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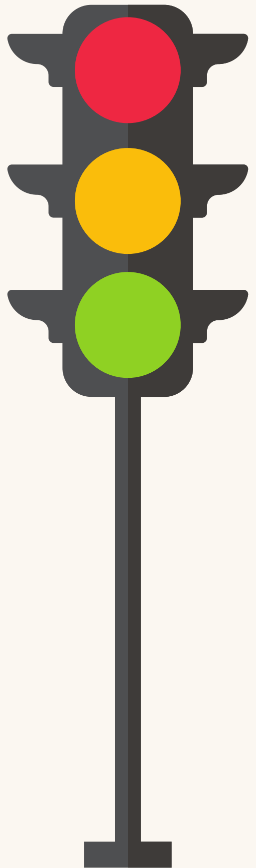
Distracted DRIVER DETECTION

Introduction

"Ever experienced frustration when the car in front doesn't move as the light turns green, or witnessed erratic driving from a seemingly distracted driver? It's a common scenario - from texting to social media scrolling or engaging in animated phone conversations, distractions behind the wheel are all too prevalent."



PROBLEM STATEMENT

Distracted Driver Detection

Can computer vision spot distracted drivers?

OBJECTIVES

- Develop a classification model for driver behavior.
- Improve safety by detecting distractions accurately.
- Improve safety for drivers, pedestrians, and other road users.
- Provide interpretable results.
- Enable continuous improvement with real-world data feedback.

Literature Review

Title	Methodology	Accuracy
Leekha et al. [13]	Proposed a CNN method trained on publicly available datasets.	98.48% (SFD3), 95.64% (AUCD2)
Qin et al. [15]	Introduced a D-HCNN model with a small parameter count.	95.59% (AUCD2), 99.87% (SFD3)
Dua et al. [16]	Enhanced performance of deep learning models for detecting drowsy drivers. Detected features such as hand gestures, facial expressions, behavioral features, and head movements.	85%
Dhakate et al. [2]	Implemented four pretrained DL architectures for distraction classification.	97% (SFD3, AUCD2)
Jabbara et al. [11]	Proposed a real-time drowsiness detection technique based on DNN. Used facial landmark key points detection for driver activity detection.	80%
Hssayeni et al. [9]	Utilized computer vision and ML for detecting drivers' behavior. Depended on transfer learning architectures such as AlexNet, VGG16, and ResNet50.	85%
Valeriano et al. [20]	Compared different deep learning methods for driver behavior classification.	96.6%
Masood et al. [21]	Proposed a CNN-based model for distraction detection and image analysis. Utilized VGG16 and VGG19 architectures.	99% (SFD3)
Majdi et al. [22]	Presented an automated supervised learning method called DriveNet for distraction detection. Reached 95% accuracy using RNN and MLP.	95%
Wöllmer et al. [23]	Proposed an LSTM technique for real-time distraction detection.	96.6%
Baheti et al.	Developed SVM-based model to detect cell phone usage.	91.57%
Abouelnaga et al.	Developed CNN-based system for detecting driver actions.	96.31%
Alshalfan & Zakariah	Applied transfer learning with modified VGG architecture.	~96.95%
Ensemble of Convolutional Neural Networks	Utilized ensemble of CNNs including AlexNet, InceptionV3, ResNet-50, and VGG-16.	90%
Arief Koesdwiady et al.	Compared VGG-19 and XGBoost frameworks for classifying driver distraction.	95%
Other Studies	Various accuracies reported, ranging from around 80% to over 95%.	inf
Pre-Trained Models and Techniques	No specific accuracy mentioned, but various techniques and models contributed to improved performance.	na

