BRIDGING CONVENTIONAL AND CONTEMPORARY APPROACHES IN DRIVER DISTRACTION DETECTION : A REVIEW WITH PROPOSED GRAPH-BASED MODEL

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Abstract

Distracted driving is a major reason for collisions. Therefore, it is crucial to constantly monitor the driving condition of drivers and offer suitable solutions to those who are distracted. Cognitive distractions typically come from being tired, talking to a fellow passenger, listening to the radio, or engaging in other mentally taxing side activities that do not need a driver to take their eyes off the road. Because there are no outward signs of driver distraction, it is one of the most difficult diversions to identify. In this manuscript, Enhancing Road Safety through Attributed Multi-order Graph Convolutional Network-based Cognitive Distraction Identification using Physiological Signals (ERD-AMGCN-CDI-PS) is proposed. The input data are collected from Emotions and Heart rate scale dataset. Then, the input data are fed into the preprocessing stage.

In preprocessing, Regularized bias-aware ensemble Kalman filter (RBAEKF) is used for removing Noise, and artifacts. The pre-processed data are given into Synchro-Transient- Extracting Transform (STET) for extracting the features such as Heart Rate and Emotion from the pre-processed data. Then, the extracted features are fed into Attributed Multi-order Graph Convolutional Network (AMGCN) for identifying the cognitive distraction. The proposed ERD-AMGCN-CDI-PS method is implemented on Python. Then, effectiveness of the ERD-AMGCN-CDI-PS method is compared with other existing models. The ERD-AMGCN-CDI-PS method attains 16.28%, 30.78% and 25.29% higher accuracy when comparing with existing techniques, such as Driver cognitive distraction detection utilizing machine learning models (DCD-ML), Driver distraction detection utilizing bidirectional long short-term network under multiscale entropy of EEG (DDD-BLSN-EEG), and Multimodal driver distraction detection utilizing dual-channel network ofCNN with Transformer (MDDD-DCN- CNN) respectively.

Keywords: Types of distraction, Analysis of current models, Attributed Multi-order Graph Convolutional Network

1. INTRODUCTION

The safety of the roadways is one of the most significant issues in our fast-paced, contemporary environment [1]. With the proliferation of technological gadgets and in-car entertainment systems, driver distraction is becoming a serious problem. Cognitive distraction, which includes mental activities unrelated to safe driving, poses a severe danger to road safety. When driving, the cognitive distractions divert attention from the important task of operating a vehicle, which can lead to poor efficiency, postponed reaction times, and an increased risk of collisions. Using a variety of techniques and sensor technologies, driver cognitive distraction detection calculates the amount of mental effort and focus a motorist is placing into their driving [2]. Dual-task paradigms, eye tracking, physiological monitoring, subjective self-reports, behavioural performance evaluations, and advanced AI-driven techniques are a few of the techniques used. Understanding a driver's cognitive state and identifying instances in which focus is taken away from the core task of driving are

The objectives. With this knowledge, the hazards related to cognitive distraction can be reduced by implementing the relevant remedies, such as adaptive cruise control, warning signs, and autonomous vehicle control in emergency situations. "Attention" is viewed in Cognitive Ergonomics as either a single resource or a collection of resources used by humans when processing information. The two main causes of driver inattention are mental fatigue and distraction [3]. Disruptions to attention can occur in several ways. For instance, multitasking might result in fragmented attention and stress can cause attention tunnelling. Distracted drivers are less mindful of their surroundings. Any secondary work, or task unrelated to driving, can be linked to driver distraction; this is especially true for tasks requiring portable electronics and the In-Vehicle Information System. Cell phones, internal distraction, and passenger-related secondary

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tasks that contributed to more count of crashes or near-crashes in the National Highway Traffic Safety Administration's (NHTSA) "100-Car Naturalistic Driving Study". The global automobile industry is progressively transitioning to digitalization and autonomous driving due to the swift advancements in artificial intelligence and vehicle automation [4]. However, autonomous driving has not yet attained asufficiently high degree of automation in terms of vehicle control. Completely automated driving (L5 level) is still unattainable at this moment. As a result, when the car is moving, the driver must always maintain concentration. In emergency situation, the driver must be ready to take over control of the vehicle. Due to the behavioural changes it generates, driver distraction may be measured using a variety of methods. It is possible to determine distraction by recording changes in heart rate, pupil size, and vehicle acceleration using sensors and other sources [5].

