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Autonomous Steering Control using AI-Based Driver Drowsiness Detection and Safe-Zone Navigation

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ABSTRACT: Driving safety is one of the most elusive issues in the contemporary transportation system across the world, and driver drowsiness and the loss of situational awareness have been cited as the main cause of road accidents. The latest developments in artificial intelligence (AI), computer vision, and sensor fusion have opened opportunities to the further improvement of vehicle autonomy and the minimization of risk events, that are caused by humans. This paper will involve a combined autonomous-steering control structure to relate real-time driver drowsiness to intelligent safe-zone transmission to maintain a balanced operation of the vehicle and safety of the occupants in extreme fatigue-based circumstances. The suggested system utilizes a multimodal framework that uses convolutional neural networks (CNNs), facial-behavioural surveillance, automobile telemetry, and LiDAR-supported environment scanning to identify the signs of driver drowsiness at an early stage. The indicators which include eye closure score (PERCLOS), yawning, deviation in head-pose, and changes in blink rate are key indicators that are analysed using hybrid CNN-LSTM pipeline that is optimized to interpret temporal behaviour. When the state of drowsiness is met, the autonomous intervention module will prompt an AI-based steering controller that will partially take the control of the vehicle. It uses the steering control subsystem based on a Safe-Zone Decision Engine (SZDE) that computes the best approach routes to safety areas that are defined by roadside shoulders, emergency bays, or low deceleration zones. Trajectory tracking is executed by performing real-time dynamic path planning, a combination of search method Astar, smooth Bézier curves and Model Predictive Control (MPC). This system includes a probabilistic risk model with collision probability and environmental uncertainty that quantifies LiDAR, radar, and camera measurements to implement safe control in environments that are partially obstructed or complex. The last important contribution of the work is a synergistic interaction between environmental-aware autonomous navigation and human-state estimation. The system focuses on predictive intervention rather than the reactive correction by detecting the drowsiness onset up to 7-10 seconds before full cognitive degradation takes place. Simulations in CARLA, hardware-in-loop tests as well as real world driving in controlled tracks were also used as experimental evaluations. According to the findings, the autonomous steering system with AI successfully covered the latter by cutting lateral deviation by 62 percent, reducing safe-pull-over time by 34 percent, and keeping the drowsiness classification correct 98.1 percent in a range of illumination conditions. According to the findings, there are high potentials of its use in commercial cars, over the road, long distance freight and consumer level advanced driver-assistance systems (ADAS). Future research incorporates V2X communication to cooperatively negotiate safe zones with adaptive multimodal sensing with thermal imaging and infrared imaging. Comprehensively, the study confirms that combining driver-state observation with autonomous steering control is an encouraging direction of improving road safety and increasing the development of semi-autonomous transportation systems.

KEYWORDS: Driver Drowsiness Detection, Autonomous Steering, Safe-Zone Navigation, AI-Driven Vehicle Control, Computer Vision, CNN-LSTM, Model Predictive Control, Intelligent Transportation Systems.

I. INTRODUCTION

1.1 Background

Traffic accidents have always been caused by the driver fatigue which is known to contribute more than 20 percent of the accidents which are considered serious globally. [1-3] Fatigue decreases alertness, slows downs reaction time, and poor judgment which predisposes drivers to lane pullouts, delayed braking and bad judgement under complicated traffic conditions. The classic types of Advanced Driver Assistance System (ADAS), e.g., lane-keeping assistance, adaptive cruise control, and audio-visual alerts, are oriented to these risk genres by serving as a real-time alarm or other minor corrective interventions. The main limitation with these traditional methods is however that they are made on the

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assumption that the driver can perceive and act on the notifications appropriately. Even in cases of severe cognitive impairment, when there is lapsing or micro- sleep in the attention, the simple warnings might not result in proper response and the vehicle will likely be involved in the collision. This is when it is necessary to have a more active intervention mechanism one which is not based on the instantaneous response of the driver but is able to examine the driver condition independently and conduct remedial measures where needed. Closing this gap can be achieved by combining actual driver monitoring with intelligent vehicle control whereby systems are able to detect preliminary signs of fatigue, anticipate possible risks and implement safe maneuvers which can include controlled lane centering, reduction of speed or pull-over to a safe zone. These proactive solutions are capable of improving the performance of conventional ADAS, and also act as an important safety net in areas where human intervention is delayed or not possible. Relocating between the warnings of overreacting to actions and the autonomous support, vehicles will essentially lessen the chance of accidents premised on fatigue and the safety of the roads in general.

