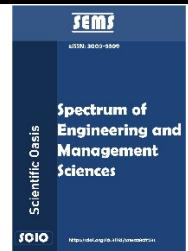




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A High-Precision Driving Behavior Classification Framework using Convolutional Neural Networks based on Vehicle Telematics Data

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ABSTRACT

The increase in road travel has a significant impact on road safety, fuel consumption, and environmental pollution. Continuous efforts have been made to increase road safety and reduce fuel consumption and pollution. One of the factors that is of great importance in this regard is driver behavior. In this study, an advanced artificial intelligence model using convolutional neural networks is used to accurately classify driving behaviors under speed threshold criteria. In this modeling, a dataset with 370 data points is used with five inputs. The input data for modeling and predicting driver behaviors include fuel flow rate/hour, engine speed, speed, acceleration, and grade. Four classes (labels) are considered: normal (class 1), moderate (class 2), aggressive (class 3), and dangerous (class 4). The obtained results indicate that the convolutional neural network model achieved very high classification performance during the modeling process. In addition to classification accuracy, the proposed framework contributes by establishing a structured behavior classification scheme based on telematics data and speed-threshold criteria, which can support intelligent safety monitoring, eco-driving assessment, and transportation management applications. Finally, the most important factors that affect driver behavior classification are the speed of cars and engine speed.

1. Introduction

The continuous increase in road travel in recent decades has had widespread consequences in the fields of safety, energy consumption, and environmental pollution [1,2]. The growth in the number of vehicles, increasing traffic density, and changing movement patterns have put significant pressure on transport infrastructure and at the same time increased the likelihood of traffic accidents and fuel consumption [3,4]. Meanwhile, driver behavior, as one of the main components of the transport system, plays a decisive role in the formation of these consequences. Differences in the way of accelerating, choosing speed, reacting to road conditions, and paying attention to traffic

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restrictions can lead to significant changes in the level of safety, fuel consumption, and pollutant production. Despite technological advances in vehicle design and improvements in safety standards, the contribution of driver behavior to the occurrence of many accidents and energy inefficiencies remains significant. On the other hand, management and control policies will have limited effectiveness without accurate knowledge of driver behavior patterns. In recent years, the expansion of vehicle data recording systems and access to telematics information has enabled the observation and analysis of driving behavior on a large scale [5]. This data has the potential to lead to a deeper understanding of driver behavioral differences. In such circumstances, accurate classification of driving behavior and differentiation between its different levels is not only essential for improving road safety but can also be the basis for reducing fuel consumption, controlling pollution, and designing smart solutions in transportation management [6,7]. Therefore, it is obvious that there is an urgent need to conduct studies that can analyze and classify driver behavior accurately and based on data.

Over the past years, in order to reduce fuel consumption, accidents, and pollutant production, much attention has been paid to analyzing driver behavior and classifying it. For example, Brahim *et al.* [8] designed a mobile phone-based system that uses machine learning methods to classify driver behavior. The system extracts information from the phone's internal sensors, such as the accelerometer and gyroscope, to identify different driving patterns, including normal, moderate, high-risk, and aggressive, in different conditions, such as speed limits and different weather conditions. The CARLA simulator was used to generate data, which allows the generation of time series data without the problems and limitations of real experiments. In this study, several machine learning algorithms were evaluated, with a focus on methods based on boosted decision trees (GBDT) and long-short-term memory (LSTM) networks to evaluate their ability to identify and classify driving behaviors. The results showed that the Light GBM model performed best compared to other methods, with an F1 score of 88%. Also, among the LSTM-based models, the FCN-LSTM structure performed best with an F1 score of 74%. The findings of this study emphasize the potential of using low-cost smartphones to monitor driver behavior in real-time and identify risky driving patterns, with the aim of increasing road safety. In this approach, sensor data is combined with artificial intelligence methods to provide a reliable and cost-effective solution for applications such as fleet management and the insurance industry, while also helping to improve traffic safety and develop autonomous driving systems. Zhang *et al.* [9] introduced a model that used low-level sensors in cars and smartphones to classify driver behavior. Accordingly, it can be said that this model uses on-board diagnostic (OBD) data and smartphone sensors and uses window-based support vector machine (SVM) for classification. In this method, they tested the model with respect to two datasets collected under controlled conditions and achieved classification accuracies of 75.83%, 85.83%, and 86.67% for the average classification, smartphone sensors, and vehicle sensors, respectively. Since combining smartphone and vehicle data significantly improves classification performance, they emphasized the importance of sensor integration. Bohsesin *et al.* [10] initially examined the different dimensions of driving behavior, then focused on previous studies between 2015 and 2022, as well as methods, types of studies, data sources, and algorithms. Their study classified driver behaviors into several categories, including abnormal, aggressive, and distracted driving. It examined the influence of contextual factors such as driver status and environmental conditions. Lindow *et al.* [11] investigated the use of data obtained from smartphone sensors and also evaluated machine learning techniques to monitor abnormal driving behavior. The results of their study indicate that drivers' behavior plays an important role in traffic safety, as differences in driver behavior patterns may lead to accidents. Given the availability of smartphone sensors to most drivers, their proposed system is designed to

