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BLOCKCHAIN-ENABLED PRIVACY-PRESERVING FEDERATED LEARNING WITH DEEP CAPSULE NETWORKS FOR ENERGY-EFFICIENT SPEED CONTROL IN AUTONOMOUS VEHICLES

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Resume

Rough roads negatively affect the ride quality and energy efficiency of autonomous vehicles (AVs) and demand adaptive speed control. To solve this, this research proposes a Deep Capsule Network integrated with Sparse Kernel K-means Clustering (DCapsNet + SK-K-means) to accurately reconstruct pavement conditions and adapt vehicle speed in real time. The Privacy-Preserving Federated Learning (PPFL) with Hyperledger Fabric blockchain allows federated learning to be trained in a secure and decentralized manner without the transfer of raw sensor data. With the BDD100K dataset, supervised and reinforcement learning are used. According to the obtained results of the experiment, there is a 10.45% increase in ride comfort, 28.23% in energy efficiency, and 98.28% in computational efficiency. The framework attains 93.73% security, 96.46% throughput and 0.83 s operation time at 250 vehicles/km.

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1 Introduction

AVs have attracted a lot of interest considering the fact that they have the potential to enhance the road safety, traffic efficiency and comfort to passengers. The current development of sensing, perception, and control technologies has facilitated the AVs to navigate through the complex traffic, but driving through the lumpy road surfaces is also an essential issue. Asymmetries in the road create vertical vibrations that negatively impact the ride of passengers and consumes more energy in the vehicle, so adaptive speed control is a significant demand of the real-life AV implementation [1-3]. Simple rule-based or optimization-based strategies are used as traditional strategies in autonomous driving to control speed. These methods work in well-organized situations but have low flexibility in situations where the road and traffic experience dynamically changing conditions. Controllers that are based on optimization can be efficient but usually require that the system is modelled

accurately, and they are expensive to compute, especially where the pavement is not smooth and with high traffic density [4-5].

To address these drawbacks, autonomous vehicle control has been studied more via the learning-based techniques. With the aid of real time sensor data, such solutions can adjust the speed of the vehicles to various driving conditions and enhance the overall performance [6-9]. Parallel with these sensor fusion and deep learning-based perception, autonomous driving systems have become more aware and robust in their respective environmental perception [10-13]. Regardless of this, the majority of the currently available learning-based speed control solutions are aimed at energy efficiency or safety and do not directly address the issue of vertical ride comfort. Furthermore, most of the current solutions presuppose the centralized data collection and training, which casts doubt on the scalability and privacy issues as well as on the secure data transmission between vehicles. Since AVs constantly produce such

high quantities of sensitive sensors, it gains increasing significance to provide privacy-preserving and secure learning mechanisms [14-15]. It is these difficulties that drive the importance of a speed control framework that would be integrated to address the three aspects of the ride comfort, energy efficiency, and privacy preservation in the autonomous vehicle systems.

1.1 Literature review

1.1.1 Learning-based speed control and energy efficiency

Learning-based methods of control have been examined by recent researchers to improve adaptability and efficiency in autonomous vehicle systems. By using expert demonstrations and attention-based representation, Vision Transformer assisted reinforcement learning frameworks have demonstrated better control performance (Elallid et al. [16]). Graph based methods of learning have also been proposed to minimize routing and energy-conscious decision-making in autonomous guided vehicles (Kazmi and Akber [17]).

The multi-objective reinforcement learning techniques have been heavily used in balancing energy efficiency, stability, and traffic flow in connected and automated cars. Coskun et al. [18] introduced a multi-objective hierarchical deep reinforcement learning algorithm for connected and automated Hybrid Electric Vehicles (HEVs) for energy management, and Wang et al. [19] proposed better ecological car-following behaviour with multi-agent reinforcement learning. Even though these techniques enhance longitudinal control and energy efficiency, vertical ride comfort on irregular pavements has not been explicitly addressed.

Autonomous driving performance has been further enhanced by the deep learning-based motion prediction and vehicle dynamics modelling. Barrios et al. [20] introduced a very broad review of motion prediction methods based on big data of autonomous driving scenarios and Cheng et al. [21] introduced an integrated dynamic model to improve the stability of vehicle handling at the driving boundaries. Nevertheless, such methods are more oriented on security and stability than on the comfort-conscious speed control.

1.1.2 Federated and distributed learning in autonomous vehicles

The model of distributed and collaborative learning has attracted interest as the way to enhance scalability and collaboration in autonomous vehicle networks. Din et al. [22] proposed the integration strategies of Augmented Intelligence with Internet of Things (IoT) to optimize the road cooperation and traffic management in autonomous driving setting. Liu et al.

[23] suggested a longitudinal control strategy based on distributed deep reinforcement learning and applicable on the connected automated vehicles, which will employ attention mechanisms to enhance coordination and control efficiency. In spite of their benefits, the current distributed learning strategies pay much attention to traffic efficiency and coordination. Ride comfort metrics and uneven pavement-conscious speed control have not been very well incorporated in such decentralized learning frameworks.

1.1.3 Security and privacy in intelligent transportation systems

The issues of security and privacy have been of main concern in autonomous and connected vehicle systems. Khattak [24] examined cybersecurity weaknesses and hardness during cooperative driving automation and identified the effect of security threats on energy efficiency and traffic stability within smart cities. Onur et al. [25] examined machine learning-based methods of detecting cybersecurity attacks on autonomous vehicle systems.

In addition to threat detection, blockchain-centric authentication systems have been suggested to improve the levels of trust and privacy in vehicular networks. An effective privacy-preserving Internet of Vehicles authentication scheme based on blockchain technology was introduced by Loganathan and Selvakumarasamy [26], and it achieves better throughput and latency. Other researchers have also studied energy-saving and smart transportation systems in interconnected settings (Huang et al. [27]; Liu et al. [28]). However, the majority of security-oriented solutions are detached from learning-based speed regulation and comfort of the rides.

1.2 Research gap

Despite the fact that existing studies have advanced the learning-based control, distributed intelligence, and security solutions to autonomous cars, they are to a large extent considered individually. The speed control approaches based on learning are mainly concerned with energy efficiency and traffic performance, distributed learning approaches are concerned with cooperation and scalability, but do not include comfort-aware goals, and security solutions are concerned with authentication and threat mitigation but not with adaptive vehicle control. As the result, there is a gap in the exploration of a single framework that simultaneously optimizes the ride comfort, energy usage, and privacy with the help of secure and decentralized learning. The main contributions of this research are summarized as follows:

- This research proposes the first integrated AV speed control framework that combines DCapsNet with

SK-KMeans for high-accuracy uneven pavement classification, effectively preserving spatial hierarchies while reducing feature redundancy.

- Additionally, design a novel hybrid control strategy that combines supervised learning and reinforcement learning with a custom multi-objective loss function, jointly optimizing ride comfort, energy efficiency, and jerk minimization.
- Develop a blockchain-enabled PPFL mechanism incorporating homomorphic encryption and zero-knowledge proofs (ZKPs) for secure model aggregation, ensuring data confidentiality, verifiable updates, and participant accountability.
- Perform extensive benchmarking against state-of-the-art baselines, including Model Predictive Control (MPC), Deep Reinforcement Learning (DRL)-only, Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM), and existing

privacy-preserving schemes, demonstrating superior performance in ride comfort, energy efficiency, computational efficiency, and adversarial attack resistance.

The structure of this research is as follows: In Section 2 is introduced the proposed methodology. In Section 3 are presented the experimental outcomes, highlighting the performance improvements of the proposed approach. In Section 4 are discussed the significance of the model, key advantages, and limitations. Finally, in Section 5 the research findings are summarized and potential future directions for further enhancements are outlined.

2 The proposed scheme

Figure 1 illustrates the proposed hybrid AV speed control and energy efficiency framework, integrating the

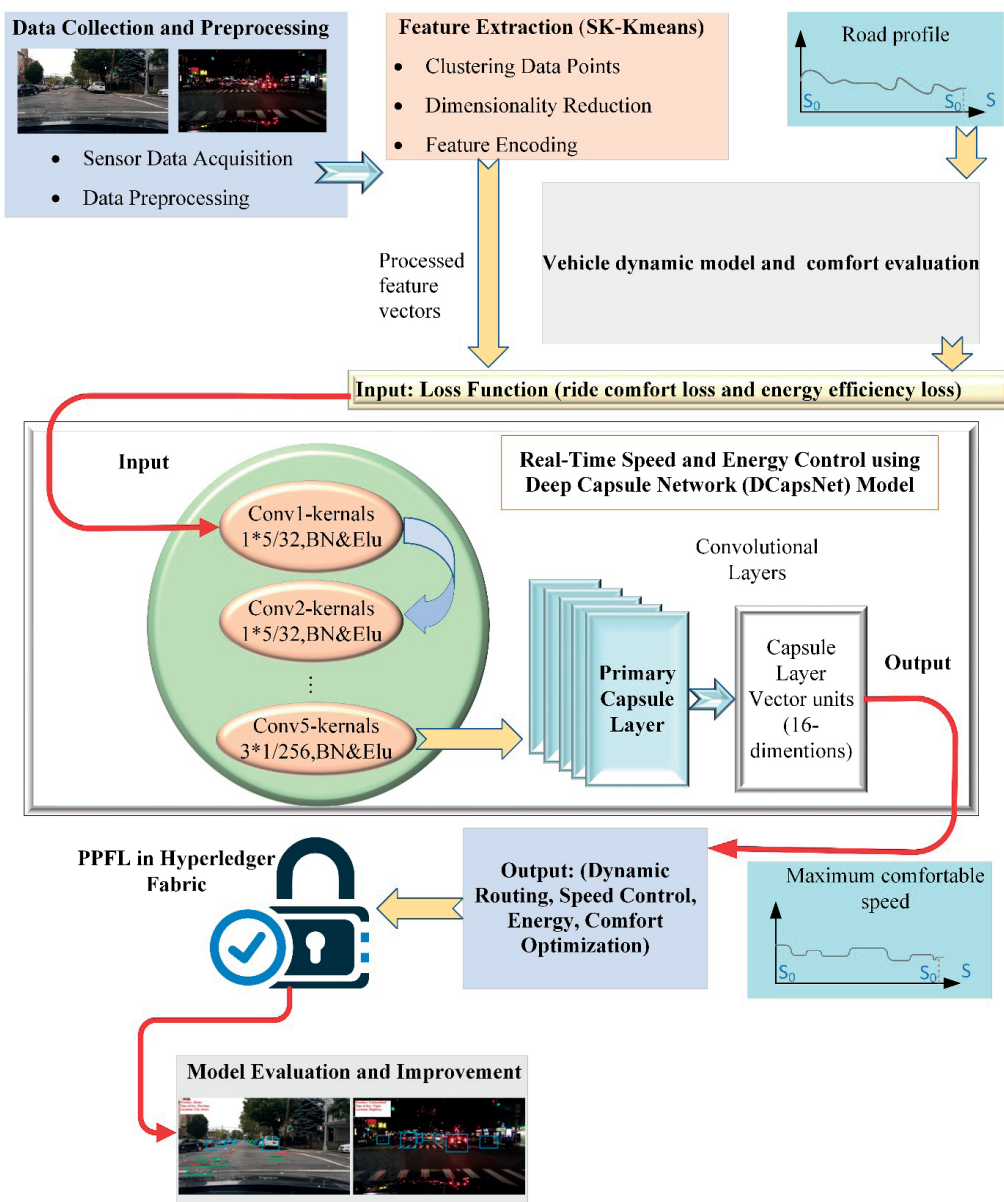


Figure 1 Control optimization of speed, energy and vehicle riding comfort

DCapsNet with SK-KMeans and PPFL in Hyperledger Fabric to ensure secure, decentralized, and scalable model training.

2.1 Data collection and preprocessing

The information utilized in this paper is gathered by a number of the onboard sensors fitted in autonomous vehicles such as LiDAR, cameras, radar, Global Navigation Satellite System (GNSS), and Inertial Measurement Units (IMUs). Those sensors work together to bring the road surface profiles, pavement irregularities, vehicle motion conditions, and positional data needed in precise control of speed and assessment of ride comfort. The areas of data capture include the vibrations caused by vertical roads which directly affect the comfort of passengers and the energy used by a vehicle.

Before training the model, it is preprocessed by going through the raw sensor data to provide consistency and reliability. The sensor streams are timed together to deal with sampling rate discrepancies and standard filtering techniques are used to remove noise artifacts in the sensor imperfections and environmental conditions. Lost or damaged samples are treated by interpolation to preserve continuous signal images. Besides, every input feature is scaled to a normal range to enhance the numerical stability in the learning process.

The raw data are preprocessed and divided into time windows of fixed length, which represent one consecutive section of the road on the path that the vehicle is on. This segmentation also allows the analysis of roads and vehicular reaction pathologies in the locality, allowing the extraction of features and downstream learning to be performed effectively. The resulting processed and cleaned data is used as input to the other ride comfort analysis and energy efficient speed control modules.

2.2 Evaluation of the ride comfort in vertical motion

The evaluation of the ride comfort in a vertical environment with the proposed hybrid speed and energy optimization framework is conducted by the full vehicle dynamics model. The vertical motion ride comfort is assessed with a full-vehicle dynamics model that calculates segmented road profiles and vehicle speeds in the measured vehicle speed along the anticipated driving path. The incoming road information is separated into consecutive blocks and passed into a vibration-sensitive suspension model to predict the vertical acceleration responses. The ride comfort is measured using the weighted root mean square acceleration (WRMSA) criterion, based on ISO 2631-1 [29] wherein the WRMSA should not exceed 0.289 m/s² is considered a comfortable ride.

2.3 Deep learning incorporated energy-efficient control

In this study is presented a hybrid AV speed control method combining SK-KMeans [30] for feature clustering and DCapsNet [31] for deep learning-based optimization. Preprocessed sensor data is used to adjust speed in real time via hybrid supervised-reinforcement learning, enhancing the ride comfort and energy efficiency with five convolutional layers for improved feature extraction. For each signal of the time series, convolution layers are used in the DCapsNet in the feature extraction stage, which extracts features of the deep discriminative scalar characteristics of the input dataset. For each time-series signal collected from onboard sensors such as LiDAR, the input sequence is denoted as $u = [f_1, f_2, \dots, f_w] \in \mathbb{R}^{d \times W}$, where W represents the input signal length and d denotes the feature dimension.

Convolutional layers generate a deep feature map $I_l^m \in \mathbb{R}^{P^m \times J}$ by applying learnable convolutional kernels to the input data f (or the output of the previous layer I_l^{m-1}). Here, P^m denotes the number of convolutional kernels in the m^{th} layer, and w represents the resulting feature length after convolution. The output of the m^{th} feature map in the n^{th} convolutional layer is computed as described in Equation (1).

$$I_l^m = \sum_{h=1}^{P^{m-1}} I_h^{m-1} v_{lh}^m + a_l^m, \quad (1)$$

where, v_{lh}^m is the kernel/filter weight of convolution layer size, P^{m-1} that connects the m^{th} feature map to the l^{th} map of feature in $(m-1)^{\text{th}}$ layer, and a_l^m is the equivalent bias.

In this paper, the DCapsNet is used as the main perception unit to characterize uneven pavements, and SK-KMeans is utilized as a preprocessing unit to eliminate unnecessary features activation and then route the capsules. The given framework does not alter the conventional convolutional operations; the only difference is incorporation of the capsule-based feature hierarchy with the use of the hybrid approach to control the pace of learning. A task-specific multi-objective loss is used to optimize the model, which directly balances the vertical ride comfort, energy efficiency, and safety constraints, which allows the model to adapt its speed effectively to changes in the roughness of the road.

2.4 Privacy-preserving federated learning (PPFL) in Hyperledger Fabric blockchain

The PPFL in the suggested model is adopted with the Hyperledger Fabric to allow a model to be trained jointly on data across several autonomous vehicles

without exposing raw data of the sensor. Individual vehicles would each learn the speed-control model locally based on on-board data and only send encrypted model updates to the authorized blockchain network, where they would be safely verified and combined into a global model. The permissioned access control and consensus mechanism provide Hyperledger Fabric with trusted participation, aggregation that cannot be tampered with, and scalable deployment.

To make the process even more privacy-intensive and trustworthy, homomorphic encryption is used to safeguard the update of the model during the transmission and aggregation, and a ZKP allows verifying the presence of a valid contribution to training without disclosing the underlying data.

3 Results and performance evaluation

All experiments were conducted on an NVIDIA RTX 4090 GPU with 24 GB VRAM, AMD Ryzen 9 7950X CPU (16 cores, 4.5 GHz), and 64 GB RAM, running Ubuntu 22.04 with CUDA 12.0. In this present research, the BDD100K dataset [32] from Berkeley AI Research Lab, which supports autonomous driving research, is utilized for the testing purpose. Figure 2 presents Experimental device and system architecture according to which experiments to speed control the autonomous vehicle is made to demonstrate the simulation environment, computing platform, federated learning nodes, blockchain

network and performance evaluation modules. The simulated autonomous vehicle node blocks represent federated learning clients within the proposed PPFL framework. The left block depicts autonomous vehicle node 1, while the right block represents autonomous vehicle node N. Each node executes the same local model architecture and training process, while utilizing its own locally collected data for decentralized learning.

3.1 Experimental benchmarking

The proposed framework was evaluated against a diverse set of baseline models to ensure a fair and comprehensive comparison:

- MPC: A classical optimization-based controller widely used for AV speed regulation.
- PID and Fractional-Order PID (FOPID) Controllers: Rule-based methods for speed control with tuned parameters.
- DRL-only: A policy-gradient-based controller trained on the same dataset without DCapsNet or SK-KMeans integration.
- CNN-based Models: Standard convolutional neural networks for pavement classification coupled with a DRL controller.
- CNN-LSTM Hybrid: Spatio-temporal model combining convolutional feature extraction and sequential learning.
- Transformer-based Model: Vision Transformer

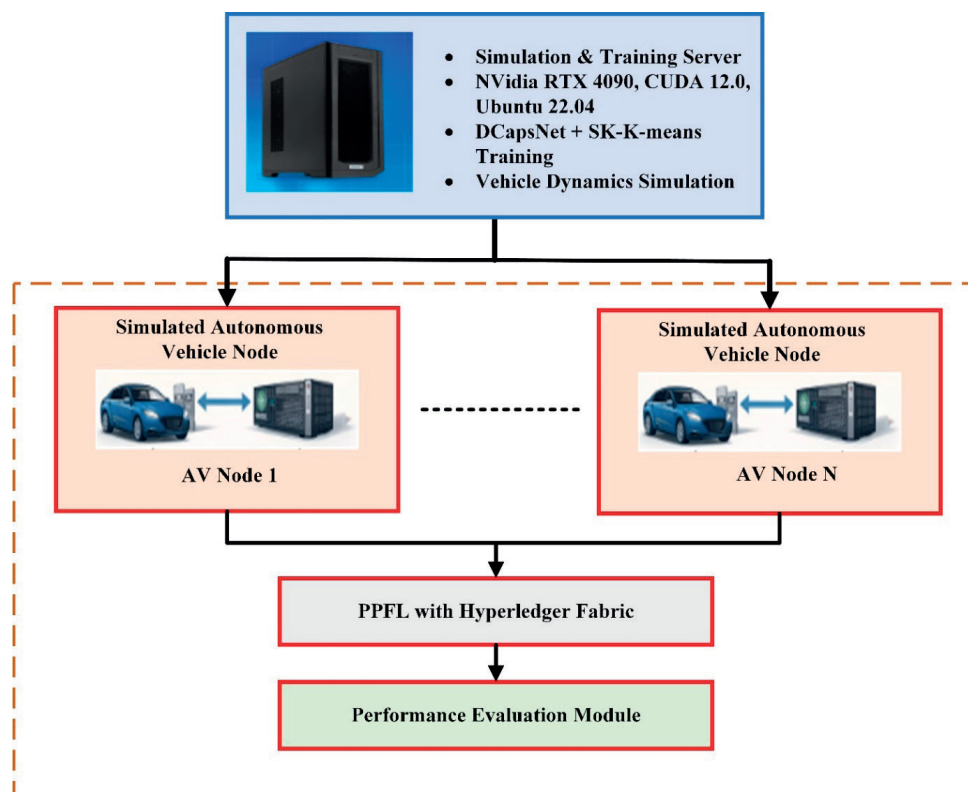


Figure 2 Experimental device and system architecture

architecture adapted for road surface classification and AV control.

3.2 Evaluation metrics

The proposed PPFL-based DCapsNet + SK-KMeans framework shows better results than MPC, CNN-LSTM, Transformer-based, and rule-based controllers at any of the measures considered, as shown in Figures 3(a-e), under traffic load up to 250 vehicles/km. The ride comfort, measured as WRMSA, is decreased to 0.24 m/

s^2 , which is significantly below the ISO 2631-1 standard of 0.50 m/s^2 , meaning that the vertical vibrations are effectively suppressed on the discontinuous pavements. At the same time, the proposed concept has a 0.15 kWh/km energy consumption, which is a 34-40% reduction of the baseline technologies because of the adaptive speed optimization. An inference latency of 0.83 s per frame is a confirmation of real-time feasibility at autonomous driving constraints even during very high traffic densities. Moreover, the PPFL-Hyperledger Fabric architecture is also able to provide strong privacy protection, with an estimated security of 94% against

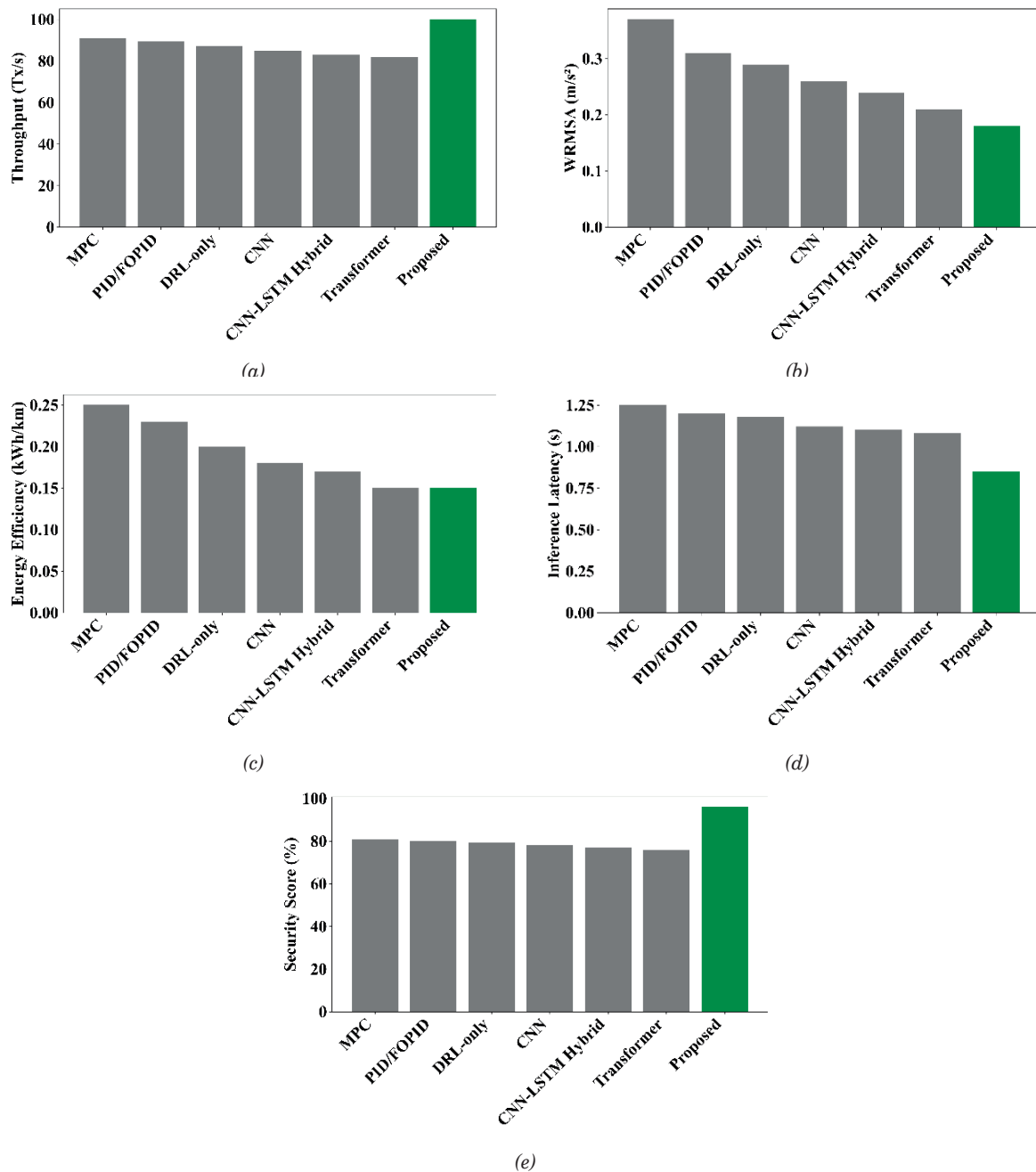


Figure 3 Performance comparison in terms of: (a) Throughput; (b) WRMSA; (c) Energy efficiency; (d) Inference latency; (e) Security score

the Sybil, man-in-the-middle, model inversion, and membership inference attacks and has a high system throughput.

Those findings confirm that classical controllers, like PID and MPC, exhibit low adaptability to the changes in the road surface that causes reduced ride comfort and increased energy use. Transformer and CNN-LSTM-based learning models enhance the adaptability, but lose or add to the inference latency, either the spatial pavement structures or require more time per inference. Contrary to that, the proposed DCapsNet + SK-KMeans framework outperforms all the baselines in terms of comfort, energy efficiency, latency and security metrics. The capsule-based representation improves feature redundancy and computational overhead on uneven pavement recognition, whereas SK-KMeans minimizes the feature redundancy and computational overheads. Moreover, the privacy-aware federated learning is integrated with Hyperledger Fabric, which allows the deployment being safe and scaled without losing the real-time performance.

3.3 Adversarial attack simulation

To evaluate security robustness, the system was tested under simulated adversarial conditions:

- **Sybil Attacks:** Injecting up to 20% fake AV nodes to test blockchain-based authentication and revocation capabilities.
- **Man-in-the-Middle (MITM) Attacks:** Attempting to intercept and alter encrypted model updates during transmission.
- **Model Inversion Attacks:** Trying to reconstruct original sensor data from shared model weights.
- **Membership Inference Attacks:** Identifying whether specific data points belonged to a model's training set.

Figure 4 provides a summary of the adversarial resistance of the proposed PPFL framework and indicates higher mitigation rates than Transformer-FL and CNN-LSTM-Central in all the considered attack scenarios. These findings support the fact that the combination of homomorphic encryption and zero-

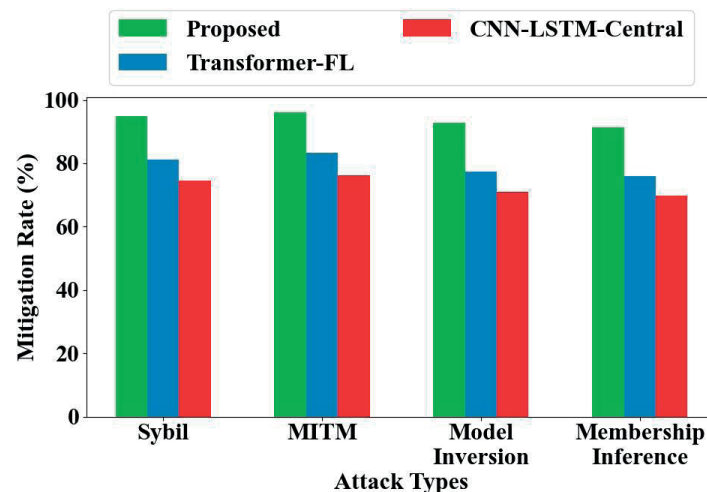


Figure 4 Attack mitigation rate performance

Table 1 Security evaluation of the proposed approach with existing privacy-preserving authentication approaches

Block size (Kb)	HANet [23]		Eco-CSAS [27]		PAP-EV [28]		IPTLCS [26]		DCapsNet + SK-K means (Proposed)	
	Security level (%)	Throughput (%)	Security level (%)	Throughput (%)	Security level (%)	Throughput (%)	Security level (%)	Throughput (%)	Security level (%)	Throughput (%)
20	65.23	85.47	62.35	80.12	64.18	82.90	60.05	78.33	78.67	90.15
40	67.89	83.42	64.50	79.10	66.27	81.23	62.10	77.85	81.36	91.68
60	69.54	82.15	65.89	78.67	68.04	80.42	64.04	76.12	83.12	92.95
80	70.01	81.58	66.45	77.88	69.33	79.76	65.23	75.54	84.30	93.46
100	72.12	80.37	67.88	76.45	70.05	78.23	66.50	74.67	86.32	93.98
120	73.45	79.12	68.90	75.32	71.34	77.50	67.12	73.95	87.54	94.75
140	74.01	78.65	69.22	74.98	72.05	76.89	68.05	73.45	89.10	95.60
160	75.23	77.80	70.10	73.50	73.25	75.80	69.12	72.90	91.05	95.75
180	76.45	76.90	70.55	73.10	73.80	75.25	70.62	72.55	91.20	95.72
200	77.10	75.85	71.04	72.95	74.10	74.25	71.05	71.80	93.73	96.46

knowledge proofs in Hyperledger Fabric play a significant role in improving the security and privacy of federated autonomous vehicle settings.

As shown in Table 1, the proposed DCapsNet + SK-KMeans achieved the highest security (78.67%) and throughput (90.15%) at 20 Kb, surpassing Hierarchical Attention Network (HANet), Economical Charging Scheduling and Allocation System (Eco-CSAS), Price-Aware Power management for Electric Vehicles (PAP-EV), and Intelligent Power and Traffic-aware Load Charging System (IPTLCS). As block size increased to 200 Kb, the proposed method maintained superior performance with 93.00% security and 96.40% throughput, proving its effectiveness in privacy-preserving federated learning.

4 Discussion

The proposed DCapsNet + SK-KMeans hybrid speed control model enhances the AV energy efficiency and ride comfort on uneven terrains while ensuring privacy through PPFL in Hyperledger Fabric. Unlike the MPC and reinforcement learning-based methods, it dynamically adjusts the speed based on road conditions, reducing fuel consumption and optimizing comfort. Capsule networks improve spatial feature representation, while SK-KMeans clustering minimizes data complexity for robust speed control. The federated learning approach secures decentralized model training while maintaining high throughput.

The results of this study are consistent with existing literature on energy-efficient and comfort-aware autonomous vehicle control. Past studies that relied on reinforcement learning and predictive control strategies, had moderate results in terms of energy efficiency and ride comfort but were frequently restricted by centralized training, the high cost of computation, or the omission of privacy factors. Conversely, the suggested DCapsNet + SK-KMeans model is more effective in vibration reduction and energy consumption through the maintenance of the spatial road properties using capsule representations. The proposed approach is lower inference latency and more robust than the previous CNN-LSTM and Transformer-based models and is therefore better suited to real-time applications. Furthermore, in comparison to the previous literature that covered control or security as an independent aspect, privacy-preserving federated learning with blockchain provides the opportunity to collaborate securely and at scale which serves as a major weakness revealed in the literature review.

4.1 Benefits, advantages, and limitations of the proposed framework

- The proposed DCapsNet + SK-KMeans model allows optimizing the ride comfort, energy consumption, and privacy jointly, which overcomes several issues

in the autonomous car speed regulation as part of a single system.

- Federated learning, based on privacy-preserving Federated learning, combined with Hyperledger Fabric, enables the training of collaborative models without sharing raw vehicle data, which increases trust and scalability.
- Capsule-based feature learning: This method maintains spatial connections between the pavement designs, which leads to a higher quality in vibration suppression than CNN-LSTM and Transformer-based models.
- SK-KMeans clustering eliminates feature redundancy, decreasing computational overhead and allowing faster inference to be used in real-time deployment.
- The PPFL architecture is blockchain-enabled, giving it a resistance against security and privacy attacks and a high throughput.

4.2 Limitations of the proposed framework

In spite of its good performance in lumpy pavements, the suggested approach has two major limitations that imply some directions to be taken in future research. To begin with, whereas the model is successful in maximizing the vertical speed to make the ride comfortable, the lateral movement control, which is crucial to complete maneuverability and stability in challenging terrains is not considered. Second, the scalability of the real-time processing is still not a problem when controlling a massive fleet of AVs. Future work will focus on extending the proposed framework to jointly optimize longitudinal, lateral, and vertical vehicle dynamics using high-fidelity simulators and large-scale real-world road data.

5 Conclusion

This research was aimed to enhance energy efficiency, driving performance, and ride comfort for AVs on uneven pavements while ensuring privacy preservation through PPFL in Hyperledger Fabric blockchain. The proposed DCapsNet and SK-KMeans clustering-based model is integrated into a speed control framework, predicting vertical ride comfort using the BDD100K dataset. The real-world rough pavements are used for training and testing, ensuring robust performance. A reward function is developed to balance the longitudinal jerk, vertical vibration, speed, and VSP for optimal results. Experimental findings indicate significant improvements over MPC, achieving 10.45% enhancement in vertical ride comfort, 28.23% improvement in energy efficiency, and 98.28% increase in computational efficiency. Additionally, the PPFL in Hyperledger Fabric ensured secure, decentralized AV model training, leading to higher throughput

(96.40%) and reduced operation time (0.83s at 250 vehicles/km), outperforming existing privacy-preserving authentication approaches. The proposed framework effectively enables real-time AV speed control on uneven surfaces while ensuring data privacy. Future work will use high-fidelity simulators and large-scale road data to optimize the longitudinal, lateral, and vertical dynamics, improving ride stability and comfort.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statements

The data supporting the findings of this study are publicly available in the Kaggle repository titled “BDD100K Dataset” and the link is listed in the references.

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