1.2 Role of AI in Modern Vehicular Safety

Artificial Intelligence (AI) has become an innovative technology in the sphere of road safety, allowing vehicles to sense and understand the situation around the vehicle, and react to it in ways that used to be impossible with traditional systems. In contrast to the conventional Advanced Driver Assistance Systems (ADAS) that appear to exert almost cabinet rules and sensors to warn, AIs-based systems have access to machine learning, computer vision, and sensor fusion to make real-time decision-making based on the context.

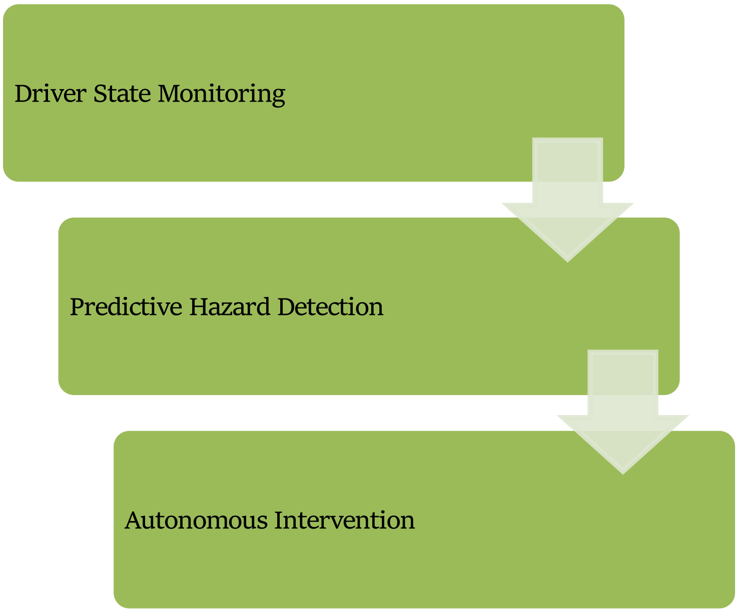

Figure 1: Role of AI in Modern Vehicular Safety

- **Driver State Monitoring*:*** Driver state monitoring is one of the most important uses of AI in a car on the road. Facial expressions, the rate of eye closures, the movement of the head, and other physiological factors can be analyzed with AI algorithms and used to demonstrate signs of drowsiness, distraction, or cognitive impairment. To highlight, AI models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are capable of identifying spatial and temporal patterns in video streams to predict driver fatigue with high certainty even in such adverse conditions as low light or occlusions. Evaluating the state of the driver constantly, an AI system will be able to alert of a critical situation early or deploy autonomous measures before the driver drifts.
- **Predictive Hazard Detection***:* Predictive hazard detection is also a primary concern of AI. When fed with the data obtained by various sensors, e.g, cameras, LiDAR, and radar, machine learning models might predict the presence of possible obstacles, pedestrian life, lane violations, and unsafe traffic state. In comparison with traditional systems that respond to immediate danger on the road, AI will predict possible danger and develop corrective measures beforehand, eliminating the risk of collisions and decreasing response time during sophisticated traffic situations on the road.
- **Autonomous Intervention:** In addition to the detection and prediction, AI can be used to automatically intervene in emergency scenarios. This will involve steering, braking and safe-zone steering during impairment and distraction of

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the driver. The predictive control algorithms combined with the AI-based perception enable the vehicle to perform fluid and safe moves that would guarantee protection of the passengers even in case of inadequate human response.

