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Enhancing Transportation Safety: An integrated Approach Using FLFS and OSNCA for Advanced Driving Behavior Analysis

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Abstract: The assessment of driving behavior, vital for ensuring passenger safety and optimizing resource utilization in transportation systems, faces challenges due to inherent unpredictability and complexity. This study addresses these challenges by introducing innovative methodologies for the extraction, classification, and prediction of diverse driving patterns, utilizing data from "On Board Diagnostics" (OBD) ports in modern vehicles. In this approach, a comprehensive suite of advanced Machine Learning (ML) and Deep Learning (DL) stechniques, including Convolutional Neural Networks (CNNs), Optimized Spectral Neural Classification (OSNCA), and Fuzzy Logical Feature Selection (FLFS), are employed. These techniques are instrumental in overcoming limitations of previous models, enhancing accuracy in driving behavior evaluation. The utilization of FLFS in conjunction with OSNCA represents a novel method in driver behavior analysis. By applying these techniques, driver characteristics and behaviors are systematically categorized into distinct classes, facilitating a nuanced understanding of driving dynamics. The integration of these advanced methodologies not only furthers the analysis of driver behavior but also significantly improves classification and prediction capabilities. This research contributes to the development of safer, more efficient transportation networks by offering a refined approach to the analysis, categorization, and prediction of driver behavior, thereby advancing the field of driving behavior analysis.

Keywords: Driving behavior analysis; Machine Learning (ML); Deep Learning (DL); On Board Diagnostics (OBD); Feature extraction; Convolutional Neural Networks (CNNs)

1. Introduction

The propensity of young drivers towards risky driving behaviors has been extensively studied. However, the intersection between driving competence, temporal orientation, and driving behavior remains under-explored, despite the significant role of time perspective as a predictor of various risky behaviors. Time perspective encompasses a comprehensive concept involving attitudes related to the past, present, and future. Specifically, (a) the past time perspective relates to the recollection of reconstructed past experiences; (b) the present time perspective involves attention to immediate and salient stimuli; and (c) the future time perspective pertains to the anticipation and projection of future occurrences.

1.1 Analysis of Driver Behavior

In the realms of behavioral modeling, auto insurance, and government-managed public transportation systems, understanding driver behavior is crucial. This understanding is of paramount importance to the automobile and intelligent transportation sectors, which seek innovative solutions for enhancing task performance. In this context, various technologies are being employed to analyze driver behavior, including assessment of driving skills, monitoring the physical state of drivers through facial recognition and physiological feature tracking, and leveraging in-vehicle telematics for real-time data collection and analysis (Zinebi et al., 2018).

1.2 Techniques in Driving Monitoring Systems

The classification of driver behavior, acknowledged as a complex subject, involves multiple factors encompassing driving and traffic conditions. It is recognized that variable traffic conditions such as road environments, vehicle motion, and driver conduct are intertwined. These variables are instrumental in the development of fuzzy sets, which enhance the understanding of diverse driving styles and conditions. Accordingly, it is imperative to integrate operations and tactics (Shi et al., 2015) to accurately assess driver behavior.

As depicted in Figure 1, the initial module of the driving monitoring system primarily focuses on the driver's background information. This module considers various attributes, such as gender, age, driving experience, educational background, employment status, income level, average annual mileage, instances of traffic law violations, and accident history in the previous year. Utilizing statistical learning models, these data points are analyzed to establish correlations between the driver's background and the probability of accident involvement. By applying these models, predictions regarding a driver's likelihood of causing a traffic accident can be formulated. The background data is systematically evaluated against specific criteria, resulting in a comprehensive driver risk assessment score (Xing et al., 2017).

