Smart Driving Style Analytics Through Multi-Stage CNN-LSTM and BiLSTM Integration

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***Abstract*— Smart Driving Style Analytics Through Multi-Stage CNN-LSTM and BiLSTM Integration presents an intelligent deep learning framework for recognizing driving behavior using vehicle operation and dynamic driving data. The proposed system is designed to improve driving style classification by combining the feature extraction capability of Convolutional Neural Networks (CNN), the temporal learning strength of Long Short-Term Memory (LSTM), and the contextual sequence modeling ability of Bidirectional LSTM (BiLSTM). Initially, driving signals such as accelerator pedal position, brake usage, steering information, and vehicle dynamics are collected and preprocessed to remove inconsistencies and prepare the data for model training. The multi-stage architecture learns both spatial and sequential driving patterns, enabling accurate identification of different driving styles. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, along with comparative analysis against conventional approaches. Experimental results indicate that the hybrid CNN-LSTM-BiLSTM framework provides higher recognition accuracy, improved temporal feature learning, and better generalization than individual deep learning models. The proposed system can support intelligent transportation, personalized driver assistance, and adaptive Advanced Driver Assistance Systems (ADAS) by providing reliable real-time driving style analysis and enhancing overall road safety.**

***Keywords*— Driving Style Analytics, CNN-LSTM, Bidirectional LSTM (BiLSTM), Deep Learning, Driver Behavior Recognition, Temporal Feature Learning, Intelligent Transportation Systems, Advanced Driver Assistance Systems (ADAS), Vehicle Data Analysis, Real-Time Driving Classification**

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) have significantly improved vehicle safety and driving comfort by providing features such as lane assistance, adaptive cruise control, and collision warning [1]. Despite these advancements, drivers have different driving habits, making it difficult for a single assistance strategy to meet everyone's needs. Differences in acceleration, braking, and steering behavior can influence the effectiveness of ADAS and driver confidence in these systems [16]. Therefore, recognizing individual driving styles has become an important requirement for developing intelligent vehicles. Personalized driving behavior analysis allows vehicles to adjust their assistance functions according to the driver's habits, improving safety, comfort, and overall driving experience [9].

Driving style recognition aims to identify driving behaviors such as aggressive, normal, and cautious driving using vehicle operation data. Earlier studies mainly relied on questionnaires and manual observation, but these methods are time-consuming and often produce subjective results [5]. Modern vehicles continuously generate sensor data related to steering, braking, acceleration, and vehicle movement, making automated driving behavior analysis more practical [11]. Analyzing these signals enables intelligent systems to understand driver behavior without affecting privacy. Such information is valuable for personalized vehicle control, improved road safety, and intelligent transportation applications [12].

Deep learning has become an effective approach for analyzing sequential driving data because it can automatically learn complex patterns from large datasets. Convolutional Neural Networks (CNNs) efficiently extract meaningful driving features, while Long Short-Term Memory (LSTM) networks learn temporal relationships among driving events [2]. These models reduce the need for manual feature engineering and improve classification performance. Similar deep learning techniques have already been successfully applied in autonomous driving tasks such as object detection and vehicle perception [3]. Their ability to process complex sensor data makes them suitable for intelligent driving behavior recognition.

Combining multiple deep learning models further improves driving style recognition. CNN layers extract important spatial features, while Bidirectional Long Short-Term Memory (BiLSTM) networks analyze driving sequences in both forward and backward directions to capture complete temporal information. This hybrid approach improves the understanding of driver behavior and increases classification accuracy. Previous studies have also shown that combining different learning techniques produces better driving behavior analysis than using individual algorithms alone [17]. In addition, advanced classification methods provide more reliable recognition across different driving conditions [21].

This study proposes a Smart Driving Style Analytics Through Multi-Stage CNN-LSTM and BiLSTM Integration framework for intelligent driving behavior recognition. The system performs data preprocessing, feature extraction, temporal learning, model training, and driving style classification using deep learning techniques. CNN extracts important driving features, while LSTM and BiLSTM learn sequential driving patterns for accurate classification. Model performance is evaluated using accuracy, precision, recall, and F1-score. The proposed framework supports personalized driver assistance, adaptive vehicle control, and intelligent transportation systems by providing accurate real-time driving style analysis [13].

