

RESEARCH ARTICLE

Clustering and Investigation of Human Driving Behavior Using Autoencoder and Risk Assessment

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ABSTRACT This paper introduces a novel methodology for evaluating human driving behavior influenced by shoe type and its impact on collision risk. While human factors, such as footwear, are recognized to affect driving safety, studies quantitatively assessing the effects of shoe types on safety has been limited. To address this, we utilize an autoencoder and human-centered risk assessment algorithms to investigate human driving behavior and collision risk. Experiments were conducted in various real-world driving scenarios, involving two distinct types of shoes. The autoencoder extracts features from the driving data and enables us to analyze the effects of shoe type on driving behavior. Additionally, collision risk analysis is used to verify the validity and impact of the feature extraction results on safe driving. This study contributes to enhancing our understanding of how footwear influences driver behavior and safety. Furthermore, this methodology establishes a groundwork for future research on applying quantitative evaluations to other human factors that influence driving behavior.

INDEX TERMS Autonomous driving, autoencoder, driving behavior, deep learning, risk assessment.

I. INTRODUCTION

Human factors are the application of knowledge about human abilities, limitations, and other characteristics to the design of equipment, tasks, and jobs [1]. In the context of driving safety, human factors research aims to understand how drivers perform as a system component in the safe operation of vehicles, and how they are influenced by environmental, psychological, and vehicle design factors [1]. Driving safety is a critical issue, as it is predicted that the global death rate from road traffic collisions will rise to 2.6 million people killed every year by 2030 [2], and the main contributor to crashes is the driver [2]. Therefore, it is important to investigate how different aspects of driving behavior and performance can be improved or impaired by various factors.

Driving safety is intricately influenced by human factors, including the type of footwear worn by drivers. Despite its importance, this area has received limited attention in existing literature, with most studies focusing on laboratory settings or simulators that do not reflect real-world complexities. This study addresses this gap by employing advanced machine learning techniques to quantitatively assess how footwear impacts driving performance and collision risk. These findings have critical implications for reducing road accidents and inform both driver education programs and the design of safer footwear. By bridging the gap between ergonomics and driving safety, this study aims to contribute a novel perspective to the growing field of human-centered risk assessment.

One such factor that has received little attention in the literature is the type of shoes worn by drivers. The relationship between shoe type and driving safety and comfort is an important but under-researched topic in human factors and ergonomics. Shoes can affect the drivers' ability to apply

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appropriate pedal force and feel, as well as their thermal comfort, moisture management, and foot fatigue [3], [4]. These factors can influence the drivers' risk assessment and decision making in urban driving environment, where they encounter various traffic situations and hazards. However, most of the existing studies on the relationship between shoe type and driving performance have been conducted in driving simulators or laboratory settings, which may not capture the realistic driving conditions and challenges [5]. Moreover, there is no clear consensus on what constitutes the best or the worst driving shoes, as different studies have suggested different criteria and preferences [4], [5], [6]. Therefore, there is a need for more empirical evidence and comprehensive analysis on the effects of shoe type on driving safety and comfort in real-world scenarios.

The analysis of driving behaviors and collision risk assessment have become increasingly important due to its potential applications in various fields such as road safety, ride comfort, and driver assistance. To analyze and/or recognize driving behavior, data-driven methods such as machine learning techniques have been extensively employed. Support vector machines (SVM) are used in driver distraction classification and in driving style classification based on vehicle data such as speed, throttle opening, time to collision, time to lane crossing, steering angle, lateral position, position of the accelerator pedal and position of the brake pedal [7], [8]. Based on vehicle data, methods to recognize driving behavior have been proposed using Hidden Markov Models [9], [10]. Recurrent Neural Networks (RNN) are used for driving behavior profiling based on the data collected from an accelerometer in a smartphone [11].

In recent years, autoencoder, a deep learning architecture, has gained popularity in various domains due to its ability to learn meaningful representations of high-dimensional data [12], [13], [14], [15], [16]. Specifically, autoencoder has been shown to be a useful tool for extracting and clustering meaningful driving behavior with promising results. Researchers have proposed driving behavior visualization using autoencoder [17], [18]. In order to visualize driving behavior, low dimensional high-level representation of driving behavior was extracted by using autoencoder from high dimensional driving behavioral data including accelerator opening rate, meter of speed, brake master-cylinder pressure, steering angle, speed of wheels, engine speed, longitudinal acceleration, transverse acceleration, yaw rate, turn signal. Also, autoencoders have been used to model and reproduce driving behavior of expert drivers for developing autonomous vehicle capable of driving safely and smoothly [19], [20]. Meaningful features of driving behavior were extracted by using autoencoder based on expert driving data such as speed, brake, steering wheel and acceleration. The extracted features of human expert driving behaviors can be used to create velocity profiles allowing an autonomous driving agent to improve ride comfort. Furthermore, detection of abnormal driving has been studied using autoencoders. In order to

detect abnormal driving, a stacked sparse autoencoder model was used to learn generic driving behavior features from throttle position, brake pressure, and vehicle speed [21]. Although the analysis of driving behavior using data-driven methods has been a highly researched area to enhance road safety, the investigation of driving behavior in relation to different types of footwear has not been explored.

The assessment of collision risk is a crucial task in identifying potential collisions, and plays a significant role in the development of collision avoidance systems and autonomous vehicles. Driving safety involves complex interaction between the driver, the vehicle, and road environment. In the development of the collision risk assessment, most studies focused on time-to-collision models based on the vehicle motion and traffic situation prediction using Monte Carlo sampling [22], [23], Kalman filter and its variants using vehicle motion models [24], [25], and Dynamical Bayesian Network [26], [27]. However, very few studies have addressed driver's behavior (braking actions) and characteristic (gender, age, and license type) [28], [29], [30]. Furthermore, the assessment of collision risk based on different types of footwear has not been thoroughly investigated.

The paper presents an investigation into human driving behavior in urban roads with different types of shoes. For evaluating the driving behavior influenced by shoe type a methodology using an autoencoder-based clustering approach is introduced. The driving data, vehicle dynamics measurement data, was collected with two types of shoes, including high heels and driving shoes, and an autoencoder was used to train the data. The resulting clusters were analyzed in various urban driving scenarios with a preceding vehicle to investigate the effect of shoe types on driving safety. Additionally, the proposed clustering analysis with probabilistic risk assessment was conducted and it demonstrated a clear correlation between footwear choice and driving safety.

The main contributions of our research are as follows.

1. A methodology using an autoencoder-based clustering approach is proposed to analyze human driving behavior influenced by different shoe types.
2. Experiments involving actual car driving are conducted across diverse driving courses and situations.
3. Safety considerations are integrated into the analysis by using a probabilistic risk assessment and a collision risk plane.

The structure of our paper is as follows. In section II, we present a brief review of evaluation of driving behavior and a preliminary study on the relationship between braking distance and shoe type. Also, we describe the method we used to collect the driving dataset and assess vehicle safety. Section III outlines the method we used to extract driving patterns by training an autoencoder on the collected dataset and clustering the encoded features. In section IV, we present the results of our analysis. Finally, we conclude our paper in section V.

II. BACKGROUND

This section provides a comprehensive overview of the foundational studies that inform our investigation into the impact of human factors, specifically shoe type, on driving behavior and collision risk. First, we examine the relationship between driving behavior and safety, focusing on how variations in foot movements and patterns associated with different types of footwear can influence critical driving outcomes such as braking distance and vehicle control. Next, we delve into the investigation of braking distance, a key metric for assessing driving safety, by reviewing existing research on factors that affect braking performance, and the methodologies employed to evaluate it. Lastly, we explore the data collection processes related to shoe types, discussing the methods and tools used to gather relevant driving data that reflect the influence of footwear on driving behavior. These collectively provide the background necessary to understand the complexities of how human-centered factors, such as shoe type, contribute to driving safety and inform the development of more effective risk assessment algorithms.

A. IMPACT OF DRIVING BEHAVIOR ON SAFETY

Driving behavior significantly impacts road safety, particularly concerning the biomechanical interactions between a driver's footwear and their vehicle controls. Previous studies have shown that different types of shoes, such as high heels, flip-flops, and sports shoes, affect the driver's foot movement and pedal control, subsequently influencing braking distance and overall vehicle handling [31]. For instance, drivers wearing high heels or loose-fitting shoes like flip-flops exhibit longer braking distances and slower response times due to reduced pedal control sensitivity and delayed foot repositioning. This alteration in driving behavior heightens the risk of collisions, especially in scenarios that require quick deceleration or emergency braking. Moreover, the state of the driver, such as fatigue or discomfort caused by inappropriate footwear, can further impair driving performance, leading to erratic driving patterns or delayed responses to road hazards [32]. Such findings highlight the importance of understanding the role of footwear in driving safety, emphasizing the need for quantitative evaluations of how these factors interact with human driving behavior to enhance safety measures and reduce collision risks.