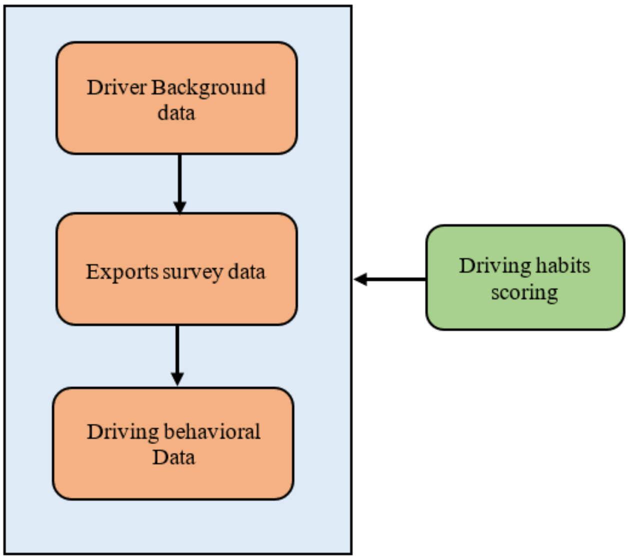

Figure 1. Driving monitoring system

In the endeavor to ascertain driver identity and driving style, a multifaceted array of factors must be evaluated. These encompass vehicle and road conditions, the driver's biological and physiological state, incident classification and identification, along with environmental influences. Despite the complexity, recent advancements in commercial and research-based systems over the past decade have significantly contributed to the analysis of driving behavior. The current paradigm in these systems focuses on assessing driving performance and offering driver assistance, sharing a unified infrastructure to monitor diverse driving systems (Alluhaibi et al., 2018).

The objective of this study is to enhance the analysis of driver behavioral data by implementing a novel classification and prediction framework. This methodology is designed to enable precise categorization of data into distinct classes, thereby markedly improving the accuracy in predicting driver behavior patterns. Employing fuzzy logic for feature selection, this approach refines the analysis of driver behavioral characteristics, yielding superior classification precision. Furthermore, the methodology utilizes relative closeness data in its intentional pattern prediction, thereby augmenting the precision of behavioral pattern predictions. This is achieved by conducting an exhaustive analysis of driver data, which underpins the enhanced prediction accuracy.

2. Literature Review

The analysis of driving behavior is acknowledged as a multifaceted concept, typically characterized by the adaptation of vehicle control to external conditions and the driving environment. Research has consistently shown that a majority of vehicular accidents are attributable to improper driving behaviors, thereby underscoring the critical need for accurate accident prevention characterization (Wang et al., 2015). In the realm of big data, algorithms designed to analyze vehicle motion have gained prominence. These algorithms play a pivotal role, as the driving styles they discern are instrumental in providing insights that can significantly reduce traffic accident risks (Hssayeni et al., 2017; Peng et al., 2021).

Studies investigating the causative factors of traffic accidents have revealed that human error is predominantly responsible. Drivers, as the primary operators of vehicles, are often implicated in these incidents. Consequently, there is an imperative need to scrutinize the elements influencing driver behavior and to develop targeted corrective strategies for mitigating negative driving behaviors. This approach is particularly vital in the interim phase leading up to the full implementation of autonomous driving. Moreover, this line of inquiry provides foundational support for the study of humanoid behaviors in the context of autonomous driving technologies.

It has been established through various studies (Hua & Cheng, 1999; Kroenung & Eckhardt, 2015; Mayhew et al., 2003) that on-road experience is a crucial factor in enhancing hazard mitigation skills and reducing instances of distracted driving (Reason et al., 1990). Evidence suggests that experienced drivers, in contrast to their novice counterparts, exhibit a lower risk of crashes (Martinussen et al., 2013), attributed to their ability to efficiently allocate attentional resources for hazard recognition (Tao et al., 2017). Novice drivers, lacking in maturity and experience, are more prone to be involved in traffic accidents (Guo et al., 2019).