II. RELATED WORK

Greenwood et al., [2022] [1] examined the awareness and understanding of Advanced Driver Assistance Systems (ADAS) among vehicle users. Their research investigated how drivers obtain information about ADAS technologies and how well they understand the available safety features. The study found that driver knowledge and trust directly influence the effective use of intelligent vehicle assistance systems. Many users were aware of ADAS functions but did not fully understand their capabilities or limitations, which affected their confidence while driving. The authors emphasized the importance of educating drivers about intelligent safety technologies to improve acceptance and safe usage. Their findings also suggested that personalized driver assistance can enhance user experience by adapting system behavior according to individual driving habits. This research provides valuable insights into the relationship between driver behavior and intelligent vehicle systems and highlights the need for adaptive driving technologies that improve both safety and driver confidence.

Ma et al., [2021] [9] proposed a driving style recognition approach based on driver behavior collected from the online car-hailing industry. Their study analyzed various driving characteristics, including acceleration, braking, steering, and vehicle movement, to distinguish different driving styles. The authors compared driving behavior across multiple driving tasks and demonstrated that behavioral patterns vary depending on traffic situations and driving objectives. The research showed that sensor-based driving data can effectively identify aggressive, normal, and cautious driving styles without requiring manual observation. The proposed approach improved the understanding of driver behavior and supported the development of personalized driving assistance systems. The study also emphasized that accurate driving style recognition contributes to safer transportation by enabling intelligent vehicles to respond according to individual driver characteristics. Their work serves as a useful reference for developing data-driven driver behavior classification systems using machine learning and intelligent transportation technologies.

Van Ly et al., [2013] [11] presented a method for driver classification and driving style recognition using inertial sensor data collected from vehicles. Their research focused on analyzing signals generated during vehicle operation, such as acceleration and motion patterns, to identify different driving behaviors. The authors demonstrated that inertial sensors provide reliable information for recognizing driver characteristics without requiring camera-based monitoring systems. Their experimental evaluation showed that sensor-based approaches can successfully classify driving styles while preserving driver privacy and reducing computational complexity. The study highlighted the importance of selecting meaningful driving features to improve classification performance. Furthermore, the proposed method offered a practical solution for intelligent transportation systems that require continuous monitoring of driver behavior. This work established the effectiveness of sensor-driven driving style recognition and provided a strong foundation for future deep learning approaches that analyze sequential driving data.

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Li et al., [2021] [18] investigated the extraction of meaningful driving patterns from vehicle data using unsupervised learning techniques. Their study focused on discovering hidden behavioral patterns without relying on predefined driving categories or labeled datasets. The authors applied clustering-based algorithms to analyze vehicle operation signals and identify natural driving behavior groups. The results demonstrated that unsupervised learning can effectively capture similarities among different driving styles while reducing the dependence on manual data labeling. The research also highlighted the importance of identifying representative driving patterns for intelligent transportation, vehicle safety, and driver behavior analysis. By automatically learning behavioral characteristics from large datasets, the proposed approach supports the development of adaptive driving systems capable of responding to different driver profiles. This study contributes to driving style analysis by showing that data-driven pattern extraction can improve intelligent vehicle applications and future driver assistance technologies.

Wang et al., [2017] [21] introduced a semi-supervised Support Vector Machine (SVM) approach for driving style classification using both labeled and unlabeled driving data. Their study addressed the challenge of limited labeled datasets by incorporating unlabeled samples into the learning process to improve classification performance. The authors demonstrated that semi-supervised learning enhances model generalization while reducing the effort required for manual data annotation. The proposed classifier successfully identified different driving styles with improved prediction accuracy compared to conventional supervised methods. The research also emphasized that combining statistical learning with real driving data enables more reliable driver behavior recognition under varying road conditions. Experimental results confirmed that the proposed framework can effectively classify driving behavior while maintaining high computational efficiency. This work provides an important contribution to intelligent transportation research by demonstrating how advanced machine learning techniques can improve personalized driving style recognition and adaptive vehicle assistance systems.