TABLE 1. Driving courses and behavior for data collection.

Driving course	Driving behavior
Course 1: straight section	Acceleration
Course 2: Toll gate area	Deceleration and then acceleration
Course 3: Circular path section	Gentle deceleration
Course 4: straight section	maintain speed
Course 5: Speed bump area	Gentle deceleration
Course 6: S-shaped section	maintain speed
Course 7: Right turn section	maintain speed
Course 8: straight section	deceleration to stop

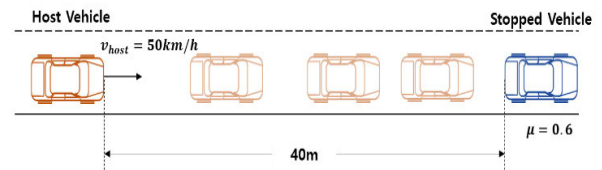


FIGURE 1. Emergency braking experiment.

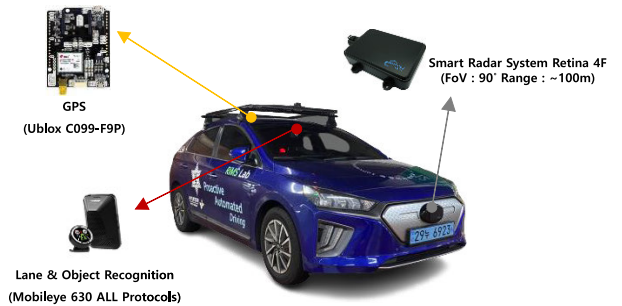


FIGURE 2. Test vehicle.

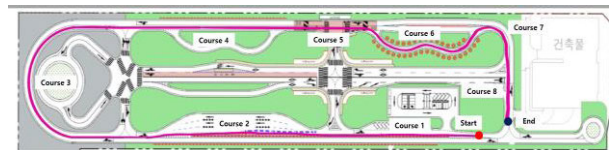


FIGURE 3. An example driving course for data collection in FMTC.

B. INVESTIGATION OF BREAKING DISTANCE

By examining the braking performance of drivers wearing different shoe types, we aim to identify any significant differences or trends that may indicate a connection between footwear choice and vehicle safety with braking distance. In order to investigate the relationship between shoe type and braking distance, emergency braking tests were conducted. A test vehicle was initially traveling at 50 km/h, and when it approached a stationary vehicle located 40 m ahead, the test vehicle initiated braking, as illustrated in Fig. 1. The test environment condition is shown in Table 2. Experiments were conducted by two drivers with each driver operating test vehicle three times while wearing driving shoes and three times while wearing high heels. The average values of the experimental results are shown in Table 3. From Table 3, we can see that the cumulative value of brake pressure has a direct impact on braking distance and braking time, with higher cumulative values resulting in shorter braking distance and time. When comparing brake performance based on different types of footwear, driving shoes showed an average of 441 psi higher cumulative value of cylinder pressure compared to high heels. As a result, the braking distance increased by an average of 0.92 meters and the braking time increased by 0.12 seconds for high heels compared to driving shoes. In Table 3, while the cumulative cylinder pressure showed a clear correlation with

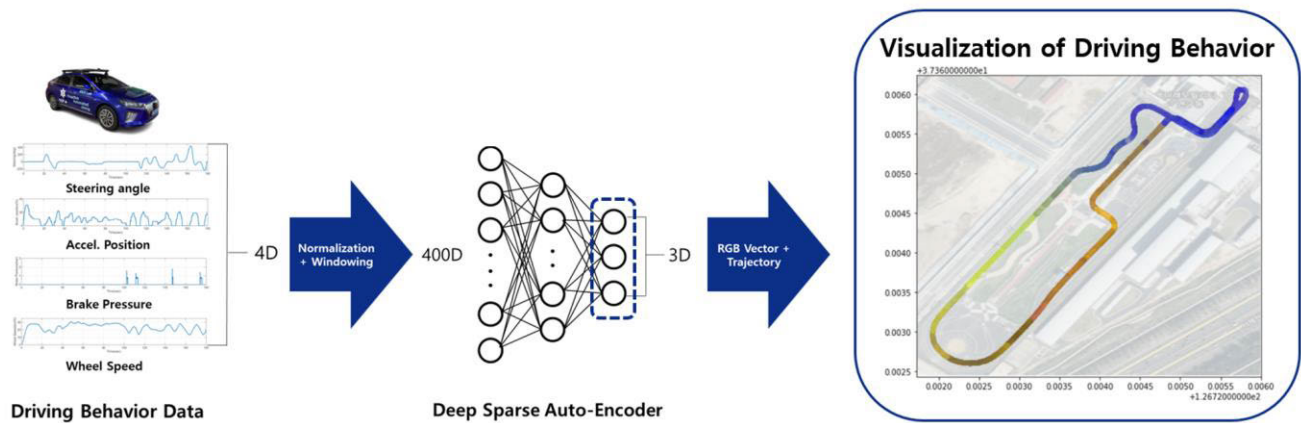


FIGURE 4. Overall methodology.

braking performance across both drivers, we observed that for Driver 1, the differences in braking distance and time between shoe types were less pronounced. This result suggests that individual driving styles and physiological factors, such as foot size and pedal pressure techniques, may mitigate the impact of footwear. These findings highlight the need for further investigations involving a larger participant pool to explore how individual differences interact with footwear to influence driving safety.

TABLE 2. Condition of test environment.

Condition	Value
Friction coefficient	0.6
Temperature	-2 °C
Wind speed	7 m/s
Tire pressure	39.5 psi

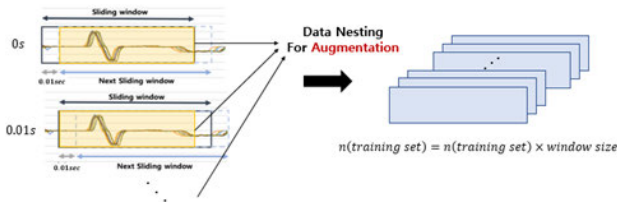


FIGURE 5. Segmentation and augmentation with sliding window method.

Based on the results, it is seen that there is a significant correlation between shoe types and braking distance. A more in-depth analysis of the driving patterns associated with different types of shoes would be beneficial for improving driving safety and comfort. In the following section, we will introduce methods for conducting a more comprehensive analysis.

C. DATA COLLECTION: SHOE TYPE

In this study, a 2019 Hyundai Ioniq Electric is used as a test vehicle as shown in Fig. 2. Vehicle dynamics measurement

data including wheel speed, brake pressure, steering angle, longitudinal acceleration, accelerator position is collected via the vehicle controller aera network (CAN) bus at 100 Hz. The distance to the preceding vehicle is also measured by using a radar (Smart Radar System, Retina 4F) and computer vision system (Mobileye 630) equipped on the test vehicle as shown in Fig. 2. Additionally, the test vehicle is equipped with an RTK-GPS (U-Blox, C099-f9p) and vehicle’s longitude and latitude positions are recorded along with its driving data.

Data collection was conducted at the Future Mobility Technology Center (FMTC) located in Siheung, South Korea. Vehicle dynamics measurement data was collected through actual driving with different types of footwear: driving shoes and high heels, on various driving courses. An example driving course for the data collection is shown in Fig. 3. Also, the vehicle driving behavior performed during the tests are summarized in Table 1. In order to replicate driving scenarios in urban driving environment, a lead vehicle was operated at a maximum speed of 50 km/h and the test vehicle followed the lead vehicle while maintaining a maximum distance of 20 m. A total of 48 driving data were obtained from two drivers who drove the test vehicle 12 times each, wearing different types of footwear.

TABLE 3. Emergency braking test results with different types of footwear.

	Braking distance	Braking time	Cumulative cylinder pressure	Pedal switching time	Vehicle stopped time
Driver 1: Driving shoes	24.418 m	3.59 s	5094.63 psi	0.39 s	3.98 s
Driver 1: High heels	24.978 m	3.62 s	4717.2 psi	0.42 s	4.04 s
Driver 2: Driving shoes	19.678 m	2.97 s	6659.6 psi	0.48 s	3.45 s
Driver 2: High heels	20.956 m	3.17 s	6153.1 psi	0.5 s	3.67 s

TABLE 4. Range of chassis data in acquisition scenario.

