Enhancing Road Safety: Detecting Aggressive Driving Behaviors on Highways Using 1D Convolutional Neural Networks

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Abstract

Road traffic accidents pose a significant global public health challenge, resulting in millions of deaths and injuries each year. This paper investigates the use of artificial intelligence (AI) and machine learning (ML) techniques to analyze and classify driver behaviors, with a particular focus on detecting aggressive driving style on highways. A one-dimensional convolutional neural network (1D CNN) was employed to process and analyze driving data from the UAH-DriveSet dataset and independently collected real datasets for safe driving, with aggressive driving data simulated from this safe driving dataset. The model developed in this research demonstrated good generalization capabilities across different drivers. The integration of this model into real-time driver monitoring systems has the potential to significantly enhance road safety by alerting drivers to dangerous behaviors and encouraging safer driving practices.
Keywords *- Road safety, driver behavior, artificial intelligence, machine learning, aggressive driving detection, Real-time monitoring.*

1 Introduction

Road traffic accidents, a major global public health burden, result in millions of deaths and injuries annually. World Health Organization (WHO) data indicate that approximately 1.19 million people die on roads each year, with an additional 20 to 50 million suffering non-fatal injuries [1]. Driver behavior monitoring plays a crucial role in promoting road safety, as aggressive driving behaviors, in particular, have often been identified as key factors contributing to serious accidents [1]. In light of this alarming trend, developing and implementing innovative solutions to enhance road safety is crucial. This article explores the application of artificial intelligence (AI) techniques to classify driver behaviors, with a particular focus on detecting aggressive driving on highways.

Researchers have made significant advancements in leveraging machine learning techniques to identify aggressive driving behaviors, paving the way for safer roads. These developments have been driven by the application of cutting-edge algorithms, including convolutional neural networks (CNNs), support vector machines (SVMs), and recurrent neural networks (RNNs), to analyze a wide range of driving data.

CNNs have proven particularly adept at decoding visual cues such as signs, lane markings, and traffic patterns, enabling them to accurately classify driving styles based on adherence to traffic rules and road etiquette. Karaduman and Eren (2017) [2] demonstrate the effectiveness of CNNs in achieving an accuracy of 88.02% in distinguishing between safe and aggressive driving behaviors.

SVMs, on the other hand, demonstrate strength in pattern recognition and classification tasks, making them well-suited for identifying aggressive driving patterns from sensor data. Wang et al. (2017) [3] showcase the potential of SVMs by presenting a system that uses a semi-supervised learning approach on simulated data to classify aggressive drivers with 86.6% accuracy.

RNNs, especially long short-term memory (LSTM) networks, have also emerged as powerful techniques for analyzing sequential data, such as the temporal patterns exhibited in driving behavior. Mumcuoglu et al. (2019) [4] take advantage of this ability by combining FCNs and LSTMs to achieve an F1 score of 95.88% in classifying normal and aggressive driving styles on the UAH-DriveSet dataset.

Moreover, researchers have explored motion-based features to identify aggressive driving patterns. For instance, Matousek et al. (2019) [5] utilized a random forest model to extract these features, achieving an impressive area under the curve (AUC) of 97.10% in predicting aggressive driving behavior.

In addition to analyzing individual driving behaviors, researchers have also investigated how situational factors influence driving styles. Zheng et al. (2017) [6] delve into this area by examining how driving behavior in online car-hailing services varies depending on the task at hand, using k-means clustering to identify aggressive, normal, and cautious driving patterns.

Chen et al. (2021) [7] present a supervised approach leveraging Labeled Latent Dirichlet Allocation (LLDA) to classify driver behavior. This method categorizes drivers into three distinct styles : aggressive, moderate, and careful driving. Notably, the LLDA model achieves an average accuracy of 60.5%, surpassing the performance of traditional classifiers like Support Vector Machines (SVM), Naive Bayes (NB), and K-Nearest Neighbors (KNN).

