International Journal of Interpreting Enigma Engineers (IJIEE)
https://ejournal.svgacademy.org/index.php/ijiee/
https://doi.org/10.62674/ijiee.2026.v3i03.003
eISSN: 3048-6300
OPEN ACCESS

ENHANCING REAL-TIME DROWSINESS DETECTION: A CONNECTIVITY-AWARE GRAPH NEURAL NETWORK APPROACH

Haranadha Reddy Busireddy Seshakagari[1], R Madhavi[2], Sharath Chandra Parashara[3]

Original Article

[1]Manager - Architecture, Valuemomentum, Erie, PA-16506, USA
[2]Assistant Professor, Department of CSE(AI), Vemu Institute of Technology, Chittor
[3]Chief Technology Officer, Fenix Commerce Inc. San Jose, California - 95129, USA

*Corresponding Author's Email: [1]haranadhareddyven@gmail.com, [2]rmadhavi100@gmail.com, [3]hellosharathchandra@gmail.com

Abstract

Drowsiness detection plays a critical role in enhancing driver safety and preventing accidents due to fatigue. Our approach integrates the advantages of several advanced machine learning algorithms to improve prediction accuracy and responsiveness. Specifically, we employ a Connectivity-Aware Graph Neural Network (CAGNN) to model the spatial and temporal dependencies in driver behavior, Graph Neural Network (GNN) coupled with a Recurrent Neural Network (RNN) architecture using Gated Recurrent Units (GRU) to capture long-term sequential patterns. Furthermore, the XGBoost algorithm is utilized for feature enhancement, and Random Forest (RF) is used to provide an ensemble learning framework for robust classification. The CAGNN framework is designed to dynamically adjust to real-time changes in connectivity and vehicle environment, ensuring seamless performance even in varying conditions. Experimental results demonstrate that our model significantly outperforms traditional drowsiness detection methods in terms of accuracy, latency, and adaptability to real-world conditions.

Keywords- Drowsiness classification, Graph Neural Network (GNN), Connectivity-aware, Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), XGBoost, Random Forest (RF), Real-time detection, Fatigue monitoring, Driver safety.

Introduction

The study examines spatial and temporal indicators of fatigue such as eye movement, facial behaviour, steering activity and related driving patterns. GNNs are used to represent the relations between these observations and GRU-based learning captures the sequential changes of these observations due to the decline of alertness over time. XGBoost selects informative features and reduces unnecessary computation load, and RF does the final classification of alert and drowsy states. The proposed method is also studied considering the variations in traffic, weather, connectivity, road conditions, and surrounding environments. Its applicability is investigated in the case of conventional, semi-autonomous and autonomous vehicles with monitoring facilities. Performance is evaluated in terms of accuracy, latency, adaptability, robustness and classification stability and compared to existing methods. Real world evaluation is also included to test the practical effectiveness and suitability for advanced driver-assistance systems. The wider aim is to reduce fatigue related accidents on the road and improve driver safety.

Although vehicle safety technologies are constantly improving, driver fatigue is still one of the main causes of accidents on the roads worldwide. Accurate real time detection of drowsiness remains challenging, as most traditional methods depend heavily on facial cues or simplistic behavioural measures that may not adequately capture a driver's state in complicated and dynamic environments. Low precision, delayed responses, and poor adaptation to traffic density, weather, road structure, illumination and surrounding environments can also impair their performance. Furthermore, some existing methods treat each sign separately and are therefore unable to capture the association among different driver behaviours or the gradual changes of driver behaviour related to fatigue onset.

These limitations require a more responsive, adaptable and context aware solution. To solve these problems, this paper proposes a Connectivity aware Graph Neural Network method by considering spatial relationships and temporal characteristics of driving behaviour. Inter related features and sequential changes of driver behaviour are investigated by Graph Neural Networks and Gated Recurrent Units, informative variable selection is performed by XGBoost, and classification stability is achieved by Random Forest. Behavioural variations can be observed continuously so that fatigue related patterns can be identified as they develop. Therefore, an integrated approach can lead to more consistent monitoring of drivers and contribute to reducing the safety risks associated with the increasing drowsiness during long driving times.

Related Work

Driver drowsiness detection is still a topic of considerable research interest, because fatigue can reduce concentration, slow reactions, affect decision making and increase the likelihood of road accidents [1]. Previous studies mainly focused on physiological signals, facial features and vehicle-related cues to detect decreasing driver alertness [2]. Vision based approaches often track signs of fatigue like long eye closure, blink rate, gaze direction, yawning, and facial expression changes [3]. Moreover, Convolutional Neural Networks (CNNs) have been employed to learn meaningful patterns directly from the facial and eye images [4], thus decreasing the reliance on handcrafted features. Although visual based methods may work well under controlled conditions, their reliability may be affected by poor illumination, face obstruction, head movement, camera-position variation, eyewear and individual differences of the driver [5]. Another source of information is the use of vehicle-based techniques which examine steering behaviour, speed variation, lane deviation and related driving responses that may indicate fatigue [6]. Sequential models like Recurrent Neural Networks and Long Short Term Memory architecture have also been employed to analyse temporal dependencies in continuous driving signals and track behavioural changes over time [7]. However, these methods can be computationally expensive and may not respond efficiently to sudden changes of driver behaviour or surrounding conditions. Performance will also vary depending on the type of road, amount of traffic, weather conditions, vehicle configuration and your driving style. Furthermore, several independent approaches utilise a small set of indicators, which limits their ability to demonstrate the interactions of multiple fatigue-related factors. These limitations point to the need for more adaptive, responsive and reliable approaches for complex real world driver monitoring.