Attribute	Min	Max
Steering Angle [deg]	-281.0	521.5
Accel. Position [%]	0	51.764
Brake Pressure [bar]	0	2.9
Wheel Speed [kph]	0	32.218

III. DRIVING BEHAVIOR EXTRACTION AND RISK ASSESSMENT

This section presents our methodology for clustering driving behavior data using an autoencoder. The autoencoder was trained using driving data collected from test driving courses with two types of shoes, including high heels. We aim to investigate the effect of shoe types on vehicle safety by analyzing the resulting clusters in various urban driving scenarios with a preceding vehicle. By using the autoencoder to compress the driving data, we were able to obtain a better understanding of the underlying patterns in driving behavior. We present the data preprocessing and the implementation of the autoencoder for the clustering of driving behavior data.

A. WORK OVERVIEW

To conduct this research, we collect vehicle dynamics measurement data using an actual car and recorded four types of data: steering angle, accelerator position, brake pressure, and wheel speed. We then segment and normalize the data appropriately and use it to train an autoencoder. The goal is to extract RGB values from the latent vectors of the encoder and visualize the results.

The first step is to segment the vehicle dynamics measurement data into appropriate sizes and normalize it. This involves dividing the driving data into overlapping windows, as explained earlier, and applying normalization techniques to ensure that the data was scaled appropriately for the autoencoder.

Next, we use the segmented and normalized driving data to train an autoencoder. The autoencoder consists of an encoder network that compresses the input data into a lower-dimensional latent space and a decoder network that reconstructed the original data from the latent vectors. By training the autoencoder on the driving data, we are able to learn a compressed representation of the data that captures the most important features.

After training the autoencoder, we extract RGB values from the latent vectors of the encoder and visualized the results. This involved mapping the latent vectors to an RGB color space and creating visualizations that allows us to explore the relationships between the different driving variables. The RGB values are assigned to different segments of the driving course, representing the clustering results. Furthermore, we conduct a collision risk analysis to evaluate the safety implications of the driving patterns. Overall, this research methodology involves collecting and preprocessing real-world driving data, training an autoencoder to learn a compressed representation of the data, and visualizing the

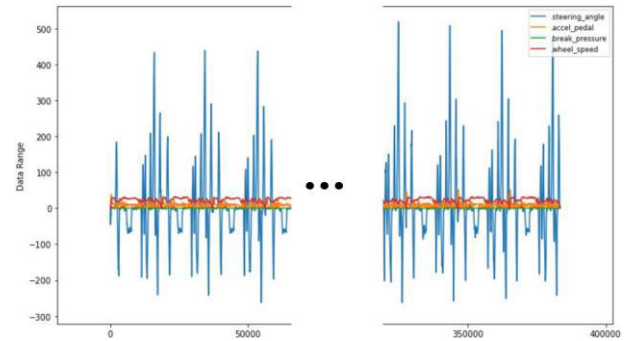


FIGURE 6. Graph of chassis data in acquisition scenario.

TABLE 5. Range of chassis data applied normalization.

Attribute	Min	Max
Steering Angle [deg]	-2.81	5.21
Accel. Position [%]	0	5.1
Brake Pressure [bar]	0	2.9
Wheel Speed [kph]	0	3.22

results to gain insights into the driving patterns. Fig. 4 represents overall methodology.

B. DATA PREPROCESSING

Since the driving data that we collected is a time-series data, the sliding window technique is an effective way to segment and augment the data [32], [33]. This technique involves dividing the time-series data into smaller segments of equal sizes, or windows, that overlap with each other. Each window is then treated as a separate data point, and the resulting dataset is larger than the original data.

We used the sliding window technique to segment the driving data that we collected into smaller windows of equal sizes. For example, it could be chosen to segment the data into windows of 1 second duration with 50% overlap between consecutive windows. The overlap between consecutive windows ensures that the windows capture a continuous sequence of data and do not miss any important features.

We then use these segmented windows as separate data points and applied normalization techniques to ensure that the data was scaled appropriately for the autoencoder [34], [35]. This approach allows us to effectively handle the time-series nature of the driving data and train an autoencoder on a larger and more diverse dataset than the original driving data.

We collected vehicle dynamics measurement data that consists of four types of features: steering angle, accelerator position, brake pressure, and wheel speed. The data was collected at a frequency of 100 Hz, which means that we have 100 observations per second.

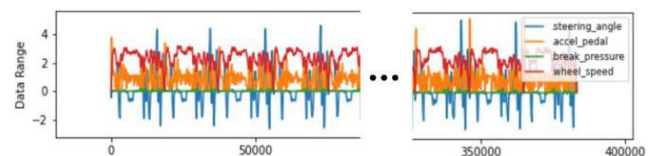


FIGURE 7. Graph of chassis data applied normalization.

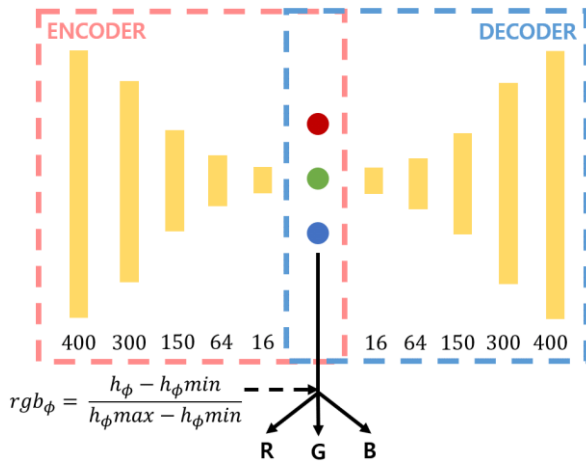


FIGURE 8. Architecture of autoencoder.

To apply the sliding window technique, we choose a window size of 100 observations. This means that we take 100 observations of each of the four features, which corresponds to a window size of 1 second of driving data. We then move the window by 1 observation every 0.01 seconds to create an overlapping segment of the driving data. Fig. 5 shows the example of sliding window method.

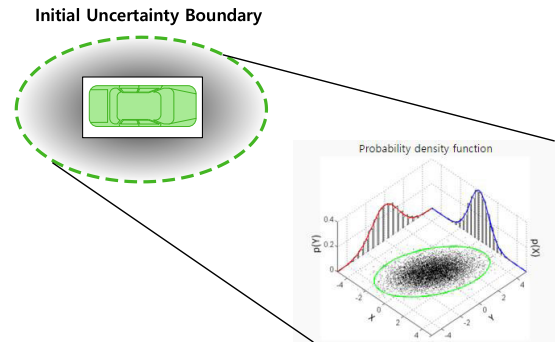
For example, if we start with the first observation, we take the first 100 observations of all four features, which corresponds to the first second of driving data. We then move the window to the second observation and take the next 100 observations of all four features, which corresponds to the second of driving data, and so on.

By segmenting the driving data into windows, we can create a larger and more diverse dataset to train our autoencoder. We then use normalization techniques to ensure that the data is scaled appropriately for the autoencoder. Finally, we extract the latent vector from the encoder and map it to an RGB color to visualize the driving data.

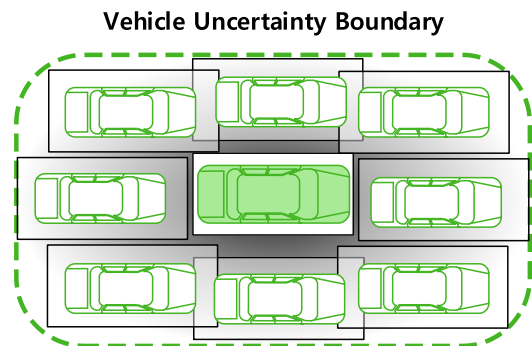
After this process, we normalize the segmented data. Normalization is a common technique used in machine learning and data analysis. By scaling the data to a fixed range, we can ensure that all the features are equally weighted during the training process. This is important because features with larger ranges may dominate the training process and produce biased models.

If we do not normalize the data, it can cause several problems during the training process. One problem is that features with larger ranges can dominate the training process, leading to biased models. Another problem is that the optimization algorithm used to train the model may converge slowly or not converge at all, especially if the features have different scales. Fig. 6 and Table 4 shows the range of collected data before normalization.

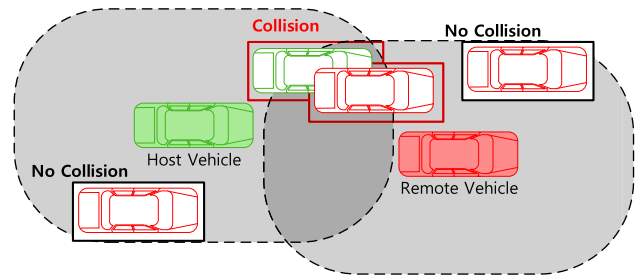
Normalization helps to alleviate these problems by scaling the features to a fixed range, ensuring that they are all equally weighted during training. This can lead to faster convergence and better performance of the model.