be a practical solution for both modern and older vehicles. The authors present a reference model for a driver decision support system by analyzing and reviewing previous studies.

Despite extensive efforts in the field of driving behavior analysis, a significant part of previous studies has either focused on a limited set of indicators or has not been able to accurately distinguish between different levels of driving behavior in real-world conditions. In many studies, the boundary between aggressive behavior and truly dangerous behavior is not clearly defined, and the simultaneous role of different telematic variables has received less attention. Moreover, the classification accuracy in some studies has not reached a level that can be used in practical applications and safety decision-making. To address these limitations, this study proposes a convolutional neural network (CNN)-based framework for driving behavior classification using vehicle telematics data under speed-threshold behavioral definitions. The main contributions of this study can be summarized as follows:

- i. Development of a CNN-based framework for distinguishing four levels of driving behavior using telematics variables.
- ii. Examination of the relative influence of vehicle motion and engine-related parameters on behavioral classification.
- iii. Evaluation of the applicability of CNN models for structured numerical transportation datasets.
- iv. Provision of a framework that may support intelligent safety monitoring and transportation management applications.

Based on the identified research gaps, this study addresses the following research questions:

- i. Can a CNN-based framework accurately classify different levels of driving behavior using vehicle telematics data?
- ii. Which telematics variables have the greatest influence on distinguishing behavioral levels?
- iii. To what extent can speed-threshold behavioral definitions improve the separation between normal, moderate, aggressive, and dangerous driving patterns?

2. Methodology

Deep learning methods typically use structures called deep neural networks. The main feature of these networks is the extensive use of neural network frameworks, and the word "deep" in this context refers to the presence of multiple hidden layers in the network structure [12]. Unlike standard neural networks, which often have only two or three hidden layers, deep neural networks can consist of a much larger number of layers, in some cases as many as 150. For this reason, deep learning is considered a separate and distinct branch of machine learning. One of the most important challenges in this area is to strike a balance between the depth of the network and its accuracy and processing speed. Typically, increasing the number of layers improves accuracy, but on the other hand, it creates more computational requirements and can ultimately lead to a slowdown in network performance [13].

The development of CNN was inspired by the way the human visual system works. These networks were initially designed for object recognition. However, over time, their applications have expanded. Today, they are used in the field of deep learning to perform a variety of tasks such as text recognition, activity recognition, classification, and regression. However, image processing and analysis remain the most common application of these networks [14,15]. Compared to many other

methods in the field of image classification, CNNs require fewer preprocessing steps. CNNs consist of a collection of neurons, each with specific weights and biases that can be trained. These neurons are essentially mathematical functions that try to simulate the behavior of biological neurons as closely as possible by calculating the weighted sum of the inputs and producing an activation value. CNNs consist of a set of different layers of artificial neurons, including an input layer, an output layer, and several hidden layers. These intermediate layers typically include convolutional, pooling, and fully connected (FC) layers [16,17].