Despite structured driving exercises during the learning phase, Pnina et al. (Özkan et al., 2006) highlighted the high incidence of errors during early license holding periods. Limited experience is a contributing factor to a driver's reduced ability to recognize potential road hazards, leading to increased risks of rear-end collisions and impaired driving incidents (Curry et al., 2017). Experienced drivers display greater proactivity and superior situational awareness when encountering on-road challenges (Huang et al., 2006; Van Gelderen et al., 2008).

The deviation from standard driving behaviors is considered an indicator of potential danger, leading to the use of driving performance metrics to study the impact of drivers' behavioral traits on their driving quality (Caponecchia & Williamson, 2018; Choudhary & Velaga, 2019). Anomalies such as frequent critical braking or rapid acceleration are often linked with risky driving behaviors (Alrassy et al., 2023). This study focuses on employing driving performance metrics derived from continuous driving profiles gathered from field data, aiming to enhance the detection of risky driving patterns. The significant contribution of this research lies in identifying unsafe driving behaviors through the analysis of continuous driving profiles collected via in-car data recording devices.

In summary, inexperienced drivers present a considerable risk to themselves, other road users, and passengers. A driver's experience is intricately linked with psychological attributes such as awareness, confidence, and attitude, as well as emergency response capabilities and peripheral monitoring skills.

3. Dataset and Description

The acquisition of live vehicle data constituted a critical component of this research, with a dataset obtained in a CSV format for comprehensive analysis. The dataset comprised data collected from the IGNIS Soul vehicle, operated by twenty diverse drivers during a consistent road trip spanning 150 km (round-trip) and encompassing approximately 40 hours of driving.

It is pertinent to highlight that the dataset encapsulated driving conditions across varied road types, such as urban, rural, and highway terrains. This variety in road settings is crucial, given its potential influence on driver behavior.

Parameters included in the dataset were extensive, covering aspects crucial to the study such as fuel consumption, vehicle dynamics, road conditions, and maintenance indicators. Engine-related parameters like engine speed, torque, and coolant temperature were also incorporated. Furthermore, the dataset was enriched with features encompassing accelerator pedal percentage, throttle position, and various metrics of the electrical system.

For the purpose of data analysis, visual inspection techniques, including scatter plots and box plots, were utilized to examine variable distributions and identify anomalies. Additionally, a rigorous outlier detection procedure, grounded in established statistical methodologies, was implemented to address aberrant data points, thereby safeguarding the dataset's integrity.

This detailed and varied dataset forms the bedrock of the research, enabling an in-depth examination of vehicle performance and driver behavior under different driving conditions.

4. Materials and Methods

In the realm of driver behavior analysis, the methodology adopted in this study is a systematic approach aimed at enhancing the precision and comprehension of various driving patterns. The process is divided into distinct stages, each contributing to the overall accuracy of the analysis.

(a) Data division and intent classification

- Data segmentation: Initially, driver behavioral data are segmented to differentiate various classes, utilizing a novel classification and prediction intent approach.
- Fuzzy logical conditions: The application of fuzzy logical conditions aids in feature selection, thereby refining the analysis and augmenting the accuracy in predicting driver behavior patterns.

• Pattern prediction enhancement: The classification, based on intent, facilitates the forecasting of values, improving the accuracy of behavioral pattern predictions through the analysis of relative closeness data.

(b) Multilayer social spider optimization technique

• Feature selection optimization: The multilayer social spider optimization technique is employed for the optimization of marginal feature selection, enhancing the classification process.

• Refined pattern predictions: This technique ensures prioritization of the most influential features, leading to more precise pattern predictions based on behavioral data points.

(c) Optimized spectral neural classification

• Behavioral pattern categorization: The integration of optimized spectral neural classification into the research framework is critical for the finalization of behavioral pattern categorization.

• Enhanced understanding of driver behavior: This advanced classification technique plays a pivotal role in deepening the understanding of driving conditions and optimizing driver behavior analysis.

(d) Active dimensional reduction and adaptation process

• Mitigation of adverse effects: An active dimensional reduction approach is implemented to address adverse effects, noise, and defective data within the dataset.