The primary contributions of this review paper are: To detect driver cognitive distraction, the study systematically reviews and classifies recent research that combines AI techniques with physiological indicators (such as eye tracking, EEG, and ECG).

It examines and contrasts different experimental designs, such as the use of AI models for real-time distraction detection, signal acquisition techniques, feature extraction methods, and secondary tasks.

The review addresses the main drawbacks of current methods, including their intrusiveness, practical deployment difficulties, and lack of standardization, and how these problems impact accuracy and practical applicability.

To improve road safety, it highlights unresolved research gaps and suggests future paths for creating robust, explainable, and inconspicuous AI-driven systems that can be incorporated into advanced driver assistance systems (ADAS).

A. Types of driver distraction

Any activity or occasion that takes a driver's focus away from the important duty of operating a vehicle safely is referred to as driver distraction. Driver distractions come in a variety of forms; however, they can be roughly divided into three categories:

i. Visual Distraction

A motorist engages in driver's visual distraction when they avert their gaze from the road or change their focus from the important duty of operating a vehicle safely. Visual disturbances can cause collisions and damage one's ability to drive. Typical instances of sight distraction in drivers include: Texting or Using a Mobile Device: Texting or using a mobile device while driving is indeed considered one of the riskiest types of visual distraction. A driver's reaction time is greatly slowed down and their attention is diverted from the road when they glance down at their phone to read or send texts. Examining maps or GPS navigation systems can cause a driver's eyesto wander, particularly if the gadget is not placed correctly. Using touchscreen displays, radios, or climate controls, among other in-car entertainment systems, can demand visual focus and divert a driver's attention from the road for extended periods of time. Reaching for a drink, a snack, or personal goods while searching inside the car can lead to visual distraction, particularly if the driver's focus is taken off the road. Although it's normal for drivers to be interested in their surroundings, spending too much time gazing at billboards or external scenery can impair their ability to recognize changes in traffic circumstances. People may reduce their speed to observe police activity, roadside events, or accidents. Both visual distraction and traffic congestion may result from this rubbernecking habit. Even a brief diversion from driving, such as checking a watch, glancing in the rearview mirror, or appreciating a vista, can cause visual distraction.

Driving when visually distracted can seriously hinder one's ability to recognize and respond to possible risks. After a visual distraction, the brain needs time to refocus on the road, which can cause delayed reaction times, a higher chance of crashes, and decreased road safety.

ii. Manual Distraction

Drivers who participate in tasks requiring manual dexterity or take their hands off the steering wheel are guilty of driver's manual distraction, which occurs when they focus on something other than the important duty of driving safely. Manual distractions can make it more difficult for a driver to maintain control of the car and react appropriately to changing road conditions.

Sending texts or emails while operating a motor vehicle is a major manual distraction. To operate the device, the driver must remove their hands off the wheel with at least one hand. Holding and adjusting objects is frequently required when consuming food or beverages while operating a vehicle. These activities take a driver's hands off the wheel. Changing an automobile's heating, air conditioning, or radio requires manual dexterity and may require the driver to take their hands off the wheel for a brief moment. Tasks requiring the use of both hands, such as shaving, combing hair, applying makeup, or altering clothes, can be distracting due to their manual nature. When interacting with a pet, a driver may need to use their hands and divert their focus from the road to pet, feed, or retrain them. A driver's hands and focus may be taken off the steering wheel and the road when they reach for objects in the glove box, canter console, or back seat. Manual input is frequently required forprogramming or modifying GPS devices or navigation systems, which can lead to manual distraction. Using your hands to light, smoke, or put out cigarettes or other tobacco products can be distracting. Operating tablets, e-readers, or other portable electronic devices may change a driver's primary attention from the steering wheel and from the road also. Rearranging baggage or cargo within the car may call considerable human labour and focus, particularly when there is shifting freight.