The convolutional layer is originally designed to extract image features, such as edges, and there is no specific limit to the number of convolutional layers in a CNN. Typically, the initial layers of the network are responsible for identifying more basic features, such as the direction of gradients and color information. In the later stages of the network, especially in the fusion layers, the computational effort is reduced by reducing the size of the feature space, a process known as dimensionality reduction. The FC layer then learns a nonlinear function in this space, adjusting parameters such as initialization, learning rate, and regularization methods via name-value pairs [18,19].

3. Driving Behavior Classification Criteria

In this study, driving behavior was categorized into four behavioral levels based on speed-threshold criteria derived from previous studies [20]. One of the most common of these categories was presented in 2022 by Brahim *et al.* [8]. They put the driving behavior into four groups and considered a range of speed for each group. The definition of these groups is as follows (Table 1):

- i. *Normal* – The driver moves within the speed limit according to the weather conditions and does not pose a danger to other road users.
- ii. *Intermediate* – The driver sometimes shows relatively aggressive behavior but still does not endanger the safety of others.
- iii. *Aggressive* – The driver is speeding, making sudden turns, and swerving between lanes.
- iv. *Dangerous* – The driver repeatedly makes risky moves, such as dangerous steering or excessive speed, which increases the likelihood of an accident.

Table 1

Degree of severity of the speeding	
Behavior aggressiveness	Speed degree
Normal	Under speed limit
Intermediate	Overspeed [10,33] %
Aggressive	Overspeed [33,66] %
Dangerous	Overspeed 66%

According to the classification provided by Brahim *et al.* [8] and according to the modeling done in this research, an average speed of 50 meters per second was considered for urban routes. The results of this classification in the project are given in Table 2.

Table 2

Driver behavior classification	
Behavior aggressiveness	Class
Normal <13.89 (m/s)	1
13.89 (m/s) < Intermediate < 15.32 (m/s)	2
15.32 (m/s) < Aggressive < 18.56 (m/s)	3
18.56 (m/s) < Dangerous	4

4. Results

In this research, a dataset of 370 data points was used to model the classification of driving behavior. The input data for modeling and predicting driver behavior include fuel consumption rate per hour (FFRH), engine speed (ERMP), speed (S), acceleration (A), and road gradient (G). Four classes are also considered for labeling:

- i. normal (class 1);
- ii. intermediate (class 2);
- iii. aggressive (class 3);
- iv. dangerous (class 4).

It should be noted that CNNs are usually used to process image data, in which images are converted into numerical vectors. The data set included measurements of some parameters from a sample of private cars (three passenger cars and one commercial vehicle) collected through the OBD interface and smartphones inside the car. The dataset was collected from vehicles operating under different urban traffic conditions and included variations in speed, acceleration, and driving responses during regular daily trips. The purpose of using this dataset was to evaluate the feasibility of behavior classification using telematics variables under realistic operating conditions rather than to establish a universal behavioral benchmark. The data collection system is based on sharing vehicle movement routes, which are recorded by mobile technology and the OBD interface, and sent by users to a central server to be processed and organized based on the desired points. The system consists of two parts. The first, user part (client), includes a mobile device that receives and stores the data sent from the OBD interface via Bluetooth. The second part is a central server based on Linux-MySQL-PHP that processes the data and returns the synchronized information.

4.1 Modeling and Results for Driving Behavior Classification

In this modeling, a CNN-type deep learning network was used to classify driver behavior. Since the data under study were numerical, some convolution layers were removed so that the data was directly fed into the network as a numerical vector. Before running the model, the dataset was normalized, and the control parameters required for the CNN network were also preset [12]. Therefore, in this modeling, a value of $1e-2$ was considered for this parameter. Other parameters examined were the learning rate reduction factor (LRDF) and the learning rate reduction period (LRDP). Several different values were tested for each. For LRDF, the numbers were 0.4, 0.5, 0.6, and 0.7. For LRDP, the values were 20, 30, 40, and 50. The next parameter is the mini-batch size; i.e., a positive integer that specifies the number of samples used in each training step. In fact, a mini-batch is a subset of training data that is used to calculate the gradient of the error function and update the weights [21,22]. In this study, a value of eight was chosen for the mini-batch. The last parameter to mention is the number of epochs. Each time the entire training data is used to update the weights, an epoch is completed. For this purpose, the model was tested with different values, such as 100, 200, 300, 400, and 500 epochs. The value of 400 showed the best performance. Then, 75% of the data (278) was considered for training. The remaining data (i.e., 10% (37)) was used for validation, while 15% (55) was employed for testing the model.

