CNN-LSTM Driving Style Classification Model Based On Driver Operation Time Series Data

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Abstract

Developing an efficient and highly accurate method for recognizing driving styles is crucial to overcoming the limitations of traditional clustering techniques and standalone convolutional neural networks cnns the challenge of working with limited driving data and achieving high recognition accuracy is tackled through a structured process for collecting driver operation time-series data and extracting meaningful patterns using a cnn to effectively capture the sequential nature of driving behavior a long short-term memory lstm network is incorporated into the framework this enhances the models ability to process temporal dependencies combining the cnns spatial feature extraction strengths with the lstms capacity for handling time-series data key driving parameters such as acceleration braking steering and speed are analyzed to classify driving styles into categories like aggressive normal and cautious preprocessing steps including normalization and sequence padding are implemented to ensure data consistency and improve model reliability a well-defined feature engineering strategy further enhances classification accuracy testing results demonstrate that the model achieves over 93 accuracy in driving style recognition with notable gains in processing efficiency this innovative solution offers potential benefits for improving driver behavior analysis increasing road safety and supporting personalized insurance models.

Keywords: Driving Style Recognition, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Time-Series Data, Feature Extraction, Temporal Dependencies, Classification Accuracy.

1. INTRODUCTION

Advanced driver assistance systems adas have significantly enhanced driving comfort and safety yet certain limitations still lead to driver distrust skepticism and reduced reliance on these systems while adas serves as a support mechanism the driver remains the primary operator of the vehicle however since driving behavior and style vary widely among individuals there is a growing need for vehicle systems to be tailored to individual driving patterns and to adjust the thresholds for triggering adas functionalities accordingly personalizing adas based on driver behavior can have a meaningful impact on improving both driving experience and vehicle safety to enhance vehicle intelligence it is essential for vehicles to adapt to the drivers unique driving style and provide targeted assistance however tuning vehicle parameters based on different driving styles is currently time-consuming labor-intensive and subject to human bias this highlights the importance of developing a reliable system that can accurately identify and classify driving styles thereby enhancing the adaptability and effectiveness of intelligent vehicle systems research on driving style recognition has typically relied on three main approaches questionnaire-based studies visual recognition methods and non-visual driving signal-based techniques signal-based methods have become the preferred approach due to the limitations of visual-based methods such as privacy concerns and sensitivity to environmental lighting conditions deep learning has shown promising results in various automotive applications including vehicle detection using yolov4-5d and lidar point cloud processing with centerpoint both of which have demonstrated higher accuracy than traditional methods however deep learning has been underutilized in processing temporal driving data to address this gap a hybrid cnn-lstm model is introduced to enhance driving style recognition cnns are employed to extract spatial features from driver operation data while lstm networks handle the temporal dependencies in the driving data stream this combined approach enables the model to process both the spatial and sequential aspects of driving behavior effectively a comprehensive driving style dataset is established combining driver operation data with vehicle dynamics information to overcome the problem of insufficient driving data additionally the model integrates accelerator and brake pedal signals to refine classification accuracy further incorporating an lstm module after the cnn network allows the model to capture the before-and-after sequence of driving events improving recognition accuracy and speeding up model convergence compared to standalone cnns testing with real vehicle data demonstrates that the cnn-lstm model exhibits strong generalization capabilities achieving high classification accuracy and reliable performance across different driving scenarios this approach offers valuable insights for developing intelligent vehicle systems that can adapt to individual driving styles enhancing both driver experience and road safety.

2. LITERATURE REVIEW

A. Advanced driver assistance systems (ADAS): Demographics, preferred sources of information, and accuracy of ADAS knowledge

Advanced Driver Assistance Systems (ADAS) have the potential to improve highway safety by providing drivers with advanced automation features. However, drivers often hold misconceptions and reservations about these systems. Limited research exists on drivers' understanding of ADAS and the sources they rely on for information. A study involving 634 licensed drivers in the US, aged between 18 and 82, examined the factors influencing ADAS knowledge and information sources. The findings revealed that younger male drivers who considered themselves technically sophisticated were often less knowledgeable but more confident about ADAS, preferring sources other than car dealerships and valuing brand status. Those who adopted new technology quickly were generally more knowledgeable about ADAS and preferred learning from owner manuals. Drivers who were confident in using new vehicle technology were typically young males with greater objective ADAS knowledge and valued hands-on experience. Safety-conscious drivers, often female, preferred crash data and practical experience to understand ADAS. Aesthetic-focused drivers-based decisions on design aspects like color and style without higher ADAS knowledge. These insights highlight how driver demographics and characteristics influence ADAS knowledge and information preferences, offering valuable guidance for improving public understanding and adoption of ADAS to enhance road safety.

