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A Mobile Crowdsourcing Approach for Smart Edge-Based Driver Drowsiness Detection

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Abstract – Drowsy driving is a major contributor to road accidents, accounting for approximately 15.5% of fatal crashes. With the increasing prevalence of mobile devices and roadside infrastructure, implementing an effective drowsiness detection system can significantly enhance road safety. While numerous approaches have been proposed, most existing solutions lack a distributed framework that ensures efficiency while safeguarding driver privacy. This paper introduces a two-stage Smart Edge-based Driver Drowsiness Detection System that leverages edge computing for real-time analysis. The system utilizes mobile devices within vehicles to monitor driver behavior without transmitting sensitive data. The decision-making process is carried out at the edge, where drowsiness is confirmed by correlating driver condition data from mobile clients with vehicle movement patterns. Our method incorporates: (1) a distributed edge framework with hierarchical nodes—Main Edge Node (MEN) and Local Edge Node (LEN)—for improved data processing, and (2) an optimized data fusion strategy, integrating (i) local detection of drowsiness through facial analysis using a Convolutional Neural Network (CNN), (ii) global movement tracking via acceleration data processed by the YoLov5 algorithm, and (iii) a two-layer Long Short-Term Memory (LSTM) model for final drowsiness assessment. The proposed approach achieves an average detection accuracy of 97.7%, demonstrating its effectiveness in preventing drowsy driving incidents.

Index Terms – Driver Drowsiness Detection, Deep learning, Smart Edge, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM)

I. INTRODUCTION

Drowsy driving is a significant risk factor for road safety, contributing to approximately 328,000 accidents each year. Studies indicate that drowsiness plays a role in about 15.5% of fatal crashes and 13.1% of incidents causing injuries. Drivers experiencing extreme fatigue may have slower reaction times, impaired judgment, and reduced awareness, increasing the likelihood of collisions. An effective, real-time drowsiness detection system could help prevent such accidents by alerting drivers before their condition leads to hazardous situations.

Various techniques have been explored for detecting driver drowsiness, typically categorized into three main approaches: vehicle behavior monitoring, physiological signal analysis, and computer vision-based methods. Vehicle behavior monitoring assesses patterns such as steering movements and lane deviations, but these methods can be unreliable due to variations in road conditions and individual driving styles. Physiological signal-based techniques rely on data from electroencephalograms (EEG) and heart rate sensors, yet they are often impractical for real-world driving due to motion-induced artifacts and the need for specialized wearable devices. Among these approaches, computer vision-based techniques—which analyze facial expressions, eye movement, and head positioning—offer a more user-friendly and non-intrusive solution. However, these methods can be affected by varying lighting conditions and require substantial computational power, which may pose challenges for real-time deployment on embedded systems. Many existing drowsiness detection systems rely on centralized architectures, where data is processed on cloud servers. While effective in some cases, these solutions introduce privacy concerns, require significant computational resources, and may experience delays due to network latency. Distributed architectures, particularly those leveraging edge computing, present a promising alternative by enabling real-time processing closer to the data source while reducing privacy risks and computational overhead.

This research aims to address key challenges in drowsiness detection by proposing a smart edge-based system that ensures (i) accurate and timely detection, (ii) efficient deployment on embedded systems, and (iii) enhanced privacy protection for drivers. Our approach integrates edge computing and data fusion to create a robust detection framework that does not rely on centralized processing. The system operates using a hierarchical edge architecture, leveraging mobile and roadside devices to assess both local facial cues and vehicle movement patterns. By utilizing deep learning models—including a Convolutional Neural Network (CNN) for facial analysis and a Long Short-Term Memory (LSTM) network for driving behavior classification—the proposed solution enhances detection accuracy while maintaining low latency. Through the integration of a two-stage detection mechanism, this study presents an innovative approach to improving road safety by detecting driver drowsiness with high accuracy and minimal reliance on cloud-based processing.