Initially, the modeling was run once with different epochs. Considering the number of control parameters taken into account, a total of 16 models were built, and the prediction accuracy of each was evaluated for the training and test data. Finally, a model with mini-batch values of eight, LRDF of 0.7, and LRDP of 50 achieved the best performance. Figure 1 shows the accuracy of this superior model.

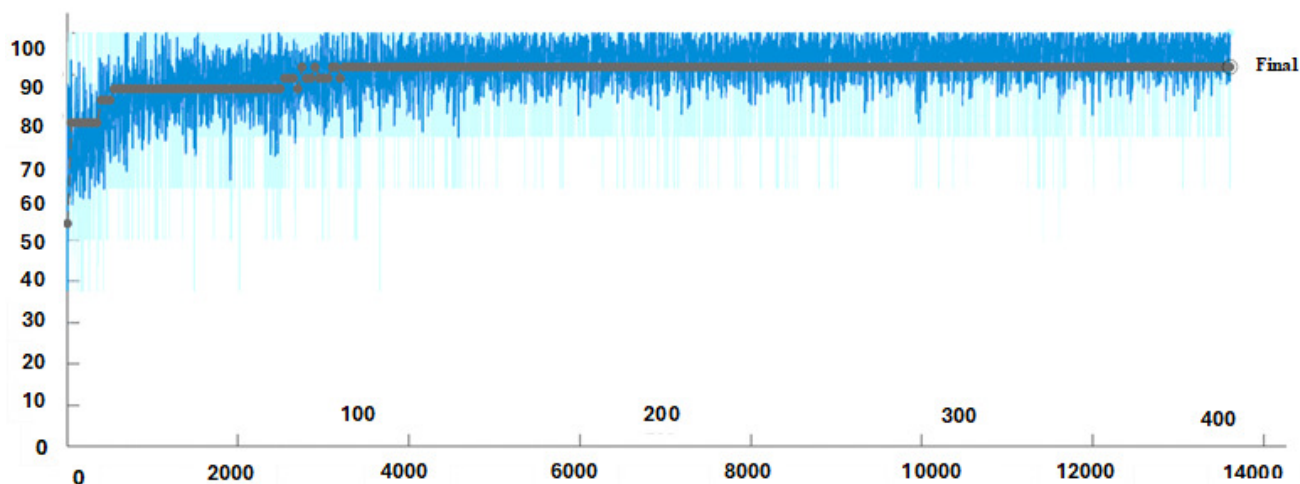


Fig. 1. The values of accuracy in 400 epochs by CNN

Figure 2(a) and Figure 2(b) show the confusion matrix for the training and testing data, respectively. According to Figure 2(a), most of the training samples are placed in their correct categories, showing that the network has learned the underlying patterns well. Only a few mix-ups appear between nearby behavior levels, which slightly lowers accuracy but does not affect overall reliability. Based on Figure 2(b), on the test set, the CNN classified Classes 1, 2, and 4 almost perfectly, with only a small spillover from Class 1 into Class 2. The main weakness is Class 3, where half of the samples were confused with Class 2, which pulls the overall accuracy down to about 90.9%.