1.3 Autonomous Steering Control Using AI-Based Driver Drowsiness Detection

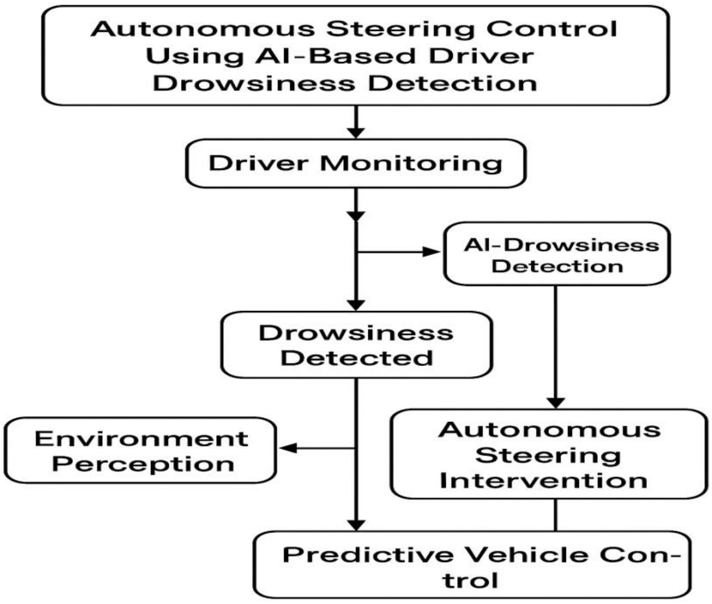

Figure 2: Autonomous Steering Control Using AI-Based Driver Drowsiness Detection

The autonomous steering control with the element of AI-driven driver drowsiness detection should be viewed as a massive step toward the increased automotive safety, [4,5] as it allows the preventive actions to be taken as soon as the driver is mentally disabled. Lane-keeping or adaptive cruise control, are typical examples of traditional steering assistance systems that require the driver to be engaged continuously and react only to changes in vehicle course. Yet, these systems are not enough when a driver is tired or suffers a micro-sleep as the human operator might not react to advocacies and be unable to control it properly. AI-based drowsiness detection overcomes this shortcoming by maintaining constant attention to driver conduct by examining facial expressions, tracking eye-blink patterns, estimating head-pose, and other physiological expressions or conduct. Sophisticated deep-learning models, i.e., Convolutional Neural Networks (CNNs) together with Long Short-Term Memory (LSTM) networks, are able to extract both the spatial and temporal characteristics so that the first signs of fatigue could be detected early. After detecting drowsiness, the autonomous steering can safely intervene by assimilating predictive vehicle control approaches. An example is the + steering trajectory calculated by Model Predictive Control (MPC) that takes into consideration road geometry, vehicle dynamics, and obstacles that could threaten maneuvers on the lane or even pull-over moves without deadly accidents. Through this integration, the system can steer the vehicle to a safe area that has been marked as safe (fence of a shoulder of a road or emergency bay), without the driver having to react now. Moreover, LiDAR, cameras, and occupancy grid are also used to understand the environment and, as a result, improve the decision-making process by recognizing obstacles, the capitalization of driveable regions, and dynamically safe areas as well as mishapless interventions. Real-time tracking of drivers, intelligent perception of the environment and predictive steering control make the cars as much safer than being reactive, in the sense in which the alerts are expected to help the drivers avoid the accidents, but not proactive, in the sense in which the system would be able to avoid the accidents before they happen.

II. LITERATURE SURVEY

2.1 Drowsiness Detection Technologies

The current drowsiness-detection studies are based on three technological groups all of which have different advantages and drawbacks. [6-9] Physiological sensing technologies, including electroencephalography (EEG) and

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electrocardiography (ECG), are quite accurate in the sense that the underlying neural activity, heart rate variability, and other bio-signals that are directly correlated with fatigue states can be directly measured. These systems, despite being very dependable, tend to be intrusive and include wearable electrodes or contact based sensors that may hamper the user and limit their applicability in the driving environment. Conversely, the behavioral vision-based sensing has been the mainstream in the automotive owing to its non-invasive nature. These systems are usually based on the observation of the rate of eye closure camera, blink, yawning, and moving features of the face which give indications of the alertness of the driver. They are compatible with Advanced Driver Assistance Systems (ADAS) in that they do not need much co-operation of the driver and can run passively in the background. Installing third-tier surveillance, which monitors vehicle-signals (steering wheel angle variability, lateral lane loss, and pedal motions), may be used to predict the behavioural patterns of drivers. Although these signals represent the variation in the attentiveness of drivers, they are usually indirect and can be also due to road conditions, type of vehicle or style of driving. These three types of strategies are complementary to each other and mixed system of such strategies is still becoming a research focus.