(a) Initial Uncertainty Boundary Generation



(b) Randomly Generated N State Vectors (Particles)



Vehicle Uncertainty Boundary

(c) Description of Collision

FIGURE 9. Procedure of collision probability computation.

In our study, we normalize the driving data to single digit after segmenting it using the sliding window technique. This allows us to ensure that the features were scaled appropriately for the autoencoder, which can lead to better performance and more accurate results. Fig. 7 and Table 5 shows the range of data after normalization.

C. MODEL ARCHITECTURE: AUTOENCODER

We trained an autoencoder using the preprocessed data. The autoencoder has 400 input neurons, corresponding to 4 types of data (steering angle, accel position, brake pressure, wheel speed), each with 100 features. The encoder consists of 4 layers, which progressively reduce the dimensionality of the input data. To determine the optimal structure of the

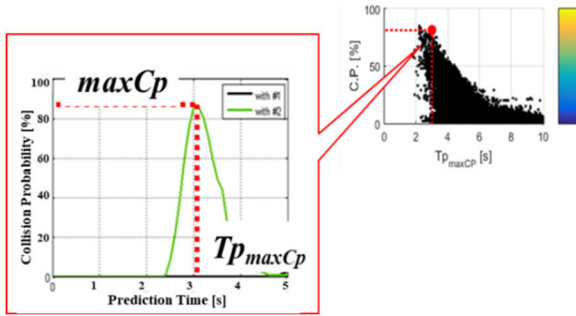


FIGURE 10. General concept of maxCp and TpmaxCp.

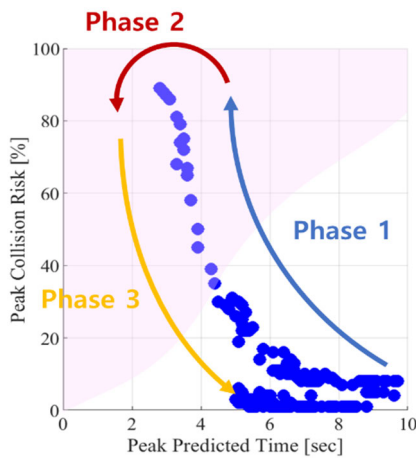


FIGURE 11. Collision risk during given prediction time horizon.

autoencoder, we experimented with the number of hidden layers, starting with a single layer and gradually increasing the depth. During this process, each layer was designed with fewer neurons than the previous layer, ensuring the dimensionality was reduced below the input size. The final layer of the encoder produces a latent vector of 3 dimensions, which is used to generate the RGB values. To calculate the reconstruction error, we employed Mean Squared Error (MSE) as the loss function, which allowed us to gauge the autoencoder's performance effectively. Fig. 8 shows the architecture of the Autoencoder.

During training, the autoencoder learns to reconstruct the input data from the latent vector, while minimizing the reconstruction error. The decoder, which is symmetric to the encoder, maps the latent vector back to the original input space. The autoencoder is trained to minimize the difference between the input data and the reconstructed data using backpropagation and stochastic gradient descent. To optimize the hyperparameters, we used grid search, and the selected hyperparameters are presented in Table 6.

After training, the encoder can be used to extract the latent vector from new input data, which can be used to generate the corresponding RGB values. This allows us to visualize the input data in a low-dimensional color space, which can reveal patterns and structures that may be difficult to detect in the original high-dimensional space.

TABLE 6. Hyper-parameters for model optimization.

Hyper-parameter	Values Tested	Optimal Value
Learning Rate	[0.001, 0.01, 0.1]	0.001
Number of Layers	[1, 2, 3, 4, 5]	4
Size of Window	[5, 10, 20]	10

TABLE 7. Risk management and driving phase.

Driving Phase	Risk Management
Phase 0	Normal Driving
Phase 1	Collision Risk Increase
Phase 2	Safety Control
Phase 3	Re-entering to Safety Zone (Safety Spacing)

D. DRIVING BEHAVIOR CLUSTERING

Spectral clustering and k-means clustering are both unsupervised learning techniques used to group similar data points together. However, they differ in their approach to clustering. K-means clustering tries to partition the data into k clusters by minimizing the sum of squared distances between the data points and their assigned cluster centers [36], [37]. It iteratively updates the cluster centers until convergence. On the other hand, spectral clustering is a graph-based clustering technique that uses the spectral decomposition of the similarity matrix to cluster the data [38], [39].

In other words, spectral clustering looks at the relationships between data points, rather than their distance in the feature space. It constructs a similarity matrix that captures the pairwise similarities between data points, and uses the eigenvectors of this matrix to find a low-dimensional representation of the data. This low-dimensional representation is then used as input to a clustering algorithm (e.g., k-means) to partition the data into clusters.

Compared to k-means clustering, spectral clustering can be more effective when dealing with non-linearly separable data and can uncover more complex structures in the data. However, it can be computationally expensive and requires tuning of the hyperparameters, such as the number of clusters and the similarity matrix construction method.

In our case, we used spectral clustering to group the data points in the low-dimensional space obtained from the latent vectors produced by the autoencoder. The similarity function used was the RBF kernel, and the Laplacian matrix was computed using the normalized graph Laplacian. The resulting clusters represent groups of data points that are similar to each other in terms of their features.

By applying spectral clustering to the feature extraction results, we were able to identify groups of features that are closely related to each other, which can help in understanding the underlying patterns and structures in the data.

E. COLLISION RISK ASSESSMENT

According to [24], incorporating human-centered risk assessment techniques can lead to a notable improvement in

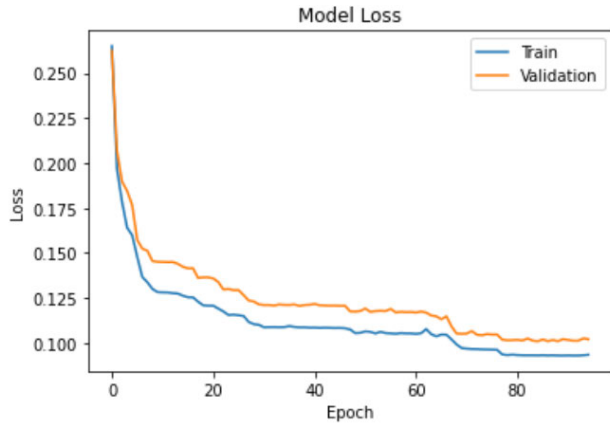


FIGURE 12. Graph of loss value.

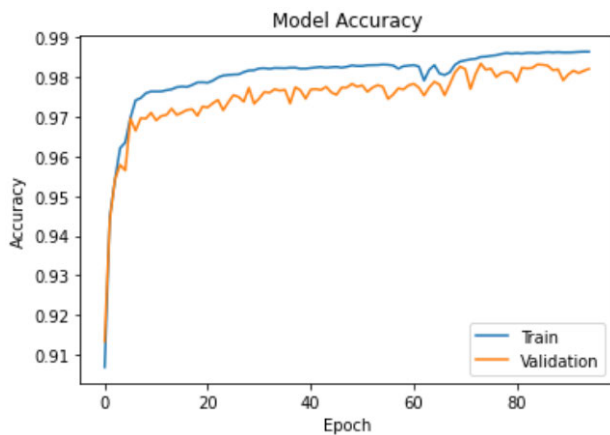


FIGURE 13. Graph of model accuracy.

threat assessment performance. “The human-centered risk assessment algorithm actively intervenes to control safety by monitoring risk and determining intervention points based on collision probability. Real-road test driving data is used to compute the threat of the vehicle ahead by analyzing the human driver’s driving pattern using collision probability. [24]. The probability of a collision between the host and remote vehicle can be calculated by dividing the number of possible collision cases by the total number of cases where the two vehicles randomly exist within an uncertainty boundary. A collision is counted when two vehicles occupy the same space, as illustrated in Fig. 9-(c). The joint probability density function can be used to model the uncertainty boundary shown in Fig. 9-(a) as stated in [35]. In Fig. 9-(a), the grey shaded ellipsoidal area around the vehicle represents the boundary that describes the reachable area. The probability density function is constructed based on the gaussian distribution using vehicle states such as vehicle position and orientation. Then, a particle filter is used to randomly generate N state vectors (particles) based on the initial probability density function, as shown in Fig. 9-(b). Vehicle-body-shaped polygons for both the host and remote vehicles are generated