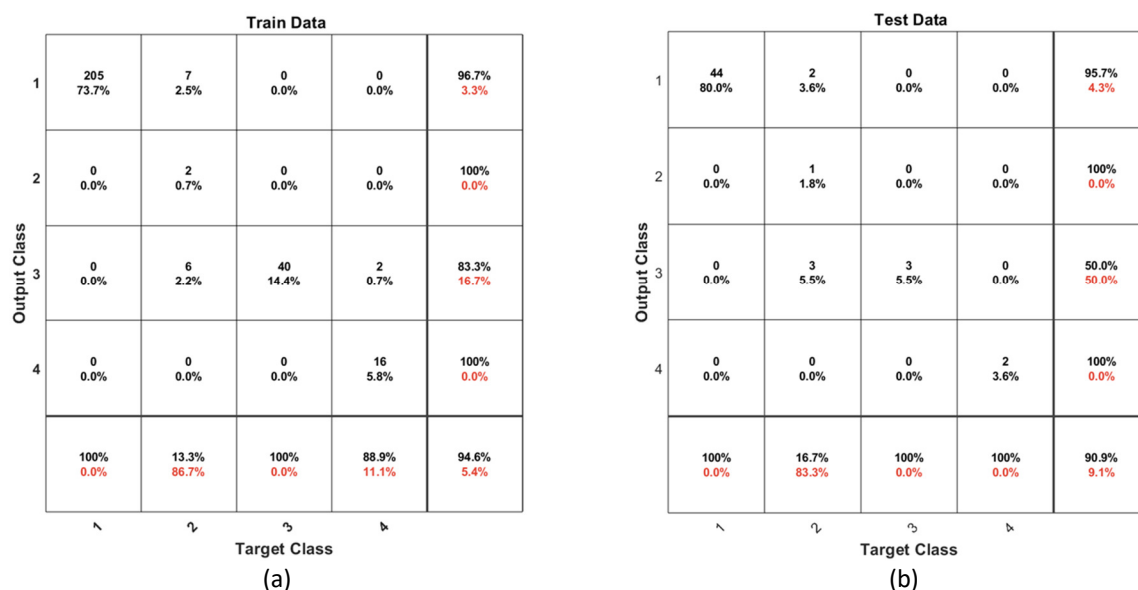


Fig. 2. Confusion matrix outcomes for the top-performing CNN model on the training (a) and testing (b) datasets

Figure 3(a) and Figure 3(b) show the ROC plot for the training and testing data. As indicated by Figure 3(a), the curves in the training set are almost close to the upper left corner, indicating that the model distinguishes the four classes with very high accuracy and the false alarm error is very small. Such performance indicates a very good fit to the training data. According to Figure 3(b), in the test set, the curves remain close to the same area, indicating that the model maintains its high discrimination ability with very few false positives. This indicates good generalizability of the classifier and maintaining high sensitivity on new data.

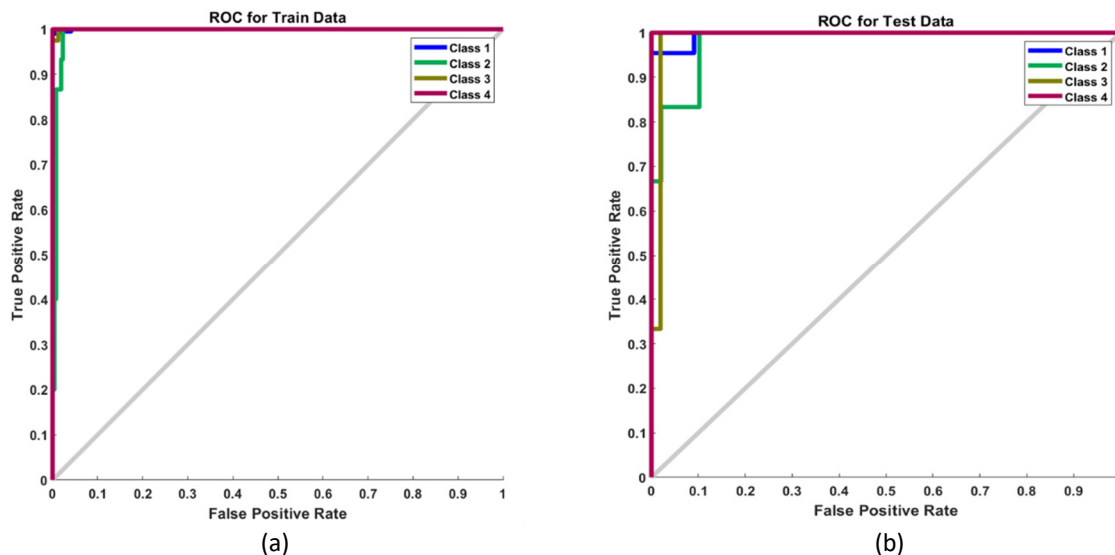


Fig. 3. ROC curve results of the best CNN model for the training (a) and the testing dataset (b)