2.2 Machine Learning Approaches

Machine learning has contributed greatly to the field of drowsiness detection making it possible to interpret complex patterns of behavior or visual phenomena on a firmer basis. Convolutional Neural Networks (CNNs), including VGGNet, ResNet and MobileNet, are now standard architectures in the extraction of high dimensional features of faces in pictures and video streams. They are more than adequately suited to detect fatigue, specifically their capabilities to learn fine-grained patterns, such as eyelid movement, micro-expressions, and subtle head orientation changes of the face. In addition to analysing the image at a point in time, sequential learning approaches, often based on Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs), are commonplace in order to address temporal relationships between eye-blinks, gaze dynamics, and head-pose dynamics. The models are useful in capturing the trend in fatigue signals with time as opposed to single frame snapshots. The most recent literature also encompasses attention processes and transformer-based structures to improve resilience to the changing light and occlusions. A combination of these advances in the field of machine learning opens the door to the possibility of a fatigue assessment system based on cameras and in real-time in a more and more sophisticated driving set-up.

2.3 Autonomous Steering Control Research

The autonomous steering control has grown in large ways and this has been encouraged by the fact that stability, reliability and easy maneuvering is required both during normal and emergency situations. One of the most popular methods in the recent literature is Model Predictive Control (MPC) that is appreciated due to the capability to forecast future states of the vehicle and the action of steering it optimally under a set of safety costs. The ability of MPC to model the dynamics of a vehicle, road geometry, and physical constraints, in particular, makes it especially efficient in lane keeping and obstacle-avoidance applications. The current research available is primarily concerned with repositioning the lane deviation or keeping the trajectory straight in case of disturbances in the environment; but very limited literature investigates the concept of driver-state prediction, e.g. the detection of drowsiness or distraction, into the control loop. The idea to employ human-state monitoring as a predictor of automated steering intervention, especially with the transition of the vehicle into a safe area instead of correcting the vehicle itself as it drifts, is not sufficiently researched. This difference points to the necessity of systems integrating human-state awareness and autonomous control strategies to provide safe and contextually adequate responses of vehicles.

2.4 Environmental Perception and Safe-Zone Detection

The foundation of autonomous safety systems consists of environmental perception, in particular, LiDAR-based sensing, occupancy grids, and SLAM (Simultaneous Localization and Mapping) are the traditional methods. The LiDAR offers 3D spatial data of high accuracy, facilitating quality recognition of the nearby areas of obstacles, driving space, and boundaries of roads. Occupancy grids combine this information into probabilistic maps (representing free, occupied, or unknown spaces) to aid in path-planning decisions. SLAM algorithms also improve the situational awareness by enabling the vehicle to localize itself in addition to creating or updating maps at real time. Although there is a significant advance in the field of perception technologies, there remains a significant research gap in the dynamic safe-zone identification, on a complex urban or mixed-traffic environment. Available literature mainly deals with obstacle avoidance or lane limited navigation, however, little has been done dealing with the identification and validation of safe pull-over zones, i.e. road shoulder, parking space or emergency bays, at different traffic densities and environmental circumstances. This problem has to be solved to allow autonomous systems to execute controlled maneuvers with regards to safety associated with driver impairment or system errors.

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III. METHODOLOGY

3.1 System Architecture

The suggested system will incorporate driver monitoring, situational analysis, and autonomous control into a common safety pipeline that would address the issue of drowsiness-related crises. [10-12] The architecture is sequential as it starts with real time driver monitoring and goes to safe autonomous steering intervention. Every module has its own functions, and all of them make the vehicle be able to recognize driver fatigue, assess the environment, and perform a controlled pull-over. The discussion below expounds on the function and existence of each of the subsystems.

