ECE 579 Intelligent Systems, Fall 2024

PROJECT FINAL REPORT

Project title: *AI System to Prevent Distracted and Drowsy Driving*

Introduction

Road safety has been a crucial concern in recent years, with distracted and drowsy driving causing a considerable increase in accident rates. This idea offers an AI-powered system that monitors driver behaviour in real time, detecting indicators of distraction and exhaustion to prevent accidents. The system analyses both visual and behavioural data, using modern technologies such as Convolutional Neural Networks (CNNs), to offer timely alarms, hence improving road safety.

The project describes the development and execution of an AI-powered system aimed at improving road safety by recognising distracted and fatigued drivers. The research tackles a key issue in transportation safety by using cutting-edge machine learning techniques, specifically Convolutional Neural Networks (CNNs), to monitor and analyse driver behaviour in real time. The goal is to develop a holistic system that not only detects unsafe behaviours but also avoids accidents by sending timely alerts. The study describes the technologies, methodologies, and experimental results that demonstrate the system's efficacy in reducing road risks.

This report provides a detailed overview of the procedures we followed to develop the AI system for preventing drowsy and distracted driving, covering all stages thet include background study,dataset selection, methodology,evaluation and testing.

Description of Technologies

Bahari and Mazalan[1] utilized a ResNet-50-based model that effectively identifies drivers looking away from the road. This methodology achieved a very good accuracy of 94% on the State Farm dataset and was able to highlight deep learning's potential for road safety. The drawback is that the model provides a narrow focus on specific distractions and is heavily dependent on the dataset. Also, there are challenges with consistent accuracy in various real-world conditions.

The paper "Driver Drowsiness Detection Using Deep Learning"[2] reviews different methods to detect driver drowsiness. It includes techniques like physiological measures, tracking eye movements, and machine learning, and also details their advantages and limitations. Here, individual variability in sleep patterns and environmental factors are identified as the key challenges in drowsiness detection. The study also outlines functional requirements for developing effective systems, including accuracy and user-friendliness. The authors also explored various machine learning algorithms for drowsiness detection including Random Forest, Support Vector Machines (SVM) and various neural network architectures, and also proposed improvements based on machine learning algorithms by utilizing EEG and ECG data of the driver.

Das et al. [3] performed a detailed study by exploring multimodal signals such as head pose, gaze, and hand movements to improve the accuracy of driver distraction detection. This approach provides a comprehensive understanding of distraction and supports a wide range of real-world behaviors that can be used to enhance in-vehicle safety systems. But the model is influenced by complex data inputs that make it resource-intensive and challenging for real-time application. Also, differences in individual behavior may affect its reliability.

In [4], the authors provided an in-depth overview of advancements in driver drowsiness detection. The paper mainly focused on techniques like facial feature tracking, monitoring of physiological signals, and machine learning algorithms. They pointed out the advantages of combining multimodal approaches for higher accuracy and emphasized challenges such as the influence of environmental factors, individual variability, and complex technicalities. This paper identifies gaps in current research, such as the need for user-friendly and real-time solutions that work effectively across diverse driver populations.

The paper "Detecting Driver Distraction Using Deep-Learning Approach"[5] inspects and utilizes convolutional neural networks (CNN), more specifically a modified architecture of VGG-16, that categorized driver distractions from a set of in-car images. This model could achieve a high accuracy of 96.95% while using the StateFarm dataset. The paper also emphasizes the relevance of using deep learning to automate driver distraction detection, which is a very essential feature in vehicle automation. This study suggests that integrating this model with additional sensors or behavioral metrics can further enhance the accuracy of detection and it helps to address limitations with similar actions. The authors propose future developments in personalized distraction detection by adjusting model sensitivity to each driver's unique patterns, which could make in-vehicle systems more adaptable and responsive. The key advantage of this method is the excellent classification accuracy and the potential to reduce road accidents by identifying specific distractions such as the usage of mobile phones or interaction with passengers. The limitation of this model is its complex architecture which limits real-time deployment. Also, it struggles with certain similar distractions, such as "Driving Normal" versus" Talking to passengers.