III. DATASET DETAILS

The dataset used in this project consists of vehicle operation signals and vehicle dynamics data collected during real driving sessions to recognize different driving styles. It includes important driving attributes such as accelerator pedal position, brake pedal position, steering wheel angle, vehicle speed, longitudinal acceleration, lateral acceleration, and other motion-related parameters recorded over time. Each driving sequence is associated with a corresponding driving style category, allowing the deep learning model to learn behavioral differences from temporal driving patterns. The collected data are organized in a structured format, making them suitable for sequential analysis using deep learning algorithms. Before model development, the dataset is carefully examined to remove incomplete records, verify signal consistency, and ensure the quality of the collected driving information. This dataset provides the foundation for learning driver behavior and accurately recognizing different driving styles under various driving conditions.

To prepare the dataset for model training, several preprocessing techniques are performed to improve data quality and learning performance. Missing or inconsistent values are handled, and the driving signals are normalized so that all features remain within a comparable range. Since the data are sequential, the continuous driving signals are divided into fixed-length time windows before being supplied to the deep learning models. The processed dataset is then shuffled and divided into 70% training data and 30% testing data to evaluate the model on previously unseen driving sequences. Proper preprocessing reduces noise, improves feature learning, and enables the CNN-LSTM and BiLSTM models to capture both spatial and temporal driving characteristics more effectively, resulting in accurate and reliable driving style classification.

IV. PROPOSED METHODOLOGY

The proposed system follows a structured approach to recognize different driving styles using a hybrid deep learning framework. Initially, the driving dataset containing vehicle operation signals and vehicle dynamics information is collected and analyzed. Data preprocessing is then performed to prepare the dataset for model training. This process includes handling missing or inconsistent values, converting the data into a suitable numerical format, normalizing the feature values, and shuffling the records to improve learning efficiency. Since the driving data are sequential, they are organized into time-based input sequences before training. After preprocessing, the dataset is divided into 80% training data and 20% testing data, enabling the models to learn driving behavior patterns and evaluate their performance on previously unseen driving sequences.

After preparing the data, three deep learning models are developed and compared: CNN, CNN-LSTM, and the proposed CNN-LSTM-Bidirectional LSTM (BiLSTM) model. The CNN model extracts important driving features, while the LSTM layer captures temporal relationships within the driving sequences. Finally, the

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Bidirectional LSTM further improves sequence learning by analyzing driving information in both forward and backward directions. The performance of all models is evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Performance comparison graphs are generated to identify the most effective model. The trained hybrid model is then used to classify new driving data into the corresponding driving style, providing accurate and reliable real-time driving behavior recognition.

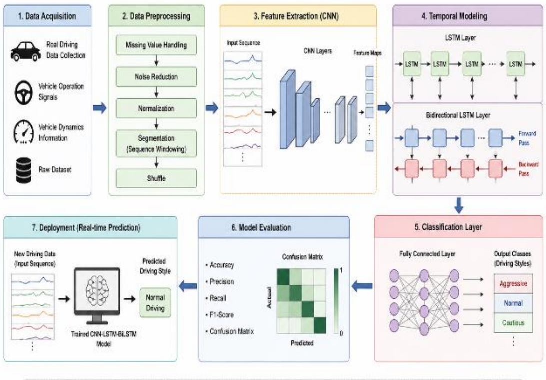

Figure [1]: Smart Driving Style Analytics System

Figure [1] shows the workflow of the proposed driving style analytics system. Driving data are collected and preprocessed through missing value handling, normalization, sequence segmentation, and shuffling before being divided into training and testing datasets. The processed data are then analyzed using a hybrid CNN-LSTM-BiLSTM model for feature extraction and temporal learning. Finally, the model is evaluated using accuracy, precision, recall, F1-score, and confusion matrix, and is used to classify new driving data into different driving style categories.