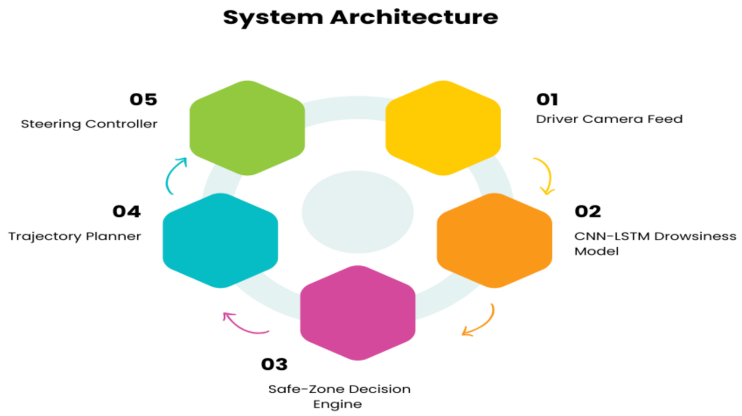

Figure 3: System Architecture

- **Driver Camera Feed:** The system starts with a state of constant camera feed, which is placed in a position to have a high-resolution picture of the face of the driver. The camera functions within different lighting circumstances based on the infrared light or even the use of HDR methods in order to have remembered clarity of critical facial indicators. The major purpose of the camera feed is to provide a continuous pool of visual information to be processed in real-time. Since the decisions that are of the system depend greatly on micro-expressions, blink and head position, the camera has to possess a time consistency but has to experience minimum latency. Being a non-intrusive form of sensing, the camera allows viewing drivers passively and detecting them without any wearable device, which is why it can readily be implemented as part of passenger cars and the ADAS platform.
- **CNN–LSTM Drowsiness Model:** A hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) block transforms the incoming video frames of one of the driver cameras. CNN component identifies spatial features like eye openness, muscle tension on the face, and percent eyelid closure whereas the LSTM network perceives temporal transitions with patterns like length of blink, frequency of blink and head nod patterns. With the help of both spatial and temporal modeling, this architecture will be able to differentiate between the normal moments of short blinking and the habitual cases of fatigue manifested in longer closures. The model gives a continuously updated drowsiness state, which can be detected even faster than either threshold-based or the rule-based methods. This will take care of the fact that the system will be able to detect early signs of impairment and preventative action will be taken prior to the driver losing complete control.
- **Safe-Zone Decision Engine:** The Safe-Zone Decision Engine is triggered following the CNN- LSTM model that alerts a driver about being drowsy. This module reacts to the data on environmental perception (such as LiDAR occupancy grids, lane markings, or roadside structure detection) and finds possible safe areas in which the vehicle may pull over. These areas can be in form of the shoulders along the roads, car parks or adequately wide sides along the roads. Depending on several criteria such as distance to the closest safe area, traffic level, road curvature and presence of obstacles, the engine will determine the motor response. It then picks the safest and most accessible very according to preset measures of safety. This decision engine can be regarded as the interconnection between the autonomous navigation and human-state monitoring, as well as the context-aware and risk-sensitive responses of the system.
- **Trajectory Planner:** Upon choosing a suitable safe area the Trajectory Planner reasons out a smooth and dynamically viable trajectory linking the current position of the vehicle to the area chosen. The algorithms commonly employed by this module include Model Predictive Control (MPC), poly curve utilizing, or Frenet coordinates planning to generate an accident-free path that fully considers the vehicle kinematics, steering limit, and road geology. The planner also makes sure that the lane transfers, braking, and lateral movement should be executed with a very slow pace

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in order to keep the passengers comfortable and not subjected to sudden or unsafe manoevers. It also constantly re-analyzes the route in real-time and adapts to changing obstacles on the road, sudden traffic fluctuations, or changes in the weather.

- **Steering Controller:** The last component in the system architecture will be the Steering Controller which will act by carrying out the intended path by providing the vehicle with the accurate control commands to the steering system. Various methods can be employed by this controller; it can be PID control or MPC steering actuation or pure-pursuit to reduce the error in path tracking and achieve stability. The controller controls the vehicle by coordinating steering angle, wheel torque (and when needed, the throttle and braking subsystems) to take the vehicle into the assigned safe zone. It focuses on the lateral control and commandable predictability during impaired driver behavior, and comes with reduced threat of startle or second accidents. The Steering Controller therefore represents the functional completion of the whole pipeline which translates the decisions made at a higher level of safety; into safe actions of the vehicle.