II. LITERATURE SURVEY

Drowsydriving is a major contributor to road accidents and fatalities. Studies have shown that fatigue impairs cognitive function and reaction time, increasing the risk of collisions. The National Safety Council has identified drowsy driving as a leading cause of highway accidents, emphasizing the need for real-time driver monitoring systems [1]. Similarly, research by the AAA Foundation highlighted that drowsy drivers are involved in approximately 9.5% of all severe crashes, further reinforcing the importance of early detection mechanisms [2].

Several approaches have been developed to assess driver drowsiness, broadly categorized into physiological and behavioral monitoring techniques. Hussein et al. provided a comprehensive survey of drowsiness detection methods, highlighting eye movement tracking, yawning detection, and head nodding as common behavioral indicators [3]. In contrast, Lawoyin et al. explored steering wheel movement analysis, demonstrating that abrupt or inconsistent steering patterns often indicate fatigue-related impairments [4]. Physiological measures such as heart rate variability (HRV) and electroencephalogram (EEG) signals have also been utilized for drowsiness detection. Iwamoto et al. developed a real-time HRV-based drowsiness detection system, proving its effectiveness in real-world driving conditions [5].

The rise of artificial intelligence (AI) and deep learning has significantly enhanced the accuracy of drowsiness detection systems. Khare et al. introduced a deep learning model for real-time drowsiness detection, leveraging convolutional neural networks (CNNs) and heterogeneous computing for improved performance on embedded systems [6]. Similarly, Park et al. applied feature representation learning using deep networks, achieving high accuracy in driver state classification [7]. Another widely adopted approach is computer vision-based fatigue detection, where visual cues such as eye closure duration, facial expressions, and head posture are analyzed using deep learning techniques. Mandal et al. proposed a bus driver fatigue detection model based on robust visual analysis, achieving high accuracy in real-world scenarios [8].

To improve robustness, researchers have combined multiple data sources for drowsiness detection. Lyu et al. introduced a multi-granularity deep framework, integrating video-based behavior analysis and physiological signals for fatigue monitoring [9]. Similarly, Hashemi et al. developed a multimodal system combining EEG, HRV, and facial recognition, demonstrating superior drowsiness classification accuracy compared to single-sensor models [10]. Recent advancements in edge computing and the Internet of Things (IoT) have enabled real-time driver drowsiness detection on mobile platforms. Lamaazi et al. proposed a crowdsensing framework leveraging mobile edge computing, allowing distributed drowsiness detection across multiple vehicles [11]. The same research team later developed Smart-3DM, an intelligent decision-making system for heterogeneous edge computing environments [12].

The implementation of drowsiness detection models in real-time embedded systems is crucial for practical deployment. Baek et al. introduced a real-time driver state monitoring algorithm, optimized for low-latency applications in automotive environments [13]. Similarly, Reddy et al. focused on deep learning model compression, enabling drowsiness detection on low-power embedded devices [14]. The development of accurate detection models relies on high-quality drowsiness detection datasets. Abtahi et al. introduced the YawDD (Yawning Detection Dataset), providing labeled images for fatigue-related facial expressions [15]. Additionally, Weng et al. proposed a hierarchical deep belief network (H-DBN) for drowsiness detection, trained on multiple datasets for generalization [16].

Several large-scale multimodal datasets have also been developed, including DROZY, which integrates visual, physiological, and vehicular data for fatigue assessment [17]. Ghoddoosian et al. proposed an early drowsiness detection dataset, focusing on temporal fatigue progression in drivers [18]. With the growing use of smartphones and wearable sensors, researchers have explored mobile-based drowsiness detection systems. Carlos et al. investigated how smartphone accelerometers can detect aggressive driving behavior, which can be correlated with driver fatigue [19]. Similarly, Zylius demonstrated that accelerometer signals can differentiate between safe and drowsy driving patterns, highlighting the potential of mobile-based drowsiness detection [20].