To examine the influence of each variable, the cosine amplitude method was applied as described in Eq. (1):

$$r_{ij} = \frac{\sum_{k=1}^n (X_{ik} \times Y_{jk})}{\sqrt{\sum_{k=1}^n X_{ik}^2 \sum_{k=1}^n Y_{jk}^2}}, \quad (1)$$

where, the symbol n refers to the number of samples in the dataset. The notation X_{ik} represents the input variables of the model, while Y_{jk} corresponds to the predicted outputs. The coefficient r_{ij} expresses the degree of correlation between inputs and outputs [23].

Based on Eq. (1), a sensitivity analysis was conducted to evaluate the relative influence of input variables on the model output, and the corresponding results are illustrated in Figure 4. As shown, Speed (S) exhibits the highest sensitivity value, followed by ERMP and FFRH, while Acceleration (A) and Grade (G) demonstrate comparatively lower effects. This outcome is logically consistent with the modeling framework, since the behavioral classes were primarily defined according to speed thresholds. Consequently, S naturally plays a dominant role in the classification process. The slight variation in the ranking of ERMP and FFRH can be attributed to their correlation with S, which indirectly affects class boundaries. It is important to note that in this study the dataset was employed for driver behavior classification, whereas previous investigations using the same dataset focused on fuel consumption and CO₂ prediction through regression models, which explains the observed differences in sensitivity patterns.

4.2 Discussion

In this part, an attempt has been made to examine the results obtained from the proposed CNN-based framework more closely and analyze them from an applied and methodological perspective. The goal is not simply to recount the numbers and statistical indicators, but rather to focus on what these findings suggest about the ability of deep learning methods to distinguish different levels of driving behavior and how they can play an effective role in improving transportation safety and increasing energy efficiency. By relying on structured telematics data and speed-based behavioral thresholds, the study provides a clearer separation between different levels of driving aggressiveness. The results clearly show the strengths of the chosen modeling approach and where it can still be improved. In particular, it was found that striking the right balance between the level of

model complexity, the way in which the optimization parameters are set, and the model's ability to generalize to new data plays a decisive role in achieving reliable classification performance.

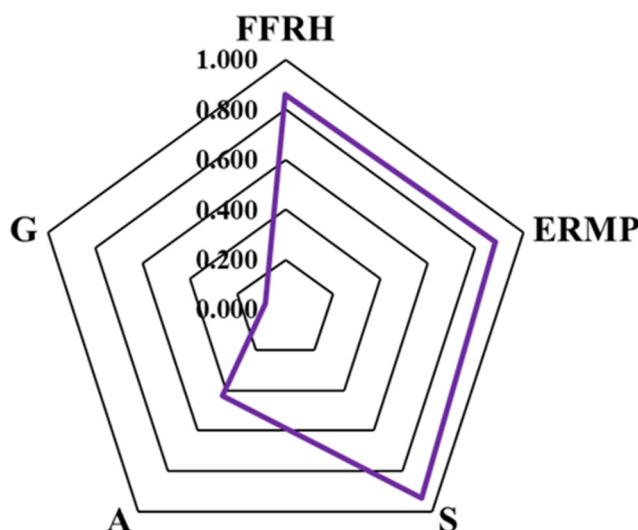


Fig. 4. Sensitivity analysis of the input variables based on the CNN model results for driving behavior classification

In terms of modeling, it can be said that the optimization section had a very important impact on achieving high prediction accuracy. The appropriate selection and adjustment of parameters such as the learning rate reduction coefficient and interval, the minibatch size, and the number of epochs significantly affected the convergence process of the model and the classification quality. Experience with running the model with different values showed that when the learning rate is reduced in a balanced manner, and the number of training iterations is considered sufficient, the network can better learn nonlinear relationships between telematic variables, without suffering from severe overfitting or remaining dependent only on the training data. Although the model achieved very high accuracy in the training phase, the slight decrease in performance in the test data, especially in the case of Class 3, shows that there is no clear boundary between some close behavioral levels. Such a situation is not far from expected in real data, because in practice, the change from moderate to aggressive driving usually occurs gradually and not with a completely clear boundary. However, the overall CNN architecture was able to demonstrate acceptable resolution, indicating that even when the inputs are mostly numerical data, convolutional networks can extract meaningful and reliable patterns from the data if the model is properly tuned.

