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CNN-Based Real-Time Driver Behaviour Monitoring for Petroleum Product Transportation: Trends, Challenges, and Prospects

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Abstract: ***The national logistics systems are very critical and high-risk, specifically in the transportation of petroleum products. This is to a larger extent in developing economies such as Nigeria, where road tankers dominate the distribution of fuels. Fatigue, distraction, and intoxication are the primary causes of most tanker accidents, which affects human safety, infrastructure, and the environment. The recent innovations in the CNN-based systems of real-time monitoring of driver behavior are critically discussed in this paper with a specific emphasis on the potential use of the given innovations in the context of petroleum logistics challenges and mitigation of human-associated risks. The review identifies the key tendencies in the deep learning field in using hybrid CNN-LSTM and CNN-Transformer networks capable of capturing spatial and temporal dynamics of behavior and multimodal networks capable of fusing visual, telemetric, and physiological information to enhance robustness. The use of edge computing and federated learning was also explored so that it may be applied in the context of real-time monitoring to minimize latency and maintain privacy. Despite enormous gains in the study, there are still challenges like the shortage of specialized petroleum information, computing capability restrictions in embedded systems, changes in the environment, and a lack of impartiality in the regulations. To offer a solution to the existing problems, the paper suggests a network of CNN, YOLOv8, and a Finite State machine that integrates both proactive safety management, which includes advanced deep learning and temporal reasoning, with practical testing, Explainable AI (XAI) integration, and regulatory systems together with the Federal Road Safety Corps (FRSC). Overall, the review demonstrates that a CNN-based driver-behavior monitoring system, when it is ethically designed and institutionally established, creates a pathway that can provide a potential solution to intelligent, data-driven, and sustainable transport safety of petroleum.***

Keywords: Convolutional neural network, CNN; Driving behavior monitoring, petroleum transportation, Realtime Systems, ITS, Intelligent Transport Systems, Deep learning, XAI: Explainable AI, and FRSC

1.Introduction

Transportation of petroleum products is deemed a significant element in the economic operations in the developing economies since other modes of transportation, like pipelines and railways, have not been effectively established. Transportation of petroleum products by road is the most popular mode of transportation in Nigeria, which makes transportation of petroleum products in the remote areas of the country flexible. Such reliance on road tankers has come with a permanent safety problem that has expressed itself in the form of high levels of accidents, risks to the environment, as well as a heavy burden of costs to life and property (Lu et al., 2022). Driver-specific issues, which include slumber, distraction, and drunk driving, have been cited to be some of the problems that cause some of the tanker-related accidents. The existing systems of monitoring are quite manual, reactive, and cannot record real-time behavioral features. In addition, the efforts of the regulatory bodies as the FRSC, through traditional safety interventions, including enforcement of speed limits and recertification of the drivers, have not achieved success in eliminating the occurrence of petroleum tanker crashes (Olajide, 2020). The gaps in safety measures in petroleum logistics could be related to the perpetual inability to incorporate high-level automated evaluations of the factors a driver is exposed to. Recent progress in AI and DL technologies has provided a radical shift in the approach towards monitoring performed in various industries. More precisely, CNNs have appeared as one of the most dominant frameworks of the visual data analysis model, which offers the potent concept of identifying those subtleties of behavior such as closed eyelids, yawning, tilted heads, and deviating gazes (Zhu et al., 2019). With these features, CNN-based systems can be able to identify fatigue, distraction, or intoxication in real time. Another very important possibility presents itself with the implementation of the systems in the transportation of petroleum products to bolster road safety. This is achieved through automated and data-driven decision processes. The vision-based AI models are capable of classification of behaviors and the analysis of continuous video streams from in-cabin cameras. These can then be used to generate proactive signals to the driver and regulatory control centers in case danger is perceived.

The current study combines the growing literature on the surveys of CNN-based real-time surveillance of driver behavior in the petroleum transport industry. It considers the modern trends in AI-based surveillance, enumerates barriers to data management and computer processes, and the deployment of rules, and foretells prospects of using CNN models in the national transport security system. Slumber, distraction, and sobriety measures are the basis for a complete real-time CNN system as postulated by Ademola et al. (2024), serving as blueprint in the oil distribution industry in Nigeria as proposed by the researcher.

This article aims atto evaluate the viability and integration of CNN-based real-time monitoring systems in petroleum transportation to enhance driver safety and infrstructure accountability.