III. METHODOLOGY

The proposed Smart Edge-based Driver Drowsiness Detection System is designed to efficiently detect drowsiness in drivers using a distributed edge computing framework. This system operates in two main stages: local detection, which takes place on the driver's mobile device, and global validation, conducted at edge nodes. The approach leverages deep learning models for analyzing facial expressions and driving patterns, ensuring accurate detection while maintaining data privacy.

1. Local Drowsiness Detection

The initial step of the system involves detecting signs of drowsiness using the driver's mobile device. A front-facing camera captures video frames, which are analyzed in real time through a **Convolutional Neural Network (CNN)** to identify fatigue indicators such as **eye closure, yawning, and head movements**. Two detection approaches are considered:

- **Face-based detection:** The entire facial region is processed to assess drowsiness.
- **Region of Interest (ROI) detection:** Specific features such as eyes and mouth are separately analyzed to improve accuracy.

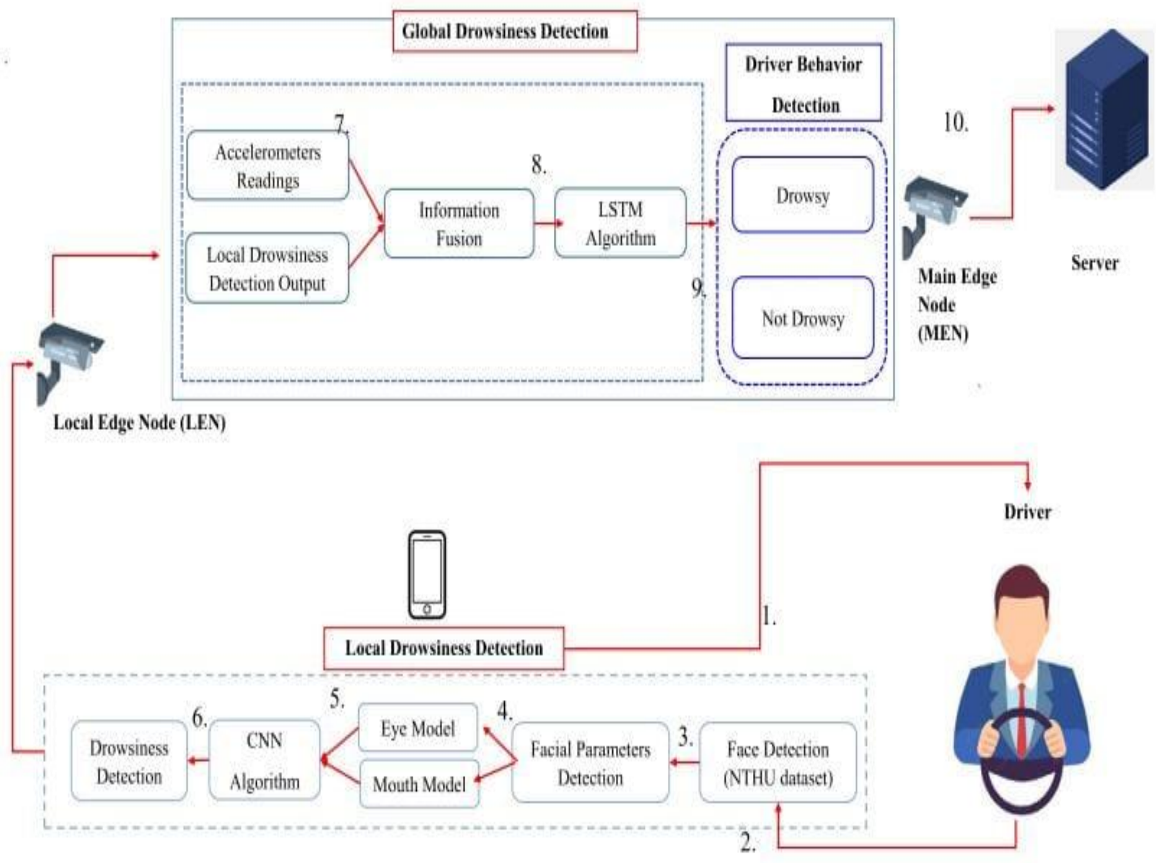


Fig 1:Distributed Edge Computing Framework

Before processing, the images undergo **pre-processing steps** including face detection, resizing, and enhancements such as brightness normalization. This ensures robustness under different lighting conditions and enhances the performance of the CNN model.