Graph Neural Networks (GNNs) have received increasing attention in recent years thanks to their capability of modelling complex relationships in interconnected data, making them appropriate for driver monitoring and intelligent transportation applications [8]. Graph based methods can organize behavioural, physiological and vehicle-related signals in a unified network of connected nodes and relationships [9], unlike traditional learning methods that study individual features separately. This property is especially useful for drowsiness detection where the change in driver alertness is not based on a single observation. Rather, fatigue may be expressed in a combination of eye activity, facial behaviour, steering patterns, head movement and vehicle dynamics. This allows GNN-based architectures to capture the spatial dependencies among these related indicators and to provide a more comprehensive representation of the driver's condition [10]. However, spatial information alone is not sufficient, because fatigue is often gradual and can be observed over successive time intervals. This limitation can be overcome with recurrent learning, which studies the evolution of behavioural patterns during continuous driving. GRUs are well suited for this task because they capture relevant sequential information while requiring less computational operations than more complex recurrent architectures [11]. Their gating mechanism allows the preservation of relevant historical patterns, and the reduction of less useful information, and thats facilitates efficient analysis of changing levels of alertness. Therefore, GRUs can detect gradual changes in the driver's behaviour and capture the temporal features related to rising fatigue [12]. Our model integrates graph based relational learning and GRU-based sequence analysis, allowing us to study spatial interactions and temporal progression within the same architecture. This combination provides a better representation of fatigue related behaviour over multiple signals and consecutive observations. Such spatiotemporal modelling can facilitate context-aware and responsive, adaptive drowsiness monitoring, especially in dynamic driving conditions when driver behaviour, vehicle movement, and surrounding factors may change continuously [13].

Because sensor based datasets often have redundant, noisy or weakly relevant variables, feature selection and ensemble learning have become important parts of modern drowsiness detection [14]. Prior machine learning studies have mainly used hand-crafted indicators such as blink frequency, gaze direction, steering behaviour, head movement and physiological responses. Such features can provide useful evidence of fatigue but their effectiveness may vary across drivers, vehicles and environmental settings which can limit generalisation in real world applications [15]. Therefore, XGBoost is used for the identification of influential variables and classification improvement by gradient boosting [16].

It can deal with high dimensional, imbalanced and complex data, therefore it is appropriate to analyse fatigue related information collected from multiple sensing sources. Random Forest (RF) also offers robust classification by creating multiple decision tree models and aggregating their outputs, which may help avoid overfitting and maintain stable predictions even in the presence of noise or uncertainty [17]. RF also provides estimates of feature importance which can give insight into the behavioural, physiological and vehicle related indicators most associated with drowsiness [18]. The prediction consistency can be enhanced by combining deep learning with XGBoost and RF in hybrid architecture, while retaining significant spatial and temporal information from driver behaviour [19]. The connectivity aware methods take a step further to consider the variations in network availability, traffic density, road conditions, weather, and surrounding environmental factors. They can also promote information exchange through connected vehicles, IoT devices, and cloud assisted platforms by integrating additional contextual data during monitoring [20]. However, there are practical challenges with computational demand, response latency, privacy, sensor reliability, real-time processing, and generalisation to different users and driving scenarios. Addressing these issues is necessary to develop adaptive, scalable and reliable drowsiness detection systems for practical use.

Proposed System Workflow

Connectivity-Aware Graph Neural Network (CAGNN) CAGNNs offer an adaptive mechanism to cope with these limitations by adapting to changes in vehicle connectivity and the surrounding environmental conditions. Road characteristics, traffic density, weather changes, etc. can be considered to maintain reliable operation in uncertain driving situations. In this work, a real-time drowsiness detection framework based on CAGNN combining Graph Neural Networks, GRU-based Recurrent Neural Networks, XGBoost and Random Forest is proposed. The proposed architecture aims to provide accurate recognition, timely response, computational efficiency and adaptability in various driving environments. Spatial relationships are modelled with graph based learning and sequential behaviour changes are investigated with GRU-based temporal analysis. The experimental results show that the proposed method is more efficient than the existing drowsiness detection methods that we have used for comparison. The results obtained also show that the integrated framework has significant potential to support reliable driver monitoring and contribute toward improved road safety.

The study seeks to develop a real time driver drowsiness detection method based on a CAGNN to enhance road safety and mitigate fatigue related accidents. The proposed architecture integrates multiple machine learning and deep learning techniques to improve recognition accuracy, response speed and operational reliability under different driving conditions. Spatial relations between the driver behaviours, vehicle related signals and surrounding contextual information are modelled using a Graph Neural Network, and the temporal relations associated with gradual changes in alertness are modelled using a GRU-based Recurrent Neural Network. This combination allows the method to consider immediate interactions, and also longer behavioural sequences associated with developing fatigue. To help feature selection and optimisation, we employed XGBoost to identify the most informative variables and to reduce the impact of less relevant inputs. Then, an ensemble classifier in the form of a Random Forest is used to make stable predictions under different data conditions. The proposed approach also takes into account changes in the network connectivity, traffic density, road characteristics, weather and other environmental factors, which enable the system to be responsive in a variety of driving situations. Such flexibility is especially important in real world environments where operating conditions can change unexpectedly. The proposed method overcomes several limitations of traditional drowsiness detection methods by integrating spatial modelling, sequential learning, feature refinement, and ensemble classification.