2.Background / Conceptual Foundation

Driver behavior monitoring is rooted in the larger system of Intelligent Transportation Systems. ITS can be described as a cross-disciplinary science, which entails a composite of sensing, communication, and computation with the view to making transport safer and more efficient. Its preceding versions were more inclined toward the mechanical aspect of measurements, like steering angles, discrepancy in speed, and exiting the lane, together with EEG, accelerometer, and gyroscopes (Dilek & Dener, 2023). These strategies' value was in providing information on driver alertness sensing, but had limited applicability in the real transport situation.

In the implementation of the priority on vision, the focus is placed on sensor-dependent approaches, and in turn on DL, including computer vision, in the monitoring and assessment of driver state. CNNs, because of their extraordinary performance, are able to recognize the significant details in a given image and a moving object; therefore, complex human behavior, which comprises distraction, sleepiness, and drunkenness, can be identified as well. Certain CNNs, like VGGNet, are designed in such a manner that they allow the detection of a richer, abstract concept of facial and posture cues through the different layers of convolutions. This makes them suitable for real-time scanning of the drivers based on the visual signs like eye movements, facial relaxation of muscles, and head position (F. Qu et al., 2024).

The employment of CNN-driven plays is significant to petroleum product transportation due to the severe nature of operating tankers. Movement of the inflammable liquids within the overcrowded road systems is a point to be considered and addressed. A minimal distraction is capable of leading to an accident that is life-threatening; therefore, an explosion, environmental pollution, and loss of life. Therefore, CNN-driven systems installed in tankers bring a proactive safety measure that augments the conventional monitoring approach and control (Adenekan et al., 2025).

Adenekan et al. (2025) provide a reflection of the latter in the framework that introduces a holistic deep learning approach aimed at measuring three indicators of behavioral signals, namely, rest, distraction, and control simultaneously. It is a 3-mode analysis model whose analysis is founded on a common framework, which takes in the real-time footage from cameras in the cabin and processes the data with parallel specialized CNN models. The submodels are then optimized to one behavioral state, and the overall outputs of the submodels are stored and analyzed using big data to forecast the risks and generate alerts.

It also takes the resampled in-cabin footage of tanker drivers in Nigeria, which is used as part of a hybrid methodology and as an open-sourced visual input tostrenghten and make the system more resilient. A hybridization strategy of such nature results in potential remedies to constrained domain-spanning data that has often plagued the African transport research. This attempt that the model has undertaken to accommodate the various profiles of drivers and environmental conditions, hence makes the model fit to be implemented at a large scale in the petroleum transport fleets.

The theoretical framework also makes it clear that the regulatory framework should include CNN-based analytics that will involve those surveillance facilities of the FRSC. It becomes a feedback tool: information on fatigue or impairment of a driver is provided to security agencies in real time so that correct actions can be taken in time. The long-term goal is to have a coherent digital ecosystem that would connect the vehicle-level AI-based monitoring with the safety data on the national level. In other words, the background and the conceptual framework define the implementation and strategic appropriateness of CNN-based real-form driver behavior surveillance in closing safety gaps that had existed throughout the history of the logistics of petroleum. It is one step closer to establishing a state of more qualitative and safer transportation networks in Nigeria and other developing environments through integrated regulatory efforts, new frameworks of artificial intelligence, and mixed sets of information.

Given the persistent safety risks in petroleum logistics and the limitations of traditional interventions, this study underscores the transformative potential of CNN-based monitoring systems in achieving proactive, data-driven safety enforcement.

3.Literature Review

Petroleum products are believed to be one of the greatest problems that plague the developing economies, and in this regard, road transportation is dominant in the chain of energy distribution. The importance of driver behavior and sobriety, in particular, distraction, and drowsiness in the occurrence of tanker-related incidents, and loss-of-containment (LOC) events is highlighted in literature (Bernatik et al., 202; George et al., 2024).

The effects of such incidents may affect human lives as well as the environment, especially those areas that are limited in critical infrastructure and lack proper regulation. Amid the impracticality of the traditional safety measures that include manual observation or frequent inspections, the advent of the new technologies, which allow making decisions by computer vision, deep learning, and effective data analysis, is favorable to carry out the immediate examination of the behavior. This literature review combines observations from literature(2018-2025) from the field of deep learning-based behavioral monitoring and video analytics, and pre-emptive risk recognition in the petroleum transportation industry.