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Several studies have focused on classifying driver aggressiveness. Works by Jahangiri et al. (2017) [8] and Moukafih et al. (2019) [9] employed Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) algorithms, respectively, to categorize driver behavior with scores reflecting aggressiveness levels. These approaches achieved impressive accuracy, reaching 86.67% and 92.8%. Beyond classification, other research has aimed to continuously track driving styles. For instance, the study by Wang et al. (2021) [10] utilized the Next Generation Simulation (NGSIM) dataset and a genetic algorithm (GA) to analyze car-following behaviors under various driving scenarios.

These advances in detecting aggressive driver behavior hold immense potential for improving road safety. By integrating these technologies into advanced driver assistance systems and in-vehicle monitoring solutions, we can effectively alert drivers to potential dangers and encourage safer driving practices. As research continues to improve these methods and explore new applications, we can anticipate a future in which aggressive driving behaviors become increasingly rare, paving the way for a safer and more harmonious driving experience for everyone.

2 METHODOLOGY

To develop an effective model for detecting aggressive driving behaviors, a systematic approach was adopted. This methodology section outlines the processes of data collection, data preprocessing, model design, and training strategy. The objective is to ensure the robustness and reliability of the model through careful selection and processing of data, followed by rigorous model training and evaluation.

2.1 Data collection

The data collection process involved two primary sources : the publicly available UAH-DriveSet dataset and an independent data collection effort. The UAH-DriveSet dataset provides comprehensive data on driver behavior, including over 500 minutes of driving data from six different drivers on highways. This dataset encompasses raw sensor data such as GPS coordinates, accelerometer readings, gyroscope data, and detailed video recordings.

In addition to the UAH-DriveSet, we conducted an independent data collection to supplement and diversify our dataset. This independent data collection involved an experienced driver navigating the highway, with data gathered using an Android application. The collected data consisted of 25 minutes of safe driving only. Aggressive driving data was then simulated from this safe driving session by manipulating parameters such as speed, safety distance, and lane changes, among other parameters.

2.2 Data preprocessing

To ensure the data was suitable for model training and evaluation, several crucial preprocessing steps were undertaken. The base variables used, along with their meanings, are detailed in Table 1.

TABLE 1 – Base variables and their meanings

Source	**Variable**	**Meaning**
UAH-DriveSet	Acceleration in Z (Gs)	Direct acceleration for speeding and braking. Key indicator of aggressive driving behaviors.
	Acceleration in Y (Gs)	Lateral acceleration. Identifies lane changes and swerving.
	Filtered Acceleration (Z & Y) (Gs)	Acceleration filtered by Kalman filter. Provides cleaner signals for detecting driving maneuvers.
	Distance to ahead vehicle (meters)	Distance to the vehicle ahead. Assesses tailgating behavior.
	Time of impact to ahead vehicle (seconds)	Time to collision based on speed and distance. Detects risky driving.
	Number of detected vehicles	Traffic density. Context for driving behavior.
	GPS speed (km/h)	Vehicle speed. Identifies speeding and sudden changes.
	Estimated current lane	Lane position. Understands lane-changing behavior.
Self-collected data	Video footage	Real-time driving sessions. Extracts safety distance, time of impact, and vehicle count using YOLO object detection.

2.2.1 *Signal processing*

The raw sensor data were processed using Fast Fourier Transform (FFT) to convert the signals from the time domain to the frequency domain. This conversion enabled the filtering of noise and the extraction of relevant features. FFT was applied four times with different component thresholds (80, 300, 600, 900), each chosen for its specific importance :

- 80 components : Captured low-frequency information, important for identifying steady and long-term driving patterns.
- 300 components : Balanced between low and mid frequencies, useful for detecting moderate changes in driving behavior.
- 600 components : Focused on mid-frequency information, which helps in identifying more dynamic driving actions.
- 900 components : Captured high-frequency details, crucial for detecting sharp and rapid driving maneuvers.

Figure 1 illustrates a signal filtered four times with different FFT component thresholds for comparison.