2. Global Drowsiness Validation using Edge Computing

If local detection suggests potential drowsiness, the system proceeds to global validation using **edge computing**. The architecture is structured into:

- **Local Edge Nodes (LENs):** These units collect and analyze vehicle movement data such as acceleration patterns, lane deviations, and abrupt changes in speed.
- **Main Edge Nodes (MENs):** Serving as higher-level aggregators, MENs process inputs from multiple LENs. A **Long Short-Term Memory (LSTM) network** is used to recognize patterns indicative of drowsiness and confirm driver fatigue.

By leveraging edge computing, the system processes data closer to the source, reducing reliance on cloud computing and addressing latency and privacy concerns.

3. Data Fusion and Decision-Making

To improve detection reliability, the system integrates data from multiple sources through a **data fusion strategy**, combining:

- **Facial expression analysis from mobile devices** (CNN-based classification of eye and mouth states).
- **Vehicle movement tracking** (analyzed through acceleration sensors and trajectory patterns).
- **Environmental conditions** (weather and road surface changes).

A final decision is made based on the combined results of local and global detection. The **LSTM model**, trained on time-series driving data, helps eliminate false positives by distinguishing between normal and drowsy driving behaviors.

4. Alert Mechanism and Driver Notification

Once drowsiness is confirmed, the system generates immediate alerts to prevent accidents. The alert mechanisms include:

- **Visual and auditory warnings** (screen notifications, alarm sounds).
- **Haptic feedback** (steering wheel or seat vibrations).
- **Cloud reporting (optional)** for fleet management or emergency intervention if required.

If multiple drowsiness incidents occur within a short timeframe, the system suggests the driver take a rest break.

5. Model Training and Optimization

The deep learning models are trained using public datasets such as **NTHU, YawDD, and DROZY**, as well as real-world driving data. Optimization strategies include:

- **CNN fine-tuning** using transfer learning to enhance feature extraction.
- **Dropout layers** to prevent overfitting.
- **LSTM training with time-series acceleration data** for improved behavior classification.

The system is tested in diverse driving environments to ensure its robustness in different lighting and road conditions.

6. Advantages of the Proposed System

Compared to conventional cloud-based solutions, this edge-based approach provides:

- **Lowerlatency** by processing data locally at edge nodes.
- **Enhanced privacy** since driver data remains on the edge network.
- **Higher accuracy** through a combination of facial and driving behavior detection.
- **Scalability** via distributed architecture deployment across multiple locations.

IV. RESULTS AND DISCUSSIONS

The proposed Smart Edge-Based Driver Drowsiness Detection System demonstrated a high accuracy of 97.7% in detecting driver fatigue by integrating deep learning models with edge computing. The system effectively identifies drowsiness through a two-stage approach, combining CNN-based facial expression analysis and LSTM-driven vehicle movement tracking while ensuring real-time processing and enhanced privacy. By leveraging a distributed framework with Local Edge Nodes (LENs) and Main Edge Nodes (MENs). The system minimizes latency and eliminates dependence on cloud-based processing. The detection mechanism was trained on extensive datasets such as NTHU, YawDD, and DROZY, with optimization techniques including transfer learning and dropout layers to improve robustness under diverse driving conditions. Real-time alerts, including visual warnings, haptic feedback, and cloud reporting, ensure timely intervention to prevent accidents. The study highlights the effectiveness of edge computing in drowsiness detection and proposes future enhancements such as physiological data integration and adaptive machine learning models to further improve detection accuracy and system scalability.