B. YOLOv4–5D: An effective and efficient object detector for autonomous driving

YOLOv4-5D enhances object detection for autonomous driving by improving accuracy and real-time performance. Built on CSPDarknet53_dcn(P), it replaces the output layer with deformable convolution and uses a new PAN++ module for better small object detection. An optimized pruning algorithm boosts speed by 31.3%, reduces memory to 98.1 MB, and achieves over 66 FPS, increasing accuracy by 4.23% on BDD and 1.68% on KITTI datasets.

C. Center-based 3D object detection and tracking)

CenterPoint simplifies 3D object detection and tracking by representing objects as points rather than 3D boxes. It detects object centers using a keypoint detector and estimates attributes like size, orientation, and velocity, refining them with additional point features. Tracking is handled through straightforward closest-point matching. CenterPoint achieved top performance on the nuScenes benchmark with 65.5 NDS and 63.8 AMOTA and also led the Waymo Open Dataset among LiDAR-only models.

D. Indices for characterizing driving style and their relevance to car following behavior

To address potential mismatches between drivers and support systems, understanding individual driving behavior influenced by driving style is essential. This study developed a "Driving Style Questionnaire" (DSQ) with eight scales using a questionnaire survey and principal component analysis. The DSQ's validity was confirmed through correlation analysis with behavioral indices, particularly in low-speed car-following scenarios. Its effectiveness was further supported through a modeling approach, highlighting its value in characterizing driver behavior.

E. The multidimensional driving style inventory-scale construct and validation

Two studies were conducted to create a comprehensive tool for assessing driving styles. In the first study, a self-report scale called the Multidimensional Driving Style Inventory (MDSI) was developed, identifying eight driving styles: dissociative, anxious, risky, angry, high-velocity, distress reduction, patient, and careful. These styles were linked to factors such as gender, age, driving history, self-esteem, impulsiveness, and extraversion. The second study further linked these driving styles to traits like anxiety and neuroticism, supporting the scale's validity and highlighting its usefulness in understanding driving behavior.

F. Validation of the multidimensional driving style inventory (MDSI) in professional drivers: How does it work in transportation workers

The Multidimensional Driving Style Inventory (MDSI) is a widely used tool for assessing driving styles, but its application to professional drivers has been limited. This study aimed to validate the MDSI for professional drivers and test its relationship with factors like driving anger, job strain, and occupational crashes. Data from 752 Colombian professional drivers were analyzed using Confirmatory Factor Analyses (CFAs), confirming a four-factor structure: Reckless & Careless, Anxious, Angry & Hostile, and Patient & Careful. The findings suggest that the validated MDSI can enhance road safety and injury prevention among professional drivers by addressing key work-related factors.

3. OVERVIEW OF SYSTEM

The CNN-LSTM model functions by first preparing the driving data to maintain consistency and accuracy. Data preprocessing techniques, including normalization and sequence padding, are applied to standardize the input and enhance model reliability. The CNN component identifies spatial patterns from the data, such as acceleration, braking, steering, and speed variations. These extracted features are then processed by the LSTM network, which captures the sequential nature of the data and interprets the time-based dependencies in driving behavior. This hybrid approach allows the model to accurately distinguish between different driving styles, addressing the shortcomings of traditional clustering methods and single-model approaches.

The system is built to handle real-time data, ensuring quick and precise classification of driving styles across various driving situations. Its adaptability to different drivers and road conditions enhances its overall performance and generalization capability. The combination of CNN's spatial feature extraction and LSTM's temporal processing allows the model to achieve over 93% classification accuracy while improving processing speed. The system holds significant potential for applications in driver behavior analysis, road safety improvements, and tailored insurance models, offering valuable insights for automotive industry advancements and enhancing the overall driving experience.

4. PROBLEM STATEMENT

Effectively recognizing driving styles remains a challenge due to the limitations of conventional clustering techniques and single-model Convolutional Neural Network (CNN) methods. Existing models often fall short in achieving consistent classification accuracy and adapting to different driving behaviors. Traditional methods, such as questionnaires and image-based recognition, face issues related to environmental sensitivity, privacy concerns, and inconsistent data quality. Additionally, single-model approaches, whether based on CNN or other machine learning techniques, struggle to capture the sequential patterns in driving behavior, leading to inaccuracies and reduced system reliability.