"Detection of Distracted Driver Using Convolutional Neural Network" [6] explores convolution neural networks that accurately detects distracted driving and identifies some specific distractions with the help of VGG-16 architecture that is fine-tuned. This model is able to achieve around 96.31% accuracy on the Abouelnaga dataset. The Abouelnaga dataset includes 10 types of distractions like eating, texting, and talking to passengers. Pros of this model are high classification accuracy and great computational efficiency. The model is able to process 42 images per second which is really good. However, it struggles with some actions which are visually similar, like safe driving versus talking to a passenger. Also, the model demands high memory requirements, which may limit deployment in real-time.

Methods Used in the Project

The project follows a structured workflow to effectively address the challenges of detecting distracted and drowsy driving behaviours in real-time. The project follows a structured workflow:

1. ***Data Collection:*** Data was gathered from two major sources: the nthuddd2 (https://www.kaggle.com/datasets/banudeep/nthuddd2) dataset with 66,500 images labelled for drowsiness and the State Farm dataset containing 22,000 images across 10 driver behaviours(https://www.kaggle.com/competitions/state-farm-distracted-driver-detection/data). These datasets provided a comprehensive base for training and testing the model. Datasets include the nthuddd2 and State Farm Distracted Driver Detection datasets, comprising over 88,500 labelled images depicting driver behaviours.
2. ***Data Pre-processing:*** The pre-processing phase included scaling, normalization, and augmentation of images using tools like OpenCV and TensorFlow. This ensured that the model received high-quality, balanced input for effective training. Images are scaled, normalized, and augmented using OpenCV and TensorFlow libraries.
3. ***Model Building*** **:** Focused on developing two distinct convolutional neural networks (CNNs) designed for specific applications: one for detecting driver drowsiness and the other for identifying distracted driving behaviors.

a. *Driver Drowsiness Detection* : The methodology for detecting driver drowsiness uses a Convolutional Neural Networks. The model consisted of three convolutional blocks with ReLU activations and max pooling, followed by a flatten layer and fully connected layers with a dropout rate of 0.5 to prevent overfitting. The output layer used softmax activation for multi-class classification. The model was compiled with the Adam optimizer (learning rate 0.0001) and sparse categorical crossentropy loss. Hyperparameter tuning was performed with an 80:20 train-test split for 10 epochs, varying convolution filters (32, 64, 128, 256), and a kernel size of (3, 3). Callbacks like ModelCheckpoint and EarlyStopping were used for model optimization and early termination.

b. *Distracted Driver Detection:* The methodology for distracted driver image classification using Convolutional Neural Networks (CNNs) involved normalizing the input images to stabilize and accelerate the training process. The model architecture consisted of four convolutional blocks, each including a convolutional layer, batch normalization, and max pooling, followed by a flatten layer to convert the 2D feature maps into a 1D array. The fully connected layers included a dense layer, dropout layer (set at 0.5 to prevent overfitting), and an output layer for classification. The model was compiled using the Adam optimizer with a learning rate of 0.0001 and categorical crossentropy as the loss function. Hyperparameter tuning involved setting the batch size to 32 for a balance between memory usage and training efficiency, and training for 30 epochs with varying convolution filters (32, 64, 128, 256) and a kernel size of (3, 3) to capture fine patterns. K-fold cross-validation (with k=5) was used for robust performance evaluation, and callbacks like ModelCheckpoint and EarlyStopping helped optimize the model and prevent overfitting.

