A

Major Project Report

On

"DRIVER ASSISTANT SYSTEM"

Submitted in partial fulfillment of the

Requirements for the award of the degree of

Bachelor of Technology

In

Computer Science & Engineering –

Artificial Intelligence & Machine Learning

By

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Laxman Reddy Avenue, Dundigal, Hyderabad-500 043, Telangana, India

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CERTIFICATE

This is to certify that the project entitled **"Driver Assistant System"** has been submitted by **Madadapu Hemanth Sai(20R21A6632), Mallela Sai Krishna(20R21A6631), Somayajula Naga Preethi(20R21A6647), Vemuri Abhinaya (20R21A6655)** in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering from Jawaharlal Nehru Technological University, Hyderabad. The results embodied in this project have not been submitted to any other University or Institution for the award of any degree or diploma.

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DECLARATION

We hereby declare that the project entitled **"Driver Assistant System"** is the work done during the period from **January 2024 to May 2024** and is submitted in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science and Engineering from Jawaharlal Nehru Technology University, Hyderabad. The results embodied in this project have not been submitted to any other university or Institution for the award of any degree or diploma.

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ABSTRACT

Road safety has always been an important subject for development and public safety as it is one of the primary causes of death and injury across the world. Active participation in the evolution of contemporary transport systems, road safety measures and other partnerships would aid in the prevention of traffic accidents. The proposed research aims to make a significant contribution to multifaceted efforts in the expansion of Advanced Driver Assistance Systems (ADASs) and Autonomous Vehicles (AVs). It consists of six pillars: drowsiness detection and alert system, lane detection, lane departure warning system, lane keeping assist system, object detection and recognition, and collision warning system. The drowsiness detection and alert system operates continuously throughout the entire duration of the drive to monitor the driver's alertness levels. Lane detection using an ultrafast lane detector follows, providing spatial awareness by identifying the lane markings on the road. Subsequently, the lane departure system activates when the vehicle deviates from its lane without signaling, promptly alerting the driver. In the event of continued lane deviation, the lane keeping assist system intervenes by autonomously adjusting the vehicle's steering to maintain lane position. Concurrently, object detection and recognition using YOLO detect various objects on the road, crucial for collision warning systems. The collision warning system, utilizing OpenCV and distance measurement monitors the vehicle's surroundings and alerts the driver to potential collision threats. This integration aims to enhance driver safety by providing timely warnings and assistance throughout the driving process.

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LIST OF ABBREVIATIONS

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	ABBREVIATIONS
ADAS	Advanced Driver Assistance Systems
AV	Autonomous Vehicle
YOLO	You Only Look Once
CNN	Convolutional Neural Networks
GAN	Generative Adversarial Networks

APPENDIX-4

REFRENCES

REFERENCES

[1] A. Rajkar, N. Kulkarni, and A. Raut, “Driver Drowsiness Detection Using Deep Learning,” 2022, pp. 73–82. doi: 10.1007/978-981-16-2008-9_7.

[2] R. K. M, R. V, and R. G. Franklin, “Alert System for Driver’s Drowsiness Using Image Processing,” in *2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, IEEE, Mar. 2019, pp. 1–5. doi: 10.1109/ViTECoN.2019.8899627.

[3] S. Mohanty, S. V Hegde, S. Prasad, and J. Manikandan, “Design of Real-time Drowsiness Detection System using Dlib,” in *2019 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, IEEE, Nov. 2019, pp. 1–4. doi: 10.1109/WIECON-ECE48653.2019.9019910.

[4] A. Fogelton and W. Benesova, “Eye blink detection based on motion vectors analysis,” *Computer Vision and Image Understanding*, vol. 148, pp. 23–33, Jul. 2016, doi: 10.1016/j.cviu.2016.03.011.

[5] Q. Gao, Y. Feng, and L. Wang, “A real-time lane detection and tracking algorithm,” in *2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, IEEE, Dec. 2017, pp. 1230–1234. doi: 10.1109/ITNEC.2017.8284972.

[6] Z. Kim, “Robust Lane Detection and Tracking in Challenging Scenarios,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 9, no. 1, pp. 16–26, Mar. 2008, doi: 10.1109/TITS.2007.908582.

[7] Abdulhakam. AM. Assidiq, O. O. Khalifa, Md. R. Islam, and S. Khan, “Real time lane detection for autonomous vehicles,” in *2008 International Conference on Computer and Communication Engineering*, IEEE, May 2008, pp. 82–88. doi: 10.1109/ICCCE.2008.4580573.

[8] Y. Wang, E. K. Teoh, and D. Shen, “Lane detection and tracking using B-Snake,” *Image Vis Comput*, vol. 22, no. 4, pp. 269–280, Apr. 2004, doi: 10.1016/j.imavis.2003.10.003.

[9] Y. Wang, D. Shen, and E. K. Teoh, “Lane detection using spline model,” *Pattern Recognit Lett*, vol. 21, no. 8, pp. 677–689, Jul. 2000, doi: 10.1016/S0167-8655(00)00021-0.

[10] S. Anbalagan, P. Srividya, B. Thilaksurya, S. G. Senthivel, G. Suganeshwari, and G. Raja, “Vision-Based Ingenious Lane Departure Warning System for Autonomous Vehicles,” *Sustainability*, vol. 15, no. 4, p. 3535, Feb. 2023, doi: 10.3390/su15043535.

[11] J. Son, H. Yoo, S. Kim, and K. Sohn, “Real-time illumination invariant lane detection for lane departure warning system,” *Expert Syst Appl*, vol. 42, no. 4, pp. 1816–1824, Mar. 2015, doi: 10.1016/j.eswa.2014.10.024.

[12] V. Gaikwad and S. Lokhande, “Lane Departure Identification for Advanced Driver Assistance,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 2, pp. 1–9, Apr. 2014, doi: 10.1109/TITS.2014.2347400.

[13] G. Cario, A. Casavola, G. Franze, and M. Lupia, “Data fusion algorithms for lane departure warning systems,” in *Proceedings of the 2010 American Control Conference*, IEEE, Jun. 2010, pp. 5344–5349. doi: 10.1109/ACC.2010.5530754.

[14] C. R. Jung and C. R. Kelber, “Lane following and lane departure using a linear-parabolic model,” *Image Vis Comput*, vol. 23, no. 13, pp. 1192–1202, Nov. 2005, doi: 10.1016/j.imavis.2005.07.018.

[15] P. P. Hong, H. H. Khanh, N. N. Vinh, N. N. Trung, A. N. Quoc, and H. T. Ngoc, “Deep Learning-Based Lane-Keeping Assist System for Self-Driving Cars Using Transfer Learning and Fine Tuning,” *Journal of Advances in Information Technology*, vol. 15, no. 3, pp. 322–329, 2024, doi: 10.12720/jait.15.3.322-329.

[16] J. Chen, H. Chen, X. Lan, B. Zhong, and W. Ran, “A Method to Develop the Driver-Adaptive Lane-Keeping Assistance System Based on Real Driver Preferences,” *Sensors*, vol. 24, no. 5, p. 1666, Mar. 2024, doi: 10.3390/s24051666.

[17] M. Munadi, B. Radityo, M. Ariyanto, and Y. Taniai, “Automated guided vehicle (AGV) lane-keeping assist based on computer vision, and fuzzy logic control under varying light intensity,” *Results in Engineering*, vol. 21, p. 101678, Mar. 2024, doi: 10.1016/j.rineng.2023.101678.

[18] J. Lee and K. Hwang, “YOLO with adaptive frame control for real-time object detection applications,” *Multimed Tools Appl*, vol. 81, no. 25, pp. 36375–36396, Oct. 2022, doi: 10.1007/s11042-021-11480-0.

[19] Q. Li *et al.*, “Detection and Identification of Moving Objects at Busy Traffic Road based on YOLO v4,” vol. 21, no. 1, p. 2289, 2021, doi: https://doi.org/10.7236/JIIBC.2021.21.1.141.

[20] G. Oltean, C. Florea, R. Orghidan, and V. Oltean, “Towards Real Time Vehicle Counting using YOLO-Tiny and Fast Motion Estimation,” in *2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging (SIITME)*, IEEE, Oct. 2019, pp. 240–243. doi: 10.1109/SIITME47687.2019.8990708.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Elevating the discourse around road safety is one of the important concerns in today's modern society. Despite remaining as a burning issue amidst the discussions on safety and public welfare, millions of people worldwide still lose their lives or suffer injuries in road accidents. The unmatched increase in rate of motorization, urbanization and population brought on by the rapid economic expansion has led to increased demand for awareness and investment in road safety infrastructures. India owns one of the largest road networks in the world and provides the public with one of the most feasible, cost-effective, and widely used source of transportation due to its level of penetration in different areas. Despite numerous efforts put in by the Indian Government, road crashes, traffic injuries and fatalities are inadmissibly high.

According to the 'Road Accidents in India' report presented by Ministry of Road Transport and Highways (MorTH) Research Wing, there has been an upsurge in the number of road accidents in recent years. These accidents encompass various types including rear-end-collisions, head-on collisions, hit-and-run incidents, side impacts, and run-off-road accidents. Causes of such collisions range from human error to road and vehicular conditions, with contributing factors like narrow lanes, sharp curves, unseparated lanes for two-way traffic, busy stretches, single-carriageway roads outside urban areas where speeds are the highest and black spots on National Highways. Additionally, speeding, drunken driving, driving on the wrong side, red-light violations, mobile phone usage and other traffic rule violations aggravate the risks.

ADAS have emerged as a promising frontier in the quest for safer roads. Leveraging various cutting-edge technologies such as computer vision, deep learning, and real-time data processing, ADAS systems hold the potential to revolutionize vehicle safety by providing drivers with critical insights and assistance in navigating complex road scenarios. With a particular focus on the Indian context, we seek to unravel the transformative potential of the ADAS and AV systems through the intricate interplay between technological innovation and road safety measures. We endeavor to shed light on drowsiness detection, lane detection, lane departure warning, lane keeping assistance, object detection and recognition, and collision warning. Our model inherits the advantage of You Only Look Once (YOLO) for real-time object detection system to predict bounding boxes and Ultrafast Lane Detector for fast and accurate lane detection. A Collision Warning System utilizes computer vision in conjunction with distance measurement technologies to alert drivers of potential collisions. For Lane Departure Warning System and Lane Keeping Assist System functionalities, the project

utilizes Ultrafast deep lane detection with hybrid anchor drive ordinal classification. Drowsiness detection is facilitated using facial landmarks stored in DAT files, enhancing driver safety by monitoring fatigue levels.

Figure 1 - Depicting Input on the left-hand side and Output on righthand side

1.2 PURPOSE OF THE PROJECT

The purpose of this project is to provide a system that monitors the behavior of a person driving the vehicle. Accidents have been emerging as the biggest public health issue which requires a multidisciplinary strategy to address. Every year, thousands of lives are lost in tragic traffic accidents. If we want to accomplish the goals of sustainable development, wealth, and progress, we cannot compromise on road safety. The idea of a driver assistant system is to reduce accidents that occur at night, in severe rain, or in other unusual circumstances. The development of the Assistant System is to provide better assistance to the drivers and for monitoring the actions of the driver. It alters the driver in an abnormal condition and can have a conversation with the system, also can control the music system using voice commands. When there is a crisis, it can transmit SOS messages.

1.3 MOTIVATION

The proposed system stands as a robust solution driven by a fundamental motivation to revolutionize driver safety and accident prevention. By amalgamating cutting-edge hardware sensors, computational prowess, and intelligent software algorithms, it aims to confront head-on the myriad challenges encountered on the road. Rooted in the unwavering commitment to enhance road safety, this system encompasses a multifaceted approach, incorporating modules such as drowsiness detection, lane departure warning, lane-keeping assistance, object detection, and collision warning. By continuously monitoring both the vehicle's surroundings and the driver's state, our system empowers drivers with the tools they need to navigate safely and confidently. The proposed system tireless pursuit of accident prevention and driver assistance embodies a paradigm shift towards a safer and more secure driving experience, heralding a new era of road safety standards.

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CHAPTER 2

LITERATURE SURVEY

We conducted a thorough literature survey by reviewing existing systems for monitoring the vehicle internally and externally. Many research papers, journals and publications have also been referred in order to prepare this survey.

2.1 EXISTING SYSTEM

Over the years, researchers have been continuously innovating in the field of driver assistance systems and road safety through the integration of computer vision, machine learning, and sensor technologies. Beginning with early works such as Jung and Kelber's lane departure detection technique in 2005 and Kim's robust lane detection algorithm in 2008, advancements have been made in various aspects including lane detection, driver state monitoring, and object detection. Techniques have evolved from traditional methods like Hough transforms to more sophisticated approaches such as convolutional neural networks (CNNs) and Generative Adversarial Networks (GANs). Recent works have focused on enhancing real-time performance, accuracy, and adaptability to diverse driving conditions, ultimately contributing to the development of safer driving environments and the realization of autonomous driving technologies.

1		
Reference in APA format	Forsman, Pia M and Vila, Bryan J and Short, Robert A and Mott, Christopher G and Van Dongen, Hans PA. (2013).” Efficient driver drowsiness detection at moderate levels of drowsiness”. Accident Analysis & Prevention, 50, 341–350.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.sciencedirect.com/science/article/abs/pii/S0001457512001571	Pia M. Forsman , Bryan J. Vila , Robert A. Short , Christopher G. Mott , Hans P.A. Van Dongen.	Driver drowsiness detection, Lane deviation metrics, Fatigue levels, Simulated shift work studies, High-fidelity simulator driving, Night shift condition, Day shift condition,

		Driving sessions, Driving metrics, Principal component analysis, Steering wheel variability, Lateral lane position variability, Transfer function.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
1. The current solution for detecting driver drowsiness at moderate levels of fatigue is based on steering wheel variability and lateral lane position variability. 2. Previous research has primarily focused on lane deviation metrics and high levels of fatigue, but this research aimed to develop a method for detecting drowsiness at more moderate levels of fatigue . Principal component analysis revealed that measures of steering wheel variability and measures of lateral lane position variability were the	**Goal/Objective of the Solution:** • The goal of the solution is to develop a method for detecting driver drowsiness at moderate levels of fatigue, well before the risk of accidents becomes imminent. • The objective is to identify driving metrics that are sensitive to drowsiness and can be used as indicators of driver fatigue. **Problem to be Solved:** • The problem that needs to be solved is the lack of a reliable and cost-effective	Components of the Solution for Driver Drowsiness Detection: • Steering wheel variability: Steering wheel movements are measured and analyzed to access the 1. variability, which serves as a basis for detecting driver drowsiness. 2. Lateral lane position variability: Changes in the vehicle's lateral lane position are measured and analyzed to determine the variability, which is correlated with driver fatigue. 3. Principal component analysis: This statistical technique is used to reduce the dimensionality of the data and identify the dominant dimensions related to steering wheel and lane position variability. Transfer function: A transfer function is derived to estimate changes in lane position based on measured steering wheel angle, providing an alternative method for detecting drowsiness. 4. High-fidelity driving simulator: The solution utilizes a high-fidelity driving simulator to conduct simulated shift work studies and

most correlated with fatigue . 3. Lateral lane position variability can be derived from measured changes in steering wheel angle through a transfer function, providing an alternative technology for invehicle driver drowsiness detection. 4. This alternative technology based on steering wheel variability offers a cost-effective and easy-to-install solution for detecting driver drowsiness at moderate levels of fatigue.	technology for detecting driver drowsiness at moderate levels of fatigue. • Existing technologies rely on lane deviation and video-based lane tracking, which have limitations such as data loss in adverse weather conditions or darkness. • The solution aims to overcome these limitations and provide an alternative technology that can accurately detect drowsiness based on steering wheel variability and lateral lane position variability	evaluate the proposed driver drowsiness detection metrics.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)

	Evaluation of driver drowsiness detection metrics proposed in the literature. Conducting simulated shift work studies using a high-fidelity driving simulator. Reducing the dimensionality of the data using principal component analysis. Correlating the metrics with an independent measure of fatigue, such as performance on a psychomotor vigilance test. Developing a transfer function to estimate changes in lane position based on measured steering wheel angle. Replicating the findings across different road segments and validating them in multiple driving sessions.	Cost-effective and easy-to-install alternative technology for in-vehicle driver drowsiness detection at moderate levels of fatigue, overcoming limitations of traditional video-based lane tracking technology.	No specific disadvantages mentioned in the provided sources.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**

Driver's drowsiness level. This is the main outcome that the researchers are interested in predicting and understanding	Steering wheel variability and lateral lane position variability. These are the main predictors used in the study to estimate the driver's drowsiness level.	The driving conditions (e.g., road type, weather, time of day) could potentially moderate the relationship between the independent variables and the dependent variable. For example, steering wheel variability might be a stronger predictor of drowsiness at night or on a monotonous highway compared to during the day or on a busy city street.	The driver's level of fatigue could be a mediating variable in this study. For example, the relationship between steering wheel variability and driver drowsiness might be mediated by the driver's level of fatigue

Relationship Among the Above 4 Variables in This article
The researchers used principal component analysis to reduce the dimensionality of the data and identify the main components (steering wheel variability and lateral lane position variability) that predict driver drowsiness. This is a form of multivariate analysis. They likely also looked at univariate relationships (e.g., the relationship between each predictor and drowsiness separately) and bivariate relationships (e.g., the relationship between steering wheel variability and lateral lane position variability).

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**

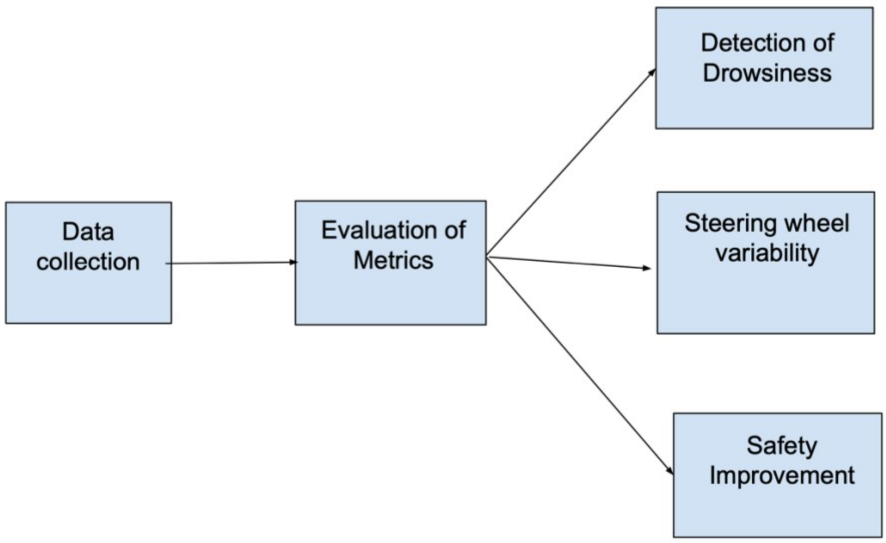
Input	Output		
The input to their method is the data collected from drivers in a controlled laboratory environment with high-fidelity simulator driving. They evaluated 87 different driver drowsiness detection metrics proposed in the literature in two simulated shift work studies.	The output of their research is the finding that steering wheel variability provides a basis for developing a cost-effective and easy-to-install alternative technology for in-vehicle driver drowsiness	1. Steering Wheel Variability: The research findings indicated that steering wheel variability provides a basis for developing a cost-effective and easy-to-install alternative technology for in-vehicle driver drowsiness detection at moderate levels of fatigue. 2. Early Detection: The method aims to detect driver drowsiness at more moderate levels of fatigue, well before accident risk is imminent. This early detection feature is crucial for preventing accidents caused by drowsy driving. 3. Cost-Effective and Easy-to-Install: The proposed solution is based on steering wheel variability, which makes it a costeffective and easy-to-install alternative technology for in-vehicle driver drowsiness detection. 4. Laboratory Tested: The method was evaluated in a controlled laboratory environment with high-fidelity simulator driving. This ensures the reliability of the results. 5. Broad Evaluation: The researchers evaluated 87 different driver drowsiness detection metrics proposed in the literature in two simulated shift work studies. This broad evaluation helps ensure the robustness of their	1. Early Detection of Drowsiness: The research focuses on detecting driver drowsiness at moderate levels of fatigue, well before accident risk is imminent. This early detection can potentially prevent accidents caused by drowsy driving. 2. Cost-Effective Solution: The findings suggest that steering wheel variability can be used to develop a cost-effective and easy-to-install alternative technology for invehicle driver drowsiness detection. 3. Broad Evaluation: The researchers evaluated 87 different driver drowsiness detection metrics proposed in the literature in two simulated shift work studies. This broad evaluation helps ensure the robustness of their findings. 4. Practical Implications: The research provides a practical solution to a real-world problem, contributing to ongoing efforts to improve driver safety. 5. Influence on Future Research: The findings of this research can guide future studies in this field, particularly those focusing on the development of cost-effective and easy-toinstall technologies for in-vehicle driver drowsiness detection.

		detection at moderate levels of fatigue. This output contributes to the ongoing efforts to improve driver safety by addressing the issue of drowsy driving at an early stage.	findings	

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
1. Early Detection: The method focuses on detecting drowsiness at moderate levels, which means it can alert drivers early before the risk of an accident increases. This early warning can give drivers enough time to take corrective	1. False Positives: The system might incorrectly identify a driver as drowsy when they are not, leading to unnecessary alerts. This could cause annoyance and potentially undermine trust in the system. 2. Privacy Concerns: Depending on the implementation, the system might require

actions such as taking a break or switching drivers. 2. Cost-Effective Technology: The study found that steering wheel variability is a good metric for drowsiness detection. This could lead to the development of cost-effective and easy-to-install technology for vehicles, making it accessible to a larger population. Prevention of Accidents: By alerting drivers about their drowsiness, this solution can potentially prevent many accidents caused by driver fatigue. This not only saves lives but also reduces the economic costs associated with these accidents	monitoring of the driver's behavior, which could raise privacy issues. 3. Over-reliance on Technology: Drivers might become overly reliant on the system and pay less attention to their own level of alertness. This could potentially lead to risky behavior if the system fails or malfunctions. Cost and Accessibility: While the research suggests that the technology could be cost-effective, there might still be costs associated with installing and maintaining the system. This could make it less accessible for some drivers, particularly in low-income regions or countries

Analyse This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
1. Purpose and Objectives: The study aims to develop a method for detecting driver drowsiness at moderate levels, which is a significant contribution to road safety. The objective is clear and addresses a real-world problem. 2. Methodology: The researchers evaluated 87 different driver drowsiness detection metrics in two simulated shift work studies. This comprehensive approach strengthens the validity of their findings. However, it's worth noting that simulated	1. Literature Review: This involves a thorough review of existing literature in the field of driver drowsiness detection. It helps in understanding the current state of research, identifying gaps, and positioning the new research within the broader context. 2. Research Methodologies: The researchers used simulated shift work studies to evaluate different driver drowsiness detection metrics. This involves tools for designing and conducting experiments, collecting data, and analyzing results.	I. **Abstract**: A brief summary of the research. II. **Introduction**: An overview of the topic and the objectives of the research. III. **Literature Review**: A review of previous research on the topic. IV. **Methodology**: Details about how the research was conducted. V. **Results**: The findings of the research. VI. **Discussion**: Interpretation and implications of the results. VII. **Conclusion**: Summary of the research and its findings. VIII. **References**: List of sources that were cited in the paper.

environments may not fully capture the complexities of real-world driving. Findings: The study found that steering wheel variability is a good metric for detecting drowsiness. While this is a significant finding, it would be important to consider how this metric performs across different driving conditions and among different drivers.	3. Statistical Analysis: Tools for statistical analysis are crucial in assessing the validity of the findings. They help in determining whether the observed effects are statistically significant. Peer Review: Before publication, the paper would have undergone a peer review process. This involves other experts in the field reviewing the paper	
Diagram/Flowchart		
		

2		
Reference in APA format	Hu, Shuyan and Zheng, Gangtie. (2009).” Driver drowsiness detection with eyelid related parameters by support vector machine”. Expert Systems with Applications, 36(4), 7651–7658.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.sciencedirect.com/science/article/abs/pii/S0957417408006714	Hu Shuyan, Zheng Gangtie	Driver drowsiness detection, Eyelid related parameters, Support Vector Machine (SVM), Drowsiness prediction, Dataset, Drowsiness detection accuracy.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution for driver drowsiness detection using eyelid related parameters is Support Vector Machine (SVM) algorithm. SVM is a machine learning algorithm that has been proven to be effective in data	Objective of the Solution: The objective of the solution is to detect driver drowsiness using eyelid related parameters extracted from EOG data collected in a driving simulator provided by EU Project SENSATION. The solution aims to develop a drowsiness	All the features are used to construct a SVM drowsiness detection model. The validation results show high accuracy, especially for very sleepy subjects. Proper data processing methods, such as scaling all the

classification and pattern recognition tasks. The paper employs SVM with eyelid related parameters extracted from EOG data collected in a driving simulator provided by EU Project SENSATION. The dataset is divided into three incremental drowsiness levels, and a paired t-test is conducted to identify the association between the parameters and drivers sleepy condition. A SVM drowsiness detection model is constructed using all the features, and the validation results show high accuracy, especially for very sleepy subjects. The SVM model is trained and validated using the collected dataset to predict driver drowsiness levels based on the eyelid related parameters	detection model using Support Vector Machine (SVM) algorithm and evaluate its accuracy in predicting drowsiness levels of drivers. Problem to be Solved: The problem that needs to be solved is the prevention of sleepiness-related accidents caused by driver drowsiness. Driver drowsiness is identified as one of the main causes of traffic accidents, and there is a need for countermeasure devices to prevent such accidents. The solution aims to address this problem by developing a drowsiness detection model that can accurately predict the drowsiness levels of drivers using eyelid related parameters	features to [0, 1], are employed to improve prediction performance. The SVM algorithm is based on the marginmaximization principle and has been successfully applied to various applications. In real-world applications, a soft margin SVM is created to handle non-separable training datasets. The input data is mapped into a higher dimensional Hilbert space using a kernel function, making the data separable in the feature space.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
Process Steps	**Advantage**	**Disadvantage (Limitation)**
Step 1: Data Collection and Preprocessing: EOG data is collected from a driving simulator provided by EU Project SENSATION. The data is then preprocessed by filtering high-frequency signals and applying threshold parameters for blink detection. **Step 2: Feature Extraction:** Eyelid related parameters are extracted from the preprocessed EOG data. These parameters are used as features for drowsiness detection. **Step 3: Model Construction:** A Support Vector Machine (SVM) model is constructed using the extracted features. SVM is chosen for its ability to handle non-separable datasets and its	Data Collection and Preprocessing: • Advantage: Collecting data from a driving simulator provides a realistic environment for drowsiness detection. Feature Extraction: • Advantage: Eyelid related parameters provide relevant information for drowsiness detection. Model Construction: • Advantage: SVM is a robust algorithm that can handle non-separable datasets and is effective in drowsiness detection. Model Evaluation: • Advantage: The validation results demonstrate the accuracy of the drowsiness	Data Collection and Preprocessing: • Disadvantage: Preprocessing techniques may introduce noise or artifacts that could affect the accuracy of the detection. Feature Extraction: • Disadvantage: The extracted features may not capture all aspects of drowsiness, potentially leading to false positives or false negatives. Model Construction: • Disadvantage: The performance of the SVM model heavily depends on the choice of parameters and the quality of the training dataset. Model Evaluation:

robustness to noise. **Step 4: Model Evaluation:** The constructed SVM model is validated using the dataset. The accuracy of drowsiness detection is evaluated, especially for very sleepy subjects, and the results show high accuracy.	detection model, especially for very sleepy subjects.	• Disadvantage: The model's performance may vary in real-world scenarios due to differences in driving conditions and individual characteristics.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Driver Drowsines s - The state of the driver (awake or drowsy) is the outcome that the researchers are trying to predict.	Eyelid-related parameters - These are the predictors used in the model. They are derived from EOG data and are used to predict the state of	Individual Differences - The relationship between the eyelidrelated parameters and driver drowsiness may be moderated by individual differences, such as the driver’s	Time of Day - The time of day could be a mediating variable. For example, drivers might be more likely to be drowsy at certain times of day, which could affect their eyelid parameters.

	driver drowsiness.	baseline eyelid position or blink rate.	