V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed deep learning framework for intelligent driving style detection using vehicle driving data. The driving dataset was first preprocessed through normalization, label encoding, and data shuffling to improve the quality of the input features. The processed dataset was then divided into training and testing sets using an 80:20 ratio, ensuring a fair evaluation of the classification models. Initially, an existing Convolutional Neural Network (CNN) model was trained and tested to classify driving behavior into three categories: Aggressive, Conservative, and Normal. The CNN model successfully extracted spatial features from the driving signals and achieved an accuracy of 98.08%, with a precision of 97.89%, recall of 98.14%, and F-measure of 97.98%. Although the CNN produced excellent classification performance, a few driving samples were still misclassified due to the temporal dependency present in sequential driving data.

To further improve recognition performance, a CNN + LSTM hybrid model was developed by integrating Long Short-Term Memory (LSTM) layers with CNN. The LSTM layer effectively captured the temporal relationships among consecutive driving records, enabling the model to learn long-term driving behavior patterns. Experimental evaluation showed that the proposed CNN + LSTM model achieved an improved accuracy of 99.04%, with corresponding precision, recall, and F-measure values of 98.90%, 99.10%, and 98.99%, respectively.

Finally, an Extended CNN + LSTM + Bidirectional LSTM architecture was implemented to enhance temporal feature extraction by learning both forward and backward contextual information. The Bidirectional LSTM significantly improved sequence learning capability and reduced classification errors. The extension model achieved the highest accuracy of 99.59%, along with a precision of 99.55%, recall of 99.58%, and F-measure of 99.57%, outperforming both the CNN and CNN + LSTM models.

The confusion matrices further validate the effectiveness of the proposed framework. The extension model correctly classified nearly all driving style samples while producing only a negligible number of misclassifications. The prediction module was also tested using unseen driving records, where it accurately predicted the driving styles as Aggressive, Conservative, or Normal. Comparison graphs and performance tables clearly demonstrate that the proposed Bidirectional LSTM-based model consistently outperforms the existing approaches across all evaluation metrics. Overall, the experimental results confirm that the proposed deep learning framework provides an accurate, reliable, and efficient solution for intelligent driving style recognition and can

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support Advanced Driver Assistance Systems (ADAS) in improving road safety and personalized driving assistance.

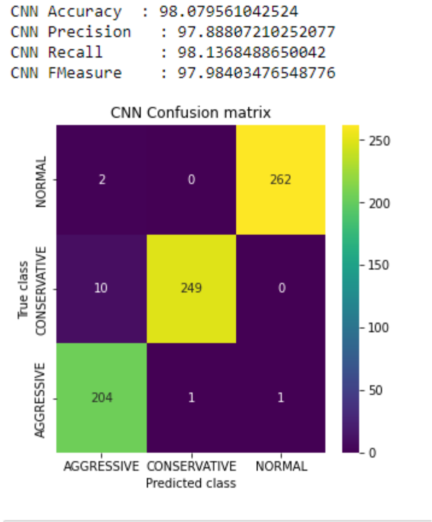


Figure [2] : Confusion Matrix of Existing CNN Classifier

Figure 2 presents the confusion matrix obtained from the existing CNN classifier. The CNN model correctly classified the majority of the driving style samples and achieved an overall accuracy of 98.08%. Most Aggressive, Conservative, and Normal driving records were correctly recognized, while only a small number of samples were incorrectly classified into neighboring categories. The confusion matrix demonstrates that the CNN effectively extracts spatial driving features but still produces a few classification errors due to temporal variations present in driving sequences.

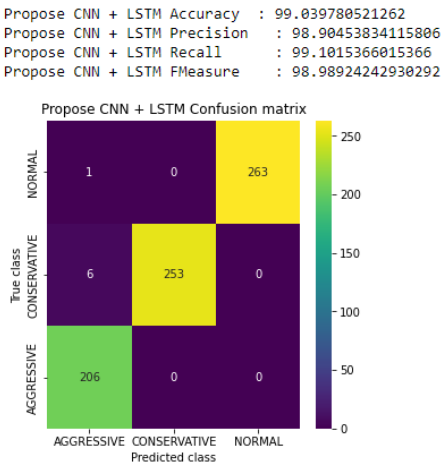
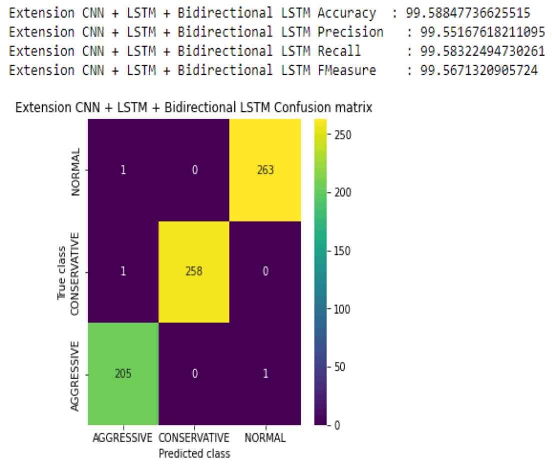