3.1. Behaviour Detection Deep learning

The approach of deep learning has revolutionized the driver behavior monitoring process to offer real-time driver behavior monitoring capabilities that are miles superior to what the previous rule-based systems could achieve. The drowsiness, distraction, and intoxication detection models have been the most popular and have been developed from CNNs and Recurrent Neural Networks (RNNs), which are trained on facial and ocular cues from live footage. To prove this, Almazroi et al. (2023) were capable of recognizing drowsiness with 94.7% accuracy with the help of CNN models, which were trained on eye closure and face characteristics. In the same way, Jeon et al. (2021) used the time samples of the video and facial markers to identify fatigue in truckers and obtained a precision of 85-90 percent in real-time situations. With the CNN classifiers and YOLOv5, the field applications, as in Civik and Yuzgec (2023) were found to be 92-97 percent accurate in petroleum fleets in South Asia. The inferences of these results are that CNN is positive in its capability to capture behavioral signs during challenging environmental factors.

However, the generalisability of datasets is still an issue being researched; Rahman et al. (2022) have made contributions to it by offering the SynDD2 dataset, which includes different illumination and occlusion states to increase the range of the model. Privacy concerns are mitigated by the development of edge computing and federated learning Kaleem et al., 2023) as the raw video that requires refining is not shared, rather on-device computing is used instead. Combinations of infrared light and alcohol sensors have been employed by Muiz et al. (2024) as part of complementary IoT approaches.

3.2 Real-Time Video Analytics in Transport Systems

Real-Time Video Analytics (RTVA) is an essential element of the intelligent transportation systems of this century because it processes raw video data into useful information. The newer applications show that they are able to identify, categorize, and inform the control department about abnormal driver behavior. Aligning with the results of Almazroi et al. (2023), 97 percent accuracy was achieved in detecting distractions with CNN-YOLOv5 models. In this respect, Liu et al. (2021) created a framework of the edge computing system that included a combination of the Edge-computing system architecture based on the YOLO architecture and SSD architecture to generate the real-time observation of the traffic to decrease the latency and enhance the performance. Ghahremannezhad (2022) proposes a hybrid CNN-RNN highways incident detection model that uses a framework built on YOLOv4 and Kalman filters, resulting in significantly reduced emergency response time. Meanwhile, Hossain and Muhammad (2019) demonstrated the advantages of a hybrid edge-cloud architecture in terms of fatigue detection, even at less accurate results of 82-88%. The effectiveness of real-time analytics to be periodically scaled to transport safety applications is demonstrated by federated frameworks, the analysis of which (Kaleem et al., 2023) achieved a high classification rate (93.27%) at a reduced bandwidth level.

3.3. Big Data Applications in Transportation Safety

The predictive safety management is founded on the principles of big data analytics that utilizes sensor, GPS, and video data by aggregating it to forecast risks and support the decision-making process in the transport industry. Bulatova (2023) emphasized the opportunities of utilizing multiple datasets during the occurrence of hazards and mentioned that there was an increase in real-time response by 28%. Qu et al. (2018) incorporated GPS and ecological data into the dynamical routing model of hazardous material, delivering a 46% reduction in the risk of transport risk. Predictive maintenance was used to reduce mechanical failure rates in logistics fleets, as illustrated in the study of Giannoulidis and Gounaris (2023). Apache Spark frameworks were adopted to deploy predictive maintenance to identify anomalies. In a similar vein, Vadivel (2023) initiated IoT-based big data systems to achieve adaptive traffic management and related a reduction in fuel consumption by a remarkable 20% and a notable phenomenal 25% reduction in collisions at intersections. According to such studies, data-driven models have the potential to enhance operational safety and efficiency, but require robust infrastructure and standardized data integration protocols in order to be sustainably scaled.

3.4. Accident Prevention and Environmental Implications

Preventing accidents in petroleum logistics requires predictive and reactive systems that can mitigate high-risk conditions. Alva & Rodríguez (2024), with a GeoAI approach, integrated remote sensing with deep learning and realized an accuracy of 99.19% in oil spill detection with U-net architectures. Latrach (2023) proposed a CNN-LSTM model on sensor data to perform predictive maintenance in oilfields and recorded 89% accuracy, while Phan et al. (2023) demonstrated 98% accuracy in real-time drowsiness detection on multi-model frameworks using embedded Jetson Nano systems. More recent innovations, such as the Empowerment-Cloud Model by Xu et al. (2025), integrate environmental and vehicle data into scenario-based risk ratings to help improve proactive logistics safety. Environmental impact assessments by Bernatik et al. (2021) and George et al. (2024) indicate that more than 65% of petroleum spills across the Nigerian ecosystem are found to occur near populated areas, placing immense demands for real-time integrated risk detection with regulatory oversight. AI-driven sensing frameworks, as indicated by Aderamo (2024), hold promise for continuous vibration monitoring with early localization of hazards and reduced false alarm rates.