The proposed system is a structured workflow for real-time driver drowsiness detection by combining multiple machine learning and deep learning techniques in a single architecture. Data acquisition is the first step of the process. The data is collected from in-vehicle cameras, onboard sensors, and surrounding driving conditions. These sources provide visual, vehicular and environmental data which are subsequently used to examine driver behaviour and identify fatigue related patterns. These inputs could be facial features, eye activity, head movement, steering behaviour, vehicle speed, road conditions, traffic information, and observations of the environment. The raw data once collected, is subjected to a preprocessing step where noise removal, missing value processing, normalisation of numerical attributes and input conversion to a common form for analysis is performed. The refined dataset is then processed using XGBoost. XGBoost allows feature selection and optimisation by keeping the most informative variables and reducing unnecessary information. After this stage, the selected features are fed into a hybrid learning architecture. The spatial relationships

among driver behaviour, vehicle state and contextual factors are modelled with a Graph Neural Network and the temporal changes related to gradual development of fatigue are modelled with a GRU-based Recurrent Neural Network. Random Forest is then used as a classifier, to increase the stability of the prediction and to help reliably distinguish between alert and drowsy states. The outputs of these integrated components are fused to obtain the final decision. This workflow is aimed at providing accurate, reactive, adaptive and reliable drowsiness recognition in different real world driving scenarios.

A. Loading Dataset

The first phase of the proposed framework is the loading of a diverse and representative dataset comprising data gathered from various sources while driving. The data may comprise live sensor readings, images and video frames captured by invehicle cameras. These inputs provide useful information about the driver's condition and the surrounding driving environment. These can be facial landmarks, head posture, eye openness, blink activity, gaze direction, and other visible behavioural cues that can be used to represent possible signs of fatigue. Operational information is better expressed by vehicle parameters such as speed, steering angle, lane position, and driving response patterns. Environmental conditions such as road type, lighting level, weather and traffic density are considered as these factors can affect the driver behaviour and detection performance. The collected observations are organised in a structured data set for subsequent efficient processing by the learning stages that follow. Supervised training is performed on labelled samples of alert and drowsy conditions to enable the model to learn to differentiate between normal and fatigue-related behaviour. Fusion of visual, vehicle and contextual information at data loading stage results in a more comprehensive representation of driving condition and forms a reliable basis for preprocessing, feature selection, model training and classification.

B. Preprocessing

The loaded dataset is subjected to an extensive preprocessing phase to improve data quality and prepare input variables for further learning and analysis. This phase begins by removing records that are irrelevant, duplicated or inconsistent and may affect the reliability of the analysis. Then the missing values are filled in with appropriate methods so that incomplete observations do not adversely affect the training of the model. Numerical features are scaled normalised or standardised to ensure that the scale is the same for different features. The raw inputs are cleaned and transformed into meaningful representations that preserve relevant spatial and temporal patterns relative to driver drowsiness. Also, we carry out feature extraction and refinement to remove the redundant information and keep the variables that are most important for prediction. XGBoost helps in this process by identifying the most influential attributes and increasing the efficiency of the selected feature set. Also, the continuous driving data are divided in consecutive time windows to study the evolution of driver behaviour in consecutive intervals and not isolated observations.

C. Model Training and Classification

During training, model parameters are optimised via backpropagation so that they can distinguish meaningful patterns associated with alert and fatigued state. After feature learning is completed, to enhance the prediction robustness and reduce sensitivity to noisy observations, Random Forest (RF) is used as the ensemble classifier. The trained architecture is then tested on the performance measures such as accuracy, response latency, robustness and adaptability under different driving conditions. The validation results are used to make the necessary parameter adjustments to improve overall reliability. After the learning process, the obtained model can be used to assist in continuous drowsiness detection in real-time using incoming behavioural, vehicular and contextual information, and be sensitive to changes in road and network conditions.