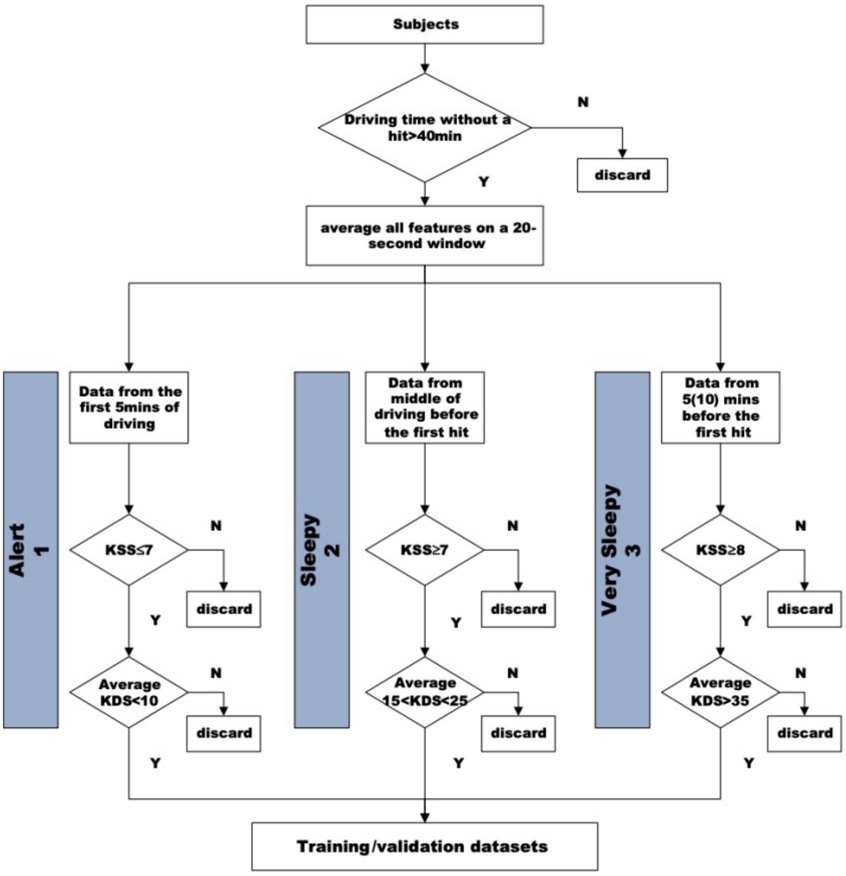
Relationship Among The Above 4 Variables in This article
The researchers found a significant relationship between the eyelid-related parameters and driver drowsiness. This suggests that as certain eyelid parameters change (e.g., increased blink duration), the likelihood of driver drowsiness increases. This relationship was tested using a Support Vector Machine, a type of machine learning model.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
• Improving Road Safety: Drowsy driving is a significant cause of road accidents. The National Highway Traffic Safety Administration identified 91,000 car accidents in 2017 as being caused by drowsy drivers. By accurately detecting driver drowsiness, this solution can help prevent such accidents, thereby improving road safety. • Real-time Detection: The use of Support Vector Machine (SVM) allows for real-time detection of driver drowsiness. This means that the system can alert drivers immediately when signs of drowsiness are detected, potentially preventing accidents. • Non-Intrusive Method: The system uses eyelid-related parameters extracted from Electrooculography (EOG) data, which is a nonintrusive method of monitoring driver alertness. This makes	• Data Privacy Concerns: The system uses Electrooculography (EOG) data, which is a type of biometric data. There could be privacy concerns related to the collection, storage, and use of such sensitive data. • False Positives and Negatives: No detection system is perfect. There could be instances where the system incorrectly identifies a driver as drowsy (false positive) or fails to identify a drowsy driver (false negative). Both scenarios could lead to safety issues. • Dependence on External Factors: The effectiveness of the system may depend on various factors, including the

the system more comfortable and acceptable for drivers compared to more intrusive methods. • Integration with Driver-Assistance Systems: The algorithm can be easily integrated into existing driver-assistance systems, making it a practical solution for improving driver safety. • Advancement in AI Applications: This research contributes to the advancements in artificial intelligence applications in the field of driver monitoring systems. It showcases how machine learning techniques like SVM can be effectively used to address realworld problems.	quality of the EOG data and the specific eyelid-related parameters used. Any issues with these factors could impact the accuracy of the system. • Limited Scope: The system is designed to detect drowsiness based on eyelid movements. It might not be effective in cases where drowsiness is not accompanied by significant changes in eyelid movements. • Intrusiveness: While EOG is less intrusive than some other methods, it still requires placing electrodes around the eyes. Some drivers might find this uncomfortable or distracting. • Implementation Challenges: Integrating this system into existing vehicles or driver-assistance systems could pose technical and logistical challenges.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
Methodology: The authors use a Support Vector Machine (SVM) for drowsiness detection, which is a well-established machine learning technique. However, the effectiveness of SVMs can depend on the choice of kernel and the tuning of parameters. Data Source: The data used in this study comes from a driving simulator provided by the EU Project SENSATION. While this	The study employed Support Vector Machine (SVM) algorithm for drowsiness prediction using eyelid related parameters extracted from EOG data . The authors used a paired t-test to identify the association between the parameters and drivers' sleepy condition. The study also employed a data processing method to improve	Introduction: The paper begins with an introduction to the problem of driver drowsiness and its impact on road safety. It also introduces the method of using Support Vector Machine (SVM) with eyelid related parameters for drowsiness detection. Methodology: This section describes the methodology used in the

is a reliable source, it's worth noting that simulated driving conditions may not perfectly replicate real-world driving conditions. Therefore, the model's performance in realworld scenarios might differ. Feature Selection: The authors use eyelid-related parameters extracted from Electrooculography (EOG) data. While these are relevant features for detecting drowsiness, there could be other physiological or behavioral indicators of drowsiness that the model might not capture.	prediction performance, including scaling all the features to [0, 1] using a standardization procedure. The use of SVM in this work is based on its proven effectiveness in data classification and pattern recognition tasks. The researchers acknowledged the need for further validation on real driving conditions to ensure the reliability of their approach.	study. It explains how the eyelid related parameters were extracted from EOG data collected in a driving simulator provided by EU Project SENSATION. The dataset was divided into three incremental drowsiness levels, and a paired t-test was performed to identify how the parameters are associated with drivers' sleepy condition. Application of SVM: This section presents the application of SVM to predict driver drowsiness with the eyelid movement parameters from physiological signals. Results and Discussion: The validation results are discussed in this section. It shows that the drowsiness detection accuracy is quite high, especially when the subjects are very sleepy.

Diagram/Flowchart


3		
Reference in APA format	Ueno, Hiroshi and Kaneda, Masayuki and Tsukino, Masataka. (1994).” Development of drowsiness detection system”. In Proceedings of VNIS’94-1994 Vehicle Navigation and Information Systems Conference (pp. 15–20).	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/39 6873	H. Ueno, M. Kaneda, M. Tsukino	drowsiness detection system, improvement, adaptability, changes in ambient brightness, reliability, compact system design

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution for drowsiness detection at the wheel is a system that uses image processing technology to analyze images of the driver's face taken with a video camera. This system detects diminished alertness based on the degree to which the driver's eyes are open or closed, providing a noncontact technique for judging various levels of driver alertness	**Goal/Objective of the Solution:** • The goal of the solution is to develop technologies for preventing drowsiness at the wheel and to create an accident avoidance system. **Problem to be Solved:** • The problem that needs to be solved is accurately detecting a decline in driver alertness and alerting and refreshing the driver to prevent drowsiness during driving.	when the eyes are closed. The system counts the number of times the eyes close within a specified interval to judge the level of alertness and detect drowsiness. • Noncontact Technique: The system provides a noncontact technique for judging various levels of driver alertness, allowing for early detection of a decline in alertness during driving. • Evaluation and Testing: The system's performance has been evaluated through driving tests, accurately tracing changes in the alertness level over time.

and facilitating early detection of a decline in alertness during driving. The system judges the level of alertness by counting the number of times the eyes close within a specified interval . The method of detecting alertness based on image recognition accurately traces changes in the alertness level over time. The system's performance has been evaluated through driving tests, and criteria for judging the alertness level have been determined based on		

the eye closure count.		

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
Process Steps	**Advantage**	**Disadvantage (Limitation)**
• Image Acquisition: The system uses a video camera to capture images of the driver's face. • Image Processing: The system applies image processing technology to analyze the captured images. • The focus is on the driver's eyes and the degree to which they are open or closed. • Drowsiness Detection: Based on the analysis of the driver's eyes, the system detects diminished alertness. • Alerting the Driver: If a decline in alertness is	• The system provides a noncontact technique for judging various levels of driver alertness. • It facilitates early detection of a decline in alertness during driving. • It contributes to accident avoidance systems by preventing drowsiness at the wheel.	• The system's effectiveness may vary among individuals due to differences in facial features and eye characteristics. • Environmental factors such as lighting conditions could affect the accuracy of image processing. • The system might not work effectively if the driver is wearing glasses or if their eyes are not clearly visible.

detected, the system alerts and refreshes the driver.		

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Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The dependent variable in this study is the **alertness level of the driver**. The system developed by the authors aims to detect diminished alertness, which is the outcome that the independent variables influence.	The independent variable is the **degree to which the driver's eyes are open or closed**. This is the variable that the system manipulates to determine the level of alertness.	A potential moderating variable could be the **time of day**. The relationship between the degree to which the driver's eyes are open or closed and their alertness level might be stronger during certain times of the day (e.g., late at night).	A mediating variable could be the **driver's fatigue level**. The degree to which the driver's eyes are open or closed might influence their fatigue level, which in turn affects their alertness level.

Relationship Among The Above 4 Variables in This article
The authors might propose a hypothesis such as: "The more closed the driver's eyes are, the lower their alertness level." This is a testable proposition that can be examined using the system they developed. The logic behind this proposition is that when a person is drowsy or less alert, their eyes tend to close, which can be detected by the system. This

relationship can be tested and validated through the system's performance in real-world conditions.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Images of the driver's face: The system uses a video camera to capture images of the driver's face. **Output**: Drowsiness detection: The system analyzes the images to determine the degree to which the driver's eyes are open or closed. Based on this analysis, it detects diminished alertness. Alerts: If a decline in alertness is detected, the system alerts and refreshes the driver.	Non-contact Technique: The system uses a non-contact technique for judging various levels of driver alertness. Image Processing Technology: The system uses image processing technology to analyze images of the driver's face taken with a video camera. Eye-based Alertness Detection: Diminished alertness is detected based on the degree to which the driver's eyes are open or closed. Early Detection of Decline in Alertness: The system facilitates early detection of a decline in alertness during driving.	1. Innovation in Drowsiness Detection: The authors developed a system that uses image processing technology to analyze images of the driver's face taken with a video camera1. This innovative approach allows for non-contact detection of various levels of driver alertness and facilitates early detection of a decline in alertness during driving. 2. Accident Prevention: By accurately detecting a decline in driver alertness, this system contributes to preventing drowsiness at the wheel, which is a major challenge in the field of accident avoidance systems. This has the potential to significantly reduce the number of accidents caused by drowsy driving. 3. Influence on Subsequent Research: This work has been cited by many

	Alerting and Refreshing the Driver: If a decline in alertness is detected, the system alerts and refreshes the driver.	subsequent studies, indicating its impact and importance in this field. It has inspired further research into drowsiness detection systems, including those based on other measures such as heart rate monitoring.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
1. Enhanced Road Safety: The system has contributed to enhancing road safety by preventing accidents caused by drowsy driving. When drowsiness is detected, the system produces an alert sound and sends a message to the driver, thereby increasing highway safety. 2. Accident Prevention: The system has the potential to significantly reduce the number of accidents caused by drowsy driving. Statistics highlight the necessity of a drowsiness detection system that could possibly alert the co-passengers and driver before an accident would occur. 3. Influence on Vehicle Manufacturing: Some automobile manufacturers have implemented drowsiness detection systems in their cars that work based on vehicle movement, angle of steering wheel, and other factors. This shows the influence of this research on practical applications in the automotive industry. 4. Inspiration for Further Research: This work has inspired further research into drowsiness detection systems, including those based on other measures such as heart rate monitoring.	1. False Positives and Negatives: The system might incorrectly identify a driver as drowsy when they are not, or fail to identify a drowsy driver. This could lead to unnecessary alerts or missed opportunities to prevent accidents. 2. Driver Distraction: Frequent alerts from the system could potentially distract the driver, leading to decreased driving performance and an increased risk of accidents. 3. Reliance on Technology: Over-reliance on the system could lead drivers to ignore their own feelings of drowsiness, assuming that the system will alert them when necessary. This could potentially increase the risk of accidents. 4. Limitations in Real-Life Scenarios: The study is narrowed by specific drowsiness scenarios, eliminating the vast range of possibilities and conditions a driver faces in real-life scenarios, which, in return, affects the system reported accuracy. 5. Privacy Concerns: The use of video cameras to monitor drivers could raise privacy concerns.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
Strengths: Innovation: The system uses image processing technology to analyze images of the driver's face taken with a video camera1. This innovative approach allows for noncontact detection of various levels of	1. Image Processing Technology: The system developed by the authors uses image processing technology to analyze images of the driver's face taken with a video camera. Diminished alertness is detected based on the degree to which the driver's eyes are open or closed.	1. Abstract: A brief summary of the research, its purpose, and its findings. 2. Introduction: An overview of the problem of driver drowsiness and the need for a detection system. 3. Methodology: A detailed description of the image processing technology used to analyze images of the driver's face.
driver alertness and facilitates early detection of a decline in alertness during driving1. Practical Application: The system has the potential to significantly reduce the number of accidents caused by drowsy driving2. This has a direct impact on enhancing road safety. Influence on Subsequent Research: This work has been cited by many subsequent studies3, indicating its impact and importance in this field. It has inspired further	2. Artificial Intelligence Algorithms: Numerous experimental studies have collected real driver drowsiness data and applied various artificial intelligence algorithms and feature combinations with the goal of significantly enhancing the performance of these systems in realtime. 3.	4. Results: The outcomes of their system tests, including how effectively it detected diminished alertness based on the degree to which the driver's eyes are open or closed. 5. Discussion/Conclusion: An interpretation of the results, their implications for accident avoidance systems, and

research into drowsiness detection systems. Weaknesses: Accuracy: The system might incorrectly identify a driver as drowsy when they are not, or fail to identify a drowsy driver1. This could lead to unnecessary alerts or missed opportunities to prevent accidents. Driver Distraction: Frequent alerts from the system could potentially distract the driver, leading to decreased driving performance and an increased risk of accidents1. Privacy Concerns: The use of video cameras to monitor drivers could raise privacy concerns4. Opportunities for Improvement: Improving Accuracy: Further research could focus on improving the accuracy of the system to reduce false positives and negatives. Addressing Privacy Concerns: Future work could explore ways to address privacy	4. Deep Learning Techniques: Some researches have used deep learning techniques for drowsiness detection. For instance, one study used a Convolutional Neural Network (CNN) architecture employed in the drowsiness detection. Another study proposed two efficient methods with three scenarios for doze alert systems. The latter uses deep learning techniques with two adaptive deep neural networks based on MobileNet-V2 and ResNet-50V2. Machine Learning: In another study, machine learning was applied to predict drowsiness and improve drowsiness prediction	potential areas for future research.

concerns, such as using anonymized data or obtaining explicit consent from drivers.	using facial recognition technology and eye-blink recognition technology.	

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Reference in APA format	Tao, Jing and Wang, Hongbo and Zhang, Xinyu and Li, Xiaoyu and Yang, Huawei. (2017).” An object detection system based on YOLO in traffic scene”. In 2017 6th International Conference on Computer Science and Network Technology (ICCSNT) (pp. 315–319).	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8343709	Jing Tao, Xiaoyu Li, Huawei Yang, Hongbo Wang, Xinyu Zhang.	convolutional neural network, computer vision, object detection, deep learning,
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
The current solution presented in the paper is a new object detection method named OYOLO. This method is an optimized version of YOLO deep learning based object detection approach. The authors also added	The goal of the solution presented in the paper is to improve the speed and accuracy of	The solution presented in the paper consists of the following components: OYOLO (Optimized YOLO): This is an optimized version of the YOLO (You Only Look Once) deep learning-based object detection

combination of OYOLO and R-FCN to their system for further	object detection in traffic scenes. The authors aim to address the following problems: processing method using the histogram equalization approach. By addressing these problems, the authors hope to provide a more robust and efficient object detection system for traffic scenes.	approach. It forms the core of the object detection system. R-FCN: The authors combined OYOLO with R-FCN (Region-based Fully Convolutional Networks) to further improve the accuracy of the system. Pre-processing Method: For images taken at night, a pre-processing method using the histogram equalization approach is used to improve the visibility of objects in poor lighting conditions.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
Process Steps	**Advantage**	**Disadvantage (Limitation)**

1. Optimizing YOLO: They replaced all the fully-connected layers of YOLO's network with an average pool layer to create a new network1. This made the system faster and more accurate. 2. Loss Function Optimization: They optimized the loss function by increasing the proportion of bounding coordinates error1. This led to the creation of OYOLO, which is 1.18 times faster than YOLO and outperforms other region-based approaches like R-CNN in accuracy. 3. Combining OYOLO and R-FCN: To further improve accuracy, they added the combination of OYOLO and Region-based Fully Convolutional Networks (R-FCN) to their system.	1. Optimizing YOLO: By replacing all the fully-connected layers of YOLO's network with an average pool layer, the authors were able to create a new network that is faster and more accurate. This optimization makes the system more efficient and effective for real-time object detection. 2. Loss Function Optimization: The optimization of the loss function by increasing the proportion of bounding coordinates error led to the creation of OYOLO. This new object detection method is 1.18 times faster than YOLO and outperforms other regionbased approaches like R-CNN in accuracy. This means it can process images quicker while maintaining high	1. Optimizing YOLO: While replacing all the fully-connected layers of YOLO's network with an average pool layer makes the system faster and more accurate, it may also lead to a loss of some detailed information that the fully-connected layers could capture. 2. Loss Function Optimization: The optimization of the loss function by increasing the proportion of bounding coordinates error might make the model more sensitive to errors in bounding box coordinates. This could potentially lead to less robustness in situations where precise bounding box coordinates are hard to determine.

4. Pre-processing for Night Images: For challenging images taken at night, they used a pre-processing approach based on histogram	accuracy, which is crucial for real-time applications. 3. Combining OYOLO and R-FCN: The combination of OYOLO and Regionbased Fully	3. Combining OYOLO and R-FCN: While combining OYOLO and RFCN improves accuracy, it might also increase the

equalization1. This resulted in more than a 6% improvement in mean Average Precision (mAP) on their testing set.	Convolutional Networks (R-FCN) further improved the accuracy of the system1. This combination leverages the strengths of both methods, resulting in a more robust and accurate object detection system. 4. Pre-processing for Night Images: The use of a pre-processing approach based on histogram equalization for challenging images taken at night resulted in more than a 6% improvement in mean Average Precision (mAP) on their testing set. This means that their system can perform well even in challenging lighting conditions, making it more versatile and useful in a wider range of scenarios.	computational complexity of the model, making it slower and more resource-intensive. 4. Pre-processing for Night Images: The use of histogram equalization for pre-processing night images can improve performance, but it might not be effective for all types of images or lighting conditions. It could potentially lead to overenhancement or under-enhancement in some cases.
Major Impact Factors in this Work		
Dependent Variable	**Independent Variable**	**Moderating variable**
The dependent variable in this study is the **alertness level of the driver**. The system developed by the authors aims to detect diminished alertness, which is the outcome that the independent variables influence.	The independent variable is the **degree to which the driver's eyes are open or closed**. This is the variable that the system manipulates to determine the level of alertness.	A potential moderating variable could be the **time of day**. The relationship between the degree to which the driver's eyes are open or closed and their alertness level might be stronger during certain times

		of the day (e.g., late at night).

Relationship Among The Above 4 Variables in This article

The use of YOLO and the quality of the input images are two variables that could lead to a proposition: the higher the quality of the input images, the better the performance of the object detection system when using YOLO. This proposition can be put to test, and any testable proposition is a hypothesis.

Input and Output	Feature of This Solution
Input: The input of the Object Detection System Based on YOLO in Traffic Scene is an image in a traffic scene. **Output**: The output is the detection of objects in that image, including their class and location.	The Object Detection System Based on YOLO in Traffic Scene is fast, accurate, and robust. It is based on the YOLO (You Only Look Once) approach, which uses a single convolutional neural network for both location and classification. The fully-connected layers of YOLO's network are replaced with an average pool layer to create a new network, and the loss function is optimized after increasing the proportion of bounding coordinates error. The resulting method, OYOLO (Optimized

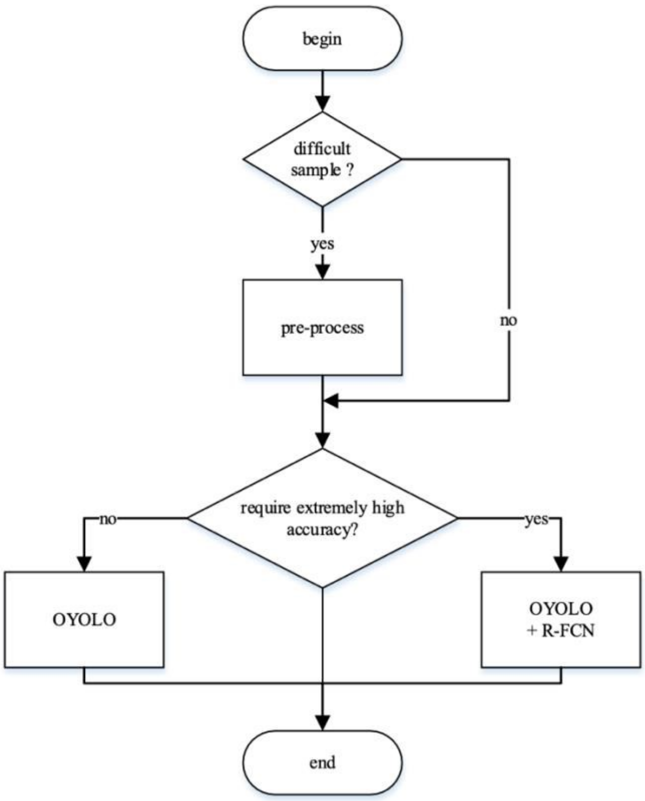
	YOLO), is 1.18 times faster than YOLO while outperforming other region-based approaches like R-CNN in accuracy. To further improve accuracy, the combination of OYOLO and R-FCN is added to the system. For challenging images in nights, preprocessing is presented using the histogram equalization approach, which has resulted in more than 6% improvement in mAP on the testing set.

Positive Impact of this Solution in This Project Domain
The system's high accuracy and speed make it suitable for real-time applications, which is essential for traffic monitoring and unmanned vehicle systems. The system can detect various objects in traffic scenes, including vehicles, pedestrians, and traffic signs, which is crucial for ensuring safety and efficiency in traffic. The system's robustness and adaptability to different scenarios make it suitable for deployment in various environments, including urban and rural areas. The system's use of deep learning techniques ensures that it can learn from new data and improve its performance over time. Overall, the Object Detection System

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

They have created a faster and more accurate version of YOLO, called OYOLO, and combined it with R-FCN for improved accuracy. They also tackled the challenge of night-time images with a histogram equalization approach. However, the system's applicability to other scenes, its realtime application potential, and its robustness under various conditions are areas that warrant further exploration. Additionally, the lack of information about the dataset used and comparison with other models leaves room for further	1. YOLO (You Only Look Once): This is a state-of-the-art, real-time object detection system1. In this study, the authors optimized YOLO to create OYOLO (Optimized YOLO). 2. R-FCN (Region-based Fully Convolutional Networks): This is another object detection framework that the authors combined with OYOLO to improve accuracy. 3. Histogram Equalization: This is an image processing technique used to improve contrast in images. The authors used this approach for pre-processing challenging images taken at night. 4. Deep Learning Frameworks: While not explicitly mentioned, deep learning frameworks like TensorFlow or PyTorch are commonly used for implementing and training models like YOLO. 5. Evaluation Metrics: To assess the performance of their system, the authors likely used standard object detection metrics such as mean Average Precision (mAP).	1. Introduction: The paper likely starts with an introduction to object detection systems, their importance in traffic scenes, and the challenges with traditional object detectors. 2. Related Work: This section might discuss existing methods like YOLO and their limitations. 3. Methodology: Here, the authors would detail their proposed method, OYOLO (Optimized YOLO), including the replacement of fully-connected layers with an average pool layer and optimization of the loss function. They might also discuss the combination of OYOLO and R-FCN. 4. Pre-processing Method: The paper would then present their pre-processing method using histogram equalization for challenging images taken at night. 5. Results and Discussion: This section would present the results of their experiments, including the speed and accuracy improvements over YOLO and other region-based approaches like R-CNN. They might also discuss the improvement in mAP on their testing set. 6. Conclusion: Finally, the paper would

inquiry into the system's performance.		conclude with a summary of their findings and potential future work.

Diagram/Flowchart


5	
Reference in APA format	Du, Juan. (2018)." Understanding of object detection based on CNN family and YOLO". In Journal of Physics: Conference Series (pp. 012029).