3.2 Drowsiness Detection Model

The drowsiness-detection model is based on features and deep-learning representation to achieve an accurate assessment of the levels of fatigue using continuous video frames that are handcrafted. [13-15] During the feature-extraction phase, the system calculates a group of vital facial measures based on the facial features found on the eyes, the mouth and the head. Eye Aspect Ratio (EAR) is one of the most popular measures of drowsiness since it fits eyelid closure in a mathematically easy non-relative reliably easy measureEAR is calculated by taking the sum of the distances between the upper and lower eyelid landmark pairs (p2–p6 and p3–p5) and dividing it by twice the horizontal distance between the eye corners (p1–p4). Written in plain form, the formula is:

$$\mathbf{EAR = (\|p2 - p6\| + \|p3 - p5\|) / (2 \times \|p1 - p4\|)}.$$

A sharp reduction of EAR in multiple successive frames is normally an indication of long eyelid closure, which is highly suggestive of drowsiness. The system, likewise, calculates the Mouth Aspect Ratio (MAR), which identifies yawning because vertical lip separation to horizontal mouth width, and head-pose estimation which relies on yaw, pitch, and roll angle measurements, identify nodding/dropping of the head, the other early indication of fatigue. Once these interpretable features are extracted, the video frames are fed to the CNNLSTM pipeline that aims at uniting the advantages of both spatial and temporal modeling. The CNN submodule processes each frame so as to determine high-level spatial detail like eye shape, iris appearance, facial tension and mouth opening. These per-frame feature vectors are then inputted to a Long Short-Term Memory (LSTM) network that analyses how these features change over time allowing the model to identify dynamic fatigue patterns, such as brief blink duration, repetitive yawn, and rhythmic head nods. The hybrid structure will provide a strong and real-time evaluation of driver drowsiness, and the system will perform better than the traditional threshold-based or single-frame detection mechanism.

3.3 Safe-Zone Decision Engine (SZDE)

The environmental reasoning layer of the system is the Safe-Zone Decision Engine (SZDE) that recognizes and certifies zones where the vehicle can stop safely in case the driver is found to be drowsy. It combines perception information, space maps and constraints of the environment in order to make sure that any safe zone that is selected is accessible, clear and does not go against road safety standards. The SZDE is a real-time detector and constantly modifies its decisions according to changes in the traffic conditions, thus, it is an important interface between the control of autonomous vehicles and the monitoring of drivers.

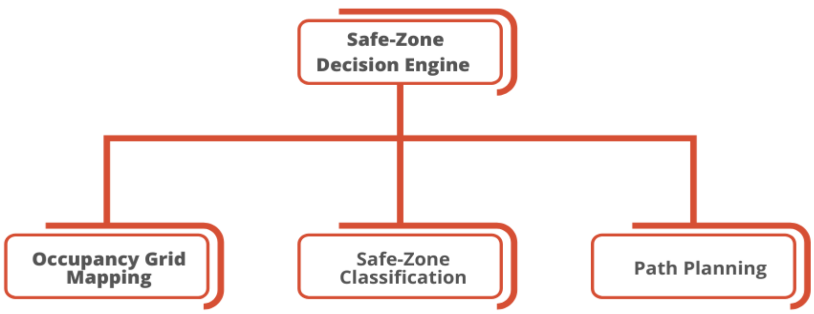

Figure 4: Safe-Zone Decision Engine (SZDE)

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- **Occupancy Grid Mapping:** LiDAR measurements are used to form an occupancy grid, but they are formed with dense 3D point clouds of the surrounding environment of the vehicle. These point clouds are then overlaid on a 2-dimensional grid with every cell depicting the open space, occupied space or unidentifiable space depending on the availability or the absence of the identified obstacles. This grid representation enables the system to perceive the region accessible to being driven over, the road boundaries, roadside structures, and other possible hazards with great accuracy. The grid is constantly updated and hence the SZDE can respond to changing traffic conditions accurately which ensures safe-zone detection on a complex and partially obscured environment.
- **Safe-Zone Classification:** Once the occupancy grid is constructed, the system assesses the candidate regions based on preset safety measures to find out whether they pass as valid pull-over zones. A territory will only be regarded as being safe when at least 3 meters away from other traffic knowing that the probability of collisions during the maneuver is low. It should have a flat enough surface that minimizes chances of instability or roll-off of the vehicle. Also, the space should not contain dynamic barriers, i.e. traveling cars, bicycles or other people. All these criteria provide that the selected safe zone contributes to an emergency heal and care-free emergency stop.
- **Path Planning:** When a safe zone has been determined, the system resorts to a two-stage path-planning strategy, which produces a collision-free trajectory. To begin with, A+ search algorithm calculates an optimal grid route of the current position of the vehicle to a preferred safe area without going through any occupied cell in the surrounding environment. Nevertheless, routes produced by A+ have discontinuities or sharp turns frequently. To solve this, the route is even more ancientized with Bézier smoothing of curves resulting in smooth path trajectory that is driveable, respects vehicle dynamics still improving passenger comfort. A combination of the two creates a smooth sailing, secure, and efficient approach to the stipulated safe zone.