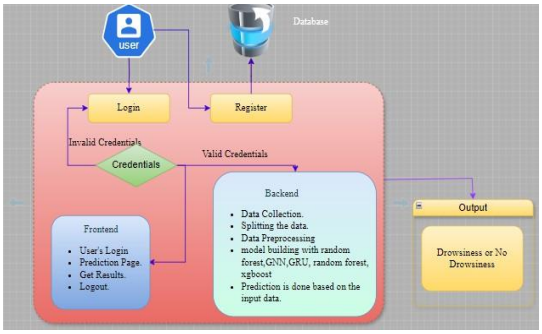


Fig 1 : *Block Flow chart of Drowsiness flow*

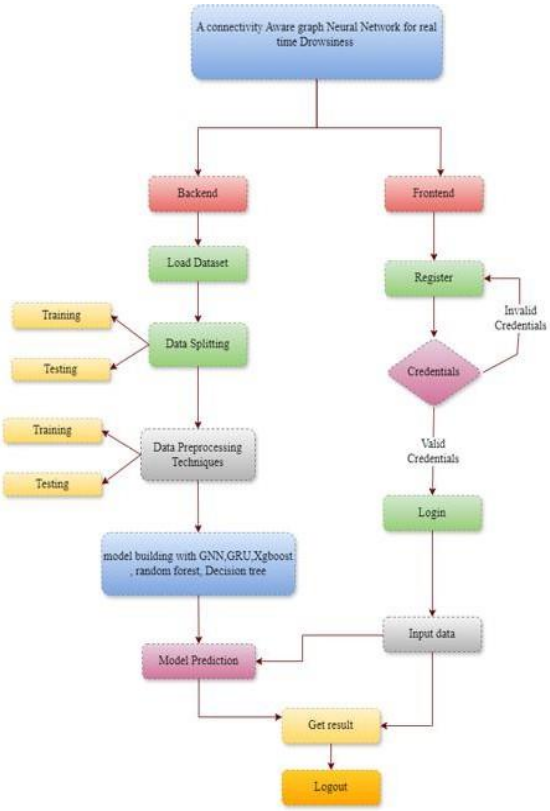
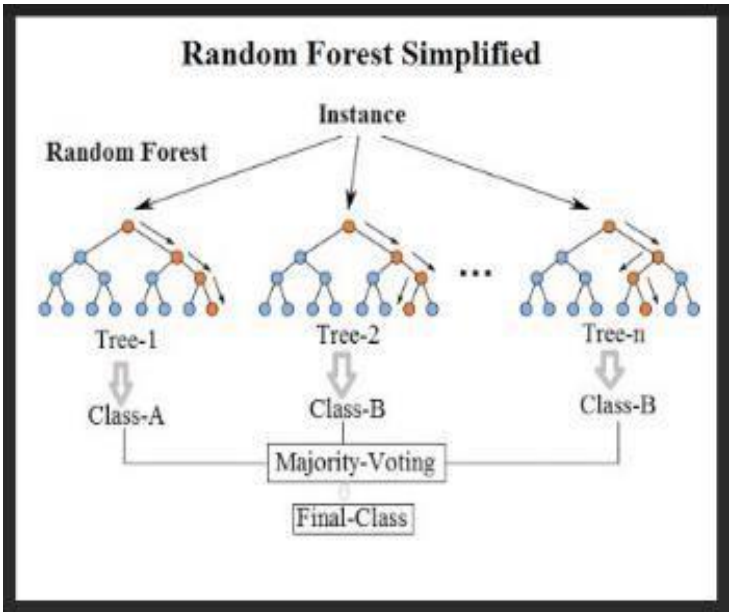


Fig 2 : *System Architecture of Drowsiness flow*

Methodology

A. Random Forest (RF)

Random Forest (RF) is an ensemble learning technique that constructs a collection of decision tree models at training time. For classification tasks, the model predicts the class that receives the most votes from the individual trees, and for regression tasks, it averages the tree outputs. RFs are known for their versatility and resilience especially with large datasets with many features and may deliver stable performance across a variety of learning problems.



The proposed Connectivity Aware Graph Neural Network for Real-Time Drowsiness Classification system embeds Random Forest into the ensemble learning framework to improve the classification performance and prediction stability. It is effective to analyse different features of driving and reduces the sensitivity to noisy observations, so that drowsiness can be detected reliably in different real time driving settings.

1) **Feature Enhancement:** Random forest improves the information extracted from driving related data, such as behavioural signals, environmental conditions and connectivity features. The method samples the data many times, creates many models of trees of choices, and combines their decisions to improve the quality and consistency of the prediction.
2) **Robust classification:** The ensemble nature of RF reduces the dependence of one decision tree and helps to reduce the possibility of overfitting. This improves the generalisation ability of the model to a variety of driving scenarios with widely different observed patterns.
3) **Adaptation to Real-Time Conditions:** In practice, the collected data while driving may be noisy, incomplete or abrupt. Such conditions may be robust for Random Forest and may provide reliable classification. This makes the algorithm useful to keep the drowsiness recognition consistent when the road, traffic or environment factors change over time.

Table 1: Performance Evaluation of Random Forest Model

	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	80053
1	1.00	1.00	1.00	79943
Accuracy			1.00	159996
Macro Avg	1.00	1.00	1.00	159996
Weighted Avg	1.00	1.00	1.00	159996

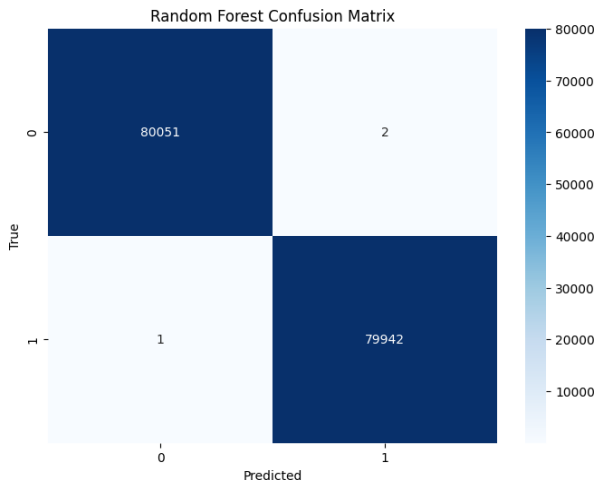
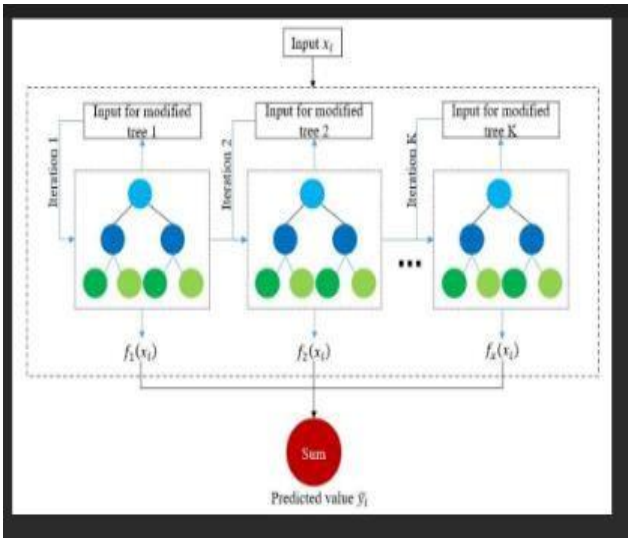


Fig 3:Confusion Matrix of Random Forest

B. XGBoost (Extreme Gradient Boosting):



XGBoost is a boosting learning algorithm, where a sequence of decision tree models are successively constructed. Each single tree fits the residual prediction errors of the previous tree, so the model is built stage wise. This algorithm is well suited for large and complex datasets, as it can efficiently deal with many features, keep good predictive performance and have a reasonable computational cost.