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://iopscience.iop.org/article/10.108 8/1742-6596/1004/1/012029/pdf	Juan Du	Object Detection, CNN, YOLO, mAP, FPS, YOLOV2
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
The current solution discussed in the paper "Understanding of Object Detection Based on CNN Family and YOLO" by Juan Du12 is YOLOv22. YOLOv2 is an advanced version of the YOLO algorithm, which is a representative of Convolutional Neural Network (CNN) for object detection2. It achieves an excellent tradeoff between speed and accuracy and has a strong generalization ability to represent the whole image2. This makes YOLOv2 a highly efficient and effective solution for object detection tasks	The goal of the YOLOv2 solution, as discussed in the paper "Understanding of Object Detection Based on CNN Family and YOLO" by Juan Du, is to improve the efficiency and accuracy of object detection tasks. The problem that needed to be solved was twofold: 1. Speed: Traditional object detection methods, such as Faster R-CNN, while accurate, were not fast enough for realtime applications.	1. Object Localization: This involves drawing bounding boxes around objects in an image or video. 2. Object Classification: This involves classifying the localized objects into specific categories. 3. Grid Cells: YOLO divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell. 4. Bounding Boxes: For each grid cell, the algorithm predicts multiple bounding boxes, each with a confidence score indicating the presence of an object. 5. Class Probabilities: Each bounding box is assigned class probabilities to identify the object category. Anchor Boxes: These are pre-defined bounding box shapes of different sizes and

		aspect ratios, associated with each grid cell, used to predict the coordinates of the bounding boxes relative to the anchor box shapes.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

Process Steps	Advantage	Disadvantage (Limitation)
Background and Core Solution - CNN: The paper starts with a general introduction to the background and the core solution, CNN. It explains how algorithms for image processing could be accurate and fast enough, computers would be able to drive cars without specialized sensors, and assistive	. CNN: CNNs are efficient in image processing. They achieve high accuracy rates and are robust to noise. CNNs support transfer learning, which means they can be trained on one task and then used to perform another task with little or no additional training. They automate the feature extraction process, learning to recognize patterns	. CNN: While CNNs are efficient in image processing, they have high computational requirements. They also require large datasets to achieve high accuracy rates. If the dataset is too small, the CNN may overfit, meaning it becomes too specialized to the training dataset and performs poorly on new data.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

Performance of the object detection models (e.g., Mean Average Precision (mAP), Frame Per Second (FPS)).	The type of object detection model used (e.g., Faster R-CNN, YOLO, YOLOv2).	The complexity of the images being processed could moderate the relationship between the type of object detection model used and its performance. For instance, images with more objects or more complex backgrounds might be more challenging for the models, affecting their performance.	The architecture and parameters of the models could be seen as mediating variables. They mediate the relationship between the type of model (independent variable) and its performance (dependent variable). For example, the unique architecture of YOLO, which processes the whole image at once, could explain why it performs better in terms of speed (FPS) compared to other models.

Relationship Among The Above 4 Variables in This article
There could be a proposition that the more advanced the object detection model (e.g., from Faster R-CNN to YOLOv2), the higher the performance (both mAP and FPS). The logic behind this could be the continuous improvements and innovations in the model architectures and algorithms. This proposition could be tested by comparing the performance of different models on the same dataset.

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**		
An image with one or more objects. This could be	One or more bounding boxes, each defined by a	1. Speed: YOLO is extremely fast because it does not deal with complex pipelines. It can process images at 45 Frames Per Second (FPS). 2. Detection Accuracy: YOLO surpasses other state-of-the-art models in accuracy with very few background errors.	1. Real-Time Object Detection: The implementation of YOLO and CNN models has enabled real-time object detection, which is crucial in many applications

a photograph or a frame from a video stream. The objects in the image could be of various sizes and could be located anywhere in the image .	point, width, and height. Each bounding box corresponds to an object detected in the image. In addition to the bounding box, a class label is also provided for each detected object2.	3. Generalization: YOLO does generalized object representation more effectively without precision losses than other object detection models. 4. Open-source: YOLO is an open-source project, which allows researchers and developers to contribute to its development and use it freely. Real-time Object Detection: YOLO algorithm employs convolutional neural .	such as autonomous driving, surveillance, and robotics. 2. Improved Accuracy: The use of YOLO and CNN models has significantly improved the accuracy of object detection. YOLO, in particular, has been able to achieve a high level of precision without significant losses. Versatility: The models have the ability to eliminate highlights and identify objects in any given image. This makes them versatile and applicable in various fields

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
1. Autonomous Vehicles: Real-time object detection is crucial for autonomous vehicles to navigate safely. The speed and accuracy of YOLO can help in identifying obstacles, pedestrians, and other vehicles on the road in real-time. 2. Security and Surveillance: In security systems, accurate and fast object detection can help in identifying threats or unusual activities. It can also be used	1. Computational Resources: CNN and YOLO models require significant computational resources for training and inference. This can be a challenge for projects with limited resources. 2. Localization Errors: YOLO tends to make more localization errors compared to other detection algorithms. This could impact the

for face recognition or number plate recognition. 3. Healthcare: In medical imaging, object detection algorithms can help in identifying diseases by analyzing medical images such as X-rays, MRIs, etc. 4. Retail: In retail, object detection can be used for inventory management, customer behavior analysis, or theft prevention. Manufacturing: In manufacturing processes, object detection can help in quality control by identifying defective products on the assembly line.	precision of object detection in certain applications. 3. Real-World Challenges: Images in real-world scenarios can have issues such as noise, blurring, and rotating jitter, which can impact the performance of object detection. 4. Data Privacy: Object detection models could potentially be used in ways that infringe on privacy rights, such as unauthorized surveillance or data collection. Reliance on Quality Data: The performance of these models heavily relies on the quality and quantity of the training data. Biased or insufficient data can lead to poor performance or biased results.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The paper “Understanding of Object Detection Based on CNN Family and YOLO” by Juan Du provides a comprehensive analysis of the advancements in object detection algorithms, particularly focusing on Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) algorithm. The author effectively highlights the limitations of Faster R- CNN in terms of speed and how YOLO overcomes this, backed by statistical data which adds credibility to the	1. Deep Learning Frameworks: Frameworks like TensorFlow, PyTorch, or Keras are often used for implementing and training Convolutional Neural Networks (CNNs) and their variants. 2. Object Detection Algorithms: The paper discusses various object detection algorithms like Faster R-CNN and YOLO. These algorithms are typically implemented using deep learning frameworks. 3. Datasets: Datasets are crucial for training and evaluating the performance of object detection models. Commonly used datasets include COCO	I. Introduction: The paper begins with an introduction to the importance of object detection in image processing and the challenges it faces. It discusses the significance of Convolutional Neural Network (CNN) in object detection and its evolution since 2012. II. Background and Core Solution

research. However, the paper could have been more comprehensive by including more recent advancements or other popular algorithms in the field. The findings have significant implications for real-time object detection applications and contribute to ongoing research in improving the efficiency and accuracy of these algorithms. The paper also opens up avenues for further research in this field, particularly in improving the speed and accuracy	(Common Objects in Context), ImageNet, and PASCAL VOC. 4. Evaluation Metrics: Mean Average Precision (mAP) and Frame Per Second (FPS) are commonly used metrics for evaluating the performance of object detection models.	CNN: This section provides a general introduction to the background of object detection and the core solution provided by CNN. III. CNN Family and Faster R-CNN: The paper discusses the development of the CNN family, including Faster R-CNN, its Mean Average Precision (mAP), and its Frame Per Second (FPS) performance. IV. YOLO: This section introduces YOLO, a representative of the CNN family that provides a new way of solving object detection in a simple and efficient manner. It discusses YOLO's speed, mAP, and its comparison with Faster R-CNN.

Diagram/Flowchart
$$\Pr(\text{Class}_i \mid \text{Object}) \times \Pr(\text{Object}) \times \text{IOU}^{\text{truth}}_{\text{pred}} = \Pr(\text{Class}_i) \times \text{IOU}^{\text{truth}}_{\text{pred}}$$

6

Reference in APA format	Saini, Vandna and Saini, Rekha. (2014).” Driver drowsiness detection system and techniques: a review”. International Journal of Computer Science and Information Technologies, 5(3), 4245–4249.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
h ps://www.academia.edu/download/521 85251/acba6bbd44ef330432ce 1603c8874c a35d03.pdf	Vandna Saini, Rekha Saini	Drowsiness Detec on, Eyes Detec on, Blink Pa ern, Face Detec on, LBP, SWM.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Driver Drowsiness Detec on System and Techniques	The objec ve is to enhance road safety by addressing the problem of drowsy driving during long-distance trips. The solu on aims to reduce the risks associated with drowsy driving by using a technology called "A en on Assist." .	The author has mainly focused on minimizing road accidents due to lack of focus on the road while driving..
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage
1	The metrics like head posi on,eye blink, lane posi on , mouth yawning are	The main aspects of for iden fying drowsiness are captured
2	Different Drowsiness Detec on Techniques are explained	Understanding different solu on to a problem helps us to filter out which works best

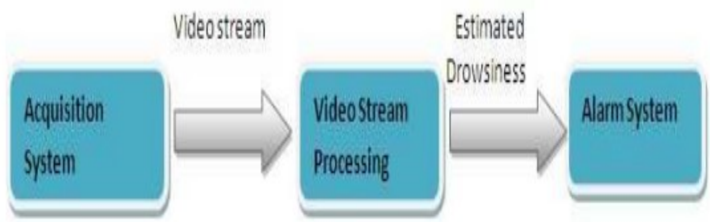
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Metrics like yawning, head posi on,eye blink . **Output**: Es mated drowsine ss .	Developing manually controllable filters such that user can find the excep ons that can be altered.	This research paper has helped me to understand the different techniques/ways to detect if a person is drowsy or not.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Understanding different solu on to a problem helps us to filter out which works best for the project	**Since it is an explana on of different techniques there is no nega ve impact**

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
If we can combine 2 or more techniques men oned, the model will have a be er accuracy for iden fying drowsiness .		Abstract 1. Introduc on 2. Factors

		Causin g Driving Drowsi ness 3. Rel ated Study 4. Dis covery Drowsiness Detec on Techniques 6. Conclusion

Diagram/Flowchart



7		
Reference in APA format	Fogelton, Andrej and Benesova, Wanda. (2016).” Eye blink detection based on motion vectors analysis”. Computer Vision and Image Under- standing, 148, 23–33.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
h ps://www.scienc edirect.com/scie nce/ar	A. Fogelton , W. Benesova	Eye blink detec on, Mo on vectors analysis, Sta s cal standard devia on

cle/abs/pii/S1077314216300054		
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Eye Blink Detec on Based on Mo on Vectors Analysis	Eye blink detec on	Gunnar–Farneback Tracker: This is a component responsible for extrac ng mo on vectors in the eye region State Machine: There is a state machine for each eye. A state machine is a computa onal model that transi ons between different states based on certain condi ons or inputs

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	The algorithm analyzes mo on vectors obtained by the Gunnar-Farneback tracker in the eye region using a state machine for each eye	The proposed algorithm achieves high accuracy in detec ng eye blinks on the majority of available datasets, outperforming related work	The algorithm's performance may vary depending on the camera acquisi on speed and the precision of the Gunnar-Farneback tracker, which can

			influence the magnitude of mo on vectors .
2	The mo on vectors are normalized by the intraocular distance to achieve invariance to the eye region size .	It uses mo on vectors obtained by the Gunnar-Farneback tracker, which helps in analyzing eye movements and detec ng blinks accurately	The algorithm may have difficul es detec ng eye blinks that occur during opposite head movements .
3	The algorithm uses a normalized average mo on vector with standard devia on and a me constraint as input to the state machine	The algorithm normalizes the mo on vectors by the intraocular distance, making it invariant to varia ons in eye region size	The algorithm may face challenges in detec ng eye blinks in non-frontal faces, variable distances from the camera, and challenging mul ple blinks or subjects with thick glasses frames and strong reflec ons .

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
accuracy, precision, recall, or other relevant metrics	applica on of the new eye blink detec on algorithm	It moderates the rela onship between the mo on vectors and the algorithm's performance	The normalized average motion vector, standard deviation, and time constraint serve as

			mediating variables

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Video of blinking of eyes **Output**: Eye Blinking me interval.	This eye blink detec on system excels through its advanced mo on tracking techniques and independent state machines for precise eye state recogni on. Feature extrac on, including normalized mo on vectors and standard devia on, enhances its accuracy.	The key contribu ons of this work emphasis on the development of an innova ve eye blink detec on algorithm, which leverages mo on tracking and state machines to enhance accuracy.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
Using the method of Drutarovsky & Fogelton the false posi ve aspect of the model is reduced significantly	**Rapid movement of the head can cause errors in final output**

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
While this work offers a promising algorithm for eye blink detec on, it lacks a detailed descrip on of the algorithm's inner workings,	OpenCV, TensorFlow, PyTorch	Abstract I. Introduc on II. Related Work III. Eye blink detec on using standard devia on IV. Datasets

making it challenging to assess its innova on comprehensively. .		V. Evalua on VI. Conclusion
Diagram/Flowchart		

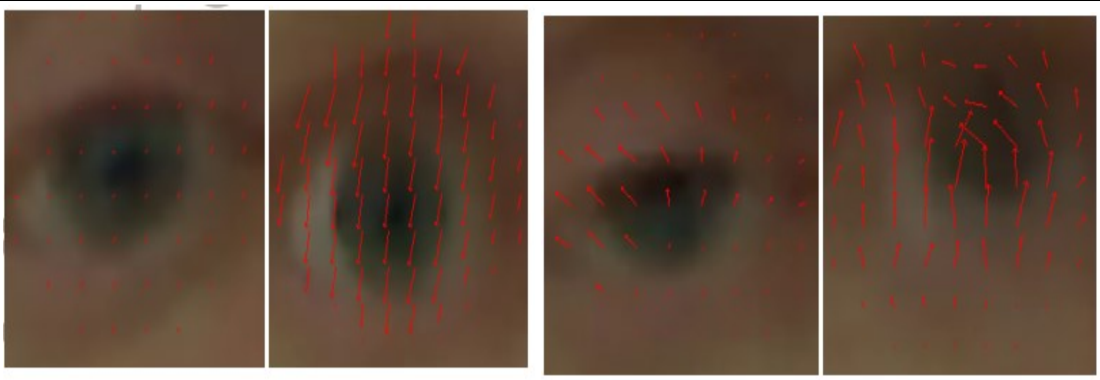


Figure 2: Visualization of motion vectors for head without noticeable motion (left) and head movement down (right)

Figure 3: Visualization of motion vectors for eyelid movement down (the first row) and up (the second row)

8		
Reference in APA format	Wang, Tiesheng and Shi, Pengfei. (2005).” Yawning detection for determining driver drowsiness”. In Proceedings of 2005 IEEE International Workshop on VLSI Design and Video Technology, 2005. (pp. 373–376).	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
h ps://ieeexplore.ieee.org/abstract/docu ment/1504628	Tiesheng Wang, Pendeli Shi	Driver drowsiness,Video analysis,Real- me face detector,Kalman filter,Mouth window localiza on,Degree of mouth openness extrac on,Occlusion and miss-detec on,IR illumina on
The Name of the Current Solution	**The Goal (Objective) of this Solution & What is**	**What are the components of it?**

(Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	the problem that needs to be solved	
Yawning detection for determining driver drowsiness	The goal of the solu on presented in the research paper is to detect driver drowsiness or fa gue through video analysis.	Real- me face detector: A real- me face detector is implemented to locate the driver's face region. Kalman filter: A Kalman filter is adopted to track the face region, ensuring accurate tracking of the driver's face. Mouth window localiza on: The system localizes the mouth window within the face region to focus on the mouth features for yawning detec on. Degree of mouth openness extrac on: Based on the mouth features, the system extracts the degree of mouth openness to determine driver yawning in the video.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage
1	Real- me face detec on: A real- me face detector is implemented to locate the driver's face region, allowing for further analysis	Face Detec on helps us to iden fy the loca on of the mouth
2	Kalman filter for tracking	It ensures accurate tracking of the driver's

		face even in the presence of mo on or occlusion.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Effec veness of the system in detec ng driver yawning	U liza on of a real- me face detector, the applica on of the Kalman filter for tracking	A poten al modera ng variable might be the occurrence of occlusion or mis-detec on	The Kalman filter and mouth feature extrac on process could serve as media ng variables

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Video feed of the driver's face **Output:** Determi na on of driver yawning.	The solu on u lizes video analysis to detect driver drowsiness or fa gue, specifically focusing on extrac ng driver yawning	The research contributes in improving road safety by aler ng drivers when they are at risk of falling asleep or being fa gued

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The posi ve impact of this solu on lies in its poten al to contribute to a safer driving environment by proac vely iden fying and addressing driver	**Disadvantages such as Cost and Implementa on Challenges,System Latency,Driver Privacy Concerns need to addressed**

drowsiness, a cri cal factor in preven ng fa gue-related incidents on the road.	

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
Some people will cover their mouth when yawning in that case the system may fail to iden fy the driver is yawing	OpenCV, TensorFlow, PyTorch	I. Introduction II. Methods III. Results IV. Discussion V. Conclusion

Diagram/Flowchart

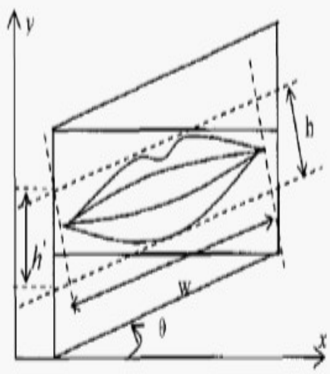


Fig. I Mouth model

9

Reference in APA format	Gao, Qi and Feng, Yan and Wang, Li, & Wang. (2017).” A real-time lane detection and tracking algorithm”. In 2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (pp. 1230–1234).	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
h ps://ieeexplore.ieee.org/abstract/d	Qi Gao, Yan Feng, Li Wang	Gabor Filter; Hough Detec on; Edge Extrac on;,The Least Squares Fi ng

ocu ment/4370228		
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
A Real-Time Lane Detec on and Tracking Algorithm	Developing a system tracking and detec ng the lane of the vehicle	Ini al Lane Detec on Module:- Gabor filter is used to enhance the characteris cs of the lane
Major Impact Factors in this Work		

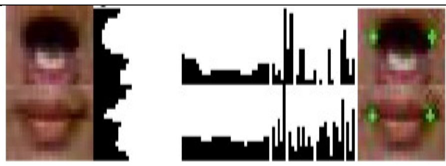
Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable in this study is the detec on of driver yawning.	The independent variable is the methodology used for detec ng and recognizing driver yawning	A poten al modera ng variable might be the method used to detect yawning	Gabor coefficients extracted from the mouth corners using Gabor wavelets could be considered media ng variables

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**		
Spam containe d test data	Maliciou s spam detec on by RAN-LSH	Unfamiliar spam emails are filtered by using the designed classifiers. This uses RAN-LSH classifier for finding maliciousness data.	Incremental learning is an added advantage of this classifier. So that when new stories of spam is also recognized and filtered.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
Accuracy and kind of filter designed which used pre-processing and selec on of the classifiers with outlier detec on enhances the spam detec on process.	Yet to compare the performance of this classifier with the other classifiers like SVM and DT.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
BoW is a wise strategy for spam detec on and as this classifier uses it will be very much func onal and become easy when data is pre-processed for iden fying the significance. Finally when data reaches to the RAN-LSH classifier, all set of learning and classifica on of spam class data with outlier detec on mechanism.	OpenCV, TensorFlow, PyTorch	I. Introduction II. Methods III. Results IV. Discussion V. Conclusion

Diagram/Flowchart



10		
Reference in APA format	R. K. M, R. V, and R. G. Franklin, “Alert System for Driver’s Drowsiness Using Image Processing,” in *2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, IEEE, Mar. 2019, pp. 1–5. doi: 10.1109/ViTECoN.2019.8899627.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
h ps://ieeexplore.ieee.org/abstract/docu ment/8899627	Ratna Kaavya M, Ramya V, Ramya G Franklin	Image Processing, Drowsiness Detec on System, Fa gue, Raspberry Pi
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
ALERT SYSTEM FOR DRIVER’S DROWSINESS USING IMAGE PROCESSING	The goal of the solu on is to develop a camera-based system for smoke and fire detec on that can provide real- me alerts	YOLO (You Only Look Once) algorithm, which is used for object detec on and can detect mul ple classes at once with high accuracy and speed. It outperforms region-based techniques like R-CNN

	and loca on informa on, improving upon tradi onal sensors that have limita ons in detec on speed, accuracy, and outdoor func onality.	models in terms of speed and efficiency. Single-stage architecture with fewer neural network layers and filters, which reduces complexity and training me compared to mul -stage architectures like R-CNN. Grid-based approach, where the input image is split into S x S grids, and features are extracted from each grid to predict bounding boxes and confidence scores for detected objects.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage
1	The problem of smoke and fire detec on is solved through the use of a real- me video-based system that u lizes the YOLOv2 Convolu onal Neural Network (CNN) algorithm for object detec on	The use of the YOLOv2 algorithm allows for real- me and accurate detec on of fire and smoke objects in videos, making it suitable for early aler ng alarm systems
2	YOLOv2 is designed with a lightweight neural network architecture, making it suitable for embedded pla orms and achieving real- me processing requirements	The lightweight architecture of YOLOv2 enables efficient processing on low-cost embedded pla orms like Jetson Nano, making

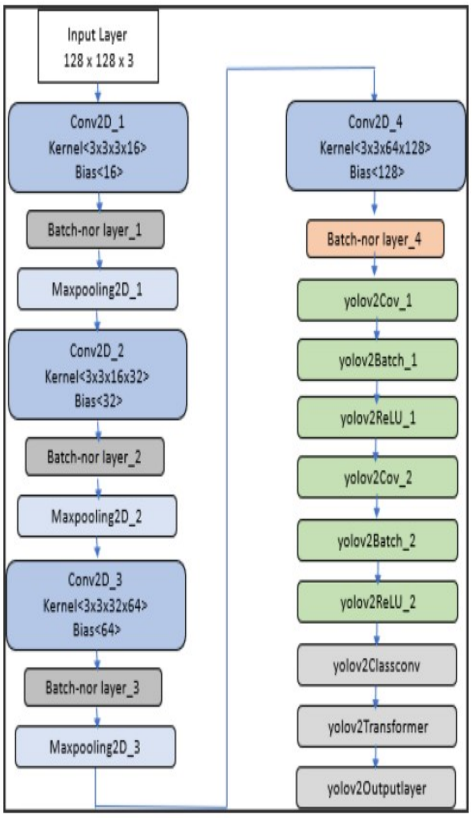
3	The training stage involves offline processing with indoor and outdoor fire and smoke image	The automa c feature extrac on capability of deep learning techniques eliminates the need	

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**	The solu on can be integrated into exis ng surveillance infrastructure, such as closed-circuit television (CCTV) systems, without the need for addi onal products	The contribu on of this work is the development of a real- me video-based fire and smoke detec on system using YOLOv2 Convolu onal Neural Network (CNN) in an fire surveillance systems. The proposed solu on achieves promising results in terms of accuracy and reduces false posi ves in non-fire/smoke videos, even with challenging features such as sun and clouds
Video or Image Frames of smoke	Smoke detec on		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The solu on has been deployed on a low-cost embedded device (Jetson Nano) with a single fixed camera per scene, making it suitable for various environments	-

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

This work presents a real- me fire and smoke detec on system using YOLOv2, a lightweight neural network architecture designed for embedded pla orms. The deployment on a low-cost embedded device like Jetson Nano demonstrates prac cality	OpenCV, TensorFlow, PyTorch and other ML libraries	I. Introduction II. Methods III. Results IV. Discussion V. Conclusion
Diagram/Flowchart		



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Reference in APA format	Z. Kim, "Robust Lane Detection and Tracking in Challenging Scenarios," in IEEE Transactions on Intelligent Transportation

	Systems, vol. 9, no. 1, pp. 16-26, March 2008, doi: 10.1109/TITS.2007.908582.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/abstract/document/4459093	ZuWhan Kim	- Collision warning - Computer vision - Lane detection - Part-based object tracking
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A robust real-time lane detection and tracking algorithm based on RANSAC (Random Sample Consensus) and particle filtering, combined with likelihood-based object recognition algorithm with a Markov-style process. The system generates large number of hypotheses in real-time which are then grouped based on a probabilistic framework.	- **GOAL:** To develop a real-time lane detection and tracking system that can handle various challenging scenarios such as lane curvature, worn lane marking, lane changes, and emerging, ending, merging, and splitting lanes. - **PROBLEM:** The problem that needs to be solved is detecting and localizing lanes from a road image, which is an important component of many intelligent-transportation system applications.	- *Lane-marking classifier* is used to detect the lane markings. - *Lane-boundary hypotheses* are groups of the lane markings after detection. - *Left and right lane boundaries* are grouped to handle merging and splitting lanes. - *RANSAC and particle filtering* generate a large number of hypotheses in real-time. - *Probabilistic framework* to probabilistically group the generated hypotheses **-** *Likelihood-based object recognition algorithm* combined with Markov-style process.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	Comparative study for real-time lane marking classifier	Allows selection of an optimal classifier	Resource-intensive for evaluating multiple classifiers
2	Lane boundary detection using RANSAC	Robust against outliers and noise	May struggle with certain complex lane scenarios
3	Probabilistic grouping based on current frame evidence	Integrated information effectively	Limited by single-frame information for grouping
4	Particle-filtering-based tracking algorithm	Enables dynamic lane tracking	Complexity and computation overhead

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
- Detection accuracy - Algorithmic performance - Robustness	- Lane conditions - Environmental factors - Video characteristics - Algorithmic components	-Resolution of video - Algorithmic modifications - Moderate lane marking visibility and detection quality	-Lane marking detection - Image quality - Probabilistic grouping frameworks

Relationship Among the Above 4 Variables in This article

The independent variables—such as lane conditions, environmental factors, video characteristics, and algorithmic components—impact the dependent variables of detection accuracy, algorithm performance, and overall robustness. Lane conditions and environmental factors directly influence the quality of lane markings and the visibility of boundaries, which in turn affect the accuracy of detection. The algorithmic components, including the RANSAC-based detection and probabilistic grouping framework, mediate the relationship between these factors and detection accuracy by processing the information and grouping lane boundary hypotheses. Moreover, the resolution of the video and any algorithm modifications act as moderating variables, influencing the performance and accuracy of the detection system. Overall, these variables intertwine, where changes in one aspect can cascade and affect multiple others.