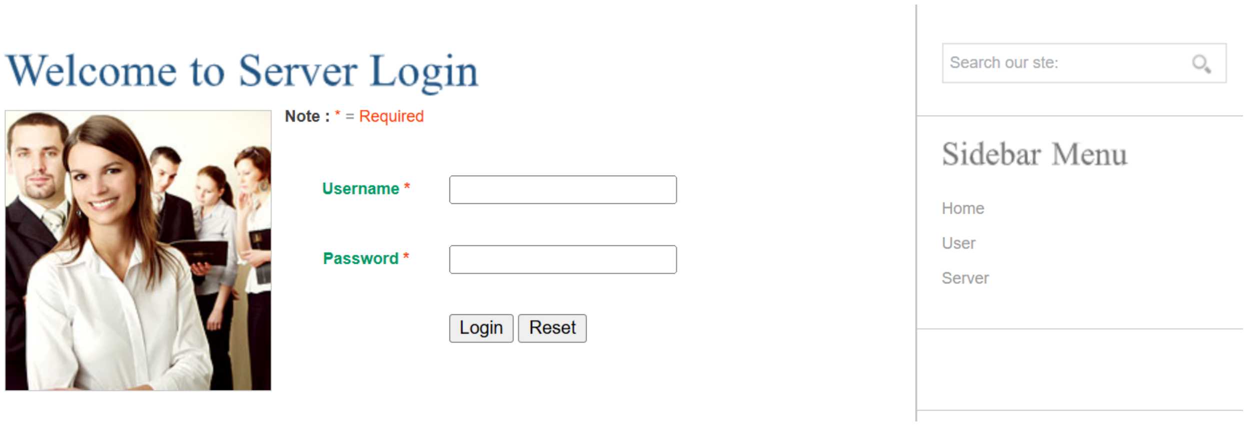
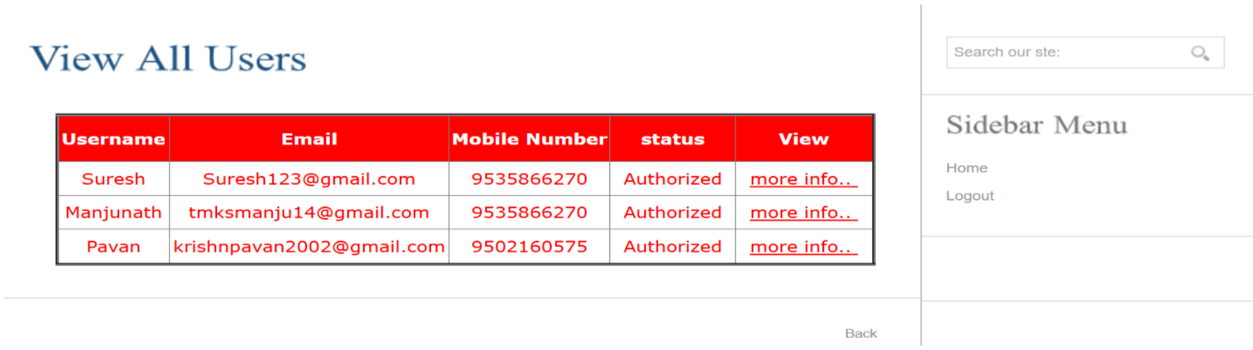
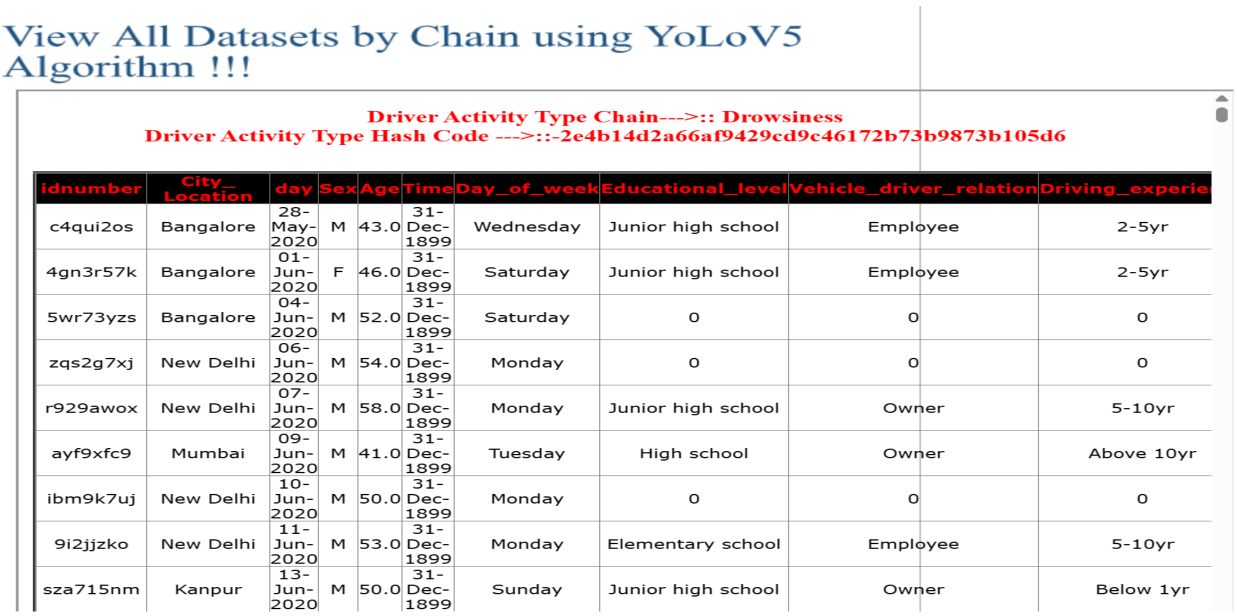