XGBoost is applied to enhance the prediction quality, fine tune feature selection and support the overall model performance. In the proposed drowsiness detection system, it is mainly in boosting, feature refinement, regularisation and real time processing.

1) Boosting Technique: XGBoost constructs the models of decision tree models sequentially. The new tree corrects the errors of the previous tree. Therefore, the prediction gets better as learning progresses.

2) Feature Engineering: XGBoost helps to find the most useful features from the data available. The selected features are analysed and classified using Random Forest and Graph Neural Network models.

3) Regularisation : L1 and L2 are used as regularisation to avoid overfitting and also keep the model stable against changes in the input data. This is useful in drowsiness detection since driving data may vary from one situation to another.

4) Real-Time Performance: XGBoost is efficient in processing data and is applicable for real-time applications. This allows ongoing tracking of driver behaviour and changing driving conditions with no added computational delay.

Table 2 :Classification report of XGBoost (Extreme Gradient Boosting)

Metric	Class 0	Class 1	Macro Average	Weighted Average
Precision	0.64	0.63	0.63	0.63
Recall	0.62	0.65	0.63	0.63
F1-Score	0.63	0.64	0.63	0.63
Support	80,053	79,943	159,996	159,996
Accuracy	-	-	0.63	0.63

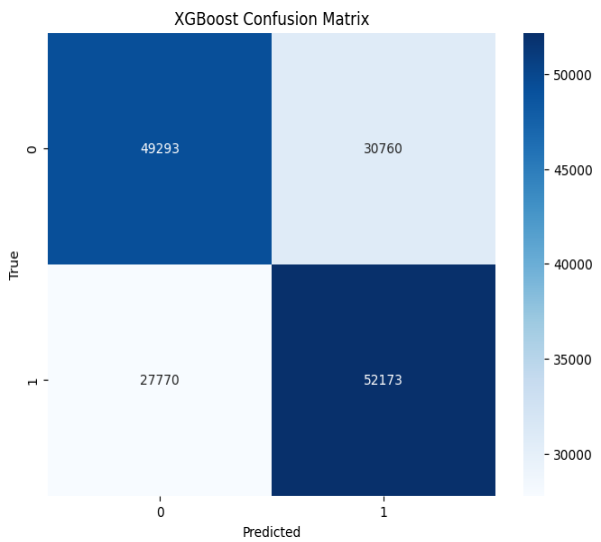
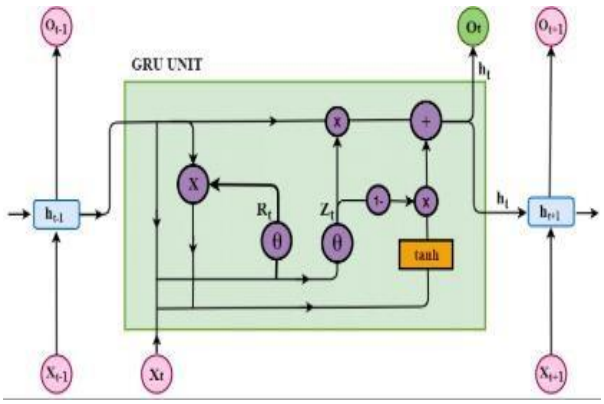


Fig 4: Confusion Matrix of XGBoost (Extreme Gradient Boosting)

C. Gated Recurrent Unit (GRU):



Gated Recurrent Unit (GRU) is a variant of Recurrent Neural Network (RNN) which is developed so that it can learn long term dependencies from sequential data. It employs gating mechanisms to control the information flow through the time steps, which alleviates the vanishing gradient problem. GRU can keep useful information from longer sequences and discard less relevant information from the past.

The proposed drowsiness detection system utilises GRU to capture the temporal changes in driver behaviour, especially those that develop gradually over time. The role it plays in the project is described below:

1. **Memory Management through Gates:** GRU has two major gates namely update gate and reset gate. The update gate regulates how much of the previous information to retain and the reset gate regulates how much of the previous information to discard.

2. **Temporal behaviour modelling:** Signs of driver fatigue typically develop over a period of time and not at a particular point in time. GRU aids in tracking these changes over consecutive time steps and preserves relevant behavioural patterns associated with declining alertness.

3. **Sequential Real-Time Processing:** GRU can process sequential inputs such as eye movement, blink activity, steering behaviour and other time dependent signals. This allows to track the changes in the driver's condition in real-time.

4. **Adaptability to Changing Conditions:** The ability of keeping useful time-related information allows GRU to adapt to the changes in driver behaviour and surrounding conditions. This is ideal for drowsiness detection where patterns can evolve during a trip.