Because manual distractions impair a driver's ability to control the car, they can be very dangerous.

iii. Cognitive Distraction

Situations where a driver's mental focus and attention are taken away from the primary goal of driving safely are referred to as driver's cognitive distraction. Unlike manual and optical distractions, cognitive distractions are mental tasks or obsessions that could impair a driver's ability to concentrate on the road and make safe driving decisions. A few common examples of cognitive distraction in drivers are as follows:

Speaking on a Mobile Handheld or Hands- Free Device: Conversing on a mobile phone—handheld or hands-free—can take a driver's focus away from the road and other traffic situations.

When a driver's attention is fixed on the road, texting or using mobile applications causes substantial cognitive distraction in addition to manual distraction.

Daydreaming or Zoning Out: Cognitive distraction, which results in a motorist becoming less attentive of their surroundings, can be caused by letting one's thoughts wander, daydreaming, or becoming lost in contemplation.

Navigating Complicated or Unfamiliar Routes: Trying to map out directions while navigating a complicated or unfamiliar route may distract a driver's cognitive attention away from the task at hand of driving.

Stress or Emotional suffering: When a driver's thoughts is focused on their emotional state rather than the road, high-stress events, anxiety, rage, or emotional suffering can cause cognitive distraction.

Drowsiness or Fatigue: Both conditions have the potential to seriously impair one's capacity for cognitive focus and decision- making, which might result in cognitive distraction. While fatigue, also known as hypervigilance, refers to the inability to stay awake due to exhaustion, which is a physiological state that makes it difficult to concentrate, it also increases the likelihood of falling asleep. Fatigue can affectcognitive function, which might affect one's ability to make decisions while driving and cause one to become less aware and react more slowly. This problem can be made worse by long-term conditions including sleep disorders or inadequate. A driver's capacity to concentrate, absorb information, and respond swiftly to changing traffic situations might be impacted by mental health diseases including depression, attention deficit hyperactivity disorder (ADHD), or cognitive deficits. Listening to serious podcasts, audiobooks, or contentious radio discussions can take a driver's focus away from operating a vehicle. Drunkenness, confusion or other cognitive impairments brought on by some prescription drugs for different medical problems may impair one's ability to drive. Having lengthy, intricate conversations with other passengers that demand a lot of mental processing might be distracting. A driver's mind can be diverted from the road by stress linked to personal or work-related issues, such as deadlines, family conflicts, or financial worries.

Cognitive distraction is especially sneaky because other drivers might not see it right away. Cognitively distracted drivers may seem physically present but mentally absent, which impairs their capacity to recognize and respond to possible threats.

By encouraging responsible technology use, creating a culture of safe and attentive driving, and increasing public understanding of the risks involved, cognitive distractions can be reduced. Modern driver aid systems and in-car technology can also lessen cognitive distractions by offering voice-activated, hands-free, or aesthetically unobtrusive entertainment and communication options.

II. LITERATURE SURVEY

Several research works presented in the literatures were based on identification of cognitive distraction using deep learning; few of them were reviewed here,

In 2023, Misra, A., [6] have presented a Driver cognitive distraction identification utilizing machine learning models. To uncover characteristics from several sources, like eye tracking, physiological, vehicle kinematics data that significant towards the categorization of distracted or non-distracted drivers, it analyze data from a driving simulator research involving 40 participants in various driving scenarios. Support vector machines, decision trees, and random forests were some of the main classification techniques that have been used. It was discovered that a reduced feature set, which includes pupil area, pupil vertical motion, and pupil horizontal motion, predicted driver distraction.In 2022, Zuo, X., [7] have presented a Driver distraction detection utilizing bidirectional long short-term network (BiLSTM) along multi-scale entropy (MSE) of EEG. A system was built on MSE in a sliding window and

BiLSTM. Initially, the EEG characteristics were extracted using MSE with a sliding window to identify the distraction position. After that, statistical analysis of the behavioural data from the car was done to confirm that driving behaviour does actually alter around the distraction position. It provides high precision and low true positive rate.