4. ***Training:*** During training, the model was optimized using the Adam optimizer with a learning rate of 0.0001, and the sparse(drowsiness) and categorical(distracted driver) crossentropy loss function was used for multi-class classification. The model was trained in batches of 32 for various epochs, with hyperparameter tuning applied to enhance performance and prevent overfitting.
5. ***Evaluation :*** Model performance was assessed using metrics like accuracy, precision, recall, and F1 scores. Confusion matrices provided insights into classification effectiveness, highlighting areas for improvement. Also the training-validation accuracy and training-validation loss graphs are plotted.
6. ***Testing :*** Finally both the models were tested with unseen, unlabelled data.

Experiments

The project involves gathering large amounts of data, preparing it for model compatibility, and creating a robust CNN architecture. The key phases were supplementing datasets to reflect real-world circumstances, fine-tuning the model for maximum efficiency, and verifying it against previously unseen data.

Data

The nthuddd2 dataset includes 66,500 photos labelled as drowsy or not drowsy. The State Farm dataset contains 22,000 photos representing ten driver behaviours such as texting, reaching behind, eating, safe driving etc.

Experiments Conducted

- Exploratory Data Analysis to plot the distribution of images across categories to analyze data balance.
- Evaluation Metrics Calculation to evaluate model performance using accuracy, precision, recall, and F1-score metrics on the test dataset.
- Confusion Matrix and Classification Report to analyze misclassifications and provide a detailed report of performance per class.

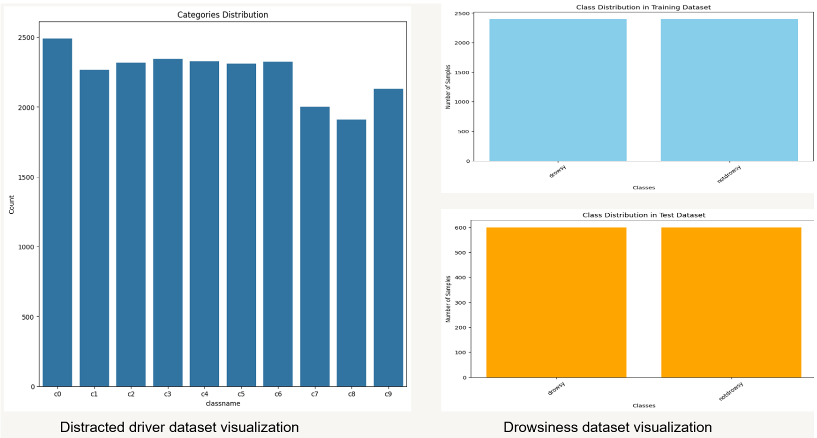


Figure 1 : *Exploratory Data Analysis*

Results

- Training and validation accuracies were consistently around 99.3%, indicating a well-generalized model.
- Confusion matrices demonstrated very few misclassifications, indicating good dependability in real-time applications.
- Evaluation measures demonstrated consistent performance across folds.
- Metrics such as F1 scores supported the model's balanced performance across all areas.

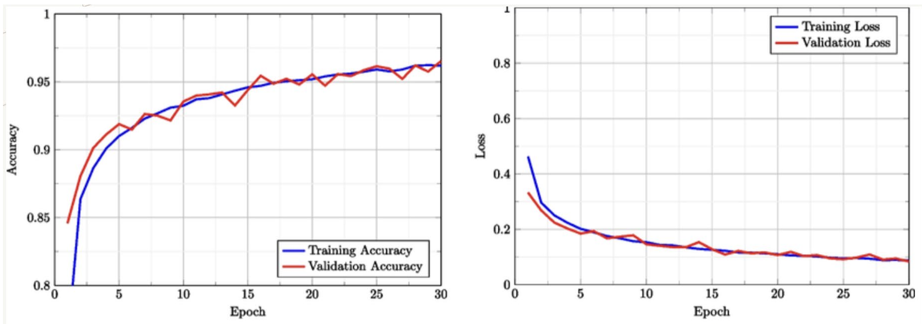
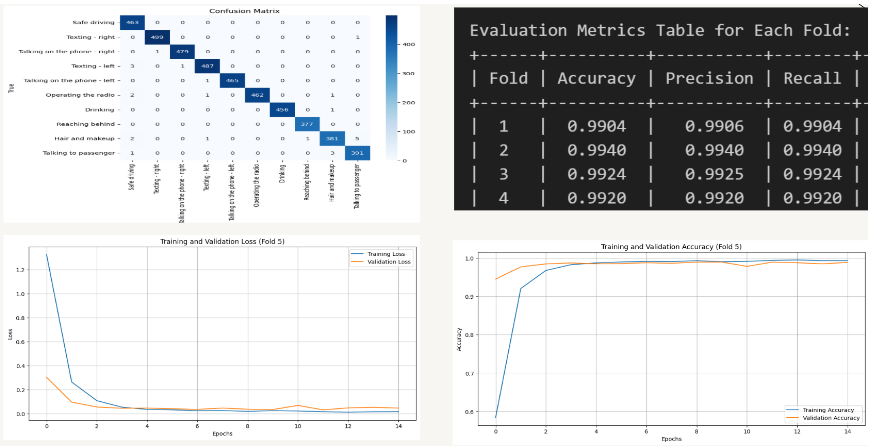