Table 3: Classification report of Gated Recurrent Unit (GRU)

Class	Precision	Recall	F1-Score	Support
0	0.52	0.55	0.54	80053
1	0.53	0.50	0.51	79943
Accuracy			0.53	159996
Macro avg	0.53	0.53	0.53	159996
Weighted avg	0.53	0.53	0.53	159996

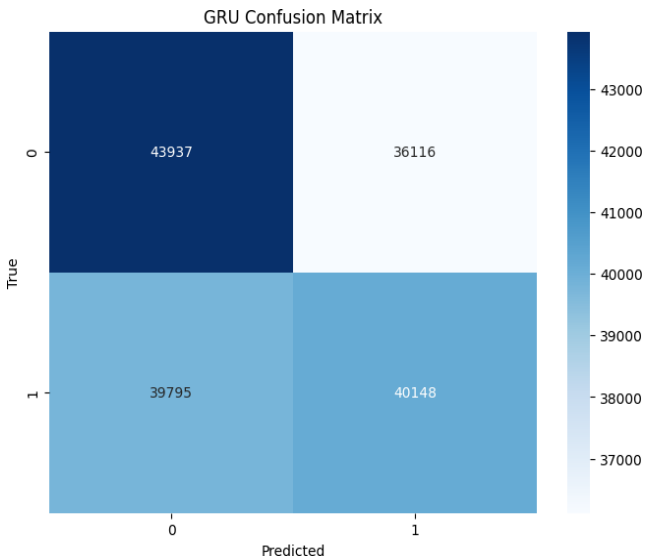
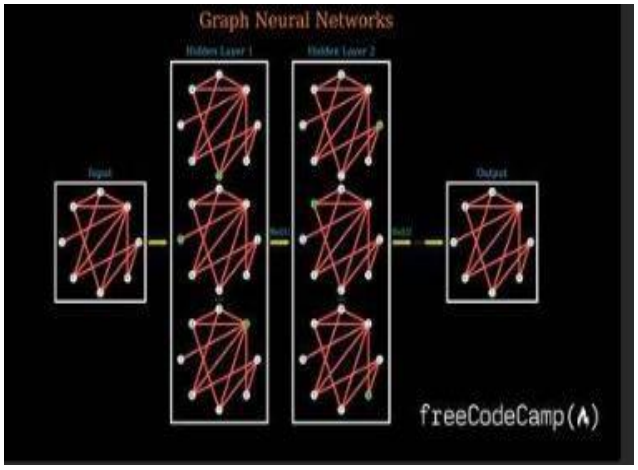


Fig 5: Confusion Matrix of Gated Recurrent Unit (GRU)

D. Graph Neural Network (GNN)



Graph Neural Networks (GNN) are deep learning models that may utilise the information encoded in the form of a graph. A graph usually consists of nodes for individual entities or features and edges for their relationships. GNNs learns these relations and discovers complex relations between different forms of data. This makes them useful for irregular and interconnected data structures such as road networks, sensor systems and transportation environments.

GNNs are primarily employed to model the relationships between driver behaviour, vehicle information, sensor observations and surrounding conditions. It is used as follows:

1. Data Representation as Graph: The available data is represented in the form of graph where the nodes can represent the features like eye movement, driver condition, steering angle, vehicle status or sensor readings. The edges are the relationships between these features. This allows the model to understand the relationship between different observations.
2. Connectivity-Aware Learning: GNN can adapt to the changes in the connectivity of the graph, when the relationships among the available inputs change. This supports the proposed system to take into account the differences in sensor information, vehicle conditions and the driving environments around the vehicle.
3. Modelling of Spatial Relationships: The network learns the dependencies among different behavioural, vehicular and contextual features. The GRU component then examines changes in terms of time, so the combined architecture is able to see how related driver features change over successive time-steps.
4. Real-time adaptivity: GNN can evaluate the dynamic correlations between incoming features during driving. This keeps the system responsive to the changes in road conditions, sensor observations or vehicle related factors and helps in consistently predicting the driver alertness in real time situations .