Fig 2: Server Login



Username	Email	Mobile Number	status	View
Suresh	Suresh123@gmail.com	9535866270	Authorized	more info..
Manjunath	tmksmanju14@gmail.com	9535866270	Authorized	more info..
Pavan	krishnpavan2002@gmail.com	9502160575	Authorized	more info..

Fig 3: User data



idnumber	City_Location	day	Sex	Age	Time	Day_of_week	Educational_level	Vehicle_driver_relation	Driving_experie
c4qui2os	Bangalore	28-May-2020	M	43.0	31-Dec-1899	Wednesday	Junior high school	Employee	2-5yr
4gn3r57k	Bangalore	01-Jun-2020	F	46.0	31-Dec-1899	Saturday	Junior high school	Employee	2-5yr
5wr73yzs	Bangalore	04-Jun-2020	M	52.0	31-Dec-1899	Saturday	0	0	0
zqs2g7xj	New Delhi	06-Jun-2020	M	54.0	31-Dec-1899	Monday	0	0	0
r929awox	New Delhi	07-Jun-2020	M	58.0	31-Dec-1899	Monday	Junior high school	Owner	5-10yr
ayf9xfc9	Mumbai	09-Jun-2020	M	41.0	31-Dec-1899	Tuesday	High school	Owner	Above 10yr
ibm9k7uj	New Delhi	10-Jun-2020	M	50.0	31-Dec-1899	Monday	0	0	0
9i2jjzko	New Delhi	11-Jun-2020	M	53.0	31-Dec-1899	Monday	Elementary school	Employee	5-10yr
sza715nm	Kanpur	13-Jun-2020	M	50.0	31-Dec-1899	Sunday	Junior high school	Owner	Below 1yr