Figure 2 : *Accuracy and loss Plots for Drowsiness Detection*



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

Figure 3 : *Results of Distracted Driver Detection*

The results demonstrate the effectiveness of using CNNs in this application. High accuracy rates and rigorous evaluation metrics show that the system can detect both distracted and drowsy driving behaviours. While the system performs well under controlled conditions, future versions should focus on improving performance in a variety of environmental scenarios, such as low lighting and extreme angles.

Conclusion

The results demonstrate the effectiveness of using CNNs in this application. High accuracy rates and rigorous evaluation metrics show that the system can detect both distracted and drowsy driving behaviours. While the system performs well under controlled conditions, future versions should focus on improving performance in a variety of environmental scenarios, such as low lighting and extreme angles.

Learnings from the Project:

From this project, we have learned that Convolutional Neural Networks (CNNs) are highly effective for detecting distracted and drowsy driving behaviors, as evidenced by high accuracy rates and robust evaluation metrics. The use of techniques like data augmentation, K-fold cross-validation, and hyperparameter tuning during training helped simulate real-world conditions, reduce bias, and enhance the model's generalization. However, the project also highlighted areas for improvement, particularly in addressing performance challenges under diverse environmental conditions, such as low lighting and extreme angles. These insights underline the importance of rigorous experiment design and the potential of CNNs for real-world applications, while also emphasizing the need for continuous refinement to ensure reliability across varied scenarios.

Code Links :

Distracted Driver Detection -
https://drive.google.com/file/d/1vEtDu_rpSJUTVcRgJ7q3c1g2dLkLDhj0/view?usp=drive_link
Drowsiness Detection -
https://drive.google.com/file/d/1F14fGmilee83gXND6nu4oGMUqCSpZ0dC/view?usp=sharing

References:

[1] 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.

[2] D. Ojha et al., "Driver Drowsiness Detection Using Deep Learning". in 2023 4th International Conference for Emerging Technology (INCET), Belgaum, India, 2023.

[3] A. Das and R. Mihalcea et al., "Detection and Recognition of Driver Distraction Using Multimodal Signals". ACM Transactions on Intelligent Systems and Technology, vol. 13, no. 2, Article 22, 2022.

[4] Yaman Albadawi, Maen Takruri."A Review of Recent Developments in Driver Drowsiness Detection Systems." PubMed Central, 2022.

[5] Alshalfan, Khalid & Zakariah. Mohammed. (2021). "Detecting Driver Distraction Using Deep-Learning Approach". Computers, Materials & Continua. 68. 689-704. DOI. 10.32604/cmc.2021.015989.

[6] B. Baheti, S. Gajre, and S. Talbar. "Detection of Distracted Driver Using Convolutional Neural Network". 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2018. DOI: 10.1109/CVPRW.2018.00150.