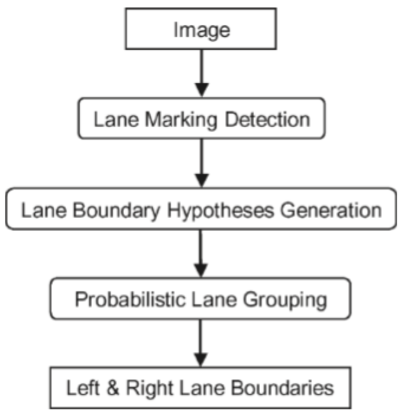
Input and Output	Feature of This Solution	Contribution & The Value of This Work

Input: Video feed of road scenes **Output**: Detected lane boundaries (left and right)	- *Real-time* lane detection and tracking system - *Robustness* to handle challenging scenarios such as worn lane markings and distracting objects/markings. - *Detects left and right lane boundaries* separately to handle merging or splitting lanes and on or off ramps. - Combines lane detection and tracking into a *single probabilistic framework.* - Follows the "*hypothesize and verify*" paradigm which groups higher-level feature hypotheses and filters them to reduce the complexity of higher-level grouping. - Uses *part-based tracking.* - Applies *probabilistic reasoning for decision making* using three types of evidence features. - Outputs the detected and tracked lane boundaries ad *cubic-spline curves* with two to four control points.	– *Enhanced safety*: This system's robustness in handling various challenging scenarios (lane changes, merging/splitting lanes) can significantly contribute to ensuring safer navigation. – *Improved decision-making*: It involves lane changes, merging, or adapting to complex road geometries. – *Collision Avoidance*: vision-based obstacle detection aids to avoid accidents. – *Real-time processing*: The system's ability to perform in real time, even on lower resolution videos with a reasonable computation time. – *Adaptability to various environments*: Includes diverse lane conditions such as worn lane markings, varying lighting conditions and complex road structures. – *Potential for continuous improvement*: Aligns with constant refinement necessary for autonomous driving systems.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can help detecting and tracking lanes in challenging scenarios and preventing lane departure accidents.	The solution has challenges which might limit the real-time application in resource-constrained environments.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

The proposed solution uses RANSAC and particle filtering combined with likelihood-based object recognition algorithm with a Markov-style process	These tools include precision, recall, F1 score for lane boundary	i Title ii Abstract iii Index terms iv Introduction v Lane-marking detection vi Lane-boundary-hypotheses generation with particle filtering and RANSAC vii Experimental Results viii Summary and future work ix References
Diagram/Flowchart		



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Reference in APA format	Wang, Y., Shen, D., & Teoh, E. K. (2000, July 1). *Lane detection using spline model*. Pattern Recognition Letters; Elsevier BV. https://doi.org/10.1016/s0167-8655(00)00021-0	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.sciencedirect.com/science/article/abs/pii/S0167865500000210	- Yue Wang - Dinggang Shen - Eam Khwang Teoh	- Lane detection - Catmull-Rom spline - Lane model - Machine vision - Maximum likelihood

		- Intelligent vehicle
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A new lane model based on the Catmull ± Rom spline combined with maximum likelihood approach via a multi-resolution strategy.	- **GOAL**: To develop a robust and accurate lane detection system in road images for intelligent vehicles. - **PROBLEM**: The problem being solved here is the challenge of reliably detecting and delineating lane boundaries in scenarios with noise, shadows, illumination variations and different road conditions. It also tries to achieve real-time performance on relatively modest computational resources.	**-** *Catmull-Rom spline-based model* is a mathematical model used to describe lane boundaries. - *Lane detection algorithm* contains vanishing point detection, control points determination, maximum likelihood method, multi-resolution strategy. - *Image processing techniques* improve robustness to noise, shadows, and illumination variations. - *Real-time implementation strategy* to execute 4-5 frames per second on relatively modest hardware.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Vanishing point detection	Helps understand the perspective effect of parallel lines and crucial for accurate lane modelling	Sensitivity to noise and complex road layouts. It also computationally expensive
2	Control point determination	Enables creation of versatile lane model	Determining optimal control points may

		and provides flexibility in describing various lane structures	be subjective and there is complexity in defining the control point sets
3	Maximum likelihood method	Quantifies matching between model and real edges while improving the accuracy of lane detection	Sensitivity to outliers or inaccuracies in edge detection
4	Multi-resolution strategy	Balances accuracy and computational cost while offering gradual refinement for an accurate solution	Increased computational complexity and potential for convergence to local optima

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
- Lane detection accuracy	- Control points of lane model - Vanishing point detection - Image characteristics - Road conditions	- Computational resources	- Multi-resolution strategy

Relationship Among the Above 4 Variables in This article

The accuracy of lane detection (dependent variable) is directly influenced by the control points of the lane model, vanishing point detection, image characteristics, and road conditions (independent variables). These factors collectively impact the precision and robustness of the Catmull-Rom spline-based model in identifying various lane structures. The computational resources act as moderating factors, influencing the execution speed and efficiency of the algorithm. Additionally, the multi-resolution strategy mediates the relationship between computational cost and solution accuracy, impacting the final accuracy of lane detection by optimizing the trade-off between these variables.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Control points of lane model</td><td>Lane model description (shape and structure)</td></tr>
</table>
</td>
<td>
- Catmull ± Rom spline-based lane model describes a wider range of lane structures compared to other lane models.

- The lane detection problem is solved by determining the sets of control points of the lane model.

- A maximum likelihood method is used to measure the matching degree between the lane model and the real road edges.

- The algorithm uses a multi-resolution approach that reduces the computational cost while achieving an accurate solution rapidly.

- The proposed method is robust to noise, shadows, illumination variations, and different road conditions.

- The algorithm detects the vanishing point and solves the lane detection problem using a maximum likelihood approach.

- Efficiency on modest hardware

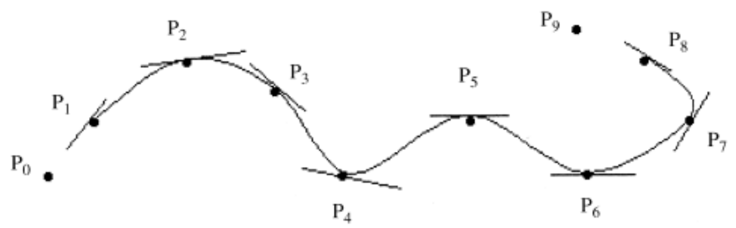
- customizable lane models
</td>
<td>
- Enhanced lane detection accuracy: Catmull-Rom spline-based models provide larger lane structure descriptions giving more accurate and comprehensive outputs and results.

- Robustness to varied conditions: Robustness to noise, shadows and illuminations variations, different road conditions are an asset.

- Algorithmic techniques: Use of maximum likelihood and multi-resolution strategy balances computational cost with accuracy.

- Adaptability and versatility: Adaptability to varied conditions improves the reliability and usefulness of the system.
</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can help ability to handle noise, shadows, illuminations, and diverse road conditions ensures consistent and reliable performance and provide a broader range of lane structures, thereby increasing the precision.	The solution has challenges which includes fine-tuning and optimization to adapt the solution to specific driving environments or vehicle might require extensive testing and refinement.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed solution presents a well-researched and detailed approach for innovative techniques that are accurate and robust in real-time .	These tools include OpenCV, MATLAB's Image Preprocessing Toolbox.	i Abstract ii Introduction iii Related Works iv Road Model v Results vi Conclusions vii References
Diagram/Flowchart		
		

13		
Reference in APA format	Jigang Tang, Songbin Li, Peng Liu, A Review of Lane Detection Methods based on Deep Learning, Pattern Recognition (2020), doi: https://doi.org/10.1016/j.patcog.2020.107623	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.sciencedirect.com/science/article/abs/pii/S003132032030426X	- Jigang Tang - Songbin Li - Peng Liu	- Lane detection - Deep learning - Semantic segmentation - Instance segmentation
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

Comprehensive review of various lane detection methods, categorizing them based on their approaches and discussing network architectures, loss functions, comparisons, and future directions.	**GOAL**: To comprehensively survey lane detection methods, discussing network architectures, loss functions, method comparisons, acknowledged challenges like computational cost, and suggests future directions, aiming to bridge traditional and deep learning approaches, offering insights, and guiding future research in lane detection.	**-** *Convolutional Neural Networks* used for image classification, object detection, and semantic segmentation etc. - *Deep learning* for lane detection using CNN - *Network architecture* discusses about the various architectures used - *Related Loss Functions*: discusses the loss functions related to the mentioned network architectures. - *Contributions and Weaknesses*: For each method, its contributions and weaknesses are introduced. - *Comparison of Representative Methods*: A brief comparison of representative methods. - *Future Directions*: current challenges, such as expensive computation and the lack of generalization.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Lane detection methods based on deep learning utilize CNNs to extract lane features effectively.	CNNs effectively extract lane features by learning hierarchical representations.	These methods might require significant computational resources for training and inference.
2	The CNNs are trained on large datasets with annotated lane markings to learn the patterns and characteristics of lanes.	Training CNNs on extensive annotated datasets enables robust learning of lane patterns.	Acquiring and annotating large datasets can be labour-intensive and costly.
3	The trained CNN models are then used to predict the position and parameters of lanes in real-time video or image frames.	Using trained CNN models for real-time lane prediction allows for quick and efficient identification of lane positions.	Computational complexity associated with real-time inference might pose challenges.
4	The computational complexity associated with real-time inference	This complexity ensures accurate and detailed analysis,	Complexity might demand significant computational

	might pose challenges, potentially causing processing delays or limiting the applicability of these models in resource-constrained systems or high-speed environments.	providing more nuanced insights and precise outputs for decision-making, especially in scenarios requiring high accuracy and detailed information.	resources, potentially leading to processing delays or restricting implementation in systems with limited computing capabilities.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
- Lane detection accuracy or performance metrics such as precision, recall, F1 score, or mean average precision (MAP).	- Network architectures and models used for lane detection - Pre-processing techniques - Post-processing algorithms	- Hardware capabilities - Computational resources available for training and inference	- Feature extraction methods - Color space conversion techniques between RGB and YCbCr or HLS

Relationship Among the Above 4 Variables in This article

The dependent variable, lane detection accuracy measured by precision, recall, F1 score, or MAP, is directly impacted by several independent variables. Network architectures and models used for lane detection play a substantial role; their complexity, depth, and design significantly influence the accuracy of detecting lane boundaries. The pre-processing techniques, such as image augmentation or normalization, and post-processing algorithms, like line fitting or curve smoothing, contribute significantly to enhancing or refining the accuracy achieved by the models. These independent variables, however, are influenced by moderating factors—hardware capabilities and computational resources. The computational power available for training and inference dictates the feasibility of employing complex network architectures or extensive pre/post-processing algorithms, ultimately affecting the performance metrics. Mediating variables, such as feature extraction methods and color space conversions, act as intermediaries. They influence how effectively the network models and pre/post-processing techniques interpret lane-related features from the images, thereby influencing the overall accuracy of lane detection.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td>
<table>
<tr><th>Input</th><th>Output</th></tr>
<tr><td>Image or a video frame captured by a camera or lidar.</td><td>Detected lane areas or lines</td></tr>
</table>
</td>
<td>- Two-step methods: Lane detection methods employ distinct steps: identifying lane markings using techniques like Hough or RANSAC, followed by fitting a lane line model to these markings.

- One-step methods: These methods directly predict lane information from input images using models like CNNs and FCNs.

- Network architectures: Discusses about classification and object detection-based methods, end-to-end image-segmentation based models, and optimization strategies</td>
<td>- Lane Detection Insights: provides a comprehensive overview of vision-based lane detection methods.

- Deep Learning in Lane Detection: deep learning methods offer valuable knowledge on leveraging advanced techniques to enhance lane detection accuracy.

- Understanding Network Architectures: gives a clear understanding of the technical frameworks to design and optimize the system's architecture.

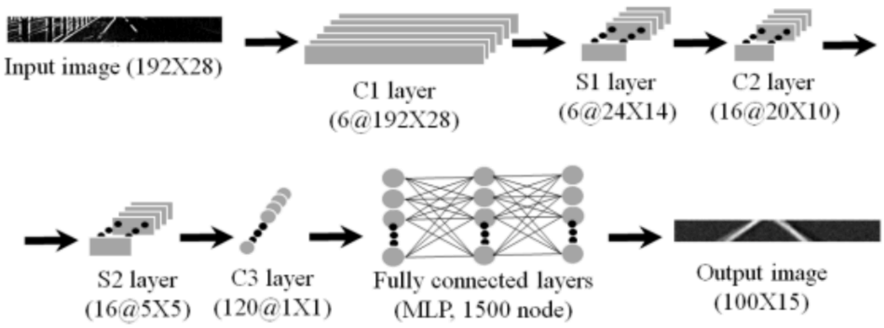
- Comparison and Evaluation: aids in the selection and evaluation of lane detection techniques.</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can helps in improving the network’s scene perception ability by continuously optimizing neural network parameters, which attain higher robustness and applicability.	The solution has challenges which includes complexity of deep learning models can make them difficult to interpret and understand, which could pose challenges for validation and certification processes crucial in safety-critical applications like autonomous driving.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The proposed solution presents progress in detection accuracy of deep learning methods..	These tools include performance metrices, lane detection methods.	i Title ii Abstract iii Keywords iv Introduction v Background of related convolutional neural networks vi Deep learning for lane detection vii Discussion and analysis viii Conclusion and future work ix Declaration of competing interest x Acknowledgement

		xi References xii Author Biography

Diagram/Flowchart



14

Reference in APA format	A. A. Assidiq, O. O. Khalifa, M. R. Islam, and S. Khan, "Real time lane detection for autonomous vehicles," 2008 International Conference on Computer and Communication Engineering, Kuala Lumpur, Malaysia, 2008, pp. 82-88, doi: 10.1109/ICCCE.2008.4580573.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/abstract/document/4580573	- Abdulhakam.AM.Assidiq - Othman O. Khalifa - Md. Rafiqul Islam - Sheroz Khan	- Driver Assistance System - Lane detection - computer vision - Intelligent vehicles
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

A vision-based lane detection algorithm utilizing image preprocessing, edge detection (Canny filter), Hough transform for line detection, and hyperbola fitting	**GOAL:** To accurately identify and delineate lane boundaries in real time by providing warnings or assistance regarding lane departures or by aiding in autonomous driving functionalities **PROBLEM:** Developing a robust, real-time lane detection system entails accurately identifying lanes amidst diverse road and environmental conditions, including different lighting, road types, shadows, and pavement changes. This system must operate reliably amid noise, variations in road types, and vehicle movement, ensuring precision and responsiveness in dynamic driving scenarios.	- *Image acquisition*: Utilizes a camera mounted on the vehicle to capture real-time front view images - *Preprocessing*: Converting the colour images to grayscale images - *Edge detection*: Uses Canny edge - *Line detection*: Uses Hough transform - *Lane boundary scan*: Uses information from the edge-detected image and Hough lines to perform a scan, collecting data points to identify lane boundaries on both sides of the road. - *Hyperbola fitting*: Fits pairs of hyperbolas to the collected data points from the lane scan

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Image acquisition and preprocessing.	Real-time capture of front-view road scenes allows continuous data input for lane detection.	Subject to image quality variations due to vehicle movement or environmental factors, impacting subsequent processing steps.
2	Edge and line detection.	Canny philtre efficiently identifies	Automatic thresholding may

		edges and sharp contrasts, crucial for delineating lane boundaries	generate excessive edge information or miss some edges in varied lighting conditions, requiring parameter adjustments
3	Lane boundary scan	Collects data points along the detected edges to identify and separate left and right lane boundaries.	Vulnerable to errors when encountering heavily obscured or ambiguous lane markings, leading to inaccuracies in delineating lanes.
4	Hyperbola fitting	Fits hyperbolas to data points, providing a visual representation of the detective lane boundaries.	Sensitivity to outliers in data points might cause deviations and hyperbola fitting accuracy impacting the visual representation of lanes.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
- Lane detection accuracy - Real-time performance	- Environmental conditions - Road types - Image quality - Algorithmic processes	- Shadow handling - Threshold selection - Lane boundary characteristics	- Hough Transform parameters - Image preprocessing techniques - Hyperbola fitting

Relationship Among the Above 4 Variables in This article

The independent variables, like road conditions, road types, and image quality, act as primary influencers on the dependent variables – lane detection accuracy and real-time performance. These independent factors affect algorithmic processes, such as image preprocessing techniques and edge detection. The moderating variables, like shadow handling and threshold selection, play a pivotal role in adjusting and fine-tuning the algorithm’s response to varying conditions. Meanwhile, the mediating variables, including Hough transform parameters and hyperbola fitting techniques, mediate between the independent and dependent variables, indirectly influencing the accuracy and responsiveness of lane detection.

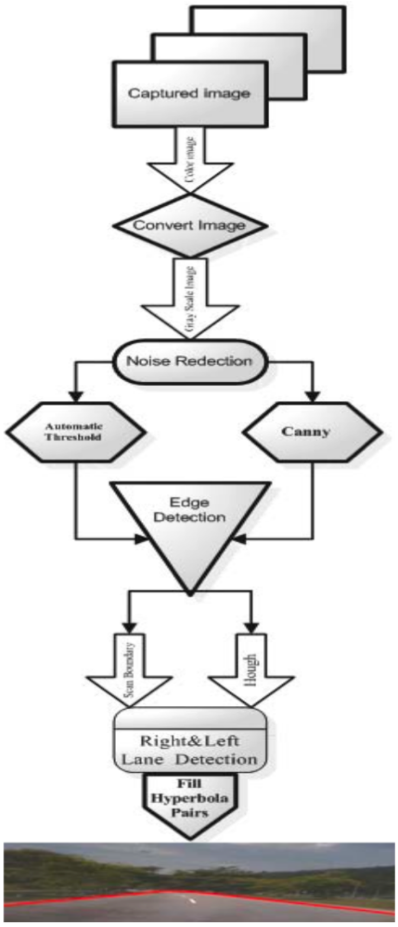
Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>Color image sequence from a vehicle - mounted camera.</td><td>Grayscale image (620x480 pixels) for processing</td></tr></table>	- *Real-time operations*: capable of processing up to 30 frames per second - *Adaptability to road conditions*: Robustness in detecting lanes in diverse environmental conditions on both highways and normal roads. - *Handling various road types*: Capable of detecting lanes on straight and curved roads, adapting to different road geometries. - *Vision based approach*: Relies on computer vision techniques utilizing a camera mounted on the vehicle, enabling the system to acquire and process front-view images.	- *Robust lane detection*: ability to detect lanes on different road types - *Real-time responsiveness*: High frame rate facilitates quick decision-making and prompt alerts or interventions to ensure driver's safety - *Adaptability to road geometrics*: Increases reliability of driving on broad and narrow roads - *Vision-based approach*: It minimizes additional hardware requirements and integration complexities.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed approach providing accurate and reliable lane detection, the solution enhances the overall user experience.	The solution has challenges which includes frequent adjustments or compliance checks for the lane detection algorithm.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed solution presents a vision-based approach that works in real-time and adaptable to the situations.	These tools include Recall, precision, F1 score.	i Abstract ii Introduction iii Related Works iv Environmental variability v overview of algorithm vi Experimental Results and Discussion

		vii Summary and Conclusions viii References

Diagram/Flowchart



15	
Reference in APA format	Lee, J., Hwang, Ki. YOLO with adaptive frame control for real-time object detection applications. *Multimed Tools Appl* **81**, 36375–36396 (2022). https://doi.org/10.1007/s11042-021-11480-0

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://link.springer.com/article/10.1007/s11042-021-11480-0	- Jeonghun Lee - Kwang-il Hwang	- Embedded systems - Frame control - Object detection - Real-time - YOLO
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
An adaptive framework control (ADC) architecture for YOLO for real-time processing with network cameras.	**GOAL**: To efficiently cope with real-time processing problems associated with network cameras in YOLO object detection applications by maintaining high precision, real-time object detection service, and minimizing total service delay. **PROBLEM**: The problem revolves around real-time processing challenges in YOLO object detection with network cameras. It entails addressing issues and optimizing performance across different hardware platforms for efficient real-time object detection while	**-** *YOLO*: Base framework for object detection used in the system - *Adaptive Frame Control*: Manages frame control, dedicated frame fetching mechanism, Synchronizer for frame rate. - *Hardware platforms*: Various systems used for testing and implementation [jetson nano GTX1060] to assess performance across different setups - *Input sources*: Network cameras, video files, USB cameras: used for diverse input scenarios using experimentation. - *Experimentation setup*: Configuration of controlled environment for testing AFC's efficiency across different hardware and input conditions. - *Real-time object detection techniques*: Applied techniques like YOLOv3 Tiny YOLO and AFC based variations for comparative analysis.

	minimizing service delay.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Object detection using YOLO. Identification of real-time processing problems.	High precision, ease of use. Pinpointing specific challenges.	Resource-intensive requires high-end hardware
2	Proposal of Adaptive Frame Control (AFC)	Enhances real-time capability	Potentially adds complexity to the system
3	AFC's Dedicated Frame Fetching Mechanism. AFC's Synchronizer for Frame Rate.	Consistent frame control, improves RT processing	Dependency on AFC functionality and might lead to redundancy
4	Comparative analysis between YOLO, AFC, and Tiny YOLO	It helps in evaluating performance differences highlighting the strengths and weaknesses	Narrow focus on variations and Results might vary in real-world complex environments.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
- Real-time object detection capability	- Hardware platform - Input source type (RTSP, Video files, USB cameras) - Frame size	- Adaptive Frame Control (AFC)	- Total service delay

Relationship Among the Above 4 Variables in This article

The hardware platform directly influences the system's processing power and capability, impacting its ability to handle varying frame sizes and input sources. Different input sources, such as RTSP, video files, or USB cameras, introduce variations in frame interarrival time (Ta), affecting the system's processing speed. Additionally, varied frame sizes impact both detection service time (Ds) and mean average precision (mAP), influencing the system's real-time ability and accuracy in detecting objects. Amidst these factors, AFC operates as a mediator and moderator. It mediates the total service delay, aligning frame fetching independently of detection service, thus alleviating the impact of hardware, input source, and frame size variations on the system's real-time processing. Simultaneously, AFC moderates these influences by adapting frame control, ensuring smoother and consistent real-time object detection across diverse hardware platforms and input conditions.

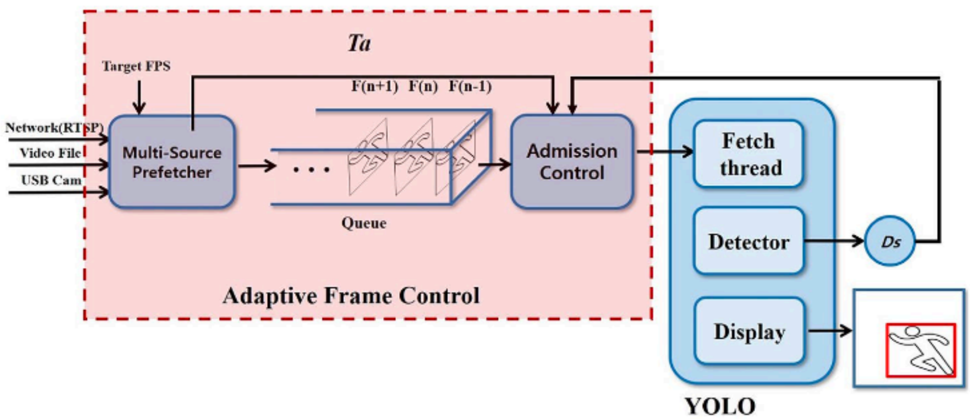
Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Video feeds from network cameras (RSTP), video files, USB cameras. **Output:** Real-time object detection results.	- Efficiently copes with *real-time processing* problems associated with network cameras in YOLO object detection applications. - Maintains the *high precision* and convenience of YOLO. - Provides *real-time object detection service* by minimizing total service delay. - Consistently *processes various inputs* (network cameras (RTSP), video files, USB cameras). - Guarantees maximum frame rate that can be supported by system hardware. - Guarantees real-time processing of each input frame (no cumulative delay).	- *Improved Safety*: timely alerts or interventions in potential hazardous situations, enhancing driver safety. - *Hardware Flexibility*: allows flexibility in designing system as it permits deployment in various vehicle types, from high-performance vehicles to those with limited computational capabilities. - *Adaptability to Different Environments*: AFC's capability to handle diverse input sources ensures it is adaptable. - *Future-proof Integration*: The system's compatibility with multiple YOLO versions allows for seamless integration with newer releases. - *Cost-Efficiency*: AFC's ability to maintain real-time processing on lower-end hardware platforms potentially reduces the overall cost of implementation.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
- *Enhanced real-time object detection*: Adaptive frame control enhances real time object detecting capabilities of YOLO, when particularly used with network cameras	- *Hardware Requirements*: YOLO with AFC may still require relatively high-end hardware for successful real-time object detection. - *Complexity*: The addition of AFC to the YOLO architecture could increase the complexity of the system.

- *Improved performance on resource-constrained systems*: The AFC allows YOLO to provide real time object detection service on AI embedded systems with resource constraints - *Reduced service delay*: By minimizing total service delay, AFC improves the responsiveness of YOLO	- *Potential for Errors*: There is always a potential for errors or false positives/negatives in object detection.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The proposed solution presents an enhanced real-time method that maintains YOLOs precision.	These tools include YOLO, AI libraries, MS COCO.	i Title ii Abstract iii Keywords iv Introduction v Requirements for real-time applications based on object detection vi Problems in real-time object detection vii Related work viii Adaptive frame control for real-time object detection applications ix Experimental results x Conclusion xi Declarations xii References

Diagram/Flowchart



16	
Reference in APA format	Ramzan, Muhammad and Khan, Hikmat Ullah and Awan, Shahid Mahmood and Ismail, Amina and Ilyas, Mahwish and Mahmood, Ahsan. (2019).” A survey on state-of-the-art drowsiness detection techniques”.

	IEEE Access, 7, 61904–61919.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/abstract/document/8704263	muhammad Ramzan, hikmat ullah khan, shahid mahmood awan, amina ismail, mahwish ilyas, ahsan mahmood	Digital image processing, driver drowsiness, sensors, fatigue detection, supervised learning, classification, support vector machine (SVM)
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A Survey on State-of-the-Art Drowsiness Detection Techniques	The aim is to provide an understanding of driver drowsiness detection systems to aid future research in this field and improve road safety.	The authors comprehensively review and categorize methods for detecting driver drowsiness into three categories- behavioural, vehicular, and physiological parameters-based techniques.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	**Behavioral parameters-based techniques**: These techniques measure drivers' fatigue through behavioral parameters such as eye closure ratio, eye blinking, head position, facial expressions, and yawning.	These techniques are non-invasive and easy to implement. They provide real-time monitoring of the driver's state by analysing facial expressions, eye movements, and other visible behaviors. This makes them highly	These techniques rely heavily on the quality of the camera and lighting conditions, which can vary greatly in real-world driving scenarios. They may also be affected by the driver's individual behaviours and habits, leading to false positives or negatives.

		suitable for real-world applications.	
2	**Vehicular parameters-based techniques:** These techniques analyze the vehicle behavior for driver drowsiness detection	These techniques provide an indirect measure of the driver's state by analyzing the vehicle's behavior. They can detect changes in driving patterns that may indicate drowsiness, such as lane deviation or erratic steering. These techniques can be easily integrated into existing vehicle systems.	These techniques may not be reliable in all situations, as changes in driving patterns can also be caused by factors other than drowsiness, such as road conditions or traffic. They also require sophisticated sensors and systems to be installed in the vehicle, which can be costly..
3	**Physiological parameters-based techniques**: These techniques analyse the biological condition of the drivers' body for driver drowsiness detection.	These techniques provide a direct measure of the driver's state by analysing physiological signals such as heart rate, brain activity, and skin conductance. They can provide a more accurate and reliable measure of drowsiness compared to behavioural and vehicular	While these techniques can provide accurate measures of drowsiness, they require specialized equipment and may be invasive, which can be uncomfortable for the driver.

