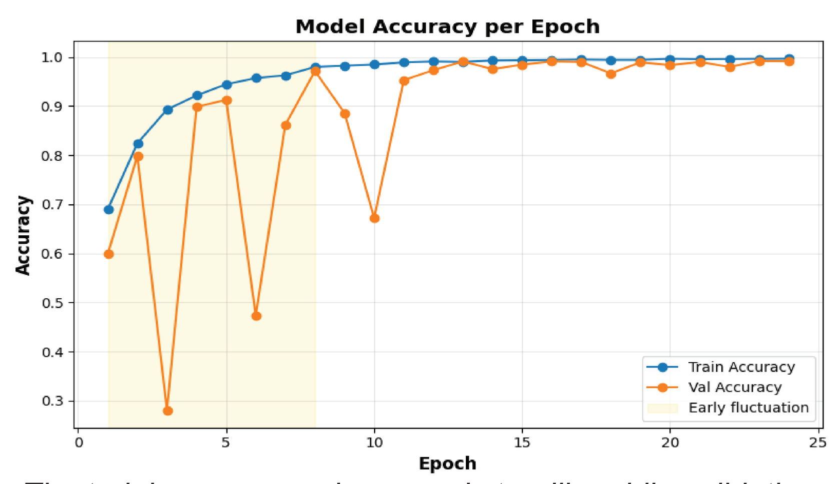
Data Collection: Used the State Farm Distracted Driver Detection dataset, focusing on three key classes: safe driving, using phone, and drinking, organised into train, validation, and test sets with metadata.
Preprocessing: Resized, normalised, and augmented images to standardise inputs and improve generalisation.
Model Training: Developed a baseline CNN and a custom CNN with dropout and class balancing, achieving over 95% test accuracy.
Video Pipeline: Extracted frames from uploaded videos, classified them, and flagged potential distractions for review.
Web Interface: Allowed public video uploads and provided reviewers with tools to assess flagged frames and record decisions.



Model Training and Results

To handle class imbalance, we applied targeted augmentation to minority classes and used class weights during training, ensuring balanced performance across all categories. The custom CNN has four convolutional layers with batch normalization and ReLU activation, max pooling for downsampling, global average pooling, and a dense layer with regularization and dropout, ending with a softmax output for the three driver behaviour classes.

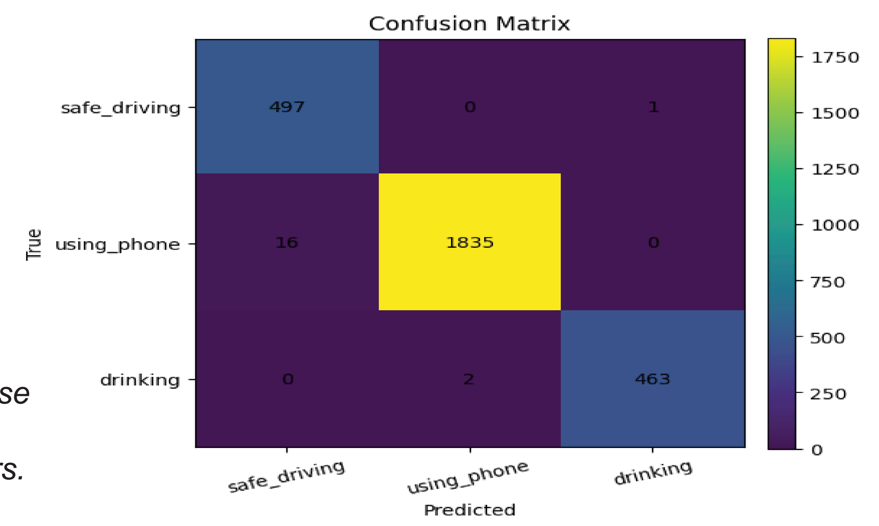




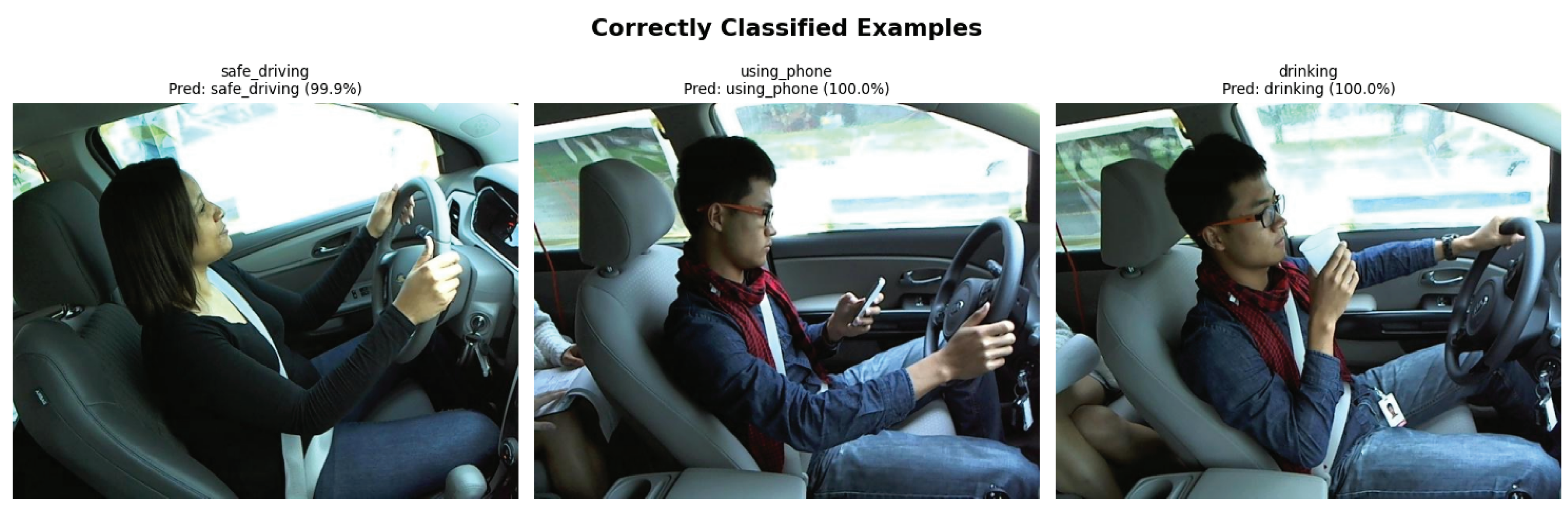
The training accuracy increased steadily, while validation accuracy showed early fluctuations due to heavy augmentation, regularisation, and class weighting effects. After epoch 8, both stabilised above 98%, indicating strong generalisation and effective handling of class imbalance.

Class	Precision	Recall	F1-score	Support
safe_driving	0.969	0.998	0.983	498
using_phone	0.999	0.991	0.995	1851
drinking	0.998	0.996	0.997	465
accuracy				2814
macro avg	0.989	0.995	0.992	2814
weighted avg	0.993	0.993	0.993	2814

The consistently high macro F1 score of 0.992 further confirms that the model performs equally well across all classes, demonstrating that class imbalance was effectively addressed.



The confusion matrix shows how well the model distinguishes between classes, with strong diagonal values indicating high accuracy. The example images highlight one correctly classified case per class, each predicted with high confidence, demonstrating the model's reliability in recognising driver behaviours.



Future Scope