Fig 4: View all datasets by chain using YoLoV5 algorithm

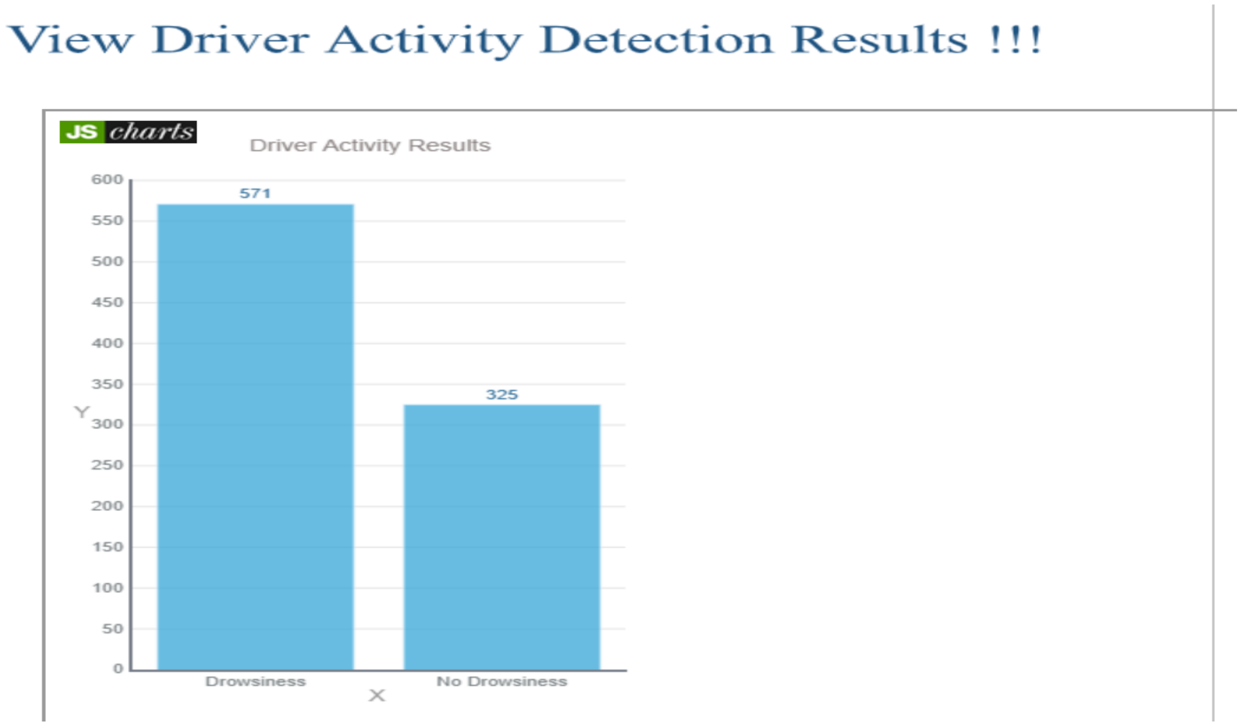


Fig 5: View driver activity detection results

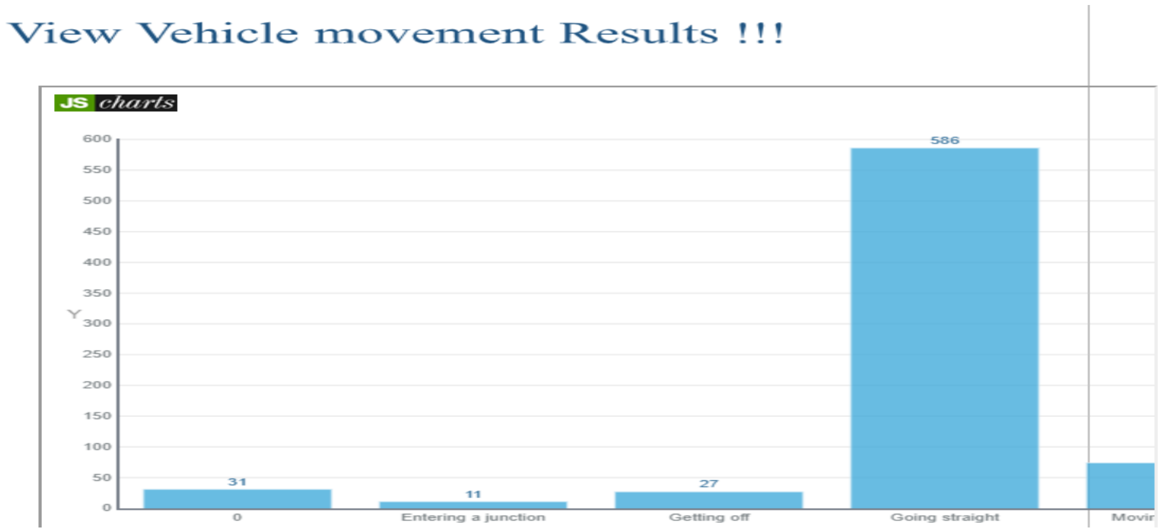


Fig 6: View vehicle movement results

Fig 7: User Login

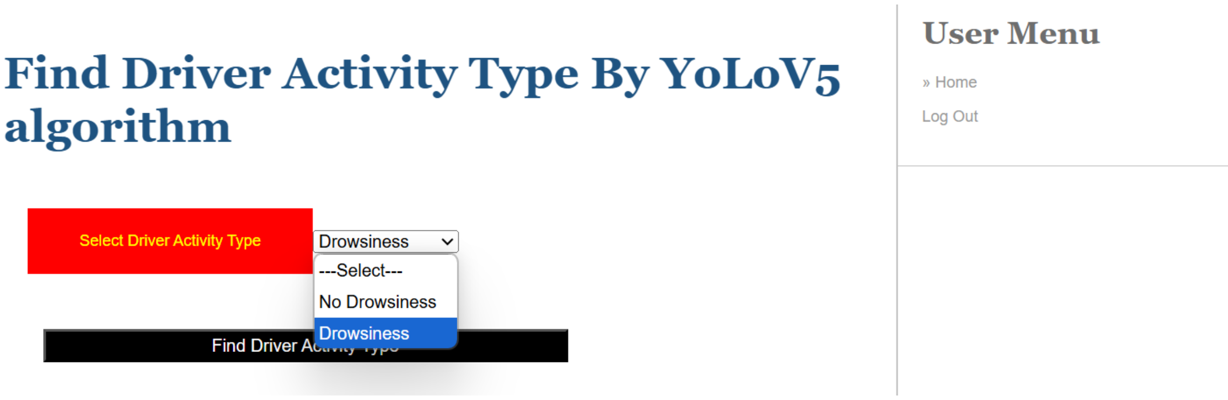


Fig 8: Driver activity type by yoLoV5 algorithm

V. CONCLUSION

This study presents an advanced smart edge-based driver drowsiness detection system that leverages a distributed computing framework to enhance road safety. By integrating real-time facial expression analysis, vehicle behavior monitoring, and deep learning-based decision-making, the system effectively detects signs of drowsiness while addressing key challenges such as latency, privacy, and computational efficiency.

The proposed solution employs a two-stage detection mechanism:

1. Local detection, which utilizes a Convolutional Neural Network (CNN) to analyze driver facial expressions in real time.
2. Global detection, which validates drowsiness through vehicle trajectory tracking and acceleration data, processed by a Long Short-Term Memory (LSTM) model at edge nodes.

Unlike traditional cloud-based systems, the edge computing approach ensures low latency, real-time responsiveness, and reduced dependence on centralized servers, making it highly suitable for safety-critical applications. Experimental results demonstrate the system's effectiveness, achieving high detection accuracy while minimizing false positives. Future work will explore additional physiological indicators such as heart rate and body sensor data to further improve detection reliability. Moreover, adaptive machine learning models can be integrated to enhance system performance under varying environmental and driving conditions. Expanding the dataset to include a broader range of real-world driving scenarios will also contribute to refining the system's accuracy and robustness.

By implementing this smart edge-based detection system, we aim to reduce drowsy driving incidents, ultimately improving road safety and preventing potential accidents.

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