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The level of drowsiness .	The facial expressions, vehicular parameters, Physiological parameters	The experience of the driving	Attention Allocation

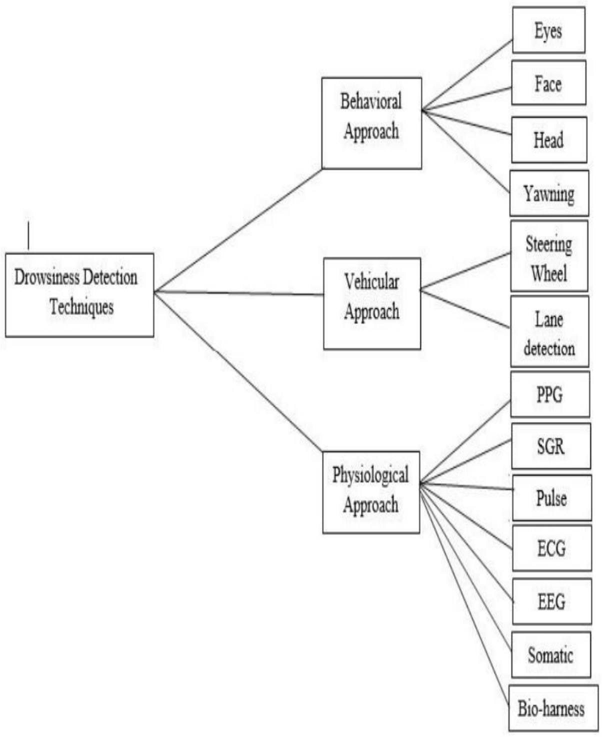
Relationship Among the Above 4 Variables in This article

The relationship can be explained by the fact that longer journeys are more likely to cause fatigue, which in turn increases the driver's drowsiness level. This can be tested by conducting a study that measures the drowsiness level of drivers before and after a long journey.		
Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
Input: Data from sensors monitoring driver behaviour, vehicle data, or physiological indicators **Output**: The system determines the driver's drowsiness level in real-time.	The proposed approach helps to enhance road safety by effectively identifying and mitigating driver drowsiness while ensuring a comfortable and reliable driving experience.	The proposed approach helps in finding different methods to categorize the drowsiness of the driver

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can helps in reducing the number of accidents, these techniques could potentially lower insurance premiums for drivers and fleet owners. In some regions, transportation companies are legally required to monitor driver fatigue. Implementing these techniques can help companies comply with these regulations.	The solution has challenges that employers might misuse this technology to overwork drivers, pushing them to their limits until the system detects drowsiness. Over-reliance on these systems could potentially make drivers complacent, trusting the technology to keep them safe instead of taking regular breaks and ensuring they are wellrested before driving. Analyse This Work By Critical Thinking The Tools That Assessed this Work Wh

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

The proposed solution introduces different techniques to categorize the drowsiness detection of the driver into three categories	These tools include Method categorization	i. Abstract ii. Introduction iii. Research Methodology iv. Drowsiness Detection Techniques v. Conclusion vi. References
Diagram/Flowchart		



17	
Reference in APA format	Ngxande, Mkhuseli and Tapamo, Jules-Raymond and Burke, Michael. (2017).” Driver drowsiness detection using behavioral measures and machine learning techniques: A review of state-of-art techniques”. 2017 pattern recognition Association of South Africa and Robotics and mechatronics (PRASA-RobMech), 156–161.

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/abstract/document/8704263	Mkhuseli, NgxandeJulesRaymond, Tapamo Michael Burke	Drowsiness Detection, facial expression, Machine learning, behavioral measures.
The Name of the Current Solution (Technique / Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Driver drowsiness detection using Behavioral measures and machine learning techniques	The aim of this solution is to review and evaluate the use of machine learning techniques, particularly focusing on behavioural measures and facial features, for driver drowsiness detection	Face detection of the driver. Feature extraction. Classification based on the features using CNN, SVM, HMM.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Data Collection: This involves gathering data related to driver behavior, specifically facial features that can be used to interpret levels of drowsiness.	The quality and quantity of data collected directly impacts the performance of the drowsiness detection system.	It is difficult to collect a large amount of high-quality data that accurately represents various driving conditions and levels of drowsiness.
2	Feature Extraction: This involves extracting relevant	Extracting relevant features from the	It requires a deep understanding of the

	features from the collected data that can be used to infer the level of drowsiness	collected data helps in reducing the dimensionality of the data. This can improve the efficiency and accuracy of the detection system.	data and the problem at hand. Selecting irrelevant features or overlooking important ones can negatively impact the performance of the detection system.
3	Machine Learning Techniques: The extracted features are then processed using various machine learning techniques for drowsiness detection	Machine learning techniques allows for automated learning and improvement based on experience. These techniques can adapt to new data and improve over time, making them highly effective	It can sometimes be complex to understand and interpret if the data is large in size
4	Meta-Analysis: The analysis reveals that support vector machine technique is the most commonly used technique to detect drowsiness, but convolutional neural networks performed better than the other two techniques	It helps in identifying the most effective techniques and areas where further research is needed.	It requires access to a large number of research papers, which may not always be possible due to paywalls or other restrictions

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The level of drowsiness of the driver .	The number of hours driven by the driver	The age of the driver	Caffeine consumption can mediate the relationship between the number of hours driven and the level of drowsiness. Caffeine can help to reduce the effects of

			drowsiness, allowing the driver to remain alert for longer periods of time.

Relationship Among the Above 4 Variables in This article
The more hours a driver spends driving, the more likely they are to experience drowsiness. This relationship can be explained by the fact that driving is a monotonous task that can lead to fatigue and drowsiness. The relationship between the number of hours driven and the level of drowsiness can be put to the test by conducting experiments that measure the level of drowsiness of drivers after different periods of driving. If the relationship is found to be statistically significant, it can be considered a hypothesis.

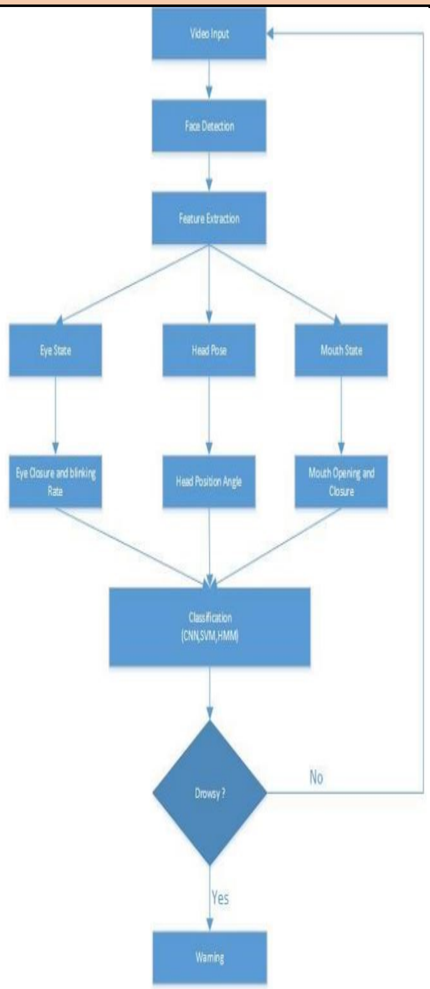
Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**	The proposed system detects the features through the input video and algorithms are used for the feature classification.	The proposed approach helps in the classification of the features extracted from the face recognition of the driving person.
Video data of the driver	Drowsiness detection and alerting the person based on the detection		

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can accurately detecting driver drowsiness, the system can alert the driver or take corrective actions to prevent potential accidents. This can significantly enhance road safety.	The solution has challenges which includes continuous monitoring of a driver's behavior might raise privacy issues. Some drivers might not be comfortable with their actions being constantly recorded and analyzed.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**

The proposed solution presents a good step that classifies the features that are extracted from the input data taken through the face recognition	These tools include Feature classification.	i Abstract ii Introduction iii Driver Drowsiness Detection iv Process v Measures and Techniques used for Detection drowsiness vi Meta-Analysis vii Conclusion viii References

Diagram/Flowchart



18		
Reference in APA format	Diwan, Tausif and Anirudh, G and Tembhurne, Jitendra V. (2023). ” Object detection using YOLO: Challenges, architectural successors, datasets and applications”. multimedia Tools and Applications, 82(6), 9243–9275.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/abstract/document/8704263	Tausif Diwan, G. Anirudh Jitendra V. Tembhurne	Object detection, segmentation, YOLO, Fast-RCNN, regression.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Object detection using YOLO	The paper aims to examine their regression formulation, architectural advancements, and performance statistics, with a particular emphasis on comparing them to two-stage detectors in terms of detection accuracy and inference time.	The proposed solution uses Object detection, classification and localization and Instance Segmentation.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

	Process Steps	Advantage	Disadvantage (Limitation)
1	The input to the YOLO model is a full image.	The model takes the entire image as input, which allows it to understand the context of the objects in the image.	The model might struggle with large images due to memory constraints.
2	The image is passed through a deep learning model (a convolutional neural network) that extracts features from the image.	Convolutional neural networks (CNNs) are excellent at extracting hierarchical features, which are crucial for object detection.	Training deep CNNs requires a lot of computational resources and labelled data.
3	The image is divided into an SxS grid. Each grid cell predicts only one object	Dividing the image into grids simplifies the problem of predicting object locations.	Each grid cell can predict only one object. If there are multiple objects in a cell, the model might fail to detect all of them.
4	At the end of the process, post-processing steps like non-maximum suppression are applied to remove duplicate detections and keep only the most confident ones.	Steps like non-maximum suppression help reduce duplicate detections and improve the final results.	If there are many classes, the model might become complex and require more training data. 6. These steps add extra computation and can slow down the detection process.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
1. Object detection accuracy 2. Inference time	1. Number of layers and filters in YOLO architecture.	The size of the dataset used in training YOLO architecture.	The number of false positives generated by YOLO architecture.

Relationship Among the Above 4 Variables in This article
The number of layers and filters in the YOLO architecture, the number of training epochs, and the learning rate are all independent variables that can affect the object

detection accuracy and inference time of the YOLO architecture. The size of the dataset used for training the architecture moderates the relationship between the independent variables and the dependent variables. False positives generated by the architecture can be reduced by using a larger dataset for training the architecture, which in turn can improve the object detection accuracy and inference time of the architecture.

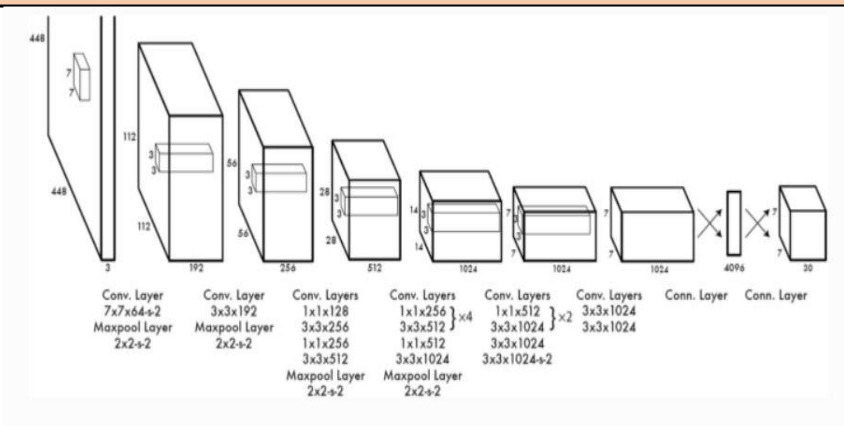
<table>
<tr><th>Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Set of digital images or video input</td><td>Detection of the name of the object</td></tr></table></td><td>The proposed solution initially detects the objects in image or video provided and then identifies the name of objects that are detected.</td><td>To the extent this work is designed for the identification of the object name from the list which are detected by the system.</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed approach YOLO can be used in Real-time applications where quick object detection is crucial. YOLO is known for its speed, continuous improvements to the architecture have also led to enhanced detection accuracy.	The proposed approach YOLO can often trade off accuracy for speed. This could lead to false positives or negatives.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed solution work on YOLO-based object detection represents a valuable contribution to the field of computer vision. Its emphasis on single-stage detectors and architectural advancements addresses the critical need for real-	Object detection and identification	i Abstract ii Introduction iii Two Stage object detection iv Convolutional neural networks and Pretrained models v Architectural design of YOLOs vi Summarization and future research directions

time, efficient object recognition.		

Diagram/Flowchart



19		
Reference in APA format	G. Oltean, C. Florea, R. Orghidan, and V. Oltean, "Towards Real Time Vehicle Counting using YOLO-Tiny and Fast Motion Estimation," in *2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging(SIITME)*, IEEE, Oct. 2019, pp. 240–243. doi: 10.1109/SIITME47687.2019.8990708.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/abstract/document/8990708	Gabriel Oltean, Camelia Florea Radu Orghidan, Victor Oltean	Vehicle counting, Tiny YOLO, motion estimation, GPU processing, real time processing.
The Name of the Current Solution (Technique / Method/ Scheme/ Algorithm/ Model/	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

Tool/ Framework/ ... etc)		
Towards Real Time Vehicle Counting using YOLO-Tiny and Fast Motion Estimation	The main goal of this solution to develop a real-time vehicle detection, tracking, and counting system using Tiny YOLO for detection and fast motion estimation for tracking and to solve lack of real-time processing of videos or errors in detection.	The model detects the objects using YOLO and then it filters the detected objects and also update the count continuously throughout the journey.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Vehicle detection using Tiny YOLO and Fast motion estimation for tracking.	Real-time monitoring and reliable data for traffic management and potential for scalability and integration with other smart city technologies.	Dependency on GPU, may not be available on low-budget devices and Tiny YOLO also have lower accuracy compared to larger models in quick access system to avoid the latency of mail delivery.

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Number of vehicles counted in real-time	• Tiny YOLO for vehicle detection. • Fast motion estimation for vehicle tracking.	The accuracy of vehicle detection and tracking.	—

Relationship Among the Above 4 Variables in This article

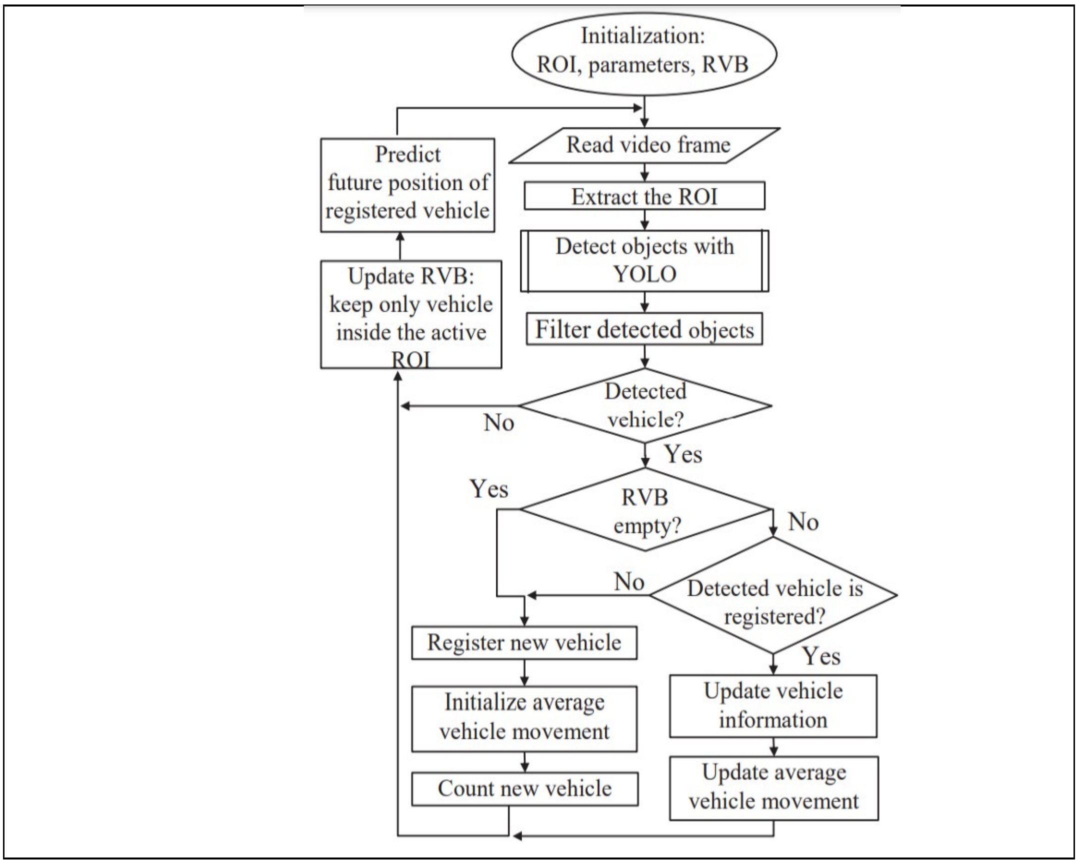
The number of vehicles counted in real-time is directly proportional to the accuracy of vehicle detection and tracking. The independent variables, Tiny YOLO and fast motion estimation, are used to detect and track vehicles in real-time, which in turn affects the dependent variable. The moderating variable, accuracy of vehicle detection and tracking, strengthens the relationship between the independent and dependent variables.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
Input: Real time video data **Output**: Count of the vehicles ahead	The system gives an idea of the number of vehicles ahead of the particular vehicle that helps the driver the position and their approximate speed.	Vehicle count is added as an advantage of this system. So that the driver knows the number of vehicles which are present ahead of it.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
This solution enhances traffic management, safety, and surveillance by providing accurate, real-time data on vehicle movements. It contributes to the overall goal of creating smarter, more efficient, and safer urban environments.	Continuous monitoring of traffic through surveillance cameras raises questions about the collection and storage of sensitive information.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This solution performs real-time vehicle detection, tracking, and counting in smart city applications. It leverages a combination of Tiny YOLO for detection and fast motion estimation for tracking, demonstrating impressive real-time performance. It	Object Detection and filtering of the objects	i Abstract ii Introduction iii Proposed Method iv Implementation and Result v Conclusion vi References

represents a significant step toward enhancing traffic management and surveillance in smart cities		

Diagram/Flowchart


20		
Reference in APA format	Y. Wang, E. K. Teoh, and D. Shen, "Lane detection and tracking using B-Snake," *Image Vis Comput*, vol. 22, no. 4, pp. 269–280, Apr. 2004, doi: 10.1016/j.imavis.2003.10.003.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.sciencedirect.com/science/article/abs/pii/S0262885603002105	Yue Wang Eam Khwang Teoh Dinggang Shen	Lane detection, B-Spline, Snake, Lane model, Machine vision, Intelligent vehicle
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Lane detection and tracking using B-Snake	The goal of the B-Snake based lane detection and tracking algorithm is to provide a robust and efficient method for detecting and tracking lanes in a variety of road conditions. The problem that needs to be solved is the accurate detection and tracking of lanes in realtime, which is a critical component for autonomous driving systems. Traditional methods often struggle with noise, shadows, and illumination variations in the captured road images.	The model tracks the lane of the vehicle and updating the lane tracking in real world time to time.

	They may also have difficulty accurately detecting lanes in different types of roads, such as marked and unmarked roads, as well as dash and solid paint line roads.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	**B-Snake Model:** The B-Snake based lane model is able to describe a wider range of lane structures since a B-Spline can form any arbitrary shape with a set of control points.	The B-Snake model is flexible and can describe a wide range of lane structures. This is because a B-Spline can form any arbitrary shape with a set of control points.	The B-Snake model can often get stuck when it is flexible in local minima states which can be counteracted by simulated annealing techniques.
2	**Detecting the Mid-line of the Lane**: The problem of detecting both sides of lane markings (or boundaries) has been formulated here as the problem of detecting the mid-line of the lane.	By formulating the problem as detecting the mid-line of the lane, it simplifies the task and reduces computational complexity. This approach also leverages the knowledge of perspective parallel lines, which is a common characteristic in road images.	This technique requires the studied road to have well-painted lines or strong lane edges, otherwise, it will fail. Moreover, as it has the disadvantage of not imposing any global constraints on the lane edge shapes.
3	**CHEVP Algorithm:** A robust algorithm called CHEVP is presented for providing a good initial position for the B-Snake.	The CHEVP algorithm provides a good initial position for the B-Snake. This is crucial as it helps in getting a good starting point for the B-Snake.	In the case of broken lane markings, CHEVP may not extend all the ways to the upper of the image. The contrast of one (or both) of the lane edges may not be high enough to detect near the bottom of the image.
4	**Minimum Mean Square Error (MMSE):**A minimum error method by MMSE is proposed to determine the control points of the B-Snake model by the overall	The MMSE method helps in accurately determining the control points of the B-Snake model by considering the overall image forces on two sides of the lane.	The accuracy of MMSE is governed by the convergence criteria used in the energy minimization technique1. This could lead to inaccuracies if not properly calibrated.

	image forces on two sides of the lane.		

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
1. Lane tracking accuracy 2. Lane tracking accuracy	1. Image quality 2. Road curvature 3. Illumination variations 4. Road markings	The quality of the initial position of the B-Snake model. A good initial position can improve the accuracy of lane detection and tracking	—

Relationship Among the Above 4 Variables in This article

The accuracy of lane detection and tracking is influenced by the quality of the independent variables. For example, poor image quality, high road curvature, and illumination variations can negatively impact the accuracy of lane detection and tracking. On the other hand, good road markings can improve the accuracy of lane detection and tracking.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**		
Image of the road	Land markings of the vehicle in certain range.	The solution addresses the real-world challenges of real-time vehicle detection and counting by combining efficient detection using Tiny YOLO, advanced tracking through fast motion estimation, and adaptability to low-budget devices.	This work makes a significant contribution to the field of smart city surveillance by presenting an innovative solution for real-time vehicle detection, tracking, and counting.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The algorithm is robust against noise, shadows, and illumination variations in the captured road images. This makes it highly reliable in diverse real-world driving conditions.	The use of B-Snake for lane detection might increase the computational complexity due to the iterative nature of the algorithm. This could potentially slow down the real-time processing speed.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
Real-time vehicle detection and counting in smart city applications. The integration of Tiny YOLO and fast motion estimation demonstrates a thoughtful combination of lightweight detection and accurate tracking techniques. The emphasis on GPU processing for real-time capabilities and the adaptability to low-budget devices like Jetson Nano reflects a pragmatic approach to scalability.	Tiny YOLO Fast Motion Estimation Techniques	i. Abstract ii. Introduction iii. Road model iv. Initialization of B-Snake Lane model: CHEVP algorithm v. B-Snake parameters updated from image data vi. Conclusion vii. References

Diagram/Flowchart

$$\Delta Q(t) = \gamma^{-1}[M^{\mathrm{T}}M]^{-1}M^{\mathrm{T}}E_{\mathrm{ext}}$$

$$E_k = E^c_{\mathrm{M\_dif}} = (E^c_{\mathrm{L}}(s) - E^c_{\mathrm{R}}(s))$$

$$E_k = \tau(k(t) - k(t-1)) = \tau\Delta k(t)$$
$$k(t) = k(t-1) + \Delta k(t)$$

$$\Delta k(t) = E_k/\tau$$

2.2 COMPARISION TABLE:

Author	Year	Approach	Description
Wang, Yue and Shen, Dinggang and Teoh, Eam Khwang	2000	The paper employs a spline model for accurate lane curve representation.	Pattern recognition techniques are used to identify lane markings, with the spline model enhancing precision in detecting boundaries.
Ueno, Hiroshi and Kaneda, Masayuki and Tsukino, Masataka	1994	The paper introduces a drowsiness detection system, focusing on the development of a mechanism to identify driver drowsiness.	The approach details the system's design and implementation, aiming to enhance road safety by detecting signs of driver drowsiness.
Wang, Yue and Teoh, Eam Khwang and Shen, Dinggang	2004	The paper employs the B-Snake algorithm for lane detection and tracking in images.	Utilizing the B-Snake algorithm, the approach enhances image and vision computing techniques for accurate and robust lane detection and tracking.
Wang, Tiesheng and Shi, Pengfei	2005	The paper proposes a method for driver drowsiness detection based on yawning detection.	The approach focuses on leveraging yawning as an indicator to determine the level of driver drowsiness, contributing to VLSI design and video technology applications.
Gao, Qi and Feng, Yan and Wang, Li	2017	The paper presents a real-time algorithm for lane detection and tracking.	The approach emphasizes the real-time aspect, providing a robust solution for accurately detecting and tracking lanes in dynamic environments.
Assidiq, Abdulhakam AM and Khalifa, Othman O and Islam, Md Rafiqul and Khan, Sheroz	2008	The paper introduces a real-time lane detection system designed for autonomous vehicles.	Focusing on real-time capabilities, the approach contributes to the development of autonomous vehicle systems by providing efficient lane detection.

Kim, ZuWhan	2008	The paper addresses robust lane detection and tracking, particularly in challenging scenarios.	Emphasizing robustness, the approach in this IEEE Transactions paper aims to improve lane detection and tracking performance, especially in adverse driving conditions.
Hu, Shuyan and Zheng, Gangtie	2009	The paper proposes a driver drowsiness detection method utilizing eyelid-related parameters and support vector machines.	Utilizing support vector machines, the approach focuses on the analysis of eyelid-related parameters for effective detection of driver drowsiness.
Forsman, Pia M and Vila, Bryan J and Short, Robert A and Mott, Christopher G and Van Dongen, Hans PA	2013	The paper discusses an efficient approach for driver drowsiness detection, particularly at moderate levels of drowsiness.	The approach concentrates on achieving efficiency in detecting driver drowsiness, targeting moderate levels to enhance accident prevention measures.
Saini, Vandna and Saini, Rekha	2014	The paper reviews various driver drowsiness detection systems and techniques.	Focusing on summarizing existing methods, the approach provides a comprehensive review of driver drowsiness detection systems and techniques in the context of computer science and information technologies.
Fogelton, Andrej and Benesova, Wanda	2016	The paper introduces an eye blink detection method based on motion vectors analysis.	Utilizing motion vectors analysis, the approach concentrates on accurate eye blink detection as a significant aspect of computer vision and image understanding.
Ngxande, Mkhuseli and Tapamo, Jules-Raymond and Burke, Michael	2017	The paper reviews state-of-the-art techniques for driver drowsiness detection, focusing on behavioral measures and machine learning.	Emphasizing behavioral measures and machine learning, the approach provides a comprehensive review of advanced techniques for effective driver drowsiness detection.
Tao, Jing and Wang, Hongbo and Zhang, Xinyu and Li, Xiaoyu and Yang, Huawei	2017	The paper presents an object detection system based on YOLO (You Only Look Once) in a traffic scene.	Utilizing the YOLO framework, the approach focuses on efficient object detection in real-time within the context of traffic scenes.
Du, Juan	2018	The paper explores the understanding of object detection based on the CNN (Convolutional Neural Network) family and YOLO.	The approach delves into the comprehension of object detection, particularly leveraging CNN and YOLO architectures

Ramzan, Muhammad and Khan, Hikmat Ullah and Awan, Shahid Mahmood and Ismail, Amina and Ilyas, Mahwish and Mahmood, Ahsan	2019	The paper conducts a survey on state-of-the-art techniques for drowsiness detection.	The approach involves an extensive survey within IEEE Access, providing insights into the latest techniques for drowsiness detection.
Oltean, Gabriel and Florea, Camelia and Orghidan, Radu and Oltean, Victor	2019	The paper explores real-time vehicle counting using YOLO-tiny and fast motion estimation.	Emphasizing real-time capabilities, the approach leverages YOLO-tiny and motion estimation for efficient vehicle counting.
Ramya, V and Franklin, Ramya G and others	2019	The paper introduces an alert system for detecting driver drowsiness using image processing techniques.	Leveraging image processing, the approach focuses on developing an alert system to detect and mitigate driver drowsiness
Tang, Jigang and Li, Songbin and Liu, Peng	2021	The paper conducts a review of lane detection methods, specifically those based on deep learning.	Emphasizing deep learning techniques, the approach reviews various methods for lane detection, contributing insights within the context of pattern recognition.
Lee, Jeonghun and Hwang, Kwang-il	2022	The paper introduces YOLO with adaptive frame control for real-time object detection applications.	Utilizing YOLO with adaptive frame control, the approach enhances real-time capabilities for efficient object detection
Diwan, Tausif and Anirudh, G and Tembhurne, Jitendra V	2023	The paper explores challenges, architectural successors, datasets, and applications in object detection using YOLO.	The approach delves into the intricacies of object detection with YOLO, addressing challenges, architectural advancements, datasets, and diverse applications within Multimedia Tools and Applications.