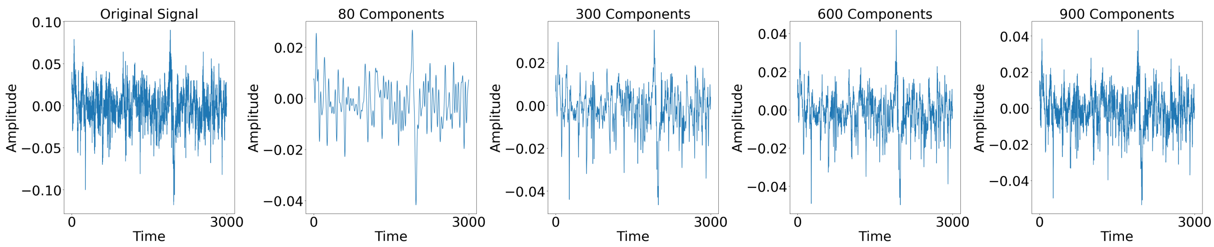

FIGURE 1 – Comparison of a signal filtered four times with different FFT component thresholds : 80, 300, 600, and 900.

2.2.2 *Additional data processing for self-collected dataset*

For the independently collected dataset, the phone camera was utilized to capture real-time video during the driving sessions. YOLO (You Only Look Once) object detection algorithm was employed to analyze the video frames :

- Safety distance calculation : YOLO was used to detect vehicles ahead by drawing bounding boxes around the vehicles. The focal length method was used to calculate the distance between the subject vehicle and the detected vehicles.
- Vehicle count : Additionally, YOLO provided the count of vehicles ahead, contributing additional context to the driving behavior data.

Figure 2 illustrates the pinhole method, which is essential for understanding how the distance calculations were performed.

2.2.3 *Sequence generation and data augmentation*

To capture the temporal dynamics of driving behaviors, fixed-length sequences of 3000 steps (approximately 100 seconds) were generated from the continuous data streams. Random start indices were employed to ensure that the sequences covered a broad spectrum of driving behaviors and conditions. This method also served as a form of data augmentation, enhancing the diversity of the training data.

Additional data augmentation was performed by manipulating driving parameters to simulate aggressive and normal driving behaviors. For aggressive driving, parameters such as speed were increased, and safety distance was decreased. Conversely, for normal driving, speed was moderated, and safety distance was increased. This approach helped in creating a more comprehensive dataset, allowing the model to learn from varied driving scenarios.

2.2.4 *Data splitting*

The dataset was divided into training and testing sets to facilitate robust model evaluation. For the data splitting, cross-validation was used with the UAH-DriveSet to ensure robust model training and validation. Specifically, a leave-one-subject-out cross-validation approach was implemented, where each time, data from one driver was set

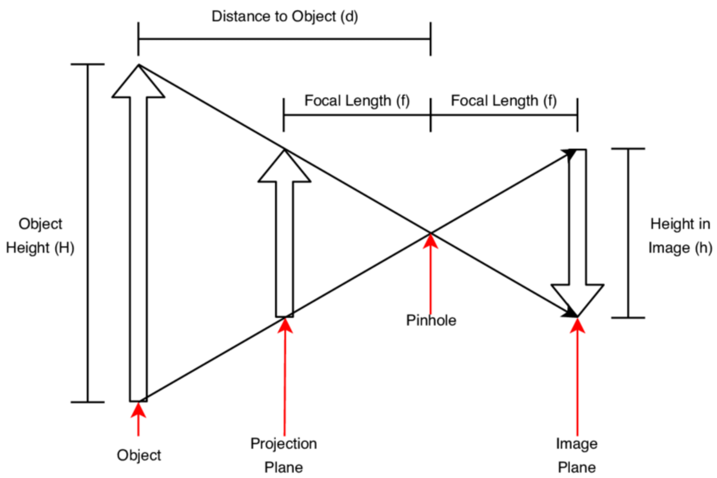

FIGURE 2 – The pinhole method for calculating distances in the context of object detection. Source : Wang, Zhang, Liu, and Lu (2021).

aside as the test set while the data from the remaining drivers were used for training the model. This process was repeated until each driver's data had been used once as the test set. The independently collected data, including the simulated aggressive driving data, was used exclusively as an additional test set. This division ensured that the model was evaluated on unseen data, providing a reliable measure of its generalization capabilities.