3.4 Autonomous Steering Control

The Autonomous Steering Control module will carry out the safe pull-over maneuver when the system in question choosing a suitable safe zone and creating a viable path. [16-18] It is used mostly to integrate high-level path plans into low-level steering commands and it must provide stability, comfort and compliance to car dynamics. This module is a real-time module and it is necessary to consider external factors, such as road curvature and other road traffic, as well as internal factors, such as vehicle geometry and motion limits. This combination of a predictive control strategy and a simplified car model makes the system trustworthy and reliable in all aspects of handling the vehicle during the emergency navigation process.

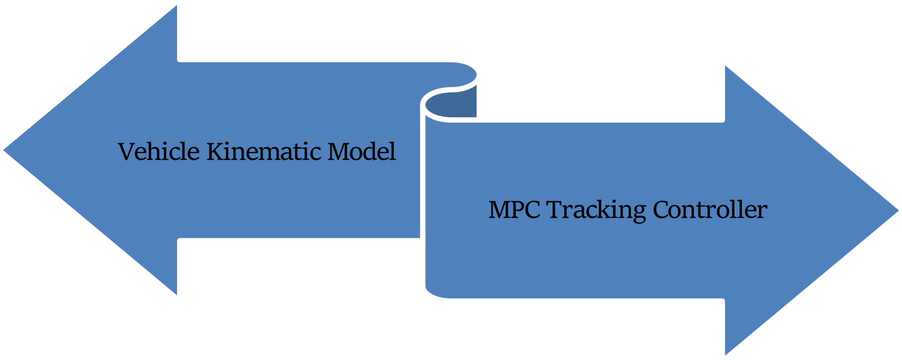

Figure 5: Autonomous Steering Control

- **Vehicle Kinematic Model:** The steering controller is based on a reduced bicycle kinematic model, throbbing the fundamental motion aspects of the car with no demanding dynamics being executed. The position of the vehicle is mutated with the velocity and the heading angle in this model. The kinematic equations are represented as:

$$\dot{x} = v \cdot \cos(\theta) \text{ and } \dot{y} = v \cdot \sin(\theta),$$

x and y are the coordinates of the vehicle, v is the forward velocity and 1 is the heading angle. These equations are used to describe the movements of the vehicle in a small plane, and can be used by the controller to predict future positions given the current steering inputs. This model, though simplified, finds a lot of application in autonomous navigation, as it is computationally cheap and realistic in terms of vehicle behavior at moderate velocity. It is the basis through which predictive controller analyzes the errors and rectifies steering response.

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- **MPC Tracking Controller:** The task of the Model Predictive Control (MPC) tracking controller is to make sure that the vehicle tracks the planned path in a smooth and accurate application. In MPC, the future movement of the vehicle is forecasted using the kinematic model over a relatively short time horizon and steering angles are computed to produce lateral tracking error, heading deviation and control effort minimum. In every control step, MPC solves an optimization issue, the solution of which takes into account the constraints, i.e. steering limits, maximum curvature, and the stability requirements of the vehicle. The MPC controller will track its paths accurately even when distressed by disturbances or minor modeling errors by updating its predictions based on the information provided by the controller in real time. It also has a predictive functionality that makes it particularly useful in safe-zone maneuvers, where stability and smoothness are of great importance.