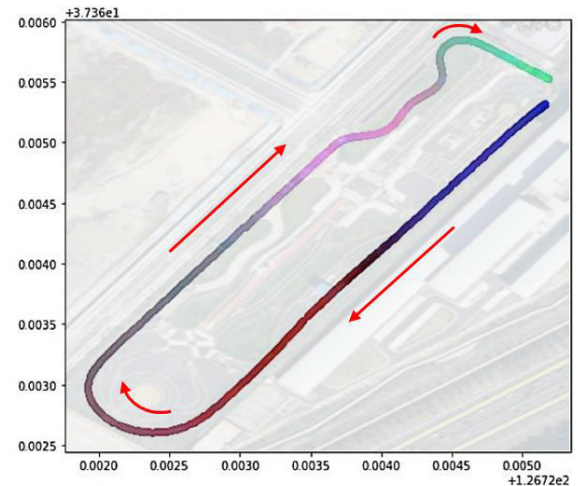


FIGURE 14. Visualization of the feature extraction result.

for each random particle, as depicted in Fig. 9-(c). If the polygons of the two randomly generated vehicles share the same space, a collision is counted. The collision probability increases as the number of space-sharing areas (collision cases) increases, as described in (1).

$$\text{Collision Probability} = Cp = \frac{\text{Collision Case}}{N - \text{state}} \times 100(\%) \quad (1)$$

where

$$N\text{-state} = 500$$

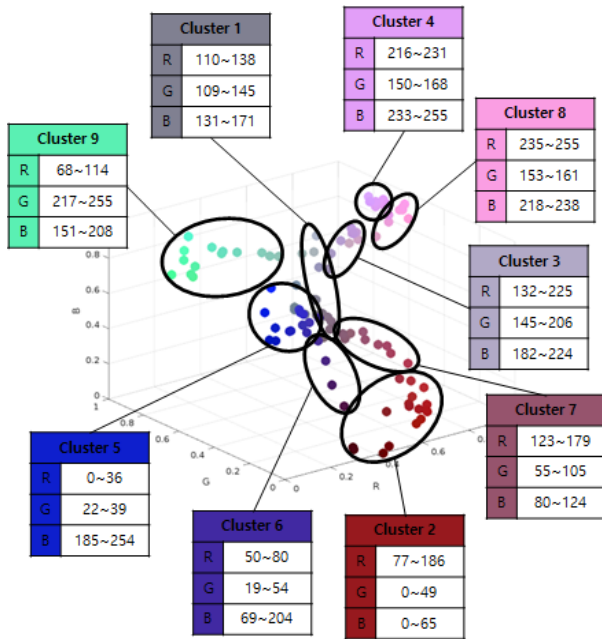
The parameter “N-state” has been selected by the user as a trade-off between computational effort and collision probability approximation accuracy.

With the general concept of the peak(maximum) collision probability, $\max Cp$, and most probable (peak) predicted collision time, $Tp\max Cp$ are introduced in Fig. 10 [24].

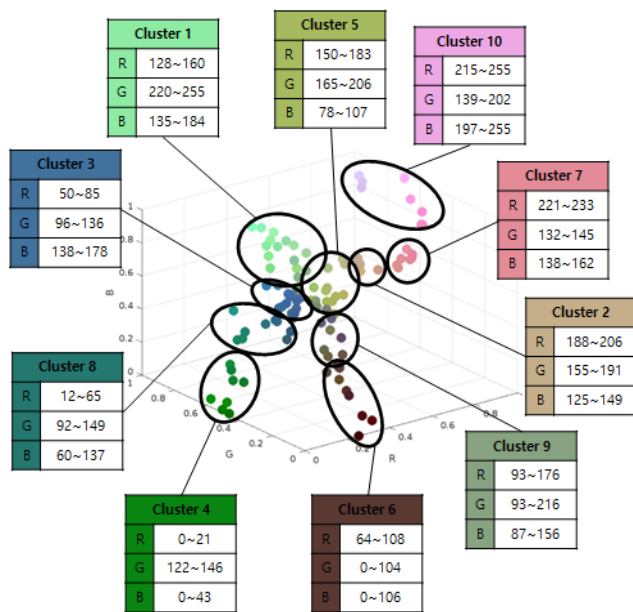
Test driving data typically includes four phases of a human driver’s risk management pattern, as illustrated in Table 7 and Fig. 11 [40]. Phase 0 represents normal driving conditions. Phase 1 is an alert situation caused by human perception failure, which can occur due to distractions or inattentive driving. Phase 2 involves hazard detection and control for collision avoidance. Phase 3 is the recovery stage where a safe distance is maintained from the vehicle ahead.

IV. VEHICLE TESTS

This section explains the impact of different shoe types on vehicle safety during driving by utilizing an Autoencoder to process data collected from test drives conducted with two distinct footwear types. After effectively training the data, we identified driving patterns in various urban scenarios where a vehicle was present ahead. To assess the safety implications of different shoe types, we confirmed the significance and influence of these driving patterns by conducting a collision risk analysis within the context of our test results.



(a) Clustering Result of Driving Shoes



(b) Clustering Result of High heels

FIGURE 15. Clustering results of two types of shoes.

A. FEATURE EXTRACTION RESULTS

We used Adam as our optimizer and Mean Squared Error (MSE) as our loss function to train the autoencoder. Both the training and validation loss decreased to below 0.1 during training, indicating that the model converged well as shown in Fig. 12. The accuracy also reached above 0.985 during training as shown in Fig. 13.

Fig. 14 shows a visualization of the feature extraction results on the driving course. The input data is mapped to a low-dimensional color space using the trained autoencoder,

TABLE 8. Behavior state of driving shoes.

ID	Color	Behavior state
1		Maintain speed with steering angle -80°
2		Gentle deceleration with brake pressure 1.8 bar
3		Slalom (fluctuation in steering angle)
4		Sharp deceleration to stop
5		Steady acceleration from 30km/h to 50km/h
6		Steady deceleration with brake pressure 1.8 bar
7		Coasting from 50km/h without any input
8		Maintain speed with fluctuation in steering angle
9		Coasting: maintain speed
10		Sharp acceleration from stop to 50km/h

TABLE 9. Behavior state of high heels.

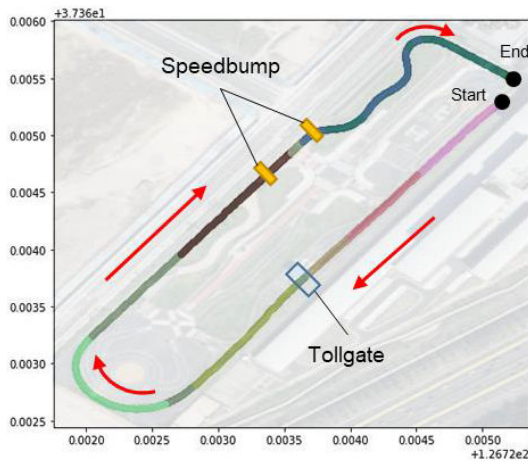
ID	Color	Behavior state
1		Maintain speed
2		Deceleration with brake pressure 1.8 bar
3		Steady deceleration with brake pressure 1.8 bar
4		Gentle deceleration with brake pressure 1.8 bar
5		Deceleration with brake pressure 8.5 bar
6		Sharp acceleration from stop to 50km/h
7		Maintain speed with steering angle -80°
8		Gentle acceleration with fluctuation in steering angle
9		Sharp deceleration to stop with brake pressure 16.2 bar

where each point in the space represents data of the driving pattern. The colors of course correspond to the RGB values generated by the autoencoder. This visualization allows us to observe patterns and structures in the driving data that may be difficult to detect in the original high-dimensional space.

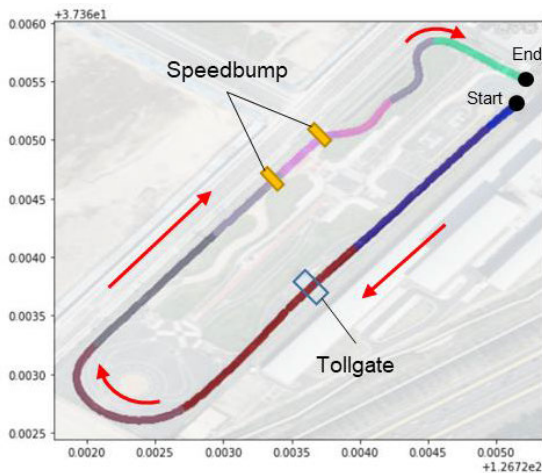
B. DRIVING BEHAVIOR CLUSTERING RESULTS

We compare the driving patterns visualized by the trained autoencoder using data collected while driving with driving shoes and high heels. Fig. 15 shows the clustering results for both types of footwear. The results indicate that the driving patterns for each type of footwear are distinct, with different regions of the latent space corresponding to different types of driving behavior. This suggests that the autoencoder is able to

capture meaningful information about driving behavior, and that it may be possible to use this information for applications such as driver monitoring or driving style analysis.