In 2023, Mou, L., et.al, [8] have presented a Multimodal driver distraction detection utilizing dual-channel network of CNN with Transformer. A brand-new dual- channel feature extraction mode built on Transformer and CNN independently through the mid-point residual structure to enhance the method's fit to time series data. The scaling factors found were considered hyperparameters in the residual structure. To automatically determine the ideal values, a penalized validation technique under bilevel optimisation was developed. It provides high sensitivity and low f1- score.

In 2022, Li, B., et.al, [9] have presented an Unsupervised deep learning (UDL) approach for fine-grained identification of driver distraction The goal of UDL was to achieve a degree of intelligence comparable to that of humans, with an emphasis on fine- grained driver distraction detection. To enhance feature extraction capabilities, it first constructs the presented approach. Afterwards, it incorporates the multilayer perceptron to make a new projection head and backbone. Lastly, a loss function using contrast learning as well as stop-gradient strategy was created to learn robust features. It provides low false positive error and low specificity. In 2022, Nakano, K. and Chakraborty, B., [10] have presented a Real-time distraction detection from driving data dependent personal driving method utilizing deep learning. It evaluated the ways to identify distracted driving depending on driving data gathered from many sensors mounted on a driving simulator under several road and cognitive load scenarios. To replicate cognitive distraction, it employed a driving simulator to gather data from drivers while they were operating a vehicle in a focused, normal condition and in a distracted state. It provides high precision and low accuracy.

III. ANALYSIS OF CURRENT MODELS

Driver Cognitive Distraction Discovery using Machine Learning Models (DCD-ML) mostly uses traditional machinelearning methods to find cognitive distractions based on features taken from behavioural data, in-vehicle detectors, or limited physiological signals. These models usually use algorithms like Support Vector Machines (SVM), Random Forests, Decision Trees, or K-Nearest Neighbours to sort drivers into groups based on things like eye movements, head position, steering wheel movement, or initial biometric readings. DCD-ML methods are not too hard to use and can run on moderate hardware in real time, but they often rely on hand-crafted features and may have trouble finding the complex, non-linear patterns that are common in high-dimensional physiological data. So, their sensitivity and stiffness can be limited when used in different driving situations and with different people, which shows that we need more advanced, flexible methods in this area.[6]

Driver distraction detection utilizing bidirectional long short-term network under multiscale entropy of EEG (DDD-BLSN-EEG) uses deep literacy and advanced EEG signal analysis to make it easier to find cognitive distractions in drivers. This method uses multiscale entropy on EEG signals to measure how complex and irregular brain activity is, giving us sensitive features that show how cognitive load changes in different

situations. These features are also sent to a Bidirectional Long Short-Term Memory (Bi-LSTM) network, which captures both once and unborn temporal dependences in the EEG data. This lets the model learn long-range patterns related to distraction better than other sequence models.[7]

When modelling the dynamic and non- linear properties of EEG signals during driving activities, the DDD-BLSN-EEG system exhibits superior delicacy and resilience in comparison to traditional machine learning techniques. The ability to automatically learn intricate temporal aspects without extensive custom point engineering and to detect minor changes in cognitive state in real time are two of its primary benefits. Nevertheless, the model's effectiveness depends on high-quality, artifact-free EEG data, and it needs sophisticated computational resources for both training and analysis. In terms of more accurate, brain-signal-based distraction detection systems for intelligent cars, this approach is a major step forward. Multimodal Driver Distraction Detection utilizing Dual-Channel Network of CNN with Transformer (MDDD-DCN-CNN) is a sophisticated system that combines and captures different data sources. This fashio n integrates visual cues (similar as aspect , head posture, and facial expressions) with physiological signals or other detector data by combining Convolutional Neural Networks(CNNs)and Motor topologies in a binary- channel network to dissect severa l modalities at formerly. While the Transformer layers model long- range dependences andcontextual liaison betwee n information across time and channels, the CNN layers efficiently prize original and spatial features from each modality.[8] By combining the advantages of both architectures, MDDD-DCN-CNN improves point representation, allowing the system to identify intricate and nuanced patterns of distraction that single-modality or single-network models could miss. This mongrel frame improves stiffness and discovering delicacy in a variety of driving scenarios and driver behaviours. Nevertheless, it needs a lot of processing capacity, particularly for real-time processing, and its efficacy is dependent on the calibre and synchronization of multimodal inputs. All things considered, this model illustrates the potential for integrating deep literacy and attention techniques for upcoming, environmentally conscious driving systems.