2.3 Model design

Given the complexity and real-time application requirements, a one-dimensional convolutional neural network (1D CNN) architecture was chosen. This model was selected for its efficiency in processing time-series data and its ability to effectively capture temporal patterns.

- Convolutional Layers : These layers extract spatial features from the input data, identifying patterns related to driving maneuvers.
- Dense Layers : Fully connected layers were used for classification, outputting probabilities for normal and aggressive driving styles.

Figure 3 illustrates the architecture of the 1D CNN model used in this study.

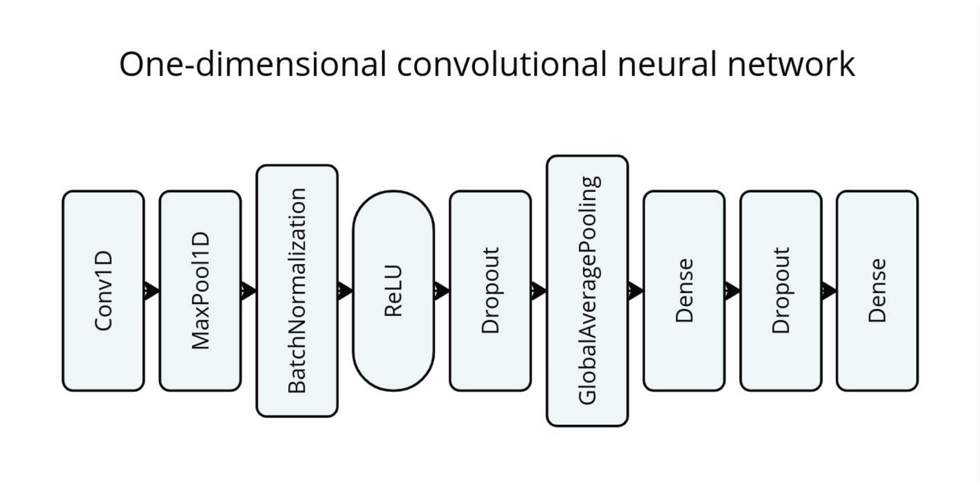

FIGURE 3 – Architecture of the 1D CNN model. Source : Authors.

2.4 Training Strategy

The model training involved careful optimization of hyperparameters and the implementation of specific techniques to enhance performance :

- Learning Rate Adjustment : The ReduceLROnPlateau callback was used to monitor validation loss and reduce the learning rate by a factor of 0.2 after two epochs without improvement, continuing until a minimum learning rate threshold was reached.
- Early Stopping : To prevent overfitting, the EarlyStopping callback halted training after five consecutive epochs without improvement in validation loss.
- Optimizer and Loss Function : The model was compiled using the 'adam' optimizer, known for its adaptive learning rate capabilities, and trained with the 'sparse categorical cross-entropy' loss function.
- Validation Split : A validation split of 30% was used to ensure the model's generalization. The model was trained for 20 epochs with a batch size of 32.

By implementing these training strategies, we aimed to optimize the model's performance and generalization capabilities, ensuring its effectiveness in real-time applications.

3 RESULTS

3.1 UAH-DriveSet drivers scores

Before evaluating the model performance, it is essential to understand the real scores of each driver provided in the UAH-DriveSet. For each trip, the driver has an aggressiveness score and a normal score, which serve as a baseline for validating the model's predictions. Table 2 provides more details about these scores.

TABLE 2 – Driver scores : Driving scores, on a scale of 10, of drivers instructed to drive aggressively on the highway. Source : Romera, Bergasa, Arroyo, (2016)[12].

Driver	**Normal behavior score**	**Aggressive behavior score**
Driver 1	5.1	4.0
Driver 2	1.2	6.1
Driver 3	5.4	3.4
Driver 4	3.7	5.3
Driver 5	1.3	7.3
Driver 6	4.8	4.6

3.2 Model performance

The one-dimensional convolutional neural network (1D CNN) was evaluated using cross-validation on the UAH-DriveSet dataset and the independently collected dataset. The following metrics were used to assess the model's performance : accuracy, precision, recall and F1-score. These metrics were calculated for both the cross-validation folds and the collected dataset to provide a comprehensive evaluation of the model.