3.5 Synthesis of Gaps and Research Contribution

Most of the available literature focuses on single characteristics of behavior, i.e., drowsiness, distraction, or intoxication, and does not formulate any form of continuous monitoring framework Muiz et al., 2024). The systems hardly accommodate such institutional actors as the Federal Road Safety Corps (FRSC), whose involvement would enhance the number of regulatory compliance and enforcement (Punch, 2025; TheBladeNG, 2024). Moreover, federated learning methods can deal with privacy, but in cases where a heterogeneous data source is involved, integration complications occur during the synchronization process. The need to offer a holistic CNN-based model that may detect a number of risks in the behavior of the antianalytics in real-time, coupled with big data analytics and regulatory feedback systems, is one of the goals of this review. The system would not only prevent human-related accidents but it would also create certainty on the safety management and environmental sustainability in the petroleum logistics.

4.Trends in CNN-Based Driver Behavior Monitoring

The recent steps have led to CNN-based Driver Behavior Monitoring Trends and their relationship with other deep learning models, which have made great progress. Traditional methods that relied on hand-crafted functions or signal-processing that relied on electroencephalogram (EEG) data or eye-tracking sensors, which had very limited generalization and sensitivity to the surrounding noise. On the other hand, CNN-based structure supplements the behavioral monitoring due to its inherent characteristics of automatically extracting features of visual information (facial expressions, head direction, and pattern of eye movement). The models are very successful in summarizing hierarchical spatial correlations of the image frames, leading to the greater detection of the occurrence of drowsiness, distraction, and intoxication among the drivers (Almazroi et al., 2023; Jeon et al., 2021).

The rejection of the conventional stagnant CNNs in favor of the state-of-the-art hybrid deep learning models that entail both spatial and temporal characteristics of driving patterns is one of the remarkable changes that went into effect in recent times. In the research papers by Latrach (2023), the topic of the growing popularity of CNNLSTM models and CNN-Transformer models that are capable of learning the spatial and time aspects of sequential video when trained on the video data is also brought up. The CNN part follows single visual components like facial features or how eyelids move over time; on the contrary, the LSTM or Transformer part follows the changing nature of facial components over time. This hybridization has significantly contributed to the precision of behavioral recognition, and real-time prediction on fatigue, inattention, and risky postures can be made within the complex driving environment. This has caused the high ability of CNN-based systems to observe the continuous driver state in the petroleum tankers over long distances in recent days due to the integration of visual, telematics, and inertial sensors.

Ali et al. (2024) presented an example to demonstrate that camera-based visual data added onto acceleromer and vehicle telemetry data allowed improvement in the stability of the detection process with different degrees of varying light and vibration settings. With the combination of CNN and real-time motion sensor information on embedded devices such as Jetson Nano, Phan and team (2023) came to a point of accuracy of detection of drowsiness and distraction reaching 98%. This multimodal solution will enhance survival in the petroleum logistics where the drivers are supposed to operate under various levels of illumination and environmental conditions that challenge the visual-only models.

Similarly,edge-based and real-time processing techniques have become much more prominent in the recent past. This is owed to the fact that critical safety processes require instant feedback. The articles by Kaleem et al. (2023) and Hossain and Muhammad (2019) confirm that the production of CNN inferences is possible with locally performed edge computing that involves in-vehicle devices. This renders it so independent of cloud infrastructure while reducing the latency of communication. This is necessary in petroleum tankars transport, enabling auditory or visual alarms for real-time responses. They can also slow the cars or report to the regulatory body in the event of dangerous behavioral incidents, such as the FRSC. Scalability has also been enhanced since CNNs with Internet of Things (IoT) arrangements can support data synchronization of vehicles, control rooms, and authorities continuously to execute safety measures at the same time (Muiz et al., 2024).