IV. PROPOSED APPROACH

This research suggests a novel method Attributed Multi-order Graph Convolutional Network-based Cognitive Distraction Identification using Physiological Signals (AMGCN-CDI-PS) to overcome the drawbacks of being a driver using cognitive distraction discovery methods. The proposed system focuses on rooting detailed neuro physiological information, like ECG and other bio signals, to directly capture the cognitive countries of drivers, in contrast to traditional machine literacy models that mainly compute on handcrafted behavioural features or basic physiological data. The model provides a more accurate foundation for distraction discovery by employing Event-Related Desynchronization (ERD) analysis to isolate tiny oscillations in brain exertion that are strongly associated with cognitive effort and attentional shifts.

The proposed ERD-AMGCN-CDI-PS is discussed in this segment. The block diagram of proposed ERD-AMGCN-CDI-PS is represented in Figure 1. Here, the input data is collected from the Emotions and Heart rate scale dataset. The input data is pre-processed using RBAEKF. The pre- processed data is given into STET for extracting features. The extracted features are given into AMGCN identifying the Cognitive Distractions.

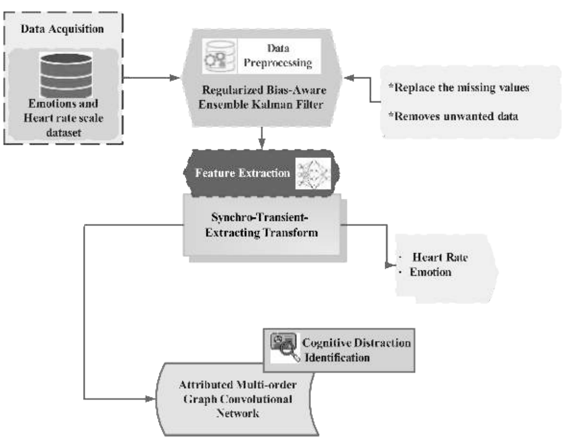

Figure 1: Block Diagram of the Proposed ERD-AMGCN-CDI-PS System

An Attributed-Multi order-Graph Convolutional Network (AMGCN), which successfully represents both spatial and temporal dependences across numerous physiological signal channels, is utilized to reuse the recovered physiological features. The network can robustly select the most relevant signal patterns and distraction-related brain areas related to the attention medium. The purpose of this integrated frame is to improve stiffness under different driving situations, generalizability across individualities, and discovery delicacy. The suggested AMGCN-CDI-PS model is a major step toward more dependable and environmentally conscious driver covering systems by fusing sophisticated signal processing with graph-based deep literacy.

Compared to conventional Driver Cognitive Distraction Detection using Machine Learning Models (DCD-ML), the proposed AMGCN-CDI-PS approach offers significant improvements in its handling of point literacy and data complexity. The suggested model makes direct use of rich neurophysiological signals like EEG and processes them through enhanced deep literacy, whereas DCD-ML depends on manually extracted characteristics that are uprooted from restricted physiological or behavioural cues. This allows the system to automatically understand complex patterns associated with cognitive distraction and does away with the requirement for extensive handmade point design. Therefore, in dynamic driving environments where handcrafted characteristics often fail to generalize well, the AMGCN-CDI-PS model offers stronger adaptability, better rigidity to various drivers, and less discovery delicacy.