2.3 WORK EVALUATION TABLE:

	Work Goal	**System's Components**	**System's Mechanism**	**Features /Characteristics**	**Performance**	**Advantages**	**Limitations /Disadvantages**	**Results**
Pia M. Forsman, Bryan J. Vila, Robert	The goal of the research was to develop a method for det	The system used a high-fidelity simulator for driving measurements, with additional hard	The system utilized measures of steering wheel variability and lateral lane position variability to	The system provided a cost-effective and easy-to-install alternative technology for in vehicle driver drowsiness detection at moderate levels	The performance of the system was evaluated through simulated shift work studies using a high-fidelity simulator in	The system provides an alternative technology for driver drowsiness	—	The research findings indicated that steering wheel variability provides a basis for developing a cost-

A. Short, Christopher G. Mott, Hans P.A. Van Dongen. 2013	ecting driver drowsiness at moderate levels of fatigue, well before the risk of accidents becom	ware and software installed externally to the simulator.	detect driver drowsiness. The steering wheel movements were analysed to determine changes in vehicle heading, which correlated.	of fatigue.	a controlled laboratory environment.	detection that is cost-effective and easy to install.		effective and easy-to-install alternative technology for in vehicle driver drowsiness detection at mode

	esimminent.							ratelevelsoffatigue
Hu Shuyan, Zheng Gangtie.	The goal of the work is to predict driver drowsiness using eyelid related parameters and Support Vector	Eyelid related parameters extracted from EOG data. Support Vector Machine (SVM) algorith	The system employs the Support Vector Machine (SVM) algorithm to cons	High accuracy in drowsiness detection, especially for very sleepy subjects	The validation results show high accuracy in drowsiness detection, particularly for	High accuracy in drowsiness detection, especi	---	The validation results show high accuracy in drowsiness

2009	Machine (SVM) Algorithm	m for drowsiness prediction.	truct a drowsiness detection model using eyelid related parameters extracted from EOG data		very sleepy subjects	ally for very sleepy subjects		detection, particularly for very sleepy subjec

								t s
H , . M , U e n o k a n e d a , M . T s u k i n o 2 0 0 2	T h e g o al o f t h e w o r k is t o d e v el o p te c h n o l	The compon ents of the drowsin ess detectio n system using image process ing technol ogy include: Ima ge proces sing technol ogy for analyzi ng images of the driver' s face taken with a video camera . Eye ball detecti on functio n and face width detecti on	The syst em uses ima ge proc essi ng tech nolo gy to anal yze ima ges of the driv er's face and dete ct dro wsin ess base d on	1. Hig hly accurate and reliable detection of drowsines s. Nonco ntact approa ch to detecti ng drowsi ness without annoya nce and interfer ence.	The perfor manc e of the syste m has been evalu ated throu gh drivin g tests, accur ately tracin g chang es in the alertn ess level over time.	Highl y accura te and reliabl e detect ion of drows iness. No nc ont act ap pro ac h to det ect ing dro ws ine ss wit ho ut an no ya nc	——	T h e res ult s of th e te st s con duc te d und er a d r o w s y st at e in th e la b o ra to r y an d on a

	ogies for preventing drowsiness at the wheel an	function. Personal computer connected to the image processor for controlling the image processing procedure and judging the processed results. Infrared lamp provided in the instrument panel to facilitate	the degree to which the driver's eyes are open or closed. It judges the level of alertness by counting the number of times the eyes close with			e and interference		test course with an actual vehicle have made the following points clear: highly accurate and reliable detection of drowsiness, and no

	d to create an accident avoidance system. The		in a specified interval						ncontact approach

	objective is to accurately detect a decline in drive							

	r alertness and alert and refresh the driver to pr							

	event drowsiness during driving.							
JingTao, Hong	The goal of th	The system's components include YOLO (You Only Look Once), OYOLO	The system is fast, accurate, and robust. It achieves a faster process speed and higher mAP compared to	The system achieves a process speed of 44ms per image, which is faster than	The system achieves an mAP of 86.4 on the testing set, outperforming R-FCN which achie	The advantages of the system include its speed, accuracy, and robustness.	—	The system achieves a process speed of

bo Wang, Xinyu Zhang, Xiaoyu Li, Huawei Yang. **2017**	ework is to build an object detection system for im	(Optimized YOLO), R-FCN (Region-based Fully Convolutional Networks), and a pre-processing procedure for challenging images in nights	YOLO and R-FCN. It outperforms other object detectors and shows improvement in accuracy for challenging images in nights	YOLO by 18. OYOLO takes 44ms to process one image and performs the fastest among other object	ves 67.7. It also shows more than 6% improvement in mAP on the testing set.	It is faster than YOLO and other object detection algorithms, while outperforming them in accuracy. It also shows		44 ms per image, an mAP of 86.4 on the testing set, and more than 6% improvement in mAP on the testing set. It ou

	ages in traffic scenes that is fast, accurate, and r					improvement in accuracy for challenging images in nights.		t performance

	o b u st .							
J u a n D u . 2 0 1 8	The goal of the work is to impr ove objec t detec tion by accel eratin g the speed while maint ainin g high accur acy and gener alizat io n abilit y. The paper intro duces the You Only Look	The system compo nents include the Convol utional Neu ral Net wor k (CN N) fami ly, spec ifica lly the Fast er R- CN N mod el, and the YO LO	The YO LO mod el brea ks thro ugh the tradi tion al appr oach of the CN N fami ly and intro duce s a new way of solv ing	YOLO achieves unparallele d speed with a Frame Per Second (FPS) of 155 and a Mean Average Precision (mAP) of 78.6, surpassing the performanc e of Faster R-CNN. YOLOv2, an improved version, offers a tradeof f betwee n speed and accurac y. It also has strong general ization ability to	YOLO achieves a Mean Average Precision (mAP) of 78.6, surpassin g the performa nce of Faster R- CNN	YOL O offers a simpl e and highl y effici ent way of solvin g object detect ion. It achie ves fast speed and high accur acy, surpa ssing the perfor manc e of Faster R- CNN.	—	Y O L O ac hie ve s a Fr am e Pe r Se co nd (FP S) of 155 and a Mea n Ave rage Prec isio n (m AP) of 78.6 , surp assi ng the pe rfo rm a nc

		model.	object detection. It achieves high efficiency and speed by processing the entire image at once, rather than using region proposals	represent the whole image.				e of Faster R-CNN

Jing Tao, Hongbo Wang, Xiaoyu Li, Huawei Yang. **2017**	drowsiness detection system for drivers	cameras, video processing algo	monitor driver behaviour, including yawning, eye closure, eye blinking, and head pose, to detect drowsiness symptoms	The system offers adjustable sensitivity and can warn drivers of inattentiveness and drowsiness in an extended speed range.	The performance of the system was evaluated through the accuracy in the detection	The system can help prevent accidents caused by driver drowsiness and inattentiveness	Limited to Yawning Detection	The overall precision and recall are good

Yue Wang, Khwang Teoh, and Dinggang Shen.	develop an eye blink detection system	motion analysis algorithms, eye region tracking using techniques and feature extraction	The system analyzes motion vectors and optical flow within the eye region to detect eye blinks	The system offers high detection rates for eye blinks, with reported results achieving rates of 95.7% and false alarm rates under 0.1%	The performance of the system was evaluated through the accuracy in the detection	The system offers high detection rates for eye blinks, achieving rates of 95.7%	Sensitivity to Environmental Factors Challenges with Incomplete Blinks Computational Resource Requirements	The overall precision and recall are good

2003								
Tiesheng Wang, Pendeli Sh	develop a system for detecting	real-time face detector, Kalman filter for tracking the face region and a mouth window loca	The system uses a combination of face detection, tracking, and mouth feature analysis	It offers real-time implementation, making it suitable for monitoring driver drowsiness in real-world scenarios	The performance of the system was evaluated through the accuracy in the detection	The system provides a non-intrusive method for detecting	Limited to Yawning Detection Dependency on Kalman Filter Accuracy	Overall good with some fal

i, 1954	driver drowsiness	lized within the face region	to detect driver yawning			driver drowsiness based on video analysis		se
XIAO FAN, BAO-CAI YIN, YA	develop a system for detectin	real-time face detector, Kalman filter	face detection, Kalman filter	The system uses a simple and efficient projection-based method for mouth feature detection	The performance of the system was evaluated through the accuracy in the detection	The system provides a non-intrusive method for detect	Dependency on Yawning as Sole Fatigue Indicator Sensitivity to Occlusions	20% improvement in there

N-FENGSUN, 2007	g driver drowsiness					ing driver drowsiness based on video analysis		cognition rate
Sergio Saponara, Abdus	detecting fire and smoke usi	YOLOv2	YOLOv2 algorithm to automatically extract features of fire and smoke fro	deep learning techniques to automatically extract features	The performance of the system was evaluated through the accuracy in the detection	The system provides a low-cost implementation for	Dependency on YOLOv2 Algorithm Impact of Reusing CCTV Cameras	Accuracy of 93% which is

salam Elhanashi, Alessio Gagliardi, 20	ng video analysis		m the video streams			fire and smoke detection on embedded platforms		good

20								
Muhammad Ramzan, Hikmat Khan,	The goal of the work is to provide a co	The processing module uses a combination of these factors to detect drowsiness, and the alert unit alerts the	The system monitors physiological and physical factors like pulse rate, yawning, closed eyes, and blink duration	The system monitors physiological and physical factors like pulse rate, yawning, closed eyes, and blink duration to detect drowsiness. It uses a combination of these	The performance of the system was evaluated through the accuracy in the detection	The system provides an alternative technology for driver drowsiness detection tha	—	The research findings indicated

Shahid Awan, Amina Ismail, and Ahsan Mahm	mprehensive analysis of existing methods of driv	driver at multiple stages according to the severity of the symptoms	using a somatic sensor. These factors are then processed to detect drowsiness. The severity of the symptoms determines the level of alert	factors to determine the level of drowsiness and generates alerts accordingly		t is cost-effective and easy to install		the level and category of drowsiness

ood.2019	erdrowsiness detection and present a detailed a		generated by the system.					

	nalysis of widely used classification techniques							

	in this regard.							
Muhammad Ramzan, Hikmat Kh	The goal of the work is to provid	The processing module uses a combination of these factors to detect drowsiness, and the	The system monitors physiological and physical factors like pulse rate, yawning, closed eyes, and	The system monitors physiological and physical factors like pulse rate, yawning, closed eyes, and blink duration to detect drowsiness. It	The performance of the system was evaluated through the accuracy in the detection	The system provides an alternative technology for driver drowsiness	—	The research findings indic

an, Shahid Awan, Amina Ismail, and Ahsan M	eacomprehensive analysis of existing methods o	alert unit alerts the driver at multiple stages according to the severity of the symptoms	blink duration using a somatic sensor. These factors are then processed to detect drowsiness. The severity of the symptoms determines	uses a combination of these factors to determine the level of drowsiness and generates alerts accordingly		detection that is cost-effective and easy to install		ated the level and category of drowsiness

ahmood. 2019	f driver drowsiness detection and present a det		the level of alert generated by the system.					

	ai le d a n al y si s o f w i d el y u s e d cl a s si fi c at i o n te c h n i							

	ques in this regard.							
Mkhuseli Ngxande, Jule	The goal of the work is to re	The system's components include the extraction of facial features such as eye	The system uses machine learning techniques to analyse behavioral measures such	The system uses behavioral measures such as eye closure and yawning to detect driver drowsiness	The performance of the system is evaluated based on the accuracy of drowsiness detection. Different techni	The advantages of the system include the use of machine	—	The results of the meta a

s	v	blin	as		ques	lea		n
R	ie	ks,	eye		and	rni		a
a	w	head	clos		classi	ng		l
y	t	mov	ure		fiers	tec		y
m	h	eme	and		have	hni		s
o	e	nts	yaw		been	qu		i
n	st	and	ning		used,	es		s
d	at	yaw	to		with	for		c
T	e	ning	infer		varyi	acc		o
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	rowsiness detection using behavioral measure	hines, convolutional neural networks, and hidden Markov models for drowsiness detection	classifiers, and if traits of drowsiness are detected, an alarm is activated to suggest that the driver takes a break			ts that can be used as benchmarks for drowsiness detection.		upport vector machine techniques is the mo

	s and machine learning techniques.							st commonly used technique for drowsiness

								s detection, but convolutional neural ne

								tworks performed better than the other tw

								otechniques.
	The goal of the work is to provide a comprehen	The paper discusses the architecture of YOLO (You Only Look On	YOLO is a single stage object detector that focuses on all spatial region	YOLOs are known for their faster inference time compared to two stage detectors. The	YOLOs are known for their faster inference time compared to two stage detectors.	The performance of YOLOs is evaluated in terms of detection accuracy	YOLOs have faster inference times compared to two stage detect	The paper provides a comprehensive review of single stage object detectors, specifically focusing on YOLOs.

	sive review of single stage object detectors, specifically focusing o	ce) and its successors. It mentions that YOLO is based on the Darknet-53 framework, which uses 3x3 and 1x	proposals for object detection in one shot. It uses a relatively simpler architecture compared to two stage	y have been adopted in various applications due to their faster inferences		and inference time. While two stage detectors generally have higher detection accuracy, single stage detectors	ors, making them suitable for real-time applications like self driving cars.	

	n YOLOs (You Only Look Once).	l convolutional filters along with shortcut connection s	detectors.			like YOLOs have better inference time.			
Gabriel Oltean,	The goal of the wor	The system component s include Tiny YOLO for vehicle	The system uses Tiny YOLO for vehicle detection and	The system achieves high accuracy at realtime speed (33.5 FPS) on real traffic videos	The system achieves high accuracy at real-time speed (33.5 FPS) on	The advantages of the system include	—	The experiment a

RaduOrghidan, CameliaFlorea, VictorOl	k is to propose an approach for realtime vehicle	detection and fast motion estimation for tracking.	fast motion estimation for tracking. It detects vehicles using anchor boxes and multilabel classification. If a vehicle is detected twic		real traffic videos.	the use of machine learning techniques for accurate drowsiness detection and the availability of publicly		l results show that the proposed approach

tean. 2019	counting using TinyYOLO for detection and fast		e in the current frame, the system filters the resulting bounding boxes to obtain a unique identified vehicle.			available datasets that can be used as benchmarks for drowsiness detection.		achieves high accuracy at real time speed

	motion estimation for tracking.							(33.5 FPS) on real traffic videos

Yue Wang, Khwang Teoh, and Dinggang Shen.	The goal of the work is to propose a BSnake bas	To propose a B-Snake based lane detection and tracking algorithm	The system uses the B-Snake based lane model to detect and track the mid-line of the lane. The midline of the lane model can be deforme	The proposed method is robust against noise, shadows, and illumination variations in road images. It is applicable to both marked and unmarked roads, as well as dash and solid paint line roads	The system achieves high accuracy at real-time speed (33.5 FPS) on real traffic videos.	The B-Snake based lane model can describe a wider range of lane structures. The proposed me	--	The experimental results show that the pr

2003	ed lane detection and tracking algorithm that can		d by external forces calculated from both the left and right sides of the lane model.			thod is robust against noise, shadows, and illumination variations in road images		oposed method is robust against noise, sh

	describe a wider range of lane structures and is							adows, and illumination variations in ro

	robust against noise, shadows, and illumination v							adimages. It is applicable to both marked

	ariations in road images							and unmarked roads, as well as dashed and sol

								i d p a i n t l i n e r o a d s .

2.4 DISADVANTAGES OF EXISTING SYSTEM

Concisely summarizing the disadvantages of the above implementations:

• Single-stage object detectors may struggle with detecting small or occluded objects compared to two-stage detectors. Variability in detection accuracies between different algorithms, impacting their reliability in real-world applications.

• Object detection systems are prone to missed detections in conditions of low resolution or poor lighting, posing potential safety hazards as critical objects may go undetected. Additionally, false positives in detection can result in unnecessary alerts or actions in autonomous systems, leading to inefficiencies and potential risks to vehicle operations.

• Usage of different types of edge-based lane detection methods like Broggi’s GOLD system may struggle with complex road scenarios, such as faded lane markings or unusual road geometries. TFALDA's automatic lane extraction may not perform optimally in all environmental conditions, especially in challenging lighting or weather situations.

• Lane detection systems are vulnerable to system failures stemming from sensor malfunctions, software bugs, or communication errors, which can compromise overall safety and performance.

• Reliance on physiological measures like EEG or ECG may require intrusive or uncomfortable sensors for continuous monitoring. Behavioral measures such as eye tracking may not be reliable indicators of drowsiness in all individuals or driving conditions.

• Most existing models reliance on video-based methods for vehicle counting may be susceptible to errors in challenging lighting or weather conditions. Difficulty in accurately tracking vehicles in congested traffic or complex road layouts.

• Undercounting or overcounting of vehicles due to inaccuracies in detection or tracking algorithms. Inability to differentiate between vehicles of similar size or shape, leading to misclassification errors.

CHAPTER 3

PROPOSED SYSTEM

3.1 PROPOSED SYSTEM

The proposed approach is to develop a model where the system monitors the behavior of a person driving the vehicle and commanding in the abnormal conditions of the person or assisting about the travelling route. The Driver Assistant System comprises a suite of advanced driving features aimed at safety, assistance, and communication. It ensures vigilant driver monitoring to prevent drowsy driving and impaired operation. A conversational assistant facilitates hands-free interaction, aiding with navigation and information. By harnessing GPS and Google Maps, the system optimizes routes and identifies traffic congestion. It excels in collision avoidance by detecting distances between vehicles and recognizing nearby objects.

3.2 OBJECTIVES OF PROPOSED SYSTEM

The objectives of the proposed system include the following:

- Drowsiness detection of the driver and giving the alerts.
- Continuous road condition monitoring, identifying heavy traffic areas, and promptly notifying drivers of congestion ahead.
- Promptly notifies nearby emergency locations with relevant details, ensuring a swift dispatch of assistance to the accident site.
- Autonomously assess distances between vehicles and identify various objects in its path.
- Identifies and differentiate various objects, including pedestrians, cyclists, and obstacles, in order to achieve a comprehensive understanding of the driving environment.

3.3 ADVANTAGES OF PROPOSED SYSTEM

- By employing advanced techniques such as CNNs and GANs, the system can accurately monitor the driver's state in real-time, providing timely alerts to prevent accidents caused by drowsiness or fatigue.
- Through continuous analysis of live video streams and data from sensors, the system can identify heavy traffic areas and congestion ahead, enabling drivers to make informed decisions and choose

alternative routes, thus reducing travel time and avoiding traffic jams.

• The system promptly notifies nearby emergency locations with relevant details in the event of an accident, facilitating the swift dispatch of assistance and potentially saving lives by reducing response times.

• Utilizing state-of-the-art algorithms and sensor technologies, the system autonomously assesses distances between vehicles and identifies various objects in its path. This capability enhances driving safety by enabling the vehicle to maintain safe distances and avoid collisions with obstacles or other vehicles.

• By accurately identifying and differentiating various objects, including pedestrians, cyclists, and obstacles, the system provides a comprehensive understanding of the driving environment. This allows for proactive measures to be taken to ensure the safety of all road users and minimize the risk of accidents.

3.4 SYSTEM REQUIREMENTS

Here are the requirements for developing and deploying the model.

3.4.1 SOFTWARE REQUIREMENTS

Below are the software requirements for the model development.

• Jetson Orion Nano Software Development Kit (SDK) for prototyping and testing purposes, necessitating familiarity with the platform's ecosystem. Python serves as the primary programming language for coding on both the Jetson Orin Nano and Arduino Nano microcontroller board. Core libraries such as OpenCV, Scikit-learn, onnxruntime, pycuda, pytorch, and Dlib are indispensable for image processing tasks, while specialized libraries like the ADXL-345 Sensor Library are essential for interfacing with specific hardware components. Additionally, software for controlling GSM communication (such as the SIM800I GSM Module Library) and GPS data acquisition (such as the NeoGPS Library) are vital for implementing features like text messaging and location tracking. Furthermore, the project involves employing development environments like Arduino IDE and integrated text editors, alongside terminal emulators for executing commands on the Linux-based Jetson platform.

• An external laptop equipped with impressive specifications is employed for development and testing tasks. The laptop features an Apple M1 chip, serving as the central processing unit. This chip boasts an 8-core GPU, enabling efficient processing of complex visual tasks with agility.

Complementing the GPU is an 8-core CPU, intelligently divided into four performance cores and four efficiency cores for optimal performance across various workloads.

- The laptop is further equipped with a robust 256 GB SSD, ensuring fast data access and storage, while 8 GB of RAM provides ample memory for running multiple software tools and applications simultaneously.

- The presence of a 16-core neural engine enhances the laptop's capability to handle AI and machine learning tasks efficiently. This powerful configuration provides the necessary resources to develop, debug, and test the modules of the project seamlessly.

3.4.2 HARDWARE REQUIREMENTS

The proposed system is designed with a comprehensive set of hardware components to ensure robust performance and real-time monitoring capabilities. The core hardware components utilized while building the prototype as are as follows.

- Jetson Orin Nano is first in the list of hardware components used. Due to its suitability in prototyping and testing phases, Jetson Nano serves as the primary processing unit for the system, enabling efficient computation and analysis of data from various sensors. With a compact design, it provides on-device processing with up to 40 TOPS AI performance with low power and low latency. The kit’s expandability features an array of rich I/Os with pre-installed Wi-Fi module, M.2 Key M slots for SSD expansion, microSD slot, MIPI CSI-4 connectors, Gigabit Ethernet, and a 40-pin GPIO interface. Its Ampere architecture GPU and a 6-core ARM CPU, enables concurrent AI application pipelines and high-performance interference, making it a versatile tool for this implementation.

- The Raspberry Pi Camera Module 3 stands out as a compact yet powerful imaging solution, with a high-quality IMX708 12-megapixel sensor with HDR capabilities and phase detection autofocus. It captures the video footage of the driver’s face for landmark features as well as captures various objects on the road for object detection and recognition, lane detection, lane departure warning, lane keeping assistance and collision detection system. Capable of capturing full HD videos and still photographs, it supports HDR mode up to 3 megapixels. Packed with features such as built-in defect pixel correction, phase detection autofocus, and QBC re-mosaic function, this camera module delivers exceptional performance in a compact form factor.

• The ADXL-345 Accelerometer detects sudden movements or impacts indicative of drowsiness events. The ADXL345 is a 3-axis accelerometer utilizing microelectromechanical systems (MEMS) technology to detect changes in acceleration along three different axes by measuring the forces acting upon tiny suspended structures within the device. The Arduino Nano manages sensor interfacing and control tasks. GSM SIM800I Module facilitates communication for sending text and making phone calls, while the GSM Neo-6m Module provides accurate geographic positioning information. The LM2596 Step-down converter regulates the voltage levels to ensure consistent power delivery to the GSM module.

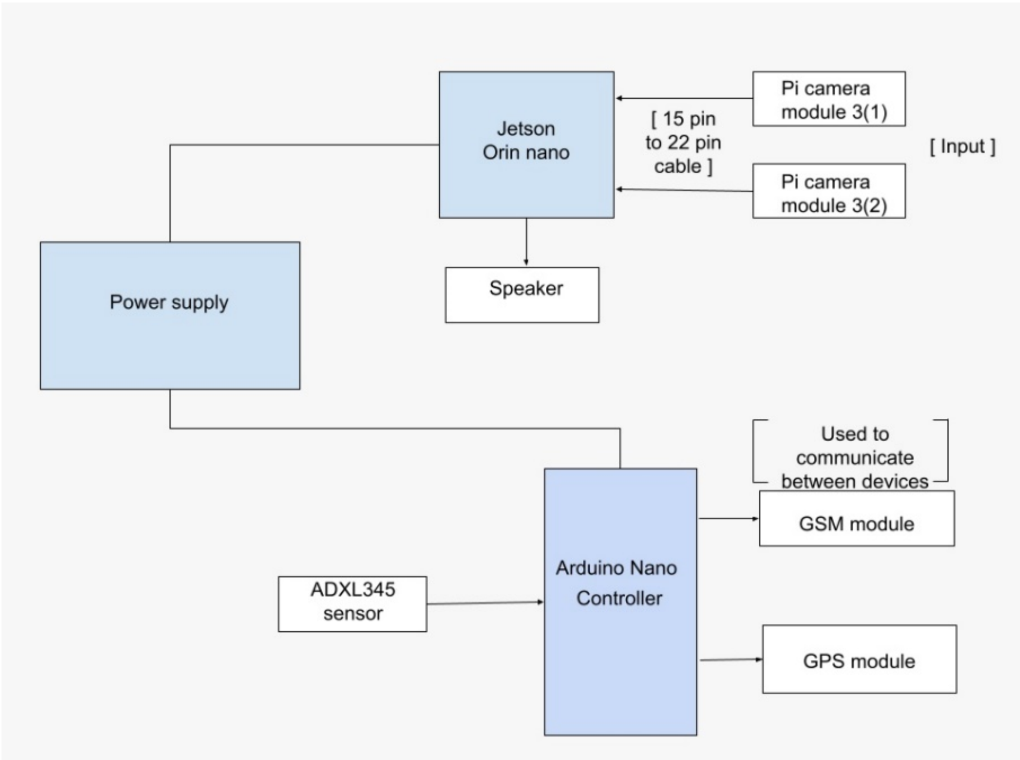

Figure 2: Block diagram of interconnection of the hardware components

3.5 CONCEPTS USED IN THE PROPOSED SYSTEM

3.5.1 YOLO v8

YOLOv8 model is used for object detection. YOLO provides real-time object detection by dividing an image into a grid and predicts bounding boxes and class probabilities for each grid cell. Mathematically, given an input image I, YOLOv8 predicts a set of bounding boxes B and their corresponding class probabilities C across the grid cells S in the image as:

$$B, C = YOLOv8(I)$$

This model is trained on a generic dataset, leveraging a diverse range of images to learn features representative of various objects. Generally, with N pre-loaded labels for prediction, denoted as L_1, L_2, …, L_N, YOLOv8 effectively classifies and localizes objects in the input data. With 81 pre-loaded labels for prediction, YOLOv8 accurately classifies and localizes objects in the input data. One of its key features is its ability to handle both loaded videos and real-time streams, making it suitable for integration into the framework.

Upon detection, the model generates bounding boxes around the identified objects, represented by the set B = {b_1, b_2, …, b_m}, where m is the total number of bounding boxes and assigns them their respective labels, facilitating easy recognition and further analysis. Each bounding box b_i is characterized by its coordinates (xi, yi, wi, hi), denoting the center coordinates and dimensions (width and height) relative to the image dimensions. It follows a single-shot detection approach, where the object detection is treated as a regression problem to spatially separated bounding boxes and associated class probabilities directly from full images in one evaluation. This means that YOLOv8 predicts bounding boxes and class probabilities simultaneously for all objects within an image. YOLOv8 predicts bounding boxes using a set of anchor boxes, which are predefined boxes of different shapes and sizes. After predicting bounding boxes and class probabilities, YOLOv8 applies NMS to remove redundant or overlapping bounding boxes. NMS ensures that each object is detected only once and selects the most confident bounding boxes for further processing.