Steady changes in investigative projects to create the level of clarity and credibility of CNN control systems are being applied. The use of AI should be able to keep the outputs of the model and explain them on regulated aspects in sectors such as petroleum transportation. To this end, the CNN models are being modified with the XAI limits in an attempt to provide the evidence and elucidation of the patterns of activations, to single out necessary features that affect the decision, and to secure the fairness of the classification outputs. An example includes Zhao et al. (2022), where the authors adopt a gradient-based class activation mapping (Grad-CAM) method to identify the locations on the face that gave rise to detecting drowsiness and thus increasing the user confidence and regulatory acceptance rates. Other researchers have proposed attention-guided CNNs based on feature attribution mechanisms to enable driver state assessment to be more understandable by human supervisors so that FRSC and transport operators can interpret system output before making relevant corrective actions.

The applicability of CNN models has also been enhanced due to the shift towards large-scale and context-sensitive data. Several datasets, like SynDD2 Rahman et al., 92022) and Continuous Emotion and Weariness (CEW) by Sun et al. 2023), have helped train CNNs to perform under complex real-world environments involving low lighting, partial occlusions, and varied facial orientations. These further ensure that regional and environmental variations are considered in the models, which is meaningful within the context of African transportation, given the tremendous difference in lighting and infrastructure compared to Western benchmarks. Synthetic data generation and data augmentation methods have also added robustness, enabling CNN-based models to learn from some rare driving events or hazardous ones without actually testing in the real world.

Lastly, some new research indicates federated and privacy-aware CNN models as an important trend in the sensitive transportation industries. Behavioral and facial information are privacy-intensive, so federated learning like that suggested by Kaleem et al. (2023) can enable CNN models to be trained on a distributed edge device and transmit only model parameters to a central aggregator. These secure the personal information and ensure high classification accuracy (more than 93 per cent) in linked fleets. This is particularly critical when it comes to petroleum privacy-based architectures. Simply put, CNN-based driver behavior monitoring reflects a paradigm shift in moving from isolated and camera-only models to hybrid, multimodal, real-time, and explainable AI systems. CNNs together with temporal learning networks, multimodal sensors, edge computing, and XAI frameworks have offered a very robust basis of attaining secure, interpretable, scalable driver tracking efforts, which will be combined with the higher objectives of intelligent transportation systems, especially in high-stakes petroleum logistics, wherein human mistakes occur most frequently and result in accidents. The greater involvement of the regulatory bodies, such as the FRSC, in AI-enhanced surveillance systems is also a sign of a significant move towards institutionalizing the new technologies, promoting data-based safety control, and efficient transportation management.

5.Challenges

Although research on deep learning-based monitoring systems has come a long way, there still persist some problems that negatively affect the reliability, scalability, and place of vision-based driver monitoring in petroleum tanker driving. The need for CNN-based models to have high-quality visual information is one of the main difficulties. It has already been demonstrated in the previous studies by Civik and Yuzgec (2023), as well as Almazroi et al. (2023), that one of the major issues with CNN involves reduced performance under unfavorable lighting conditions, occlusion, or variations in head pose. These restrictions are conspicuously high in the industry of transportation of tankers, where the drivers used to work in conditions of low visibility, which are related to night trips, as well as glare and visibility barriers, such as weather conditions like rain or fog.

The second challenge is that most of the existing models have limited behavioral coverage. According to previous versions, much attention was paid to the driver behavior, such as fatigue or distraction, and other high-risk situations, such as intoxication or cognitive impairment, were overlooked (Muiz et al., 2024). The perspective restricts behavioral profiling, which is a necessity in high-stakes petroleum logistics. The current CNN systems equally process images independently without the inclusion of temporal constraints that restrict consistency in identifying temporally localized behaviors such as yawning, blinking, or nodding off (Wu et al., 2020).

Other obstacles are expressed as computational efficiency and real-time responsiveness. The majority of the legacy frameworks are based on centralized or cloud-based computing. This creates latency and reliance on stable internet connections that cannot be maintained in operations along long-distance roads. Such type of delays influence the efficiency of real-time alerts in preventing accidents. Other risks are the model interpretability and trust. Deep learning models are usually ‘black boxes’, and thus the decisions made by them are non-transparent to human regulators, such as the FRSC. Enhancing the transparency of our actions can go a long way in cultivating trust in the methods, lobbying for the adoption of legal structures, and ensuring equalization of the policies to effectively implement them.

Lastly, the weaknesses of the datasets are an emergent problem. Even though existing datasets of the population are not yet sufficient to reflect the diverse nature of Nigerian drivers and the roads they drive, it is just a lesson that can be learned to focus on the area and improve the situation in the future. This is one of the reasons why models that are developed on international data can experience challenges in adjusting to adjust into the local climate.