(a) Visualization Result of Driving Shoes



(b) Visualization Result of High Heels

FIGURE 16. Visualization results of two types of shoes.

Fig. 16 presents the visualization of the clustering results on the driving course from Fig. 15 for different types of shoes. The different colors on the map represent different clusters of driving patterns. By comparing the colors of the clusters for driving with driving shoes and high heels, we can observe that the driving patterns for the two types of shoes are completely different.

The visualization results reveal that different segments of the driving course are associated with different clusters, suggesting that specific driving scenarios evoke distinct driving responses based on the type of footwear. Notably, driving with driving shoes exhibits more dynamic changes in cluster patterns, especially before entering speed bumps and tollgates. This observation implies that drivers wearing driving shoes are more responsive to such situations, whereas drivers wearing high heels tend to show delayed braking responses,

resulting in less cluster variation with a single clustering result in the case of repetitive speed bump.

The visualization indicates that driving patterns can vary depending on the driving shoes, as some segments are associated with one cluster for both types of shoes, while others are associated with different clusters for the two types of shoes. These findings strongly indicate that the choice of footwear has a profound impact on driving behavior. Such insights can be instrumental in guiding the design and development of more suitable driving shoes for various driving conditions.

According to emergency braking tests that were conducted in the Section II-(b), we found that the cumulative brake pressure directly according to shoe type influences both braking distance and braking time, with higher cumulative values leading to reduced braking distance and time. Fig. 16-(a) and 16-(b) further substantiate these findings by examining our driving behavior clustering results, reflecting deceleration pattern differences during speed bump navigation and tollgate approaches. The clustering results also reveal potential variations in driving behavior concerning the application of nuanced throttle pedal force during acceleration, which may be attributed to the type of footwear worn by the driver. This demonstrates the potential influence of shoe type on driving performance across various driving scenarios.

Table 8 and Table 9 represent the driver's behavior for each clustered segment. Each row in the tables corresponds to a segment and displays the percentage of time the driver spent on specific driving behaviors within that segment, such as maintaining speed, or sharp deceleration. Table 7 shows the behavior of drivers wearing driving shoes, while Table 8 shows the behavior of drivers wearing high heels. These tables provide insight into how the driving behavior differs between the two types of shoes and help to identify patterns or tendencies in the way each group of drivers behaves while driving.

Based on the analysis reflected in Fig. 17, it is clear that the clustering methodology employed is effective in capturing the distinct driving patterns associated with wearing high heels. The comparison between the clustered segments and the actual vehicle signals (accel position, brake pressure, and velocity) demonstrates that the variations in signal values across different sections of the course are accurately captured. This sensitive capturing of driving behavior variations strongly supports the reliability and validity of the clustering approach. The results confirm that the clustering method accurately reflects the driving patterns, making it a dependable tool for analyzing the impact of different footwear on driving behavior.

C. COLLISION RISK ANALYSIS: EFFECTS OF SHOE TYPES

In this section, we present the experimental results of our study, which aimed to investigate the impact of shoe types on safe driving described in Fig. 18-(a) and Fig. 19-(a). The validity and influence of the clustering results were examined through a collision risk analysis, providing insights into the safety effects of different footwear choices on driving

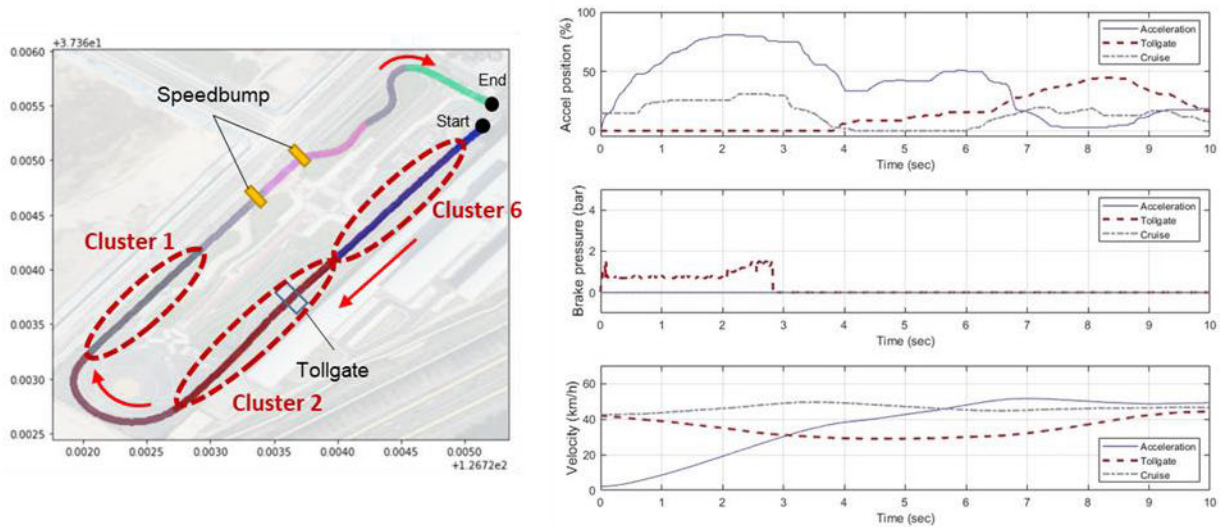
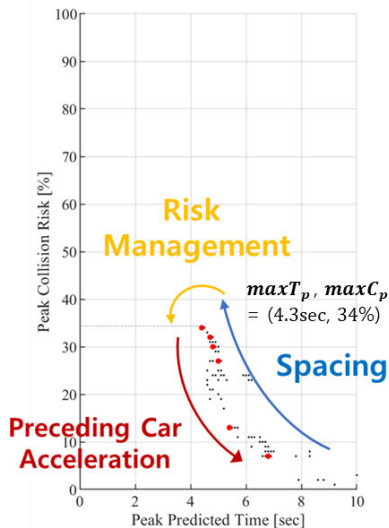


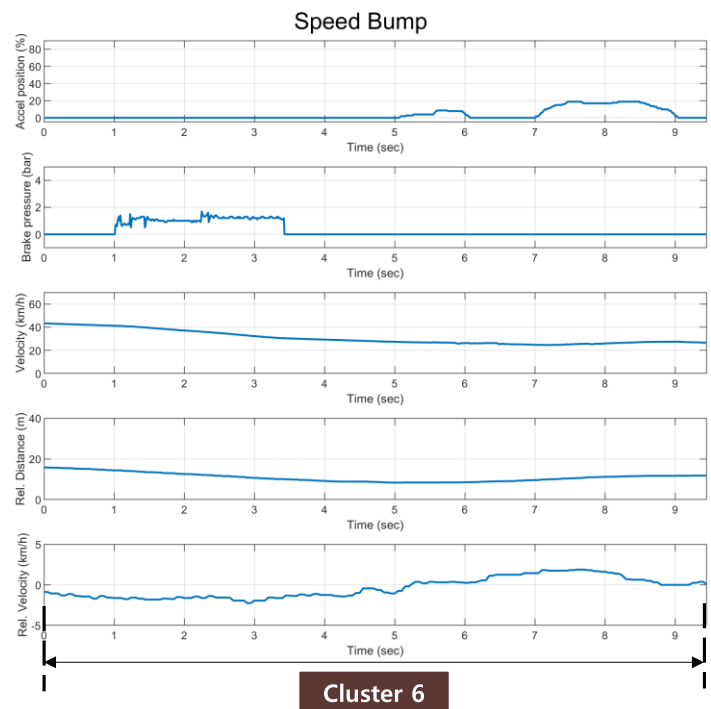
FIGURE 17. Clustering results of driving patterns while wearing high heels. The left side shows the map with clusters (Cluster 1, Cluster 2, and Cluster 6) identified on the driving course, while the right side presents the actual vehicle signals corresponding to each cluster. The graphs depict Accel Position, Brake Pressure, and Velocity, highlighting the differences in driving behavior across different segments of the course.



(a) Front view of the driver and shoes



(b) Probabilistic Collision Risk



(c) Vehicle Measurement Data

FIGURE 18. Peak collision risk based predicted distance (Distance to Collision): Driving Shoes.