Figure [3] Confusion Matrix of Proposed CNN + LSTM Classifier

Figure 3 illustrates the confusion matrix of the proposed CNN + LSTM model. By incorporating LSTM layers, the model successfully captures temporal dependencies among driving signals, resulting in improved classification performance. The CNN + LSTM model achieved an overall accuracy of 99.04%, correctly identifying nearly all Aggressive, Conservative, and Normal driving styles while significantly reducing misclassification errors compared with the CNN model.



Figure[4] : Confusion Matrix of Extension CNN + LSTM + Bidirectional LSTM Classifier

Figure 4 presents the confusion matrix of the Extension CNN + LSTM + Bidirectional LSTM classifier. The Bidirectional LSTM learns driving behavior patterns from both forward and backward temporal directions, leading to superior classification capability. The proposed extension achieved the highest accuracy of 99.59%, correctly classifying almost every driving sample with only one or two misclassifications. These results confirm the effectiveness of Bidirectional LSTM in improving temporal sequence learning for intelligent driving style recognition.

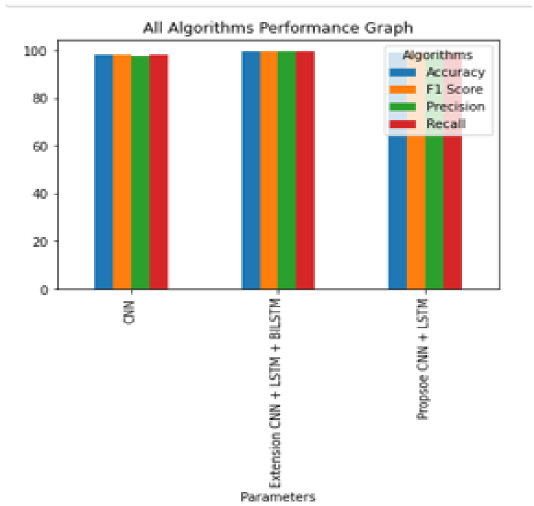


Figure [5] Comparison Graph of Classification Models

Figure 5 compares the performance of CNN, CNN + LSTM, and Extension CNN + LSTM + Bidirectional LSTM using Accuracy, Precision, Recall, and F-Measure. The graph clearly shows that the Extension model consistently achieves the highest performance across all evaluation metrics. The addition of Bidirectional LSTM significantly improves temporal feature extraction, resulting in superior classification accuracy and overall prediction reliability.

Algorithm Name	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	98.08	97.89	98.14	97.98

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Algorithm Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed CNN + LSTM	99.04	98.90	99.10	98.99
Extension CNN + LSTM + Bidirectional LSTM	99.59	99.55	99.58	99.57

Table [1]: Model Performance Metrics

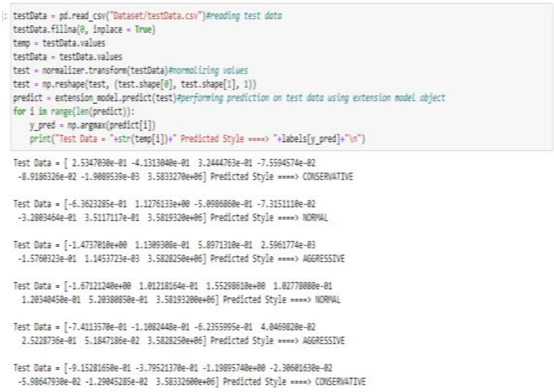

Figure [7]: Prediction Output of Intelligent Driving Style Detection System

Figure 6 displays the prediction module of the proposed Intelligent Driving Style Detection System. The system reads unseen driving test data, preprocesses the input features, and predicts the driving behavior using the trained Extension CNN + LSTM + Bidirectional LSTM model. The prediction results successfully classify the input samples into Aggressive, Conservative, or Normal driving styles. The output demonstrates that the trained model generalizes well to unseen driving records and provides highly accurate real-time driving style recognition.