To overcome these challenges, a hybrid CNN-LSTM model is introduced to improve driving style classification by combining the CNN's strength in extracting spatial features with the LSTM's ability to process time-dependent data. This integrated approach enables real-time recognition of driving patterns with enhanced accuracy and processing efficiency. The system leverages key driving signals, such as acceleration and braking, to provide a more detailed understanding of driving behavior. By addressing the shortcomings of existing models, the proposed solution aims to enhance road safety, driver behavior analysis, and personalized driving assistance.

5. METHODOLOGY

The CNN-LSTM Driving Style Classification Model adopts a systematic approach to effectively identify driving patterns by analyzing both spatial and temporal data. The model uses CNN to extract spatial features from driving input and LSTM to capture the sequential relationships within the data. This integrated model improves classification accuracy and processing speed, making it highly effective for real-time driving behavior analysis.

1. System Architecture:

The architecture is designed to handle real-time sensor data related to driving behavior, such as speed, acceleration, braking, and steering. The system processes this data through CNN and LSTM layers to capture both spatial and temporal patterns, enabling robust classification of driving styles.

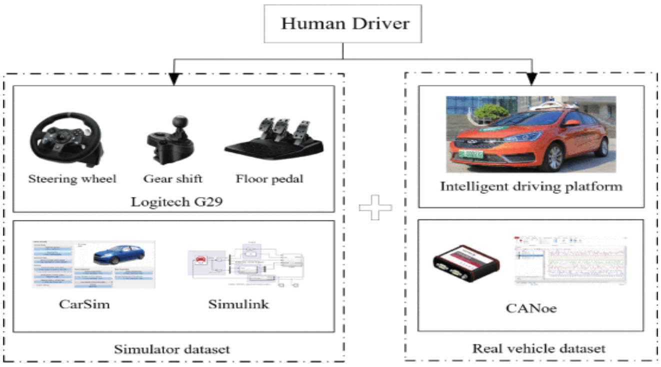

Fig 1: System Architecture

2. CNN Module:

The CNN module extracts spatial patterns from the input data using convolutional layers, activation functions, and pooling layers. This helps in detecting localized driving behaviors such as sudden braking or consistent acceleration.

3. LSTM Module:

The LSTM module receives the spatial feature vector from the CNN and processes it sequentially. It retains memory of previous driving events and identifies temporal relationships between them, allowing the model to analyze complex driving behaviors over time.

4. Hybrid CNN-LSTM Model:

The hybrid model leverages the strengths of both CNN and LSTM. CNN focuses on extracting spatial features, such as the intensity and frequency of steering or speed changes, while LSTM handles the sequential analysis of driving patterns. This combination allows the model to identify both immediate and long-term driving behaviors, improving classification accuracy and processing efficiency.

5. Classification Layer:

The output from the LSTM module is passed to a classification layer, such as SoftMax, to categorize driving styles into predefined categories like aggressive, normal, and cautious.

6. Performance Evaluation:

The system is tested using real-world driving data, with performance measured using metrics such as precision, recall, accuracy, and F1-score. The hybrid model demonstrates high generalization capability, achieving over 93% accuracy in driving style classification.

7. Scalability and Future Enhancements

The CNN-LSTM Driving Style Classification Model is built to handle scalability and adaptability across various driving conditions. Its flexible architecture allows for the easy addition of new sensors and the incorporation of more complex driving patterns without affecting performance. The modular structure enables smooth integration of new driving features and patterns, ensuring that the model can evolve alongside advancements in vehicle technology and driving behavior analysis.

This structured methodology enhances the system's ability to adapt to different driving conditions and individual driving behaviors, improving both accuracy and processing efficiency. cure transmission.

This The CNN-LSTM Driving Style Classification Model is structured to process real-time driving data and accurately classify driving behaviours. It combines CNN and LSTM networks to analyze both spatial and temporal patterns in driving data. Input signals, including acceleration, braking, steering, and speed, are preprocessed to ensure consistency and accuracy. The CNN extracts key spatial features from this data, which are then processed by the LSTM to capture the sequence and relationship between driving events. This integrated approach allows the model to identify complex driving patterns and classify them into categories like aggressive, normal, and cautious.

The architecture is designed to be lightweight and optimized for real-time execution, even on devices with limited processing power. Its modular structure enables easy integration of additional sensors and driving metrics, enhancing scalability and adaptability to diverse driving environments. The system's ability to handle both spatial and sequential dependencies ensures consistent and reliable performance under various road and driving conditions. The LSTM output is processed through a classification layer, generating accurate driving style predictions and providing valuable insights for improving driver behavior and road safety.