• Swift adaptation to evolving driver styles: The system incorporates a swift adaptation process to accommodate changes in driver styles, especially those influenced by the advent of new vehicle technologies.

• Optimal feature recommendations: This adaptation process is guided by optimal feature recommendations, ensuring the system's agility and responsiveness to evolving driving dynamics.

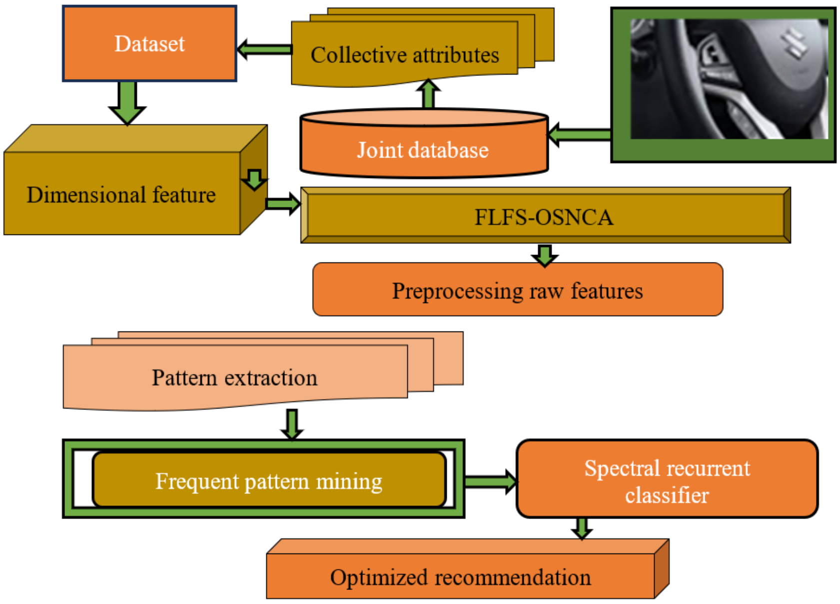

Figure 2. Architecture diagram of the proposed FLFS-OSNCA

The architecture diagram, as depicted in Figure 2, visually illustrates the systematic progression of the methodology. It encompasses steps from data segmentation and intent classification to the finalization of behavioral pattern categorization. This diagram underscores the integral role of feature selection, optimization techniques, and adaptation processes in the pursuit of enhanced accuracy and understanding of driver behavior.

Algorithm

The algorithm employed in this study is designed to normalize cluster point variations in k-means clustering and generate fuzzy rule predictions based on maximization of upper and lower bound limit values to predict marginal weightage values. The procedure is as follows:

Algorithm: Evaluation of fuzzy logical subsets
Input: Data collection X, fuzzy margin Nn
Output: Diminished data collection Rx
Initialization:

Step 1: Data collection X and fuzzy margin Nn are read.
Step 2: Neural networks are established with a predetermined number of layers and attributes. The function InitializeNeuralNetworks() is invoked.
Step 3: Fuzzy rule theory is applied for feature selection.

For each feature f in the dataset:

a. Mid-layer margin is applied to separate upper and lower weight margin features through ApplyMidLayerMargin(fuzzyMargin).
b. Maximum weight and minimum features for each layer are determined using FindMaxWeightAndMinFeatures(f).
c. Features are identified based on selection weight via IdentifyFeaturesBySelectionWeight(f, maxWeight, minFeatures).
d. Identified features are added to the reduced dataset with AddToReducedDataSet(identifiedFeatures).

Step 4: Redundant features Ts are retrieved with GetRedundantFeatures().

5. Result and Discussion

The performance of drivers, monitored over various time frames, is established based on a driver performance pattern. This pattern is predicated on parameters such as signal state, fuel consumption, speed, acceleration, and traffic assumptions. The approach generates various methods for class performance evaluation based on the features supplied. Similarly, the system quantifies neuronal activation using the Performance Aspect Ratio (PAR), rated in several class formats. The PAR value is instrumental in determining the driver class, with recurrent neural activation applied across all training features in the hidden layer for classification.