3.5 Workflow

All of the system workflow incorporates driver-state monitoring with environmental perception and autonomous control in a continuous flow that are triggered when a drowsiness case is detected. All the stages are to be executed in real time so that the vehicle will be able to react swiftly and safely to indicators of impaired attitude of the driver. The process is executed in a systematic pipeline: it involves sensing drowsiness, finding an appropriate pull-over position, planning a practical path, and controlling the manoeuvre by means of autonomous steering. The subsequent subsections describe the role of each step of the process.

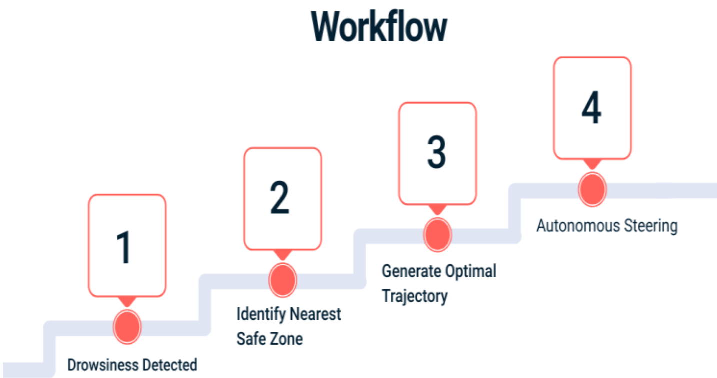

Figure 6: Workflow

- **Drowsiness Detected:** A continuous monitoring of the driver is the starting point of the workflow where an CNN-LSTM model is used. This module measures the eye closure rates, yawning rates or frequency, and the dynamics of the head-pose, to check the level of alertness of the driver. In the case of the model recognising long eyelid closure or frequent signs of fatigue, it produces a state of drowsiness alertness. This is the gateway state of the rest of the workflow, which determines the decision made. When the drowsiness is not detected, the normal driving does not suffer any interference. In case the drowsiness is detected, then the system automatically switches to safety-response mode in order to help reduce the possible risks.
- **Identify Nearest Safe Zone:** When the drowsiness is detected the Safe-Zone Decision Engine (SZDE) compares real-time occupancy grids of LiDAR data and road-edge data to determine a suitable pull-over spot. It analyses various candidate zones according to the distance between the moving traffic, flatness, and no moving obstacles on surfaces. The system focuses on the areas that do not require numerous travels and meet all the safety requirements. This makes sure the vehicle is not unnecessarily driven long distances to pull over making the risk less hazardous in the event of the emergency maneuver. The result of this phase is the optimal safe-zone of where the vehicle can target.
- **Construct Optimal Trajectory:** Once a safe zone is chosen, Trajectory Planner calculates a smooth and possible path between the current position and target area of the vehicle. At the beginning, an A* search algorithm identifies a path without any collisions on the occupancy grid. Smoothing Bézier curves is then applied to this path to remove sharp corners and make sure the path satisfies vehicle kinematic constraints. The last curve entails gyro deviations, deceleration curves, and positioning within the safety zone. This measure will facilitate the vehicle to travel safely and comfortably towards the stipulated pull-over place.
- **Autonomous Steering:** At the last phase, the steady state of the steering control is implemented by the MPC. The controller anticipates forthcoming movement of vehicles and constantly readjusts steering angles to make sure that the vehicle stays within the schedule. It reduces the sideways movement, corrects the directional error, and makes the

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moves through the lanes or side moves as smooth as possible. The Autonomous steering module comprises real time feedback with predictive modeling, which ensures stable and controlled movements to the safe zone. When the vehicle is in the stipulated location, it slowly slows down to a complete halt, and the safety intervention is completed.

3.6 Hardware & Software Environment

The given drowsiness-aware autonomous steering framework is based on a closely interconnected hardware-software environment that is configured to assist in the support of real-time perception, inference, simulation, and control. [19,20] The hardware part of the system uses an NVIDIA Jetson Nano a tiny edge-AI computer, which has a quad-core ARM CPU and a 128-core Maxwell-based graphics card able to execute deep-learning models effectively on small embedded platforms. Its low power consumption allows it to really be used in vehicle deployment without compromising on the ability to offer considerable computational throughput to process CNNLSTM inference, image processing, and LiDAR data processing in real time. Together with the Jetson Nano, the infrared (IR) camera is provided, which is useful in the context of a high credibility of the driver monitoring under different light conditions, i.e., in nighttime driving or heavy