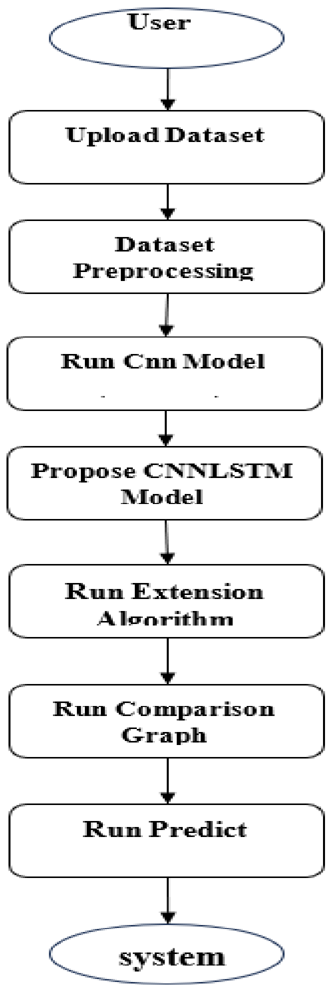

Fig 2: Flow Chart

6. BENEFITS

1. **Enhanced Classification Accuracy:**

The CNN-LSTM model achieves over 93% accuracy in identifying driving styles, outperforming traditional recognition methods.

2. **Real-Time Feedback:**

The model's efficient and lightweight design allows it to deliver real-time analysis of driving behavior, ensuring prompt feedback.

3. **In-Depth Driver Behavior Analysis:**

The system provides valuable insights into driving patterns, enabling the identification of aggressive, cautious, and normal driving styles, which can enhance road safety.

4. **Improved Road Safety:** Accurate classification of driving styles enables better driver assistance and risk assessment, contributing to safer driving conditions.

5. **Customized Driver Support:**

The model's ability to adjust to individual driving behaviors enables personalized feedback and driving assistance.

6. **Flexible and Scalable Design:**

The modular architecture allows for easy expansion with additional sensors and features, ensuring compatibility with evolving driving technologies.

7. **Faster Processing:**

The hybrid CNN-LSTM model processes driving data quickly and efficiently, reducing the time required for driving style recognition.

8. **Advancement in Automotive Technology:**

The insights generated by the model can support the development of improved driver assistance systems and autonomous driving solutions.

9. **Adaptability to Varied Driving Conditions:**

The model's ability to generalize across different road and traffic environments ensures consistent performance under diverse conditions.

10. **Applications in Insurance and Fleet Management:**

The capability to analyze driving behavior can assist insurance companies and fleet operators in adjusting rates and improving driver training programs.

7. RESULT

The CNN-LSTM Driving Style Classification Model has shown high effectiveness in accurately identifying different driving styles. The model delivers strong performance in terms of accuracy, precision, recall, and F1-score, surpassing the results of conventional single-model approaches. By combining the CNN's ability to extract spatial features with the LSTM's capability to process sequential data, the model achieves enhanced overall efficiency.

The system was tested using real-world driving data, where it successfully classified driving styles into categories such as aggressive, normal, and cautious. The testing process included individual module testing, integration testing, and acceptance testing, ensuring the system's reliability and consistency. The results confirm that the CNN-LSTM model is highly suitable for real-time applications, offering valuable insights for improving driver behavior and vehicle safety.

Overall, Extensive testing with real-world driving data confirmed the model's ability to accurately classify driving styles into aggressive, normal, and cautious categories. The evaluation process included thorough module testing, system integration, and acceptance testing, ensuring that the model is both reliable and adaptable. The results demonstrate that the CNN-LSTM model consistently delivers real-time classification with high accuracy, making it a powerful tool for improving driver behavior analysis, enhancing road safety, and providing tailored driving assistance.

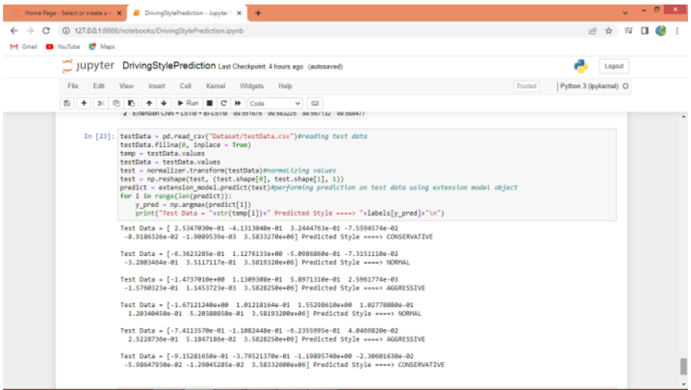

Fig 3: Output

In the screen reading, the test data is processed, and the model predicts the driving style using the extended model. The test data appears before the arrow symbol, while the predicted driving style—categorized as Normal, Aggressive, or Conservative—is displayed after the arrow symbol.