DISCUSSION

The experimental findings demonstrate that deep learning techniques provide an effective solution for intelligent driving style detection using vehicle driving data. The driving dataset contained three behavioral categories—Aggressive, Conservative, and Normal—which enabled the models to learn diverse driving characteristics. The existing CNN model successfully extracted spatial features from the dataset and achieved high classification performance. However, because CNN primarily focuses on spatial feature extraction, it was unable to fully capture the temporal dependencies that exist in sequential driving behavior, resulting in a small number of misclassifications.

The integration of LSTM with CNN significantly improved recognition accuracy by learning long-term temporal relationships among driving records. Furthermore, the proposed Extension CNN + LSTM + Bidirectional LSTM model achieved the best overall performance by processing driving sequences in both forward and backward directions. This bidirectional temporal learning enabled the model to recognize complex driving behavior more effectively while minimizing classification errors. The confusion matrices confirmed that the extension model produced almost perfect predictions across all three driving style classes. The comparison graph and performance metrics further validated the superiority of the proposed model over the existing CNN and CNN + LSTM approaches. Additionally, the prediction module accurately classified unseen driving samples, demonstrating strong generalization capability and practical applicability. Overall, the proposed intelligent driving style detection framework offers a highly reliable, accurate, and efficient solution for real-time driving behavior analysis and can significantly enhance Advanced Driver Assistance Systems (ADAS), personalized driver monitoring, and intelligent transportation systems.

VI. CONCLUSION

In this paper, a driving style classification method based on driver operating signals and vehicle dynamics is presented. Driving data from different road conditions and different drivers in a simulator environment is collected in this paper, and then the driving style labels are obtained using a combination of unsupervised clustering and voting methods. A CNN+LSTM network was then trained using the labels and driving data, to realize the detection of driving styles. In the examination of real car data, the network proposed in this paper demonstrates high generalization ability, along with the advantages of low cost and high efficiency. Finally, it is proposed that the driver of the car and the surrounding vehicles can be signaled to plan the driving route in time to improve efficiency. Future work includes optimizing the network structure to improve recognition accuracy and generalization of detection capabilities in different driving scenarios, analyzing the driving style of the corresponding driver by collecting form data from surrounding vehicles through the sensing system and incorporating driving style into the vehicle's ADAS functions to improve driver acceptance.

REFERENCES

[1] P. M. Greenwood, J. K. Lenneman, and C. L. Baldwin, ''Advanced driver assistance systems (ADAS): Demographics, preferred sources of information, and accuracy of ADAS knowledge,'' Transp. Res. F, Traffic Psychol. Behav., vol. 86, pp. 131–150, Apr. 2022.

[2] Y. Cai, T. Luan, H. Gao, H. Wang, L. Chen, Y. Li, M. A. Sotelo, and Z. Li, ''YOLOv4–5D: An effective and efficient object detector for autonomous driving,'' IEEE Trans. Instrum. Meas., vol. 70, pp. 1–13, 2021.

[3] T. Yin, X. Zhou, and P. Krähenbühl, ''Center-based 3D object detection and tracking,'' in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2021, pp. 11779–11788.

[4] M. Ishibashi, M. Okuwa, S. Doi, and M. Akamatsu, ''Indices for characterizing driving style and their relevance to car following behavior,'' in Proc. SICE Annu. Conf., Sep. 2007, pp. 1132–1137.

[5] T. B. A. Orit, M. Mario, and G. Omri, ''The multidimensional driving style inventory-scale construct and validation,'' Accident Anal. Prevention, vol. 36, no. 3, pp. 323–332, May 2004.