For comprehensive assessment, the FLFS-OSNC approach's baseline technique selection is crucial for comparative analysis. Each baseline technique, including Support Vector Machine (SVM), Principal Component Analysis (PCA), Hierarchical Dirichlet Process (HDP), and Genetic Algorithm-based Fuzzy C-Means (GA-FCM), is carefully chosen for its applicability to driver behavior analysis. Previously, these methods were utilized in predicting driving behaviors, highlighting areas for enhancement. The IGNIS dataset serves as a trial model set to establish the efficacy of FLFS-OSNC. The results presented in this study provide a foundation for broader spectrum analysis in future research. SVM is employed as a standard benchmark to evaluate the performance of FLFS-OSNC. PCA is used to compare how FLFS-OSNC captures feature significance against a dimensionality reduction-centered method. HDP's inclusion addresses the temporal dependencies in driver behavior analysis, offering insights into sequential data modeling. GA-FCM provides a benchmark against methods that leverage evolutionary algorithms and fuzzy clustering. This study ensures a thorough evaluation of the dataset, allowing for comparisons against traditional, contemporary, and specialized approaches. The rationale for each selection underscores the necessity to comprehend FLFS-OSNC's effectiveness and uniqueness in predicting driver behavior patterns. The capabilities of FLFS-OSNC not only enhance current systems but also offer tailored interventions attuned to specific contexts. Moreover, the predictive and context-aware capabilities of FLFS-OSNC have potential applications beyond driving behavior analysis, including sectors like finance, retail, manufacturing, education, security, and customer service.

In the context of driver behavior analysis, the proposed personalized web search method utilizes feature selection and spectral classification to infer relevant categories based on the retrieval history of driver behavior searches. This approach has demonstrated efficacy in context clustering, with hybrid data patterning (HDP) showing improved performance over previous methodologies.

Table 1. Dataset specifics

Parameter	Value
Number of drivers	20
Features	15
Datasets used	IGNIS car
Tool	Python Anaconda framework

Table 1 provides an exhaustive overview of the dataset employed to evaluate the effectiveness of the proposed strategy, which is based on the multi-attribute opinion rate support measure. The evaluation of FLFS-OSNCA incorporates metrics such as clustering accuracy (cs), precision, recall, and time complexity.

$$\text{Clustering accuracy } (cs) = \sum_{k=0}^{k=n} \times \frac{\text{Retrived number of interest terms cluster } (Cds) \text{ predictedlinks}}{\text{Total related datsets } (Tr) \text{ from search links}}$$

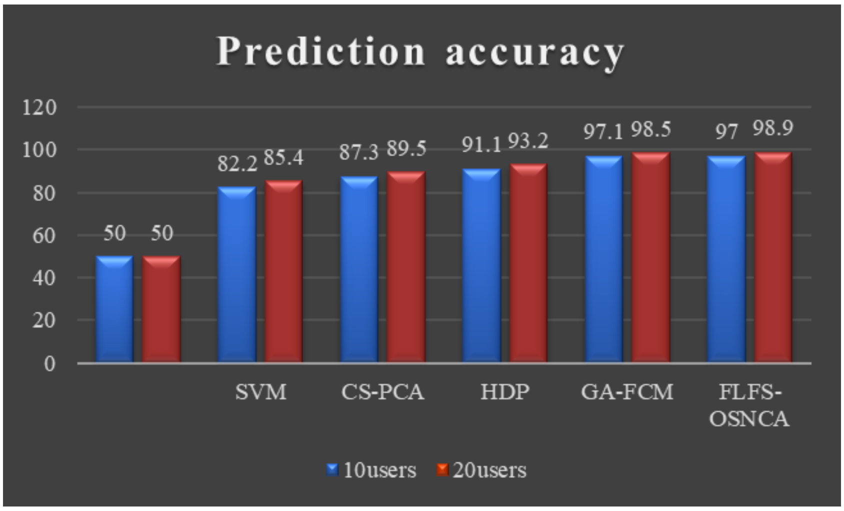

Figure 3. Comparison of the accuracy of pattern predictions

Figure 3 depicts the prediction accuracy of two systems. The comparison reveals that the GA-FCM method, as part of the proposed strategy, yielded higher clustering accuracy than the comparative system.