3.2.1 Cross-validation results

The leave-one-subject-out cross-validation approach applied to the UAH-DriveSet provided detailed performance metrics for each driver. The performance metrics across all cross-validation folds are summarized in Table 3 , and confusion matrices for each driver are provided in Figure 4.

	Driver 3, 4, 5			Driver 1			Driver 2			Driver 6		
Style	Pre	Recall	F1 Score	Pre	Recall	F1 Score	Pre	Recall	F1 Score	Pre	Recall	F1 Score
Aggressive	1.00	1.00	1.00	0.00	0.00	0.00	1.00	0.60	0.75	1.00	0.73	0.84
Normal	1.00	1.00	1.00	0.50	1.00	0.67	0.71	1.00	0.83	0.79	1.00	0.88
Average	1.00	1.00	1.00	0.25	0.50	0.33	0.86	0.80	0.79	0.89	0.86	0.86

TABLE 3 – Driver performance metrics : Precision, Recall, and F1 Score for normal and aggressive driving styles

3.2.2 Collected dataset results

The results for the independently collected dataset are as follows :

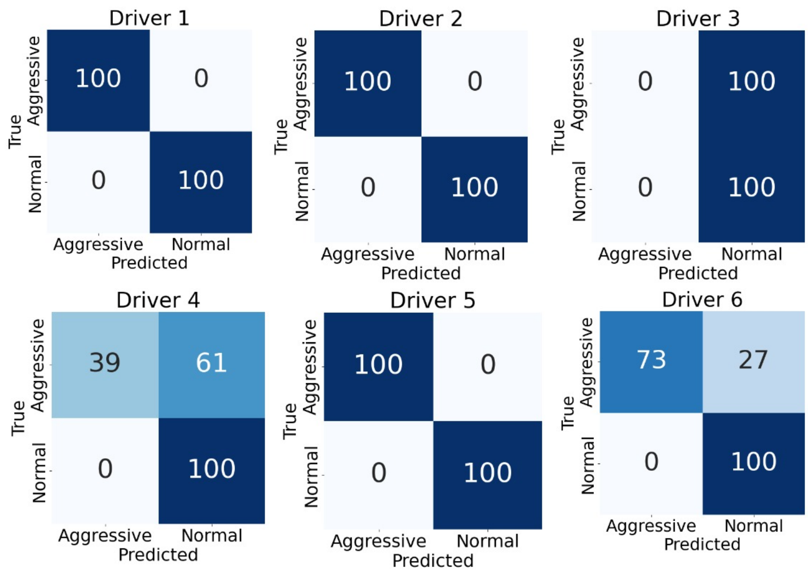

FIGURE 4 – Confusion matrices for each driver. Source : Authors.

- Accuracy : 99%
- Precision : 99%
- Recall : 99%
- F1-score : 99%

3.2.3 Model efficiency and lightweight characteristics

An essential aspect of the 1D CNN model is its lightweight architecture, making it suitable for real-time applications on devices with limited computational resources. The model's size, number of parameters, and inference time were evaluated to illustrate its efficiency. The 1D CNN model contains approximately 15,474 parameters, resulting in a total model size of 60.45 KB. The inference time was measured on Google Colaboratory CPU (Intel(R) Xeon(R) Platinum 8259CL CPU @ 2.50GHz) at approximately 0.12 seconds per prediction, highlighting the model's capability for real-time performance.

4 DISCUSSION

4.1 Comparison with UAH-DriveSet real scores

The performance of the 1D CNN model was thoroughly evaluated against the real scores provided in the UAH-DriveSet. Each driver's aggressiveness and normal driving scores were compared with the model's confusion matrices to validate the accuracy of the model's predictions. The comparison is summarized in Table 4.