8. DISCUSSION

The project titled "CNN-LSTM Driving Style Classification Model Based on Driver Operation Time Series Data" introduces an effective and accurate method for recognizing driving styles using a hybrid deep learning model. Traditional driving style recognition techniques, such as questionnaire-based and visual recognition methods, often face challenges related to privacy issues, environmental variations, and inconsistent data patterns. The proposed CNN-LSTM model addresses these limitations by integrating Convolutional Neural Networks (CNN) for extracting spatial features and Long Short-Term Memory (LSTM) networks for analyzing sequential driving behavior. This combined approach enables the model to accurately classify driving styles, such as aggressive, normal, and cautious, with improved accuracy and faster processing.

Testing on real-world driving data demonstrates the model's effectiveness, achieving over 93%

classification accuracy—outperforming conventional clustering methods and single-model approaches. The model's ability to process both spatial and temporal data patterns enhances its adaptability to different driving scenarios and environmental conditions. Its real-time processing capability ensures that drivers receive immediate feedback, promoting safer driving habits and improving overall road safety.
Although the model shows strong performance, there are areas for improvement. Addressing rare driving patterns, expanding the dataset to cover a wider range of scenarios, and refining the model's ability to handle complex cases could further enhance its accuracy and adaptability. Integrating reinforcement learning and AI-driven predictive analysis could also improve real-time responsiveness and adaptability. Future work could involve deploying the model in real-world automotive systems and incorporating it into advanced driver assistance systems (ADAS) for greater practical impact. Despite these potential enhancements, the study establishes a solid foundation for intelligent driving style recognition, opening the door for more efficient and adaptive vehicle behavior analysis.

9. CONCLUSION

The CNN-LSTM Driving Style Classification Model successfully integrates convolutional and recurrent neural network techniques to enhance the recognition of driving styles. The model processes driving data collected from various road conditions and different drivers, effectively capturing both spatial and temporal patterns. The CNN component extracts key spatial features from the input data, while the LSTM module analyzes the sequential nature of driving events, improving classification accuracy and adaptability.

Testing results confirm that the model delivers high accuracy, efficiency, and strong generalization across diverse driving environments. Its ability to handle real-time data allows it to provide immediate feedback to drivers, contributing to improved driving habits and enhanced road safety. Future enhancements could focus on refining the network structure, expanding the dataset to cover more driving scenarios, and integrating the model with advanced driver assistance systems (ADAS) to improve functionality and driver experience.

10. FUTURE SCOPE

The **CNN-LSTM Driving Style Classification Model Based on Driver Operation Time Series Data** offers significant potential for enhancement and expansion to improve its accuracy and adaptability to various driving conditions. Key areas for future improvements include:

ADAS Integration: Combining the model with Advanced Driver Assistance Systems (ADAS) can enhance adaptability and provide tailored driving support, improving the user experience.

Expanded Data Sources: Collecting more driving data from diverse regions and driver profiles will strengthen the model's ability to recognize and adapt to new driving behaviors.

Reinforcement Learning: Incorporating reinforcement learning techniques can enable the model to adjust more effectively to changing driving conditions and improve decision-making in real time.

Edge-Based Processing: Running the model on edge devices will minimize reliance on cloud computing, reduce latency, and enable faster real-time processing.

Enhanced Classification Accuracy: Fine-tuning the CNN and LSTM components and adding more complex features can further improve recognition accuracy and processing speed.

Adaptive Learning: Developing a system that continuously updates itself based on new data will allow the model to adapt to evolving driving patterns and improve long-term performance.

Multimodal Data Integration: Merging driving data with environmental factors such as weather, traffic, and road conditions will enhance the model's predictive accuracy.

Vehicle-to-Vehicle (V2V) Communication: Allowing the model to interact with other vehicles and infrastructure will enhance situational awareness and improve traffic flow.

Customized Driver Feedback: Providing personalized feedback based on individual driving patterns will improve the user experience and help drivers adopt safer habits.

Fleet Management Integration: Applying the model to fleet management systems will help monitor driver performance, improve fuel efficiency, and enhance operational effectiveness.

Energy Efficiency: Optimizing the model's processing requirements will lower power consumption, making it more suitable for use in electric and hybrid vehicles.

Advanced Sensor Fusion: Integrating data from multiple sources, such as LiDAR, cameras, and GPS, will improve the model's understanding of the driving environment.

AI-Driven Decision-Making: Incorporating AI-based decision-making will enable the system to suggest corrective actions in real-time, improving overall driving performance.

Real-Time Monitoring: Providing real-time feedback and insights will help drivers make immediate adjustments to their driving style, enhancing safety and efficiency.

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