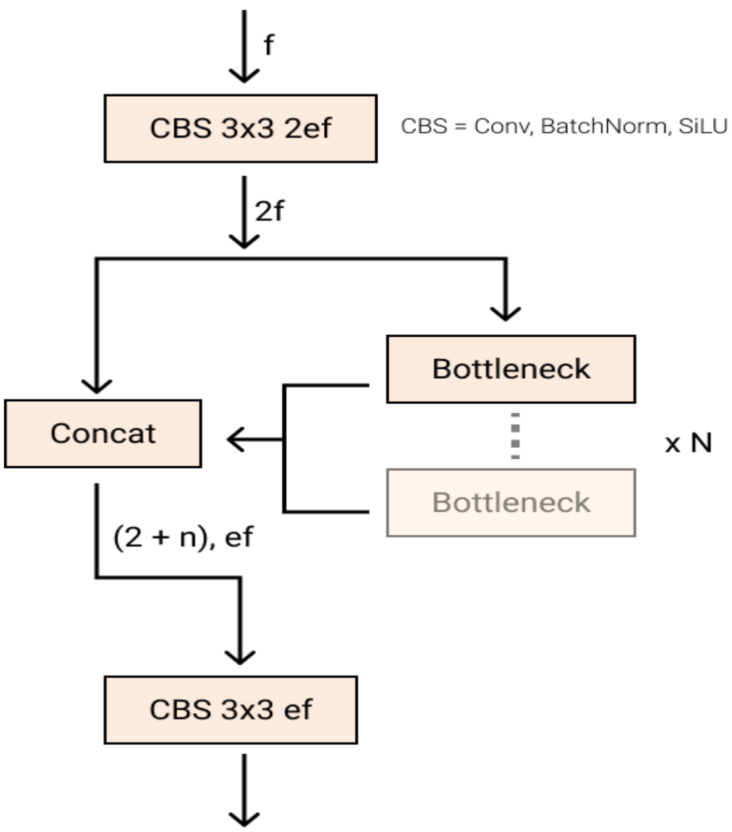

Figure 3: Workflow of YOLO v8

3.5.2 Ultrafast Lane Detector V2

Ultrafast Lane Detector V2 using ONNX and TensorRT used for implementing efficient inference of lane detection models. The TensorRT Engine and ONNX Engine classes handle the initialization and inference of the respective models. Finally, the Ultrafast Lane Detector V2 class integrates both engines to perform lane detection on input frames. The lane detection process involves parsing the output of the model to identify lane markings on the road. This is achieved through a combination of post-processing techniques such as SoftMax normalization and polynomial fitting. By processing the model output, the system can determine the coordinates of lane markings, allowing for visualization and further analysis. Lane detection is fundamental for ensuring driver safety and enabling various ADAS features.

The Lane Departure Warning System component utilizes lane detection results to monitor the vehicle's position within the lane. If the system detects that the vehicle is drifting out of its lane without signaling, it triggers a warning to alert the driver and adjusts the speed. This functionality helps prevent accidents caused by unintended lane departures, enhancing overall road safety. In conjunction with lane detection, the Lane Keeping Assist System actively intervenes to assist the driver in maintaining proper lane position. By analyzing the detected lane markings, the system can provide corrective steering inputs to keep the vehicle centered within the lane. This feature enhances driving comfort and reduces the risk of collisions due to lane deviations. Each of these components relies on accurate and efficient lane detection provided by the Ultrafast Lane Detector V2. By leveraging ONNX and TensorRT for model inference, the system achieves real-time performance, making it suitable for deployment in automotive environments where low latency is crucial.

3.5.3 Open CV

OpenCV is used to implements a collision warning system in proposed system for real-time object detection and distance estimation. This system operates on a single-camera setup, leveraging functions to calculate the distance of predefined objects such as pedestrians, bicycles, and vehicles, crucial for preemptive collision avoidance strategies. The object distances are measured based on their detected sizes in pixels and the focal length of the camera. By initializing with a predefined list of objects and their reference sizes, the system dynamically computes the distance of detected objects using the formula:

$$distance = \frac{reference\ size\ x\ focal\ length}{size\ in\ pixels}$$

This mathematical model enables the system to precisely estimate the distance of potential collision objects, thus laying the groundwork for timely warning signals to the driver.

Moreover, the system's capability extends beyond mere distance estimation by incorporating a method, which intelligently determines if the detected objects intersect with the main lane lines, a critical component for collision avoidance. This intersection analysis, facilitated through polygonal techniques, ensures that the system not only detects nearby objects but also evaluates their spatial relationship with respect to the vehicle's trajectory. Practically, such visualization facilitates vision by overlaying the detected objects on the video frame, accompanied by informative text displaying their calculated distances. The system dynamically adjusts the text size and font scale based on the estimated distance, thereby ensuring optimal readability for the driver.

CHAPTER 4

SYSTEM DESIGN

4.1 PROPOSED SYSTEM ARCHITECTURE

The suggested design of the proposed system seeks to offer a robust solution for driver assistance, leveraging a combination of hardware sensors, computational resources, and intelligent software algorithms to enhance driver safety and mitigate the risks associated with driving. The six modules that compose the overall system are: (1) Drowsiness detection and alert system; (2) Lane Detection; (3) Lane Departure Warning System; (4) Lane Keeping Assist System; (5) Object Detection and Recognition; and (6) Collision Warning System. Below is a detailed explanation of the system's complete ideology.

At the outset, the system initializes its core components, including cameras, sensors, and other processing units. This step ensures that all the necessary hardware is ready for operation. This foundational step lays groundwork for the subsequent functionalities aimed at proactive accident prevention and driver assistance. The system's operation begins with the monitoring of the vehicle's surrounding using one of the cameras focused on the road ahead. Through sophisticated algorithms, it analyzes the lanes and estimates traffic density by detecting and counting vehicles. This information serves as the basis for multiple functionalities, particularly lane detection, lane departure warning, and lane-keeping assistance. As the vehicle traverses the road, the system continuously monitors its position within the lane. Should the vehicle veer slightly off course, the lane-keeping assist system intervenes to maintain its trajectory within the lane boundaries, promoting stability and safety. However, in cases of significant deviations that pose a potential risk, the system promptly alerts the driver and may even autonomously adjust the vehicle's speed to mitigate the threat of a collision, ensuring swift and appropriate responses to varying levels of lane departure severity. Concurrently, the system employs a separate camera to monitor the driver's condition, detecting signs of drowsiness, fatigue, or other factors indicative of diminished alertness. Upon identifying such indicators, the system issues audio alerts to prompt the driver's attention, thereby reducing the likelihood of accidents resulting from driver impairment. This continuous monitoring ensures that the driver remains vigilant throughout the journey, enhancing overall safety. Moreover, the system incorporates a collision warning system to detect potential collisions with other vehicles or obstacles on the road. Leveraging advanced sensor technologies, it swiftly identifies imminent collisions and initiates emergency protocols. In the event of a detected collision, the system promptly dispatches emergency messages and initiates calls to presaved contacts, providing them with precise location details to facilitate rapid assistance and response.

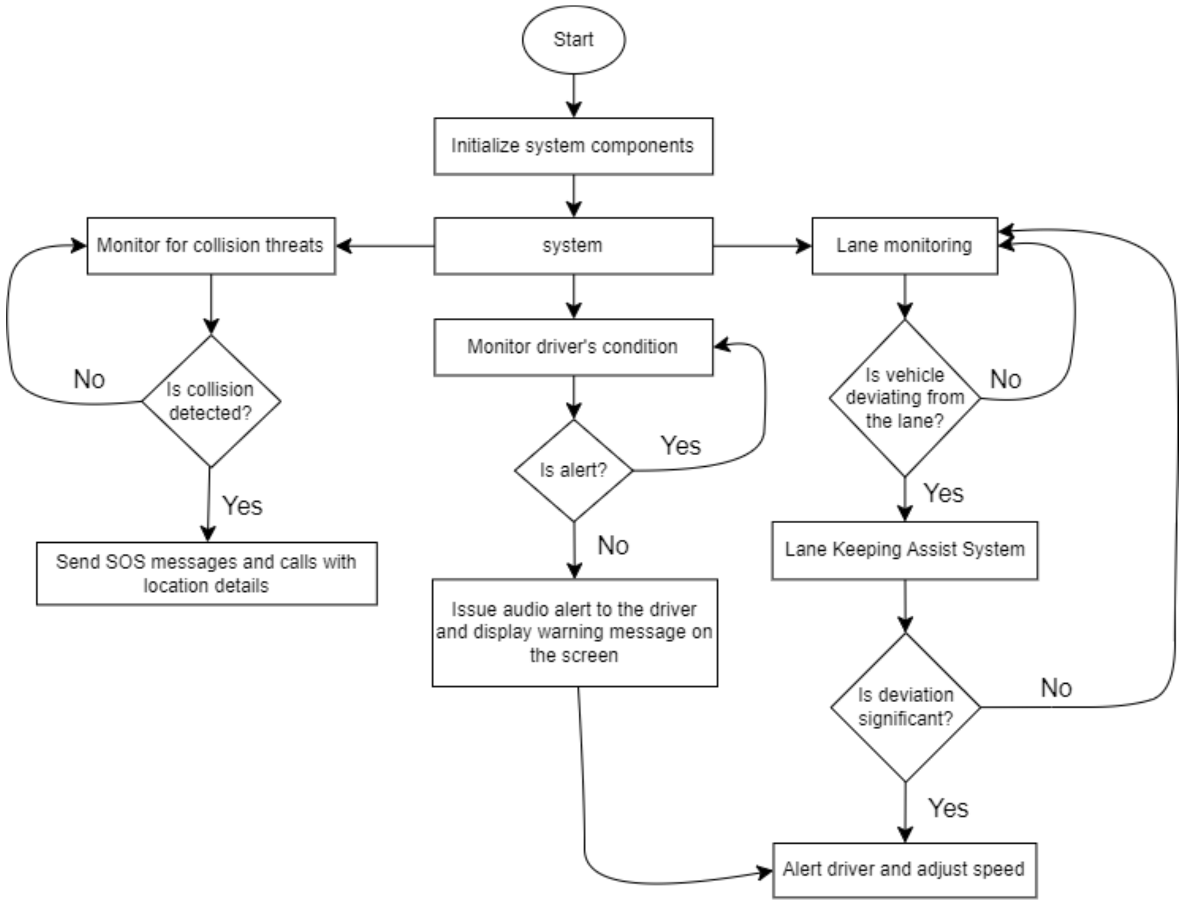

Figure 4: Overall workflow of the proposed system

4.2 UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. In its current form, UML comprises of two major components: a Meta-model and a notation. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modelling and other non-software systems. The UML uses mostly graphical notations to express the design of software projects.

4.3.1 USE CASE DIAGRAM

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

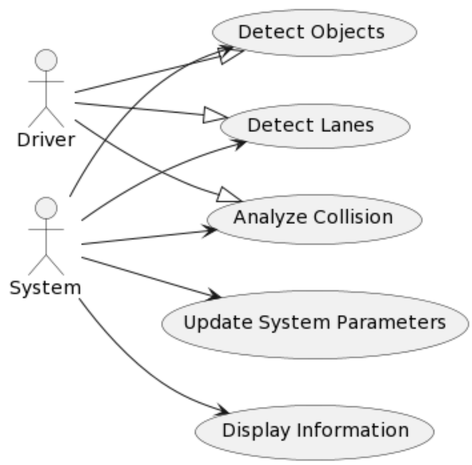

Figure 5: Use case diagram

4.3.2 CLASS DIAGRAM

In software engineering, a class diagram in the Unified Modelling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.

Point of view (POV) - 1:

Figure 6.1 : Class diagram

Point of view (POV) – 2:

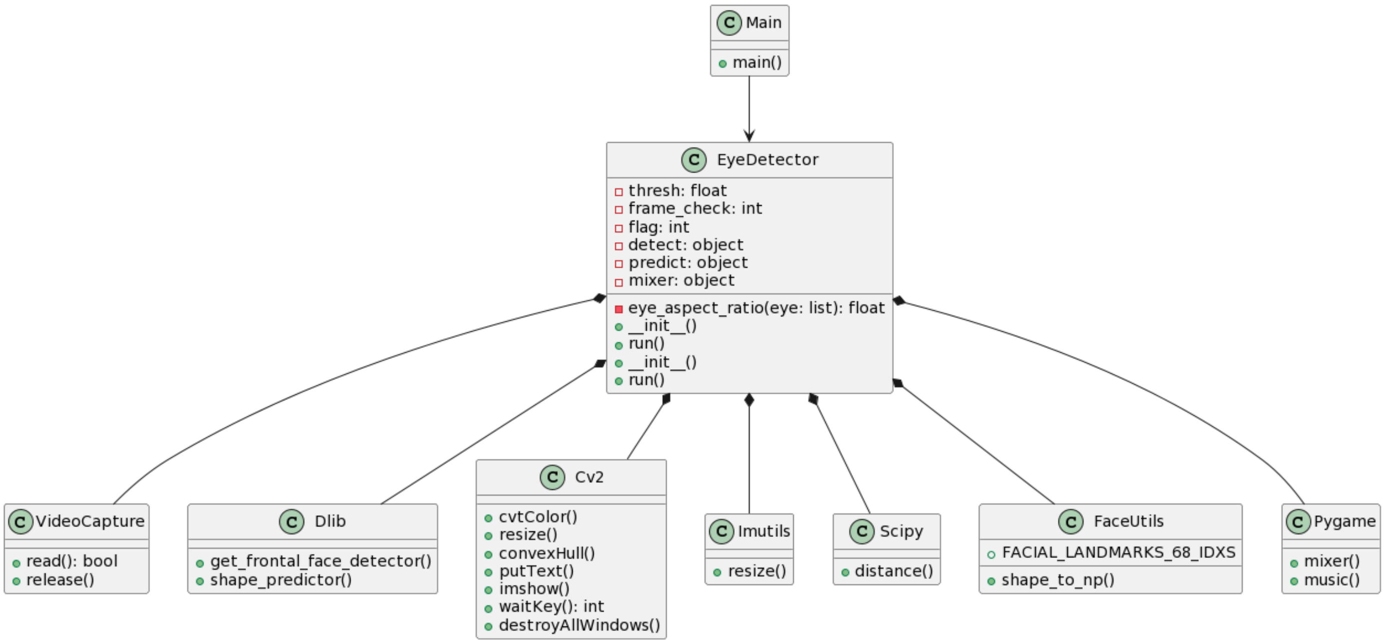

Figure 6.2 : Class diagram

4.3.3 SEQUENCE DIAGRAM

The sequence diagram depicts the processes involved and the sequence of message exchanges between the processes needed to carry out the functionalities.

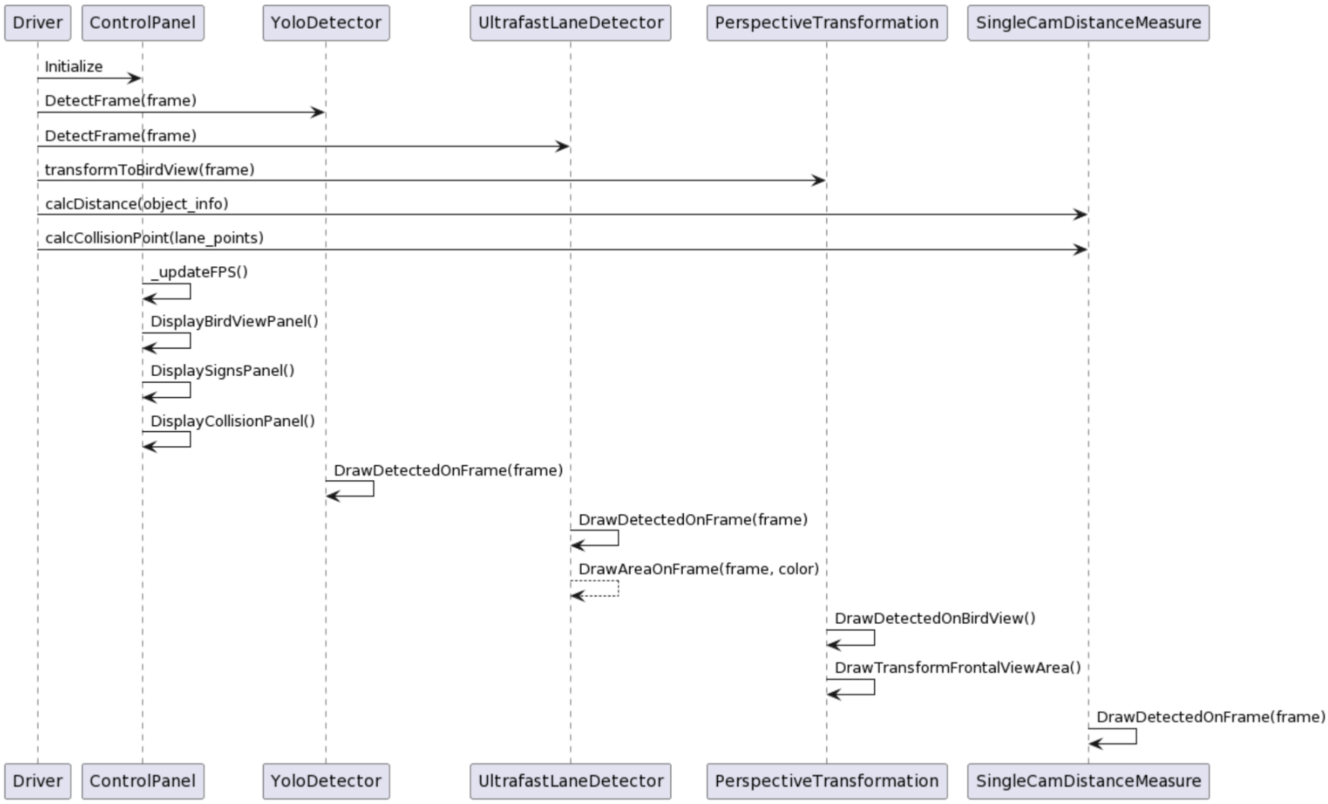

Figure 7: Sequence Diagram

4.3.4 COLLABORATION DIAGRAM

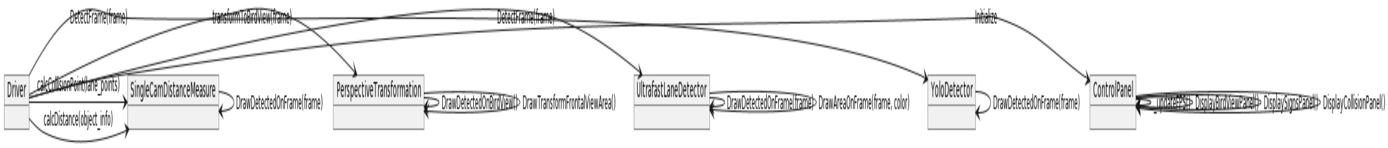

Figure 8: Collaboration diagram

CHAPTER 5

IMPLEMENTATION

5.1 SOURCE CODE

detect.py

```
from scipy.spatial import distance

from imutils import face_utils

from pygame import mixer

import imutils

import dlib

import cv2


mixer.init()

mixer.music.load("/Users/hemu/Major Project/Drowsiness detector/alram music.wav")


def eye_aspect_ratio(eye):

  A = distance.euclidean(eye[1], eye[5])

  B = distance.euclidean(eye[2], eye[4])

  C = distance.euclidean(eye[0], eye[3])

  ear = (A + B) / (2.0 * C)

  return ear


thresh = 0.21
```

```
frame_check = 20

detect = dlib.get_frontal_face_detector()

predict = dlib.shape_predictor("./shape_predictor_68_face_landmarks.dat")


(lStart,lEnd) = face_utils.FACIAL_LANDMARKS_68_IDXS["left_eye"]

(rStart,rEnd) = face_utils.FACIAL_LANDMARKS_68_IDXS["right_eye"]

cap=cv2.VideoCapture(0)

flag=0

while True:

  ret, frame=cap.read()

  frame = imutils.resize(frame, width=450)

  gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

  subjects = detect(gray,0)

  for subject in subjects:

        shape = predict(gray, subject)

        shape = face_utils.shape_to_np(shape)

        leftEye = shape[lStart:lEnd]

        rightEye = shape[rStart:rEnd]

        leftEAR = eye_aspect_ratio(leftEye)

        rightEAR = eye_aspect_ratio(rightEye)

        ear = (leftEAR + rightEAR) / 2.0

        leftEyeHull = cv2.convexHull(leftEye)

        rightEyeHull = cv2.convexHull(rightEye)
```

```
            cv2.drawContours(frame, [leftEyeHull], -1, (0, 255, 0), 1)

            cv2.drawContours(frame, [rightEyeHull], -1, (0, 255, 0), 1)

            cv2.putText(frame, "E.A.R: {:.2f}".format(ear), (300,
30),cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

            if ear < thresh:

                flag += 1

                print (flag)

                if flag >= frame_check:

                    cv2.putText(frame,"DROWSINESS ALERT!", (10,
30),cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

                        #cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 0, 255), 2)

                    mixer.music.play()

            else:

                flag=0

    cv2.imshow("Frame", frame)

    key = cv2.waitKey(1) & 0xFF

    if key == ord("q"):

            break

cv2.destroyAllWindows()

cap.release()
```