6.Propositions and Future Research

The proposed CNN-YOLOv8-FSM framework provides a good opportunity to overcome the key issues seen in CNN-based monitoring of driver behaviour in the transportation of petroleum products. The suggested integrated framework will be projected to be an innovative conceptual change to unify deep learning, mathematical modelling, and regulatory agencies, including the FRSC. This architecture represents a combination of frame-level visual detection and temporal reasoning based on a Finite State Machine (FSM) architecture and thus the system can sense emergent behavioral patterns. The framework will have a reduced number of false alarms and increase the reliability of behavioural recognition in real world conditions by confirming driver states, including drowsy, distracted, and intoxicated states, over a series of frames instead of a single frame.

One of the most prominent approaches involves methods is the operation of the confidence-based adaptive thresholding which is to be operated to regulate time precision and recall on the go. This reactive system will make sure that the behavior-associated alerts, i.e. Drowsy Warning or Distraction Alert will be produced when the confidence of detection is above the empirically set level of the threshold value. Such an environment is also able to prevent driver alert fatigue while being very sensitive to the actual behavioral deviations.

The next step of this framework offers to introduce an easy way to integrate it with other regulatory systems, such as FRSC, using cloud-linked monitoring checkpoints. This would bring a new sophisticated safety control system capable of real-time warning to the driver and authorities. Bringing technological innovation and regulation into context, the safety of the transportation of petroleum products is turned into a more efficient data-based response system as opposed to a reactive response system.

Technically, the stage of evolution of the framework will be supplemented by new methods of data augmentation, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), mosaic synthesis, and image flipping, all of which can supplement model generalization in many illumination and environmental conditions. Future research can improve this framework by incorporating multimodal sensing where visual, telemetric, and physiological information (e.g., heart rate, EEG, and GPS) are combined to establish a complete picture of the behavior of the driver. More importantly, the incorporation of XAI is planned to bring the predictions to a better understanding to provide it with greater transparency, and in line with the most suitable regulatory standards.

New edge computing solutions coupled with federated learning offer solid opportunities towards the design of the proposed framework. Embedded hardware, Neural networking. The NVIDIA Jetson Nano might be deployed to perform low-latency inference necessary to address privacy concerns and to enable continuous training of models on a distributed set of vehicles without access to raw video insight. Federated Learning (FL) architectures would enable continuous product enhancement on a distributed set of vehicles without necessarily sharing raw video information. The forward-looking bit of this integration of strategies sees a future in which smart, ethical, and scalable CNN-based surveillance systems form the basis on which anticipatory accident prevention and sustainable management of oil logistics can be achieved.

7.Conclusion

This review has critically assessed and synthesized research literature that has CNN-oriented structures to track the work of drivers in real-time, in this case, in relation to their application in oil products transport. The paper has also pointed out more and more powerful contributions to behavioral analysis using deep learning such as CNN-LSTM hybrid architectures and CNN-Transformer, the inclusion of multimodal sensing, and the emergence of edge and federated computing to enable real-time and privacy-preserving behavioral analysis. Despite the success around ITU, there remain a number of issues, such as the generalization of datasets, interpretability of the model, and the addition of regulatory compliance.

The existing limitations are addressed in this paper in terms of suggesting a new conceptual framework to integrate CNN, YOLOv8, and FSM with the assistance of deep learning, time analysis, and compliance with control to enhance safety in the field of transportation. The system of proposed research should identify various behavioral conditions of tanker drivers, including drowsiness, distraction, and intoxication, in the context of a real-time driving behavior monitoring system. The presented model will offer preventive measures against accidents during petroleum logistics involving the connection of intelligent in-vehicle detection to cloud monitoring by the regulatory institution, such as the FRSC.

Future work will concentrate on the implementation and empirical validation of this framework within an operational setting, with a particular emphasis on the optimization of model thresholds, enhancement of robustness across various environmental conditions, and XAI components for greater transparency. Moreover, extending multimodal approaches with physiological and telemetric data may further improve predictive accuracy and regulatory relevance.

This review ultimately shows that the application of CNN for driver monitoring represents a major step toward enhancing safety, accountability, and sustainability in the transport of petroleum resources. This proposed model establishes a conceptual and methodological basis that shall guide future implementation and evaluation to lead us to intelligent data-driven transportation safety management systems that can help save lives and protect critical infrastructure.

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