In the analysis of driver behavior, the results showed that some telematic variables, such as fuel flow rate and engine speed, have a significant relationship with different levels of driving aggression. The high accuracy of the model in identifying normal and dangerous behaviors indicates that extreme driving patterns usually have a clear reflection in the vehicle performance data and somehow leave their mark on these data. In contrast, the observed overlap between moderate and aggressive levels reflects the fact that driving behavior is not a completely discrete phenomenon, and the change between these levels occurs gradually. Drivers change their driving style depending on traffic conditions, road conditions, and even their individual circumstances, and do not necessarily remain at a constant level. This shows that for a more accurate analysis of driver behavior, it is necessary to rely on several parameters simultaneously and not only on speed thresholds. The results also highlight the practical value of such classification systems for fleet monitoring, eco-driving feedback,

and insurance risk assessment, where identifying risky changes in behavior may be more important than labeling fixed categories.

The findings of this study also have broader implications for both research and transportation management practice. From a theoretical viewpoint, the results indicate that CNNs can effectively classify driving behavior using structured telematics variables even when the dataset consists of numerical transportation data rather than image-based information. The study further emphasizes the importance of combining speed-threshold definitions with vehicle performance indicators to improve behavioral differentiation.

In practical terms, the proposed framework may support transportation agencies, fleet operators, and insurance-related monitoring systems in identifying risky driving patterns more efficiently. The findings may also contribute to the development of driver monitoring programs, eco-driving policies, and safety-oriented transportation management strategies.

5. Conclusions

In this study, a data-driven framework for driving behavior classification using vehicle telematics information and a CNN model was developed. The findings show that the proposed framework is able to distinguish four behavioral levels with high reliability, even when the inputs include numerical engine and motion parameters instead of images. The model maintained its strong performance not only during training but also on unseen test data, indicating acceptable generalization ability. The findings showed that *S* and ERMP play a decisive role in distinguishing driving patterns, which confirms their effectiveness in real monitoring systems. Although in some cases, the boundary between close behavioral levels was not completely clear, the coherence and reliability of the results were generally maintained. Accordingly, the proposed framework can be a practical basis for the development of intelligent safety systems, management and evaluation of transportation fleets, as well as the formulation of policies based on driver behavior. Overall, this research shows that the simultaneous use of telematics data and deep learning methods can lead to more accurate and practical analysis of driving behavior in real-world conditions.

Despite the acceptable results of this study, some limitations should be noted. First, the data used was limited in terms of the number of input variables and the number of vehicles, which could affect the generalizability of the results to different driving conditions and between different groups of drivers. Therefore, the findings should be interpreted as an initial validation of the proposed framework rather than a universally generalizable classification model. Expanding the dataset with additional vehicles, drivers, and roadway conditions would further improve the robustness and transferability of the results. It seems that if variables such as steering angle, brake pedal pressure, throttle opening, or even indicators related to traffic conditions were added to the data, a more comprehensive and accurate picture of driving behavior could be obtained. Such information could help to better understand behavioral differences between drivers. Also, although the CNN model performed reasonably well in terms of accuracy, interpretable methods such as SHAP were not used in this study to determine the effect of each variable on the model output. As a result, the internal decision-making process of the model remains difficult to interpret in detail.

Future studies may focus on expanding the dataset under different roadway and traffic conditions and evaluating additional deep learning architectures for driver behavior classification. The application of interpretable artificial intelligence techniques may also improve understanding of the decision-making process of the model and increase the practical reliability of behavior classification systems.

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Conflicts of Interest

The authors declare no conflicts of interest.

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