Table 9:Comparision table for all the algorithms

	Algorithm	Accuracy
0	Random Forest	0.99
1	Xgboost	0.63
2	GRU	0.53
3	GNN	0.5432

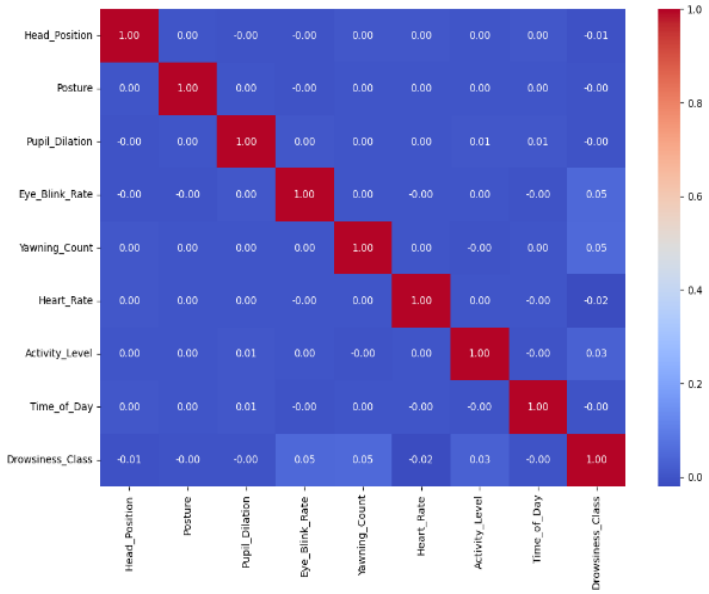


Table 10. Correlation Analysis Among Dataset Features

Results and Discussions

Herein, we propose a real-time driver drowsiness detection method by integrating a Connectivity Aware Graph Neural Network (GNN) and a Gated Recurrent Unit (GRU) based Recurrent Neural Network. The main strength of the proposed method is to study spatial relationships and temporal changes of driver behaviour, which are important to identify fatigue accurately. Current methods for detecting drowsiness usually rely on a limited set of cues, including eye movement, facial expression or head position. These features can be informative, but their reliability may be affected by poor lighting conditions, camera angle variation, face occlusion, or other environmental factors. Conversely, the GNN part models the relationships between multiple input features and gives a broader view of the driver's condition in varying driving situations. The GRU-based model also contributes to the analysis as it can capture sequential patterns that develop slowly in time and thus can observe prolonged changes in alertness in a more effective manner. The combination of these components provides a more reliable basis for the detection of subtle fatigue related behaviour that might be difficult to identify when individual signals are considered separately. XGBoost is used to select and refine the most informative features for the classification stage, and Random Forest uses ensemble learning to make stable and consistent decisions. Experimental evaluation of the proposed architecture shows better recognition performance and lower response latency than the conventional methods tackled in the study. The classification result also shows less false alert and drowsy predictions which are especially important in safety critical driver monitoring systems. Furthermore, the connectivity aware design allows the model to adapt to changes in vehicle motion, environmental conditions, sensor information, and driver related factors. Its low latency processing ability also helps to respond in time during operation, which makes the system more suitable for real-time in-vehicle monitoring and advanced driver-assistance applications. The architecture also demonstrated the ability to operate with variations in sensor quality and connectivity which may be useful in semi autonomous and autonomous driving environments. But there're still some limitations. The reliability of the camera based features can be affected by extreme illumination changes, adverse weather and poor quality visual inputs. Moreover, the varying sensor configuration among different vehicles can be a challenge in practical deployment. Future work should therefore be directed toward increasing robustness in difficult environments, accomodating more sensor configurations and reducing computational demand. In conclusion, the results indicate that the fusion of graph based learning, temporal modelling, feature optimisation and ensemble classification is a promising direction for reliable and adaptive real time driver drowsiness detection.

The paper proposes a Connectivity Aware Graph Neural Network (GNN) framework for real time driver drowsiness detection. The proposed approach combines GNN for spatial modelling, GRU for temporal learning, XGBoost for feature selection and Random Forest for final classification. The combined architecture allows the detection process to take into account how different driver related signals interact with each other and how fatigue gradually develops over time. Experiments show that the proposed framework can achieve strong classification performance with limited response delay, which is critical for driver monitoring in safety-critical situations. The system can respond to changes in connectivity, traffic flow, road conditions and surrounding environmental factors to further enhance its practical value. Thanks to its flexibility, the method can be used in different driving scenarios, from dense urban roads to long highway trips. However, there are still some difficulties that need attention. Detection reliability can be affected by changes in illumination, bad weather, variations in sensor quality and different vehicle sensor setups. Thus, further investigation is necessary to enhance robustness and to facilitate the application of the approach to a broader range of real world conditions. Overall, the results indicate the promising nature of the combination of graph-based learning, temporal analysis, feature refinement, and ensemble classification for next-generation drowsiness monitoring. This framework allows earlier detection of changes related to fatigue and promotes safer driving through a more consistent assessment of driver alertness.

Future Enhancement

Although the Connectivity-Aware Graph Neural Network framework performs promisingly, there are still many aspects to be improved to make it more reliable and practically applicable. A key direction is to incorporate additional sensor modalities. The present approach is mainly based on visual information and selected physiological or vehicle related inputs. Future extensions may include EEG signals, wearable devices, skin temperature or galvanic skin response to better represent driver condition. Such multimodal information could provide an improvement in reliability when the camera based features are less effective due to poor illumination, facial occlusion or other environmental limitations. Another research avenue is to enhance generalisation across various vehicle types and operating conditions. In practice, the model should be robust to the changes in cabin layout, sensor location, road environment, car design and driving behaviour. This would be more flexible and could be used in more places and modes of transportation. Explainable

Artificial Intelligence can also be incorporated in an effort to provide greater transparency. Since GNN and recurrent architecture can be difficult to interpret, explanation mechanisms could help clarify what behavioural or contextual factors influence a specific drowsiness decision. Such would be useful for safety critical applications where interpretable predictions can increase trust and acceptance of the system. Another important issue is real time efficiency. In future work we plan to reduce computational demand and optimise the architecture for embedded hardware with limited memory and processing capability. The lightweight implementation could allow deployment in commercial vehicles, semi autonomous systems and other resource constrained platforms. Furthermore, future studies can test the framework on larger and diverse datasets collected under realistic driving conditions. To summarise, the proposed system's practical value may be improved and wider application in continuous driver monitoring may be facilitated by further advances in multimodal sensing, generalisation, interpretability, computational efficiency and real world validation.