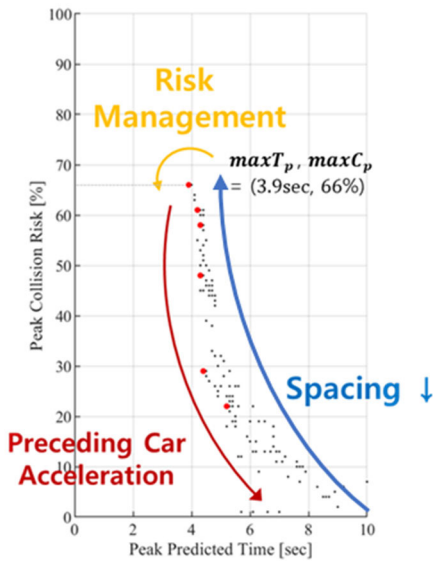
performance. The validity and impact of the clustering results on safe driving were verified through collision risk analysis in order to investigate the safety effects of shoe types.

In Fig. 18, we provide evidence that the clustering results (Cluster 6) obtained in the Fig. 15-(a) have accurately

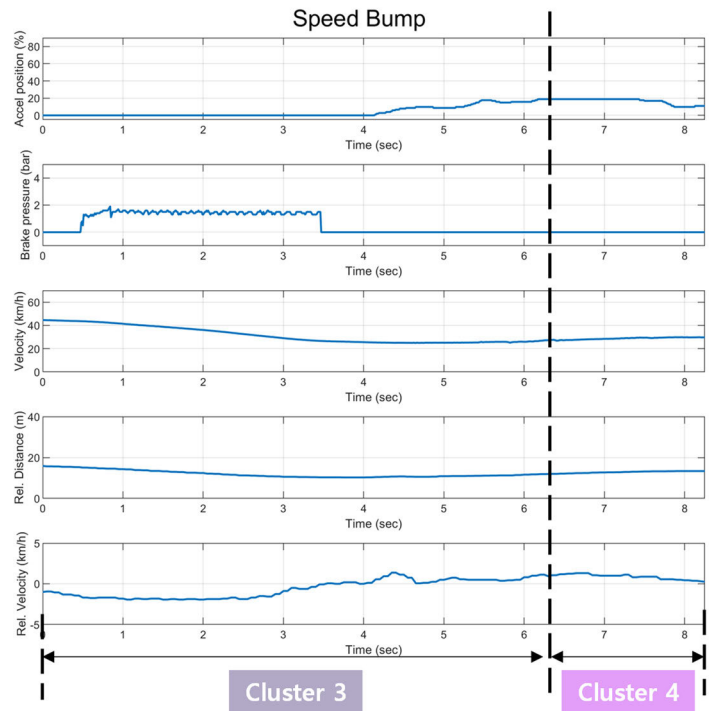
classified driving patterns based on the type of driving shoes. This assertion is supported by a thorough collision risk analysis and vehicle dynamics measurement data in Fig. 18, which together demonstrate the effectiveness of the clustering approach in differentiating the impact of various shoe



a) Front view of the driver and shoes



(b) Probabilistic Collision Risk



(c) Vehicle Measurement Data

FIGURE 19. Peak collision risk based predicted distance (Distance to Collision): High Heels.

types on driving performance. Fig. 18 presents compelling evidence that the clustering results obtained in the Fig. 15-(b) have effectively categorized driving patterns (Cluster 3, 4) corresponding to the use of high heels. This claim is substantiated by a comprehensive collision risk analysis and vehicle dynamics measurement data in Fig. 18, which together emphasize the efficacy of the clustering technique in delineating the impact of high heels on driving performance.

As discussed in Section II-B and Section IV-B, our collision risk analysis is used to verify the validity and impact of the clustering results on safe driving. It has been revealed that specific clusters showed a significant difference in the risk management performance associated with each shoe type; driving shoes and high heels demonstrated 43% and 66% of maximum collision probability, respectively. The results indicated a clear correlation between footwear choice and driving safety, with certain shoe types presenting a 23% of higher likelihood of causing accidents compared to others. Furthermore, the vehicle dynamics measurement data in the Fig. 18-(c) and Fig. 19-(c) substantiated these findings, showcasing marked differences in parameters such as position of accelerator, relative distance, and longitudinal velocity profiles among the distinct clusters.

The observed differences in collision risk when wearing driving shoes or high heels can be attributed to the human factor perspective, particularly concerning the operation of

the accelerator pedal. When wearing high heels, drivers tend to exhibit less precise control over the accelerator pedal compared to when wearing driving shoes. This imprecision leads to unintentional excessive pressure on the pedal while wearing high heels, resulting in a more aggressive acceleration profile.

Consequently, the distance between the driver's vehicle and the preceding vehicle decreases, thereby increasing the collision risk. In contrast, drivers wearing driving shoes demonstrate more refined control over the accelerator pedal, ultimately contributing to a safer driving experience by maintaining an appropriate distance from other vehicles and reducing the likelihood of accidents.

V. CONCLUSION

In conclusion, this paper investigates the effects of shoe type on risk assessment in an urban driving environment, utilizing feature extraction through an autoencoder to analyze driving patterns. We have demonstrated the importance of examining driving patterns when wearing shoes such as high heels, which are known to adversely affect safe driving due to increased braking distances. To achieve this, we implemented an autoencoder to train driving data acquired from test driving courses with two types of shoes—driving shoes and high heels. The successfully trained data allowed for the clustering

of driving characteristics across various urban driving scenarios when a preceding vehicle is present.

Our findings, validated through collision risk analysis, revealed that wearing driving shoes results in a significantly safer driving experience compared to wearing high heels. Specifically, the maximum collision probability was reduced by 23%, and the maximum collision time was improved by 0.4 seconds when driving shoes were worn. This study emphasizes the critical impact of shoe type on driving safety and highlights the importance of choosing appropriate footwear to reduce collision risk and promote safer driving behaviors in urban environments.

DISCUSSION & FUTURE WORKS

Although the proposed methodology has been validated through experiments on various driving courses and actual driving data, it primarily focuses on single-vehicle operations in urban scenarios and examines the effects of only two shoe types: high-heeled shoes and driving shoes. This focused approach provides foundational insights into how footwear influences driving behavior and collision risk, offering a controlled framework to establish clear correlations. However, to enhance the applicability and generalizability of the findings, future research should address several limitations.

Future studies will aim to incorporate multi-vehicle interactions to capture more complex dynamics of real-world driving environments. Additionally, expanding the range of footwear types to include sneakers, flip-flops, and work boots will provide a more comprehensive understanding of how shoe design affects driving safety. This expansion will help validate the current findings across diverse scenarios and support the development of adaptive safety systems that account for various human factors.

The findings of this study have practical implications for road safety, particularly in designing footwear optimized for driving and in enhancing driver monitoring systems for safety-critical scenarios. For example, integrating the insights gained from this research into driver-assistance technologies could enable adaptive systems that adjust braking and acceleration sensitivities based on the driver's footwear. Such features could significantly improve driving safety by mitigating the risks associated with inappropriate footwear choices.

Moreover, while this study primarily focused on validating the efficacy of our approach using autoencoders and clustering, we have also initiated benchmarking experiments with state-of-the-art models such as LSTM, self-attention, and transformer-based methods shows promise for extending the analysis. Preliminary results suggest that these advanced techniques offer complementary perspectives on driving behavior. The comparative findings are being organized for publication in a separate study, where they will be presented in greater detail. This follow-up research will offer further validation of our methodology and extend its contributions to the broader field of driving safety and machine learning.

By addressing these limitations and building upon the current findings, this research aims to advance the understanding of human factors in driving safety and contribute to the design of more intelligent and adaptive systems for risk mitigation.