demo.py

```
import cv2, time

import numpy as np

import logging

import pycuda.driver as drv



from taskConditions import TaskConditions, Logger

from ObjectDetector.yoloDetector import YoloDetector

from ObjectDetector.utils import ObjectModelType,  CollisionType

from ObjectDetector.distanceMeasure import SingleCamDistanceMeasure

from TrafficLaneDetector.ultrafastLaneDetector.ultrafastLaneDetector import
UltrafastLaneDetector

from TrafficLaneDetector.ultrafastLaneDetector.ultrafastLaneDetectorV2 import
UltrafastLaneDetectorV2

from TrafficLaneDetector.ultrafastLaneDetector.perspectiveTransformation import
PerspectiveTransformation

from TrafficLaneDetector.ultrafastLaneDetector.utils import LaneModelType, OffsetType,
CurvatureType

LOGGER = Logger(None, logging.INFO, logging.INFO )

video_path = "./TrafficLaneDetector/temp/demo-2.mp4"

lane_config = {

  "model_path": "./TrafficLaneDetector/models/culane_res18_fp16.trt",

  "model_type" : LaneModelType.UFLDV2_CULANE

}

object_config = {
```

```
  "model_path": './ObjectDetector/models/yolov9c-coco_fp16.trt',
  "model_type" : ObjectModelType.YOLOV9,
  "classes_path" : './ObjectDetector/models/coco_label.txt',
  "box_score" : 0.4,
  "box_nms_iou" : 0.45
}
# Priority : FCWS > LDWS > LKAS
class ControlPanel(object):
  CollisionDict = {
                        CollisionType.UNKNOWN : (0, 255, 255),
                        CollisionType.NORMAL : (0, 255, 0),
                        CollisionType.PROMPT : (0, 102, 255),
                        CollisionType.WARNING : (0, 0, 255)
                    }
  OffsetDict = {OffsetType.UNKNOWN : (0, 255, 255),
                    OffsetType.RIGHT :  (0, 0, 255),
                    OffsetType.LEFT : (0, 0, 255),
                    OffsetType.CENTER : (0, 255, 0)
                }
  CurvatureDict = {CurvatureType.UNKNOWN : (0, 255, 255),
                        CurvatureType.STRAIGHT : (0, 255, 0),
                        CurvatureType.EASY_LEFT : (0, 102, 255),
                        CurvatureType.EASY_RIGHT : (0, 102, 255),
```

```
                    CurvatureType.HARD_LEFT : (0, 0, 255),

                    CurvatureType.HARD_RIGHT : (0, 0, 255)

                }

    def __init__(self):

        collision_warning_img = cv2.imread('./assets/FCWS-warning.png',
cv2.IMREAD_UNCHANGED)

        self.collision_warning_img = cv2.resize(collision_warning_img, (100, 100))

        collision_prompt_img = cv2.imread('./assets/FCWS-prompt.png',
cv2.IMREAD_UNCHANGED)

        self.collision_prompt_img = cv2.resize(collision_prompt_img, (100, 100))

        collision_normal_img = cv2.imread('./assets/FCWS-normal.png',
cv2.IMREAD_UNCHANGED)

        self.collision_normal_img = cv2.resize(collision_normal_img, (100, 100))

        left_curve_img = cv2.imread('./assets/left_turn.png', cv2.IMREAD_UNCHANGED)

        self.left_curve_img = cv2.resize(left_curve_img, (200, 200))

        right_curve_img = cv2.imread('./assets/right_turn.png', cv2.IMREAD_UNCHANGED)

        self.right_curve_img = cv2.resize(right_curve_img, (200, 200))

        keep_straight_img = cv2.imread('./assets/straight.png', cv2.IMREAD_UNCHANGED)

        self.keep_straight_img = cv2.resize(keep_straight_img, (200, 200))

        determined_img = cv2.imread('./assets/warn.png', cv2.IMREAD_UNCHANGED)

        self.determined_img = cv2.resize(determined_img, (200, 200))

        left_lanes_img = cv2.imread('./assets/LTA-left_lanes.png',
cv2.IMREAD_UNCHANGED)

        self.left_lanes_img = cv2.resize(left_lanes_img, (300, 200))
```

```
        right_lanes_img = cv2.imread('./assets/LTA-right_lanes.png',
cv2.IMREAD_UNCHANGED)

        self.right_lanes_img = cv2.resize(right_lanes_img, (300, 200))

        # FPS

        self.fps = 0

        self.frame_count = 0

        self.start = time.time()

        self.curve_status = None

    def _updateFPS(self) :

        """

        Update FPS.



        Args:

            None

        Returns:

            None

        """

        self.frame_count += 1

        if self.frame_count >= 30:

            self.end = time.time()

            self.fps = self.frame_count / (self.end - self.start)

            self.frame_count = 0

            self.start = time.time()
```

```
  def DisplayBirdViewPanel(self, main_show, min_show, show_ratio=0.25) :

        """

        Display BirdView Panel on image.

        Args:

              main_show: video image.

              min_show: bird view image.

              show_ratio: display scale of bird view image.



        Returns:

              main_show: Draw bird view on frame.

        """

        W = int(main_show.shape[1]* show_ratio)

        H = int(main_show.shape[0]* show_ratio)

        min_birdview_show = cv2.resize(min_show, (W, H))

        min_birdview_show = cv2.copyMakeBorder(min_birdview_show, 10, 10, 10, 10,
cv2.BORDER_CONSTANT, value=[0, 0, 0]) # 添加边框

        main_show[0:min_birdview_show.shape[0], -min_birdview_show.shape[1]: ] =
min_birdview_show

  def DisplaySignsPanel(self, main_show, offset_type, curvature_type) :

        """

        Display Signs Panel on image.

        Args:

              main_show: image.
```

```
                offset_type: offset status by OffsetType.
(UNKNOWN/CENTER/RIGHT/LEFT)

                curvature_type: curature status by CurvatureType.
(UNKNOWN/STRAIGHT/HARD_LEFT/EASY_LEFT/HARD_RIGHT/EASY_RIGHT)

        Returns:

                main_show: Draw sings info on frame.

        """

        W = 400

        H = 365

        widget = np.copy(main_show[:H, :W])

        widget //= 2

        widget[0:3,:] = [0, 0, 255]  # top

        widget[-3:-1,:] = [0, 0, 255] # bottom

        widget[:,0:3] = [0, 0, 255]  #left

        widget[:,-3:-1] = [0, 0, 255] # right

        main_show[:H, :W] = widget

        if curvature_type == CurvatureType.UNKNOWN and offset_type in {
OffsetType.UNKNOWN, OffsetType.CENTER } :

                y, x = self.determined_img[:,:,3].nonzero()

                main_show[y+10, x-100+W//2] = self.determined_img[y, x, :3]

                self.curve_status = None

        elif (curvature_type == CurvatureType.HARD_LEFT or self.curve_status== "Left")
and \

                (curvature_type not in { CurvatureType.EASY_RIGHT,
CurvatureType.HARD_RIGHT }) :
```

```
                y, x = self.left_curve_img[:,:,3].nonzero()

                main_show[y+10, x-100+W//2] = self.left_curve_img[y, x, :3]

                self.curve_status = "Left"



        elif (curvature_type == CurvatureType.HARD_RIGHT or self.curve_status== "Right")
and \

                (curvature_type not in { CurvatureType.EASY_LEFT,
CurvatureType.HARD_LEFT }) :

                y, x = self.right_curve_img[:,:,3].nonzero()

                main_show[y+10, x-100+W//2] = self.right_curve_img[y, x, :3]

                self.curve_status = "Right"

        if ( offset_type == OffsetType.RIGHT ) :

                y, x = self.left_lanes_img[:,:,2].nonzero()

                main_show[y+10, x-150+W//2] = self.left_lanes_img[y, x, :3]

        elif ( offset_type == OffsetType.LEFT ) :

                y, x = self.right_lanes_img[:,:,2].nonzero()

                main_show[y+10, x-150+W//2] = self.right_lanes_img[y, x, :3]

        elif curvature_type == CurvatureType.STRAIGHT or self.curve_status == "Straight" :

                y, x = self.keep_straight_img[:,:,3].nonzero()

                main_show[y+10, x-100+W//2] = self.keep_straight_img[y, x, :3]

                self.curve_status = "Straight"

        self._updateFPS()

        cv2.putText(main_show, "LDWS : " + offset_type.value, (10, 240),
fontFace=cv2.FONT_HERSHEY_SIMPLEX, fontScale=0.7, color=self.OffsetDict[offset_type],
thickness=2)
```

```
        cv2.putText(main_show, "LKAS : " + curvature_type.value, org=(10, 280),
fontFace=cv2.FONT_HERSHEY_SIMPLEX, fontScale=0.7,
color=self.CurvatureDict[curvature_type], thickness=2)

        cv2.putText(main_show, "FPS  : %.2f" % self.fps, (10, widget.shape[0] - 20),
cv2.FONT_HERSHEY_SIMPLEX, 0.6, (255, 255, 255), 2, cv2.LINE_AA)

  def DisplayCollisionPanel(self, main_show, collision_type, obect_infer_time, lane_infer_time,
show_ratio=0.25) :

        """

        Display Collision Panel on image.

        Args:

                main_show: image.

                collision_type: collision status by CollisionType.
(WARNING/PROMPT/NORMAL)

                obect_infer_time: object detection time -> float.

                lane_infer_time:  lane detection time -> float.

        Returns:

                main_show: Draw collision info on frame.

        """

        W = int(main_show.shape[1]* show_ratio)

        H = int(main_show.shape[0]* show_ratio)

        widget = np.copy(main_show[H+20:2*H, -W-20:])

        widget //= 2

        widget[0:3,:] = [0, 0, 255]  # top

        widget[-3:-1,:] = [0, 0, 255] # bottom

        widget[:,-3:-1] = [0, 0, 255] #left
```

```
            widget[:,0:3] = [0, 0, 255]  # right

            main_show[H+20:2*H, -W-20:] = widget

            if (collision_type == CollisionType.WARNING) :

                    y, x = self.collision_warning_img[:,:,3].nonzero()

                    main_show[H+y+50, (x-W-5)] = self.collision_warning_img[y, x, :3]

            elif (collision_type == CollisionType.PROMPT) :

                    y, x =self.collision_prompt_img[:,:,3].nonzero()

                    main_show[H+y+50, (x-W-5)] = self.collision_prompt_img[y, x, :3]

            elif (collision_type == CollisionType.NORMAL) :

                    y, x = self.collision_normal_img[:,:,3].nonzero()

                    main_show[H+y+50, (x-W-5)] = self.collision_normal_img[y, x, :3]

            cv2.putText(main_show, "FCWS : " + collision_type.value, ( main_show.shape[1]-
int(W) + 100 , 240), fontFace=cv2.FONT_HERSHEY_SIMPLEX, fontScale=0.6,
color=self.CollisionDict[collision_type], thickness=2)

            cv2.putText(main_show, "object-infer : %.2f s" % obect_infer_time, (
main_show.shape[1]- int(W) + 100, 300), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (230, 230,
230), 1, cv2.LINE_AA)

            cv2.putText(main_show, "lane-infer : %.2f s" % lane_infer_time, (
main_show.shape[1]- int(W) + 100, 320), cv2.FONT_HERSHEY_SIMPLEX, 0.5, (230, 230,
230), 1, cv2.LINE_AA)


if __name__ == "__main__":

  # Initialize read and save video

  cap = cv2.VideoCapture(video_path)

  if (not cap.isOpened()) :
```

```
        raise Exception("video path is error. please check it.")
    width  = int(cap.get(cv2.CAP_PROP_FRAME_WIDTH))
    height = int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT))
    fourcc = cv2.VideoWriter_fourcc('m', 'p', '4', 'v')
    vout = cv2.VideoWriter(video_path[:-4]+'_out.mp4', fourcc , 30.0, (width, height))
    cv2.namedWindow("ADAS Simulation", cv2.WINDOW_NORMAL)
    #==========================================================
    #                      Initialize Class
    #==========================================================
    LOGGER.info("[Pycuda] Cuda Version: {}".format(drv.get_version()))
    LOGGER.info("[Driver] Cuda Version: {}".format(drv.get_driver_version()))
    LOGGER.info("-"*40)
    # lane detection model
    LOGGER.info("UfldDetector Model Type : {}".format(lane_config["model_type"].name))
    if ( "UFLDV2" in lane_config["model_type"].name) :
        UltrafastLaneDetectorV2.set_defaults(lane_config)
        laneDetector = UltrafastLaneDetectorV2(logger=LOGGER)
    else :
        UltrafastLaneDetector.set_defaults(lane_config)
        laneDetector = UltrafastLaneDetector(logger=LOGGER)
    transformView = PerspectiveTransformation( (width, height) , logger=LOGGER)
    # object detection model
    LOGGER.info("YoloDetector Model Type : {}".format(object_config["model_type"].name))
```

```
  YoloDetector.set_defaults(object_config)

  objectDetector = YoloDetector(logger=LOGGER)

  distanceDetector = SingleCamDistanceMeasure()

  # display panel

  displayPanel = ControlPanel()

  analyzeMsg = TaskConditions()

  while cap.isOpened():

          ret, frame = cap.read() # Read frame from the video

          if ret:

                  frame_show = frame.copy()

                  #=========================== Detect Model
==========================

                  obect_time = time.time()

                  objectDetector.DetectFrame(frame)

                  obect_infer_time = round(time.time() - obect_time, 2)

                  lane_time = time.time()

                  laneDetector.DetectFrame(frame)

                  lane_infer_time = round(time.time() - lane_time, 4)

                  #========================== Analyze Status
=========================

                  distanceDetector.calcDistance(objectDetector.object_info)

                  vehicle_distance =
distanceDetector.calcCollisionPoint(laneDetector.draw_area_points)

                  analyzeMsg.UpdateCollisionStatus(vehicle_distance, laneDetector.draw_area)
```

```
                    if (analyzeMsg.CheckStatus() and laneDetector.draw_area ) :

                              transformView.updateTransformParams(laneDetector.lanes_points[1],
laneDetector.lanes_points[2], analyzeMsg.transform_status)

                    birdview_show = transformView.transformToBirdView(frame_show)

                    birdview_lanes_points =
[transformView.transformToBirdViewPoints(lanes_point) for lanes_point in
laneDetector.lanes_points]

                    (vehicle_direction, vehicle_curvature) , vehicle_offset =
transformView.calcCurveAndOffset(birdview_show, birdview_lanes_points[1],
birdview_lanes_points[2])

                    analyzeMsg.UpdateOffsetStatus(vehicle_offset)

                    analyzeMsg.UpdateRouteStatus(vehicle_direction, vehicle_curvature)

                    #========================== Draw Results
=========================

                    transformView.DrawDetectedOnBirdView(birdview_show,
birdview_lanes_points, analyzeMsg.offset_msg)

                    if (LOGGER.clevel == logging.DEBUG) :
transformView.DrawTransformFrontalViewArea(frame_show)

                    laneDetector.DrawDetectedOnFrame(frame_show, analyzeMsg.offset_msg)

                    laneDetector.DrawAreaOnFrame(frame_show,
displayPanel.CollisionDict[analyzeMsg.collision_msg])

                    objectDetector.DrawDetectedOnFrame(frame_show)

                    distanceDetector.DrawDetectedOnFrame(frame_show)

                    displayPanel.DisplayBirdViewPanel(frame_show, birdview_show)

                    displayPanel.DisplaySignsPanel(frame_show, analyzeMsg.offset_msg,
analyzeMsg.curvature_msg)

                    displayPanel.DisplayCollisionPanel(frame_show, analyzeMsg.collision_msg,
obect_infer_time, lane_infer_time )

                    cv2.imshow("ADAS Simulation", frame_show)
```

```
        else:
            break
        vout.write(frame_show)
        if cv2.waitKey(1) == ord('q'): # Press key q to stop
            break
vout.release()
cap.release()
cv2.destroyAllWindows()
```

CHAPTER 6

RESULTS

6.1 OUTPUT

1.

Figure 9 – Drowsiness not detected as the target's eyes are open

2.

Figure 10 – Drowsiness detected as the eyes of the target are closed

3.

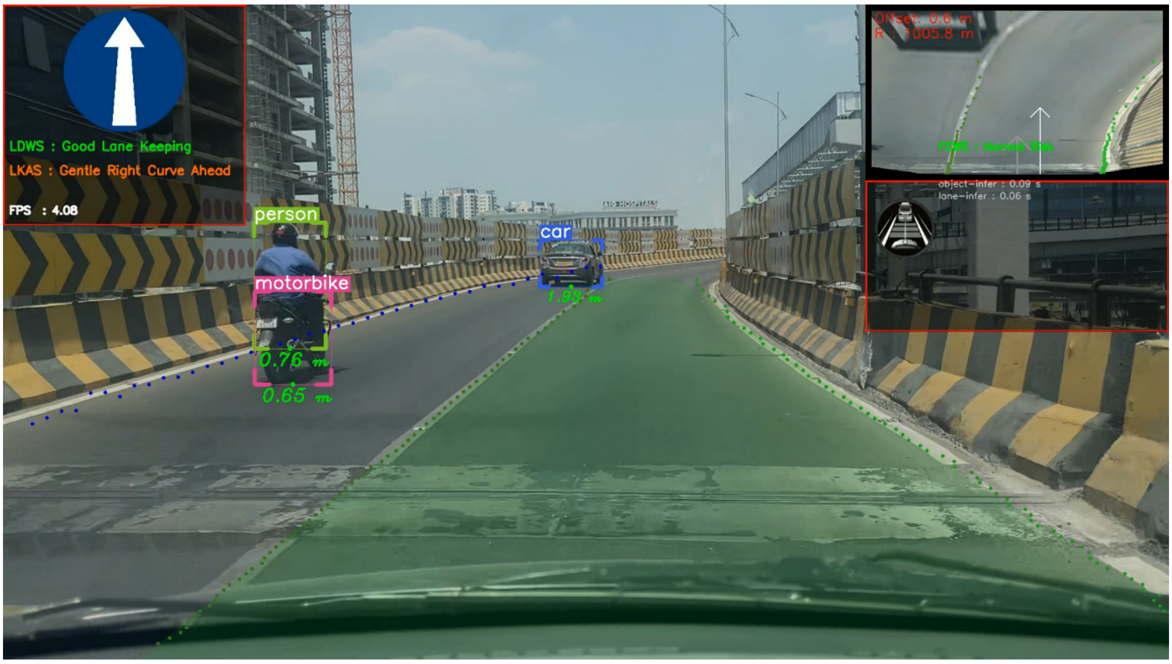

Figure 11 – Lane Keeping Assist System showing a gentle right curve ahead

4.

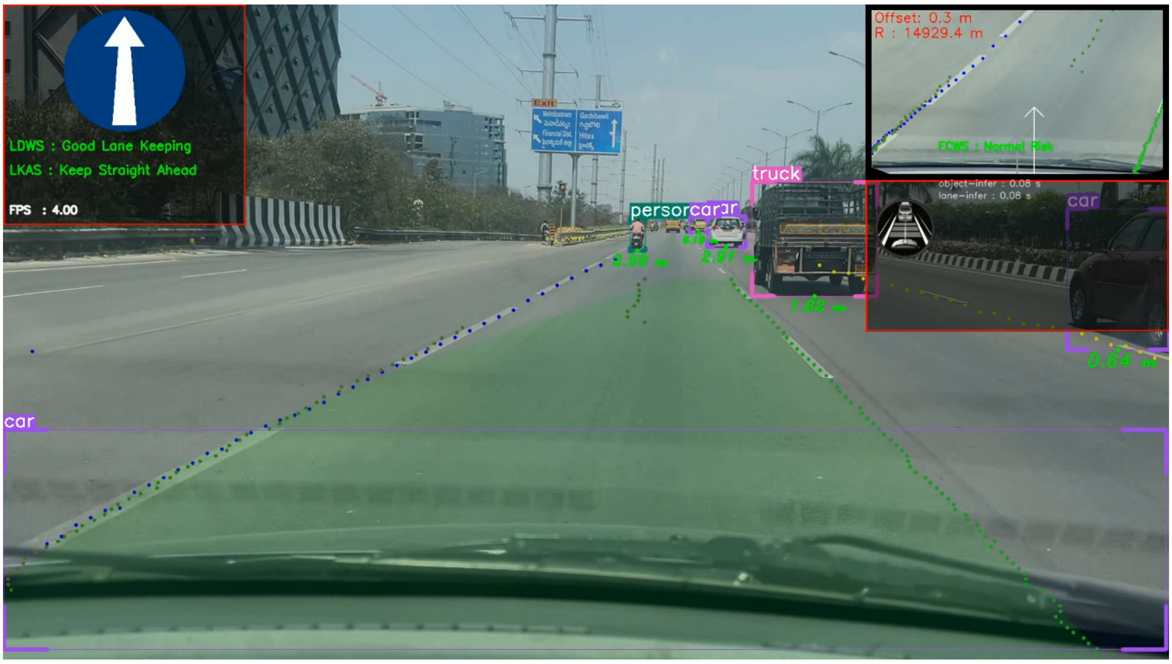

Figure 12 – Lane departure and lane keeping system showing acceptable parameters with less chances of collision

5.

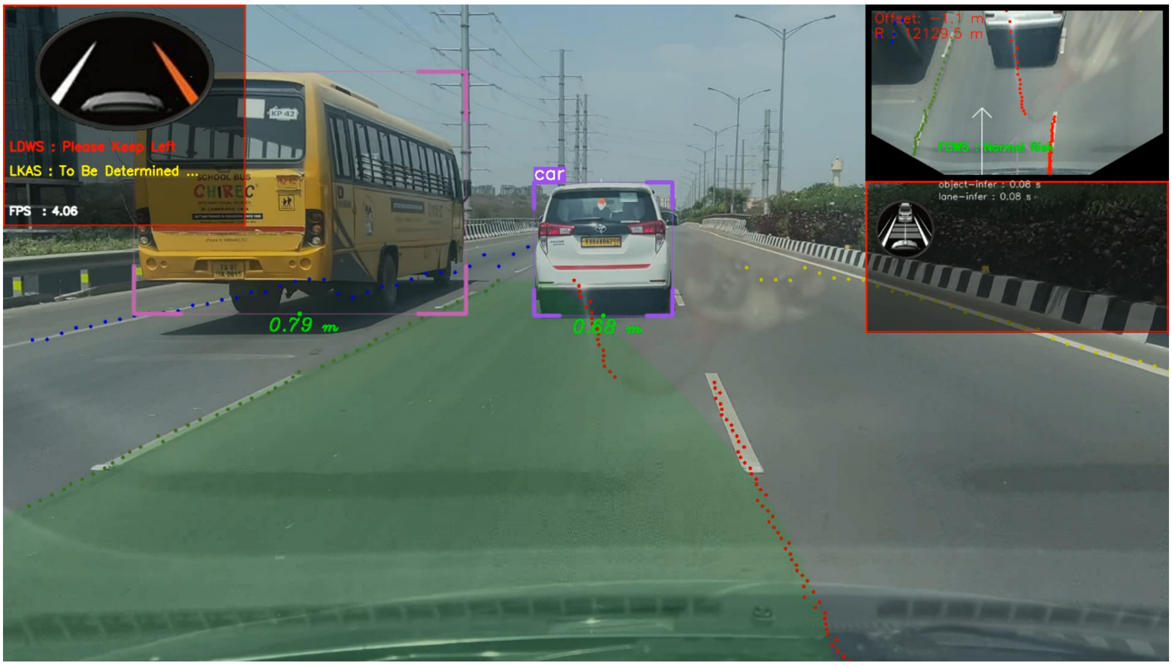

Figure 13 – Lane Departure System giving a warning to keep left

6.

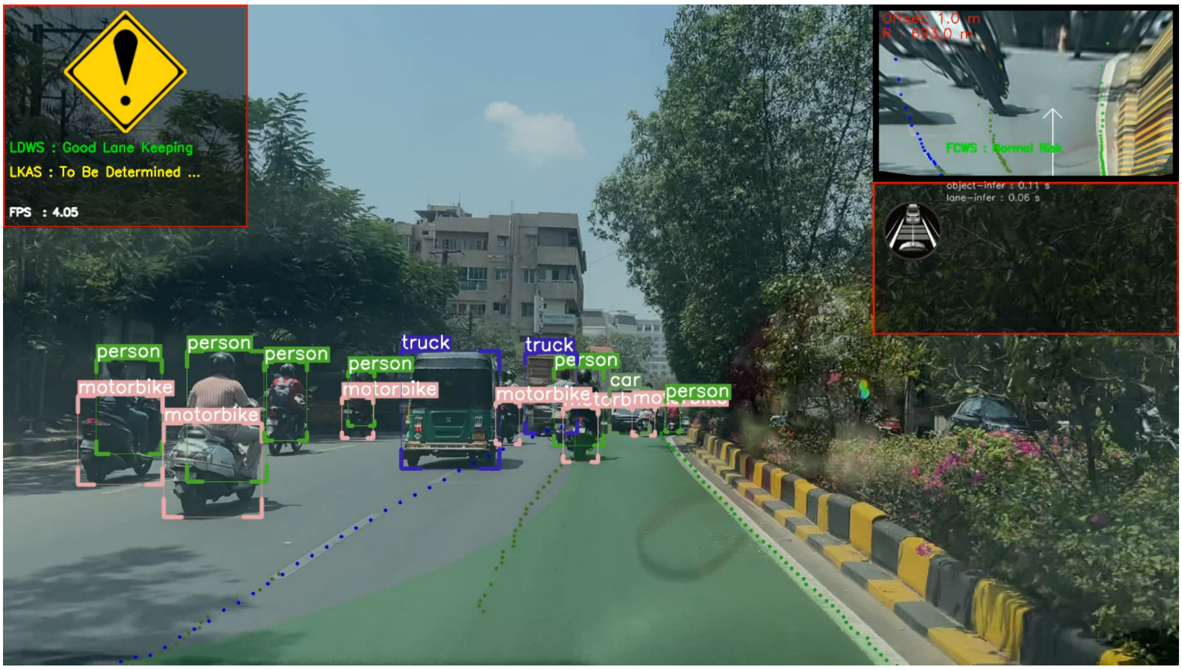

Figure 14 – Lane keeping assist system determining its path

7.

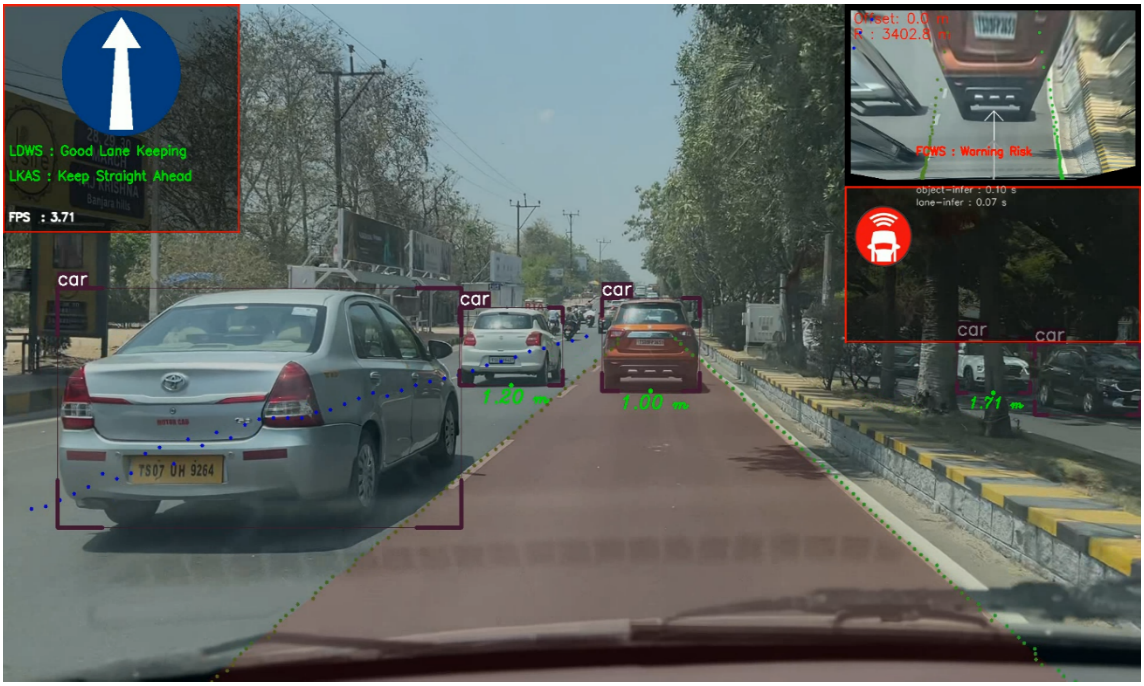

Figure 15 – Lane departure and lane keeping system showing acceptable parameters but warning issued by the collision warning system

8.

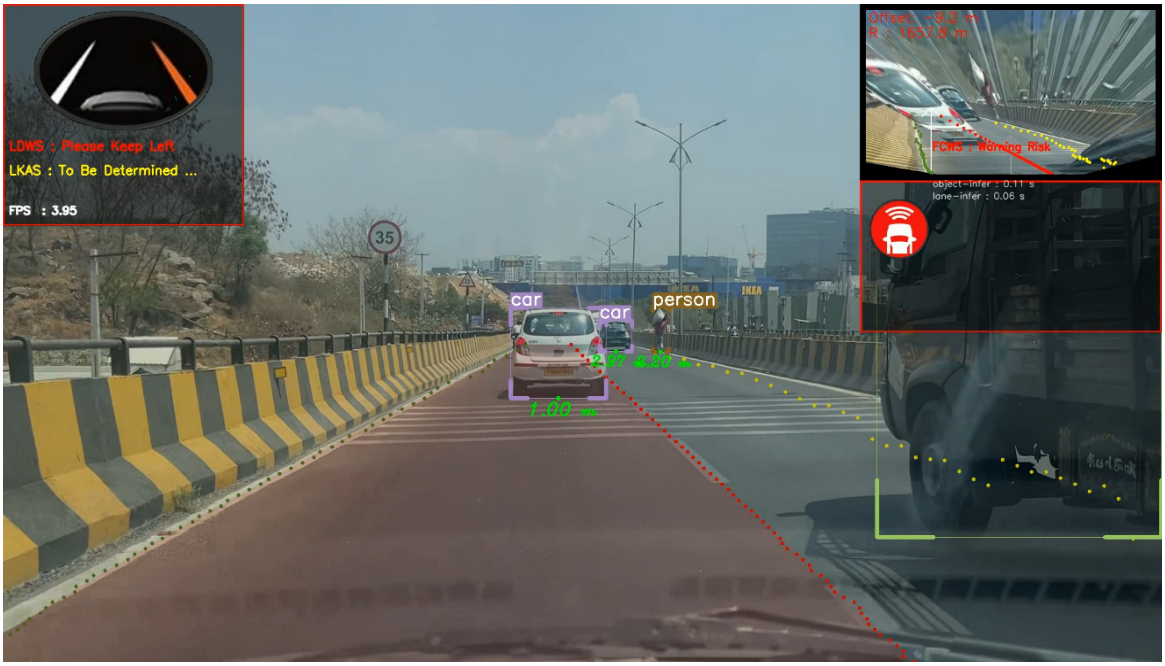

Figure 16 – Lane departure system, lane keeping system, and collision warning system showing negative parameters

CHAPTER 7

CONCLUSION

The proposed system includes a comprehensive methodology and system design for a driver assistance system aimed at enhancing road safety through proactive accident prevention measures, integrates a range of hardware components, including the Jetson Orin Nano for efficient data processing, Raspberry Pi Camera Module 3 for high-quality imaging, ADXL-345 Accelerometer for detecting sudden movements indicative of collisions, and GSM and GPS modules for communication and location tracking, respectively. Software implementation involves utilizing Python and essential libraries like OpenCV, Dlib, and TensorRT for image processing, object detection, and lane detection. The system comprises six modules, including drowsiness detection, lane detection, lane departure warning, lane-keeping assistance, object detection, and collision warning, each contributing to different aspects of driver safety. The utilization of facial landmarks and the eye aspect ratio (EAR) calculation for drowsiness detection, an Ultrafast Lane Detector V2 using ONNX and TensorRT for efficient inference of lane detection models, and the pre-trained YOLOv8 model for object detection emphasize accuracy in analysis and prediction. The collision warning system utilizes OpenCV for real-time object detection and distance estimation, employing polygonal techniques to assess potential collision risks and generate timely warnings to the driver. Overall, the proposed system demonstrates a holistic approach to driver assistance, leveraging advanced hardware and software technologies to mitigate road accidents and enhance overall road safety.

FUTURE ENHANCEMENTS AND DISCUSSIONS

The driver assistance system stretches beyond individual vehicles to deliver greater social benefits and sustainable enhancements. Collaboration across developers, transportation authorities, and emergency services can result in the development of intelligent transportation systems (ITS) that improve traffic flow, reduce congestion, and expedite emergency response times. The incorporation of smart city initiatives in connected vehicle technology can result in advantages among transportation networks, public services, and community stakeholders, enabling a more secure and effective urban environment for all. Overall, the development of automated driver assistance creates opportunities for dramatic advancements in transport security, efficiency, and sustainability.