References

1. Awachat, S., Mundada, K., Dewangan, P., & Ranjan, C. (2024). DrowseGuard - DeepAlert Driver Vigilance System. 2024 2nd World Conference on Communication and Computing, WCONF 2024. https://doi.org/10.1109/WCONF61366.2024.10692043

2. Balamurugan, R., Chen, J., Meng, C., & Liu, Y. (2024). Data-driven approaches for fatigue prediction of Ti–6Al–4V parts fabricated by laser powder bed fusion. International Journal of Fatigue, 182, 108167. https://doi.org/10.1016/J.IJFATIGUE.2024.108167

3. Barka, R. E., & Politis, I. (2024). Driving into the future: A scoping review of smartwatch use for real-time driver monitoring. Transportation Research Interdisciplinary Perspectives, 25, 101098. https://doi.org/10.1016/J.TRIP.2024.101098

4. El-Nabi, S. A., El-Shafai, W., El-Rabaie, E. S. M., Ramadan, K. F., Abd El-Samie, F. E., & Mohsen, S. (2024). Machine learning and deep learning techniques for driver fatigue and drowsiness detection: a review. Multimedia Tools and Applications, 83(3), 9441–9477. https://doi.org/10.1007/S11042-023-15054-0/METRICS

5. Kim, B., Sri Preethaa, K. R., Song, S., Lukacs, R. R., An, J., Chen, Z., An, E., & Kim, S. (2024). Internet of things and ensemble learning-based mental and physical fatigue monitoring for smart construction sites. Journal of Big Data, 11(1), 1–37. https://doi.org/10.1186/S40537-024-00978-7/TABLES/1

6. Qu, F., Dang, N., Furht, B., & Nojoumian, M. (2024). Comprehensive study of driver behavior monitoring systems using computer vision and machine learning techniques. Journal of Big Data, 11(1), 1–44. https://doi.org/10.1186/S40537-024-00890-0/TABLES/5

7. Sargolzaei, S., Hatchett, S., Okashita, M., & Sargolzaei, A. (2024). Decoding Driving Neural Dynamics: An Exploratory Survey of EEG Applications in Unraveling Cognitive Processes in Virtual Reality Environments. Conference Proceedings - IEEE SOUTHEASTCON, 830–836. https://doi.org/10.1109/SOUTHEASTCON52093.2024.10500163

8. Siddhad, G., Dey, S., & Roy, P. P. (2025). DrowzEE-G-Mamba: Leveraging EEG and State Space Models for Driver Drowsiness Detection. 281–295. https://doi.org/10.1007/978-3-031-78398-2_19

9. Tang, J., Zhou, W., Zheng, W., Zeng, Z., Li, J., Su, R., Adili, T., Chen, W., Chen, C., & Luo, J. (2024). Attention-Guided Multiscale Convolutional Neural Network for Driving Fatigue Detection. IEEE Sensors Journal, 24(14), 23280–23290. https://doi.org/10.1109/JSEN.2024.3406047

10. Trabelsi, N., Maaloul, R., Fourati, L. C., & Jaafar, W. (2024). Deep Reinforcement Learning for Sleep Control in 5G and Beyond Radio Access Networks: An Overview. 20th International Wireless Communications and Mobile Computing Conference, IWCMC 2024, 1404–1411. https://doi.org/10.1109/IWCMC61514.2024.10592464

11. Vishnu, K. N., & Gupta, C. N. (2024). Systematic review of experimental paradigms and deep neural networks for electroencephalography-based cognitive workload detection. Progress in Biomedical Engineering, 6(4), 042004. https://doi.org/10.1088/2516-1091/AD8530

12. Wang, X., Hu, X., Jia, X., & Jiao, Z. (2024). Research on setting method of fatigue warning sign on desert expressway based on driver's heart and myoelectric index. Heliyon, 10(17). https://doi.org/10.1016/j.heliyon.2024.e36431

13. Wu, Q., Li, Y., Zhu, G., Mei, B., Xu, J., & Xu, M. (2024). Prediction-Aware Adaptive Task Assignment for Spatial Crowdsourcing. IEEE Transactions on Mobile Computing. https://doi.org/10.1109/TMC.2024.3423396

14. Xiao, Y., Liu, D., Cui, L., & Wang, H. (2024). Heterogeneous graph representation-driven multiplex aggregation graph neural network for remaining useful life prediction of bearings. Mechanical Systems and Signal Processing, 220, 111679. https://doi.org/10.1016/J.YMSSP.2024.111679

15. Yogarajan, G., Singh, R. N., Nandhu, S. A., & Rudhran, R. M. (2024). Drowsiness detection system using deep learning based data fusion approach. Multimedia Tools and Applications, 83(12), 36081–36095. https://doi.org/10.1007/S11042-023-17096-W/METRICS

16. Zhang, H., Liu, T., Zou, X., Zhu, Y., Chi, M., Wu, D., Jiang, K., Zhu, S., Zhai, W., Wang, S., Nie, S., & Wang, Z. (2024). Real-time data visual monitoring of triboelectric nanogenerators enabled by Deep learning. Nano Energy, 130, 110186. https://doi.org/10.1016/J.NANOEN.2024.110186

17. Zhang, X., Zhang, X., Huang, Q., Lv, Y., & Chen, F. (2024). A review of automated sleep stage based on EEG signals. Biocybernetics and Biomedical Engineering, 44(3), 651–673. https://doi.org/10.1016/J.BBE.2024.06.004

18. Zhang, Y., Jia, M., Chen, T., Li, M., Wang, J., Hu, X., & Xu, Z. (2024). A neuroergonomics model for evaluating nuclear power plants operators' performance under heat stress driven by ECG time-frequency spectrums and fNIRS prefrontal cortex network: A CNN-GAT fusion model. Advanced Engineering Informatics, 62, 102563. https://doi.org/10.1016/J.AEI.2024.102563

19. Zhao, M., Taal, C., Baggerohr, S., & Fink, O. (2024). Graph Neural Networks for Virtual Sensing in Complex Systems: Addressing Heterogeneous Temporal Dynamics. https://arxiv.org/abs/2407.18691v1