Table 2. Comparison of pattern prediction accuracy

	Impact of Pattern Prediction Accuracy (%)				
Methods/Number of Records	**SVM**	**CS-PCA**	**HDP**	**GA-FCM**	**FLFS-OSNCA**
10 drivers	82.2	87.3	91.1	96.1	97
20 drivers	85.4	89.5	93.2	97.5	98.9

The data indicate in Table 2 that the prediction accuracy for 10 drivers is 97% and for 20 drivers is 98.9%, demonstrating that the proposed FLFS-OSNCA approach yields higher clustering accuracy compared to the PCA neural network.

5.1 Analysis of Precision

Precision (Pr) is defined as the ratio of the total number of accurately predicted patterns to the total number of driver behavior relations. This metric is calculated using the relevant pattern (R) derived from the confusion matrix.

$$\text{Precision } (Pr) = \frac{\text{Relevant links } (R)}{\text{Total number of retrieved Links } (A)} \times 100$$

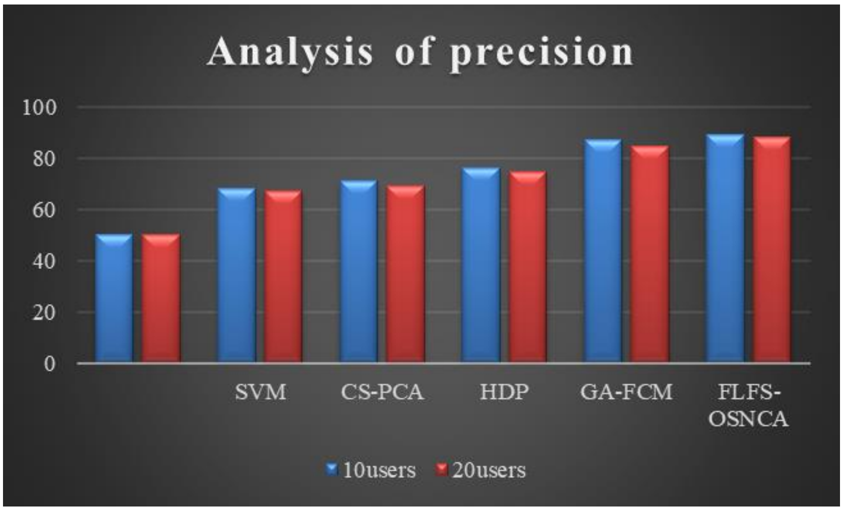

Figure 4. Comparison of precision

Figure 4 illustrates the comparison of precision achieved by different methods. It is observed that the proposed FLFS-OSNCA method outperforms other methodologies in terms of precision.

Table 3. Comparison of precision

	Impact of Precision (%)				
Methods/Number of Drivers	**SVM**	**CS-PCA**	**HDP**	**GA-FCM**	**FLFS-OSNCA**
10 drivers	68.2	71.2	76.3	87.3	89.4
20 drivers	76.4	69.4	74.8	84.6	88.3

The precision of 89.4% for 10 drivers and 88.3% for 20 drivers, as indicated in Table 3, demonstrate that the FLFS-OSNCA approach outperforms other methods in precision.