REFERENCES

- [1] *Human Factors* | NHTSA. Accessed: Apr. 14, 2023. [Online]. Available: <https://www.nhtsa.gov/research-data/human-factors>
- [2] *Ergonomics, Human Factors and Driver Safety*. Accessed: Apr. 14, 2023. [Online]. Available: https://www.cranfield.ac.uk/academic-disciplines/ergonomics-human-factors-and-driver-safety?utm_term=&utm_source=adwords&utm_campaign=U.K.+%7C+Performance+Max+%7C+SOM+%7C+Portfolio+-+Executive&utm_medium=ppc&hsa_mt=&hsa_kw=&hsa_net=adwords&hsa_acc=6249696022&hsa_ad=&hsa_cam=19546476436&hsa_src=x&hsa_t
- [3] *About Shoes, Feet and Safe Driving | Did You Know Cars*. Accessed: Apr. 14, 2023. [Online]. Available: <https://didiyouknowcars.com/about-shoes-feet-and-safe-driving/>
- [4] *Best Driving Shoes (Review & Buying Guide) in 2023 | the Drive*. Accessed: Apr. 14, 2023. [Online]. Available: <https://www.thedrive.com/reviews/28649/best-driving-shoes>
- [5] S. Mačuzić, J. Lukić, J. Glišović, and D. Miloradović, "Pedal force determination respect to ride comfort," *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 252, Oct. 2017, Art. no. 012010. [Online]. Available: <https://iopscience.iop.org/article/10.1088/1757-899X/252/1/012010/meta>
- [6] P.-H. Ting, J.-R. Hwang, J.-L. Doong, and M.-C. Jeng, "Driver fatigue and highway driving: A simulator study," *Physiol. Behav.*, vol. 94, no. 3, pp. 448–453, Jun. 2008.
- [7] F. Tango and M. Botta, "Real-time detection system of driver distraction using machine learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 2, pp. 894–905, Jun. 2013.
- [8] W. Wang, J. Xi, A. Chong, and L. Li, "Driving style classification using a semisupervised support vector machine," *IEEE Trans. Human-Mach. Syst.*, vol. 47, no. 5, pp. 650–660, Oct. 2017.
- [9] D. Mitrovic, "Reliable method for driving events recognition," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 198–205, Jun. 2005.
- [10] P. Boyraz, M. Acar, and D. Kerr, "Signal modelling and hidden Markov models for driving manoeuvre recognition and driver fault diagnosis in an urban road scenario," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2007, pp. 987–992.
- [11] E. Carvalho, B. V. Ferreira, J. Ferreira, C. de Souza, H. V. Carvalho, Y. Suhara, A. S. Pentland, and G. Pessin, "Exploiting the use of recurrent neural networks for driver behavior profiling," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, May 2017, pp. 3016–3021.
- [12] C.-W. Tsai, K.-C. Chiang, H.-Y. Hsieh, C.-W. Yang, J. Lin, and Y.-C. Chang, "Feature extraction of anomaly electricity usage behavior in residence using autoencoder," *Electronics*, vol. 11, no. 9, p. 1450, Apr. 2022.
- [13] Y. Huang, C.-H. Chen, and C.-J. Huang, "Motor fault detection and feature extraction using RNN-based variational autoencoder," *IEEE Access*, vol. 7, pp. 139086–139096, 2019.
- [14] J. Yu, X. Zheng, and S. Wang, "Stacked denoising autoencoder-based feature learning for out-of-control source recognition in multivariate manufacturing process," *Qual. Rel. Eng. Int.*, vol. 35, no. 1, pp. 204–223, Feb. 2019.
- [15] S. Ryu, H. Choi, H. Lee, and H. Kim, "Convolutional autoencoder based feature extraction and clustering for customer load analysis," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1048–1060, Mar. 2020.
- [16] K. Jun, D.-W. Lee, K. Lee, S. Lee, and M. S. Kim, "Feature extraction using an RNN autoencoder for skeleton-based abnormal gait recognition," *IEEE Access*, vol. 8, pp. 19196–19207, 2020.
- [17] H. Liu, T. Taniguchi, Y. Tanaka, K. Takenaka, and T. Bando, "Visualization of driving behavior based on hidden feature extraction by using deep learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 9, pp. 2477–2489, Sep. 2017.
- [18] H. Liu, T. Taniguchi, T. Takano, Y. Tanaka, K. Takenaka, and T. Bando, "Visualization of driving behavior using deep sparse autoencoder," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2014, pp. 1427–1434.

- [19] K. Sama, Y. Morales, N. Akai, H. Liu, E. Takeuchi, and K. Takeda, "Driving feature extraction and behavior classification using an autoencoder to reproduce the velocity styles of experts," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1337–1343.
- [20] K. Sama, Y. Morales, H. Liu, N. Akai, A. Carballo, E. Takeuchi, and K. Takeda, "Extracting human-like driving behaviors from expert driver data using deep learning," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9315–9329, Sep. 2020.
- [21] J. Hu, X. Zhang, and S. Maybank, "Abnormal driving detection with normalized driving behavior data: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. 69, no. 7, pp. 6943–6951, Jul. 2020.
- [22] S. Danielsson, L. Petersson, and A. Eidehall, "Monte Carlo based threat assessment: Analysis and improvements," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2007, pp. 233–238.
- [23] A. Eidehall and L. Petersson, "Statistical threat assessment for general road scenes using Monte Carlo sampling," *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 1, pp. 137–147, Mar. 2008.
- [24] D. Shin, B. Kim, K. Yi, A. Carvalho, and F. Borrelli, "Human-centered risk assessment of an automated vehicle using vehicular wireless communication," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 2, pp. 667–681, Feb. 2019.
- [25] G. R. de Campos, A. H. Runarsson, F. Granum, P. Falcone, and K. Alenljung, "Collision avoidance at intersections: A probabilistic threat-assessment and decision-making system for safety interventions," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 649–654.
- [26] T. Gindele, S. Brechtel, and R. Dillmann, "Learning driver behavior models from traffic observations for decision making and planning," *IEEE Intell. Transp. Syst. Mag.*, vol. 7, no. 1, pp. 69–79, Spring. 2015.
- [27] C. Katrakazas, M. Quddus, and W.-H. Chen, "A new integrated collision risk assessment methodology for autonomous vehicles," *Accident Anal. Prevention*, vol. 127, pp. 61–79, Jun. 2019.
- [28] R. J. Kiefer, D. J. LeBlanc, and C. A. Flannagan, "Developing an inverse time-to-collision crash alert timing approach based on drivers' last-second braking and steering judgments," *Accident Anal. Prevention*, vol. 37, no. 2, pp. 295–303, Mar. 2005.
- [29] Y.-J. Joo, S.-Y. Kho, D.-K. Kim, and H.-C. Park, "A data-driven Bayesian network for probabilistic crash risk assessment of individual driver with traffic violation and crash records," *Accident Anal. Prevention*, vol. 176, Oct. 2022, Art. no. 106790.
- [30] L. Peng, M. A. Sotelo, Y. He, Y. Ai, and Z. Li, "Rough set based method for vehicle collision risk assessment through inferring driver's braking actions in near-crash situations," *IEEE Intell. Transp. Syst. Mag.*, vol. 11, no. 2, pp. 54–69, Summer. 2019.
- [31] A. M. Al-Kabbany, M. K. Mohamed, M. M. Youssef, E. Ma, and W. Y. Ali, "Proper selection of foot insole for slippers," *J. Egyptian Soc. Tribol.*, vol. 21, no. 3, pp. 12–20, Jul. 2024.
- [32] L. Wang, M. Zhang, J. Zhou, W. Zhong, R. Deng, and S. Chen, *Fatigue Driving Detection and Early Warning System Based on EEG Signals*. Accessed: Sep. 20, 2024. [Online]. Available: <https://pdfs.semanticscholar.org/bbff/826d4197055bb3f628ed9c7d132d4d59ac4d.pdf>
- [33] S. Laxman and P. S. Sastry, "A survey of temporal data mining," *Sadhana*, vol. 31, no. 2, pp. 173–198, Apr. 2006.
- [34] M. A. R. Ahad, A. D. Antar, and M. Ahmed, "Deep learning for sensor-based activity recognition: Recent trends," *IoT Sensor-Based Activity Recognit., Hum. Activity Recognit.*, pp. 149–173, Jul. 2020.
- [35] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *Proc. Int. Conf. Mach. Learn.*, Jan. 2015, pp. 448–456.
- [36] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proc. 13th Int. Conf. Artif. Intell. Statist., JMLR Workshop Conf.*, Mar. 2010, pp. 249–256.
- [37] M. Ahmed, R. Seraj, and S. M. S. Islam, "The k-means algorithm: A comprehensive survey and performance evaluation," *Electronics*, vol. 9, no. 8, p. 1295, Aug. 2020.
- [38] P. Kumar and A. Kanavalli, "A similarity based K-means clustering technique for categorical data in data mining application," *Int. J. Intell. Eng. Syst.*, vol. 14, no. 2, pp. 43–51, Apr. 2021.
- [39] X. Yang, C. Deng, F. Zheng, J. Yan, and W. Liu, "Deep spectral clustering using dual autoencoder network," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 4061–4070.
- [40] R. Chandra, T. Guan, S. Panuganti, T. Mittal, U. Bhattacharya, A. Bera, and D. Manocha, "Forecasting trajectory and behavior of road-agents using spectral clustering in graph-LSTMs," *IEEE Robot. Autom. Lett.*, vol. 5, no. 3, pp. 4882–4890, Jul. 2020.
- [41] D. Shin, B. Kim, and K. Yi, "Probabilistic threat assessment of vehicle states using wireless communications for application to integrated risk management system," in *Proc. FAST-Zero 3rd Int. Symp. Future Act. Saf. Technol. Toward Zero Traffic Accidents*, 2015. Accessed: Aug. 18, 2024. [Online]. Available: <https://trid.trb.org/View/1412232>



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