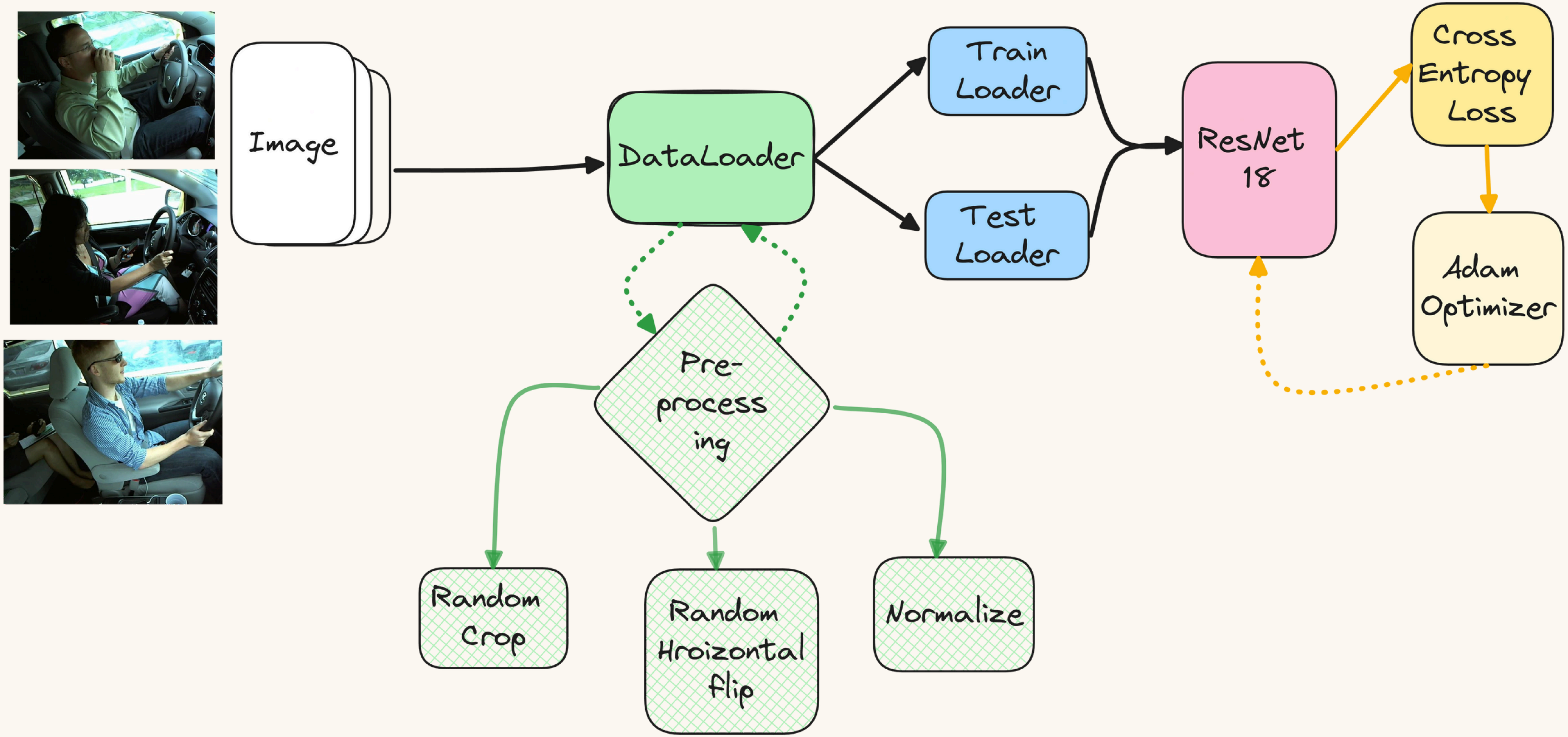
DATASET

DRIVER IMAGES, EACH TAKEN IN A CAR WITH A DRIVER DOING SOMETHING IN THE CAR (TEXTING, EATING, TALKING ON THE PHONE, MAKEUP, REACHING BEHIND, ETC).

THE 10 CLASSES TO PREDICT ARE:

- C0: 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

METHODOLOGY



RESULT

	Resnet 18	VGG-16
Training	92%	40%
Validation	49%	10%

Future work

1. Real-time Detection Systems:
2. Personalization and User Feedback:
3. Education and Awareness Campaigns:

REFRENCES

https://www.kaggle.com/competitions/state-farm-distracted-driver-detection/code

https://www.sciencedirect.com/science/article/pii/S2667305322000163

https://arxiv.org/pdf/2204.03371

https://www.mdpi.com/1424-8220/23/8/3835

https://pytorch.org/vision/main/models/generated/torchvision.models.resnet18.html

THANK YOU!