5.2 Recall Analysis

Recall (Rc) represents the percentage of accurately retrieved driver behavior patterns with relevant positive values.

$$\text{Recall } (Rc) = \frac{\text{total retrieved from relevant links } (RA)}{\text{relevant links}(R)} \times 100$$

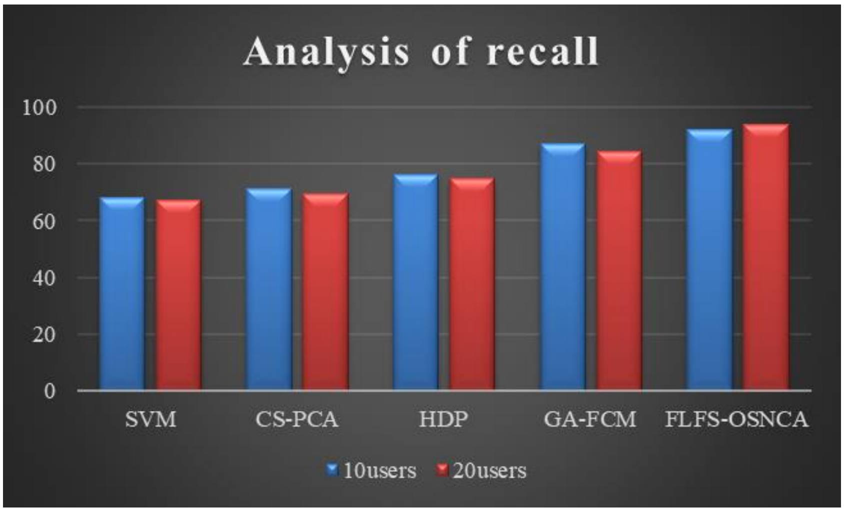

Figure 5. Comparison of recall

Figure 5 illustrates the comparative analysis of false recall generated by various methods. The FLFS-OSNCA method is observed to surpass other techniques in performance.

Table 4. Comparison of recall

	Impact of Recall (%)				
Methods/Number of Records	**SVM**	**CS-PCA**	**HDP**	**GA-FCM**	**FLFS-OSNCA**
10 drivers	68.2	71.2	76.3	87.3	92
20 drivers	67.4	69.4	74.8	84.6	93.9

Table 4 compares the recall from pattern analysis, where FLFS-OSNCA is shown to achieve superior performance compared to alternative methods.

5.3 Analysis of Time Complexity

$$\text{Time complexity } (Tc) = \sum_{k=0}^{k=n} \times \frac{\text{prediction of clustering Accuracy } (cs) + \text{false classification } (Fcr)}{\text{Time taken } (Ts)}$$

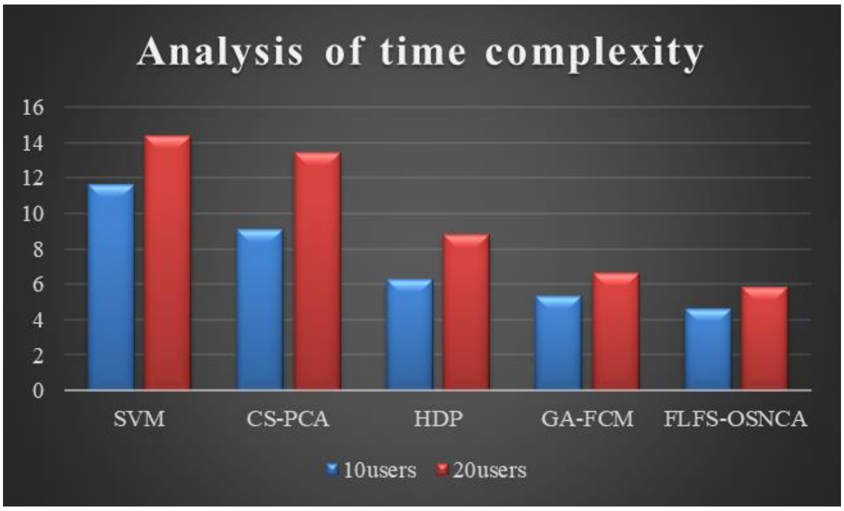

Figure 6. Comparison of time complexity

Figure 6 presents a comparison of the time complexity generated by various methods, indicating that the proposed FLFS-OSNCA methodology exhibits lower time complexity compared to other approaches.