[6] S. A. Useche, B. Cendales, F. Alonso, J. C. Pastor, and L. Montoro, ''Validation of the multidimensional driving style inventory (MDSI) in professional drivers: How does it work in transportation workers?'' Transp. Res. F, Traffic Psychol. Behav., vol. 67, pp. 155–163, Nov. 2019.

[7] C. Streiffer, R. Raghavendra, T. Benson, and M. Srivatsa, ''DarNet: A deep learning solution for distracted driving detection,'' Presented at the 18th ACM/IFIP/USENIX Middleware Conf.,

[8] E. E. Galarza, F. D. Egas, F. M. Silva, P. M. Velasco, and E. D. Galarza, ''Real time driver drowsiness detection based on driver's face image behavior using a system of human computer interaction implemented in a smartphone,'' in Proc. Int. Conf. Inf. Technol. Syst. (ICITS). Cham, Switzerland: Springer, 2018, pp. 563–572.

[9] Y. Ma, W. Li, K. Tang, Z. Zhang, and S. Chen, ''Driving style recognition and comparisons among driving tasks based on driver behavior in the online car-hailing industry,'' Accident Anal. Prevention, vol. 154, May 2021, Art. no. 106096.

[10] V. Manzoni, A. Corti, P. De Luca, and S. M. Savaresi, ''Driving style estimation via inertial measurements,'' in Proc. 13th Int. IEEE Conf. Intell. Transp. Syst., Sep. 2010, pp. 777–782.

[11] M. Van Ly, S. Martin, and M. M. Trivedi, ''Driver classification and driving style recognition using inertial sensors,'' in Proc. IEEE Intell. Vehicles Symp. (IV), Jun. 2013, pp. 1040–1045.

[12] W. Wang, J. Xi, and D. Zhao, ''Driving style analysis using primitive driving patterns with Bayesian nonparametric approaches,'' IEEE Trans. Intell. Transp. Syst., vol. 20, no. 8, pp. 2986–2998, Aug. 2019.

[13] S. Xu and J. Zhu, ''Estimating risk levels of driving scenarios through analysis of driving styles for autonomous vehicles,'' 2019, arXiv:1904.10176. Accessed: Apr. 1, 2019.

ISSN:3049-0952
www.jsetms.com

[14] E. Suzdaleva and I. Nagy, ''An online estimation of driving style using data-dependent pointer model,'' Transp. Res. C, Emerg. Technol., vol. 86, pp. 23–36, Jan. 2018.
[15] E. Suzdaleva and I. Nagy, ''Two-layer pointer model of driving style depending on the driving environment,'' Transp. Res. B, Methodol., vol. 128, pp. 254–270, Oct. 2019

[16] F. Ekman, M. Johansson, M. Karlsson, H. Strömberg, and L.-O. Bligård, ''Trust in what? Exploring the interdependency between an automated vehicle's driving style and traffic situations,'' Transp. Res. F, Traffic Psychol. Behav., vol. 76, pp. 59–71, Jan. 2021.

[17] L. Tong, F. Rui, Z. Mingfang, and T. Shun, ''Study on driving style clustering based on K-means and Gaussian mixture model,'' China Saf. Sci. J., vol. 29, no. 12, pp. 40–45, 2019.

[18] G. Li, Y. Chen, D. Cao, X. Qu, B. Cheng, and K. Li, ''Extraction of descriptive driving patterns from driving data using unsupervised algorithms,'' Mech. Syst. Signal Process., vol. 156, Jul. 2021, Art. no. 107589.

[19] A. Mohammadnazar, R. Arvin, and A. J. Khattak, ''Classifying travelers' driving style using basic safety messages generated by connected vehicles: Application of unsupervised machine learning,'' Transp. Res. C, Emerg. Technol., vol. 122, Jan. 2021, Art. no. 102917.

[20] L. Mingjun, Z. Zhenghao, S. Xiaolin, C. Haotian, and Y. Binlin, ''Driving style classification model based on a multi-label semi-supervised learning algorithm,'' J. Hunan Univ., Natural Sci., vol. 47, no. 4, pp. 10–15, 2020.

[21] 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.