When compared to the Driver Distraction Detection utilizing Bidirectional Long Short-Term Network under Multiscale Entropy of EEG (DDD- BLSN-EEG) Significant benefits are added by the suggested methodology when simulating intricate spatial relationships between multi-channel EEG signals. DDD- BLSN-EEG does not fully utilize the spatial linkages between EEG channels or other physiological inputs, even while it successfully captures temporal dependences with a Bi-LSTM and enhancessignal characterization utilizing multiscale entropy. The ERD-AMGCN-CDI-PS technique firmly highlights the most relevant brain areas and signal portions while concurrently modelling both spatial and temporal dependences by combining a Multi-Graph Convolutional Network with an attention medium. This leads to improved accuracy and sensitivity in identifying minute changes in cognitive strain.

In comparison to the Multimodal Driver Distraction Detection utilizing Dual- Channel Network of CNN with Transformer (MDDD-DCN-CNN), Instead of relying on general multimodal inputs like face images or aspects paired with signals, the suggested model places a greater emphasis on physiological signal dynamics. While the CNN-Transformer mongrel is excellent at combining several data sources, it has the potential to tamper with the particular temporal-spatial complexity of EEG or other bio signals. The attention medium offers fine-granulated interpretability of signal application, and the graph-based structure of the suggested model is adapted to capture non-linear inter-channel linkages. When sequestration or camera-grounded monitoring are not feasible, these characteristics work together to give AMGCN-CDI-PS the ability to provide more technical, accurate, and interpretable distraction finding using physiological data alone.

V. RESULT AND DISCUSSIONS

Here, we addressed the experimental results of the specified techniques. The proposed model is implemented on the Windows operating system using Python. The results of the proposed system were compared with the current approaches is shown in the table1.

Table 1. Accuracy compared to other models.

Method	Accuracy
Eye Tracking	85%
ECG Signal Analysis	78%
Facial Recognition	82%
Steering Pattern Analysis	74%
AMGCN-CDI-PS (Proposed Model)	94%

By using both direct and multi-order connections to describe intricate interactions and dependencies within the data, the AMGCN significantly improves accuracy. As a result, the network can comprehend complex patterns and nuanced signs linked to cognitive distraction.

The accuracy rate attained as compared to other three models as below in fig1.

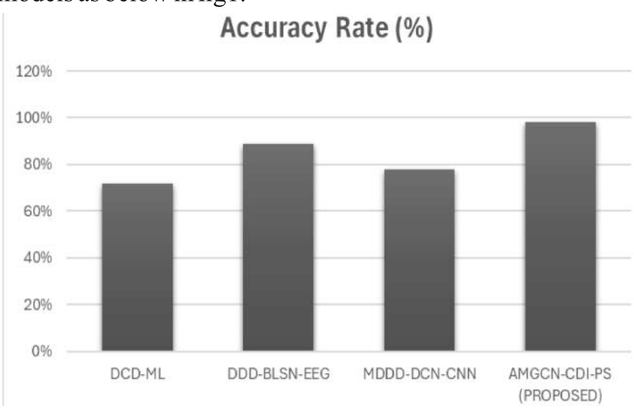

Fig 1. Accuracy rate compared with DCD- ML,DDD-BLSN-EEG,MDDD-DCN-CNN

VI. CONCLUSION

By contrasting conventional machine learning techniques (DCD-ML), sophisticated deep learning frameworks such as Bi-LSTM with multiscale entropy (DDD-BLSN-EEG), and multimodal architectures combining CNNs with Transformers (MDDD-DCN- CNN), we investigated the elaboration of motorist cognitive distraction discovery styles in this review. Although these methods have greatly advanced real-time communication and discovering delicacy, they are all limited in their ability to fully comprehend the intricacies of neurophysiological signals and adapt to different driving environments.

The suggested Distraction Identification using Physiological Signals (AMGCN- CDI-PS) model fills these deficiencies by combining an attention-enhanced multi-graph convolutional network with accurate ERD-based feature extraction to create a more complete framework. The realistic modelling of temporal and spatial interdependence in multi-channel physiological signals made possible by this method improves interpretability, generalizability, and detection accuracy. The suggested method establishes the foundation for next-generation, context- aware driver monitoring solutions that can improve road safety and intelligent vehicle systems by combining the advantages of graph-based deep learning with neurophysiological signal processing. To make this intriguing strategy workable and scalable, future research will concentrate on large-scale validation, edge-device optimization, and real-world deployment.

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