TABLE 4 – Comparison of UAH-DriveSet real scores and our model Predictions

Driver	**UAH-DriveSet real scores**		**Our model predictions**		**Alignment**
	Normal	**Aggressive**	**Normal**	**Aggressive**	
Driver 1	5.1	4.0	0	100	Good
Driver 2	1.2	6.1	0	100	Perfect
Driver 3	5.4	3.4	100	0	Good
Driver 4	3.7	5.3	61	39	Not bad
Driver 5	1.3	7.3	0	100	Perfect
Driver 6	4.8	4.6	27	73	Good

The alignment between the model's predictions and the UAH-DriveSet real scores demonstrates that the 1D CNN effectively identifies aggressive and normal driving behaviors. This validation confirms the model's robustness and reliability in practical scenarios. Moreover, the consistent performance across various drivers indicates the model's strong generalization capability. This ability to accurately predict driving behaviors across different individuals showcases the model's potential for widespread application in real-world settings, ensuring that it can adapt to diverse driving patterns and styles.

Another essential characteristic of the this model is its lightweight nature. With a total of 15,474 parameters and a model size of 60.45 KB, the model is compact enough for real-time applications. The inference time of approximately 0.12 seconds further supports its suitability for deployment in resource-constrained environments, such as mobile devices and in-vehicle systems.

4.2 Classification of self-collected and simulated driving data

The model's ability to classify both collected normal data and simulated-aggressive data demonstrates its sensitivity to the modified variables. This evaluation was crucial in confirming that the 1D CNN model not only performs well on standard datasets but also adapts effectively to variations introduced in the driving behavior.

The aggressive data was simulated by altering several key driving variables, including :

- Speed : Increased speeds to mimic aggressive driving behavior.
- Lane Changing : More frequent and abrupt lane changes.
- Traffic Volume : Increased traffic volume to simulate more complex driving scenarios.
- Safety Distance : Reduced safety distances to ahead vehicles, representing riskier driving patterns.
- Time of Impact : Decreased time of impact to the vehicle ahead, indicating more aggressive following behavior.

The results showed that the model effectively recognized these changes and classified the driving behavior accurately. This demonstrates that the 1D CNN model takes into account the modified variables to simulate aggressive driving, confirming its robustness and sensitivity to different driving conditions. This sensitivity is essential for real-world applications where driving behaviors can vary significantly, ensuring that the model remains reliable and effective in diverse environments.

4.3 Limitations and future work

While the model shows promising results, several limitations were identified :

- Variability in driving behavior : The natural variability among different drivers can pose challenges for model generalization. Further training with a more diverse driver population is recommended.
- Simulated data limitations : Although the simulated aggressive driving data provided useful testing scenarios, it may not fully capture the complexity of real-world aggressive driving behaviors. Future research should focus on collecting more authentic aggressive driving data.
- Real-time constraints : Although the model itself is fast, the data preprocessing steps, particularly the safety distance measuring and vehicle count using YOLO, need to be optimized for real-time application in systems with limited computational resources.

Future work should aim to address these limitations by expanding the dataset with more diverse and realistic driving behaviors, optimizing the model for various hardware platforms, and exploring additional features that could further enhance the model's performance.

5 CONCLUSION

This study aimed to develop and evaluate a lightweight one-dimensional convolutional neural network (1D CNN) model for detecting aggressive driving behaviors using both the publicly available dataset UAH-DriveSet and an independently collected dataset. A key objective of the study was to ensure the model's generalizability across different drivers, thereby enhancing its applicability in diverse real-world scenarios. The model's performance was validated against real scores from the UAH-DriveSet, demonstrating high accuracy and robustness in identifying normal and aggressive driving patterns.

Key findings include :

- High performance and generalizability : The alignment between the model's confusion matrices and the UAH-DriveSet real scores for each driver confirms its reliability and highlights its strong capability to generalize across different drivers. This ability to consistently perform well across a diverse set of drivers is the

main goal of the study, showcasing the model's potential for widespread application in real-world settings.
• Efficiency : The model's lightweight architecture makes it suitable for real-time applications. However, optimization of the preprocessing steps, particularly the safety distance measuring and vehicle count using YOLO, is necessary for deployment in resource-constrained environments.

In conclusion, the 1D CNN model developed in this study demonstrates significant promise for real-time driver behavior monitoring systems, providing a valuable tool for enhancing road safety and reducing the incidence of aggressive driving.

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