Table 5. Comparison of time complexity

	Impact of Time Complexity (ms)				
Methods/Number of Records	**SVM**	**CS-PCA**	**HDP**	**GA-FCM**	**FLFS-OSNCA**
10 drivers	11.6	9.1	6.3	5.3	4.6
20 drivers	14.4	13.4	8.8	6.6	5.8

Table 5 demonstrates that the FLFS-OSNCA method achieved a time complexity of 4.6 milliseconds for 10 drivers and 5.8 milliseconds for 20 drivers, thus validating the efficiency of the proposed approach.

The FLFS-OSNC method, specifically designed for driver behavior analysis, opens promising avenues for future research and applications in various domains. Future directions include adapting the methodology for real-time applications in advanced driver assistance systems, addressing limitations in predicting behavior during hazardous scenarios, and integrating multimodal data sources for comprehensive analysis. The method's potential extension to other transportation modes, contribution to health and wellness monitoring within vehicles, and application in human-computer interaction are noteworthy. Exploratory research involving variations with advanced ML models, cross-domain applications, and robustness against security considerations are essential. Collaboration with industry partners is encouraged to facilitate the integration of FLFS-OSNC into emerging technologies, contributing significantly to the development of intelligent and context-aware transportation systems. The method exhibits versatility and holds potential for significant advancements in fields beyond driver behavior analysis.

6. Conclusion

The implementation of the FLFS-OSNC method in this research has demonstrated its efficacy in predicting driver behavioral patterns and providing optimal recommendations to enhance driving behaviors. A robust system for driver behavior analysis has been established through the integration of feature selection and classification approaches within the proposed methodology.

In comparison with advanced techniques such as SVM, PCA, Hierarchical Dirichlet Process (HDL), and GA-FCM, the FLFS-OSNC approach has exhibited superior performance. It achieved an accuracy of 98.9%, a precision of 88.3%, and a recall of 93.9%. These metrics underscore the method's ability to minimize classification errors and reduce time complexity, especially in the context of large-dimensional datasets.

However, it is imperative to acknowledge that the current iteration of the method is limited in providing driving patterns during risky situations. Future research efforts will be directed towards expanding the methodology to include real-time driving behavior features and analyzing trends during hazardous scenarios. This research thus sets a strong foundation for furthering the field of driver behavior prediction and analysis.

The integration of the FLFS-OSNC method with existing driver assistance systems has the potential to facilitate the swift processing of real-time data, effectively addressing communication delays and ensuring synchronization with current components. This integration, however, introduces complexities in the management of riskier driving patterns. These complexities encompass challenges in defining and identifying risks, navigating ethical considerations, garnering driver acceptance, and adhering to the dynamic legal and regulatory frameworks. The successful implementation of FLFS-OSNC has demonstrated its proficiency in predicting driving behaviors, thereby enabling improvements in various aspects such as vehicle dynamics, fuel consumption, and maintenance of key components like clutches and brake shoes. This contributes to an overall enhancement in engine and vehicle performance.

Nevertheless, integrating the FLFS-OSNC approach with driver assistance systems presents both potential benefits and challenges. Key challenges may arise in terms of data processing speed and latency, necessitating a careful evaluation of system responsiveness. It is imperative to balance these aspects to ensure successful integration, which could significantly augment the efficacy of driver assistance systems and contribute to advancements in road safety.

Ethical Approval

This study adheres to strict ethical guidelines, ensuring the rights and privacy of participants. Informed consent was obtained from all participants, and personal information was protected throughout the study. The methodology and procedures of this research have been approved by the appropriate ethics committee. Participants were informed of their rights, including the right to withdraw from the study at any time. All collected data is used solely for the purpose of this research and is stored and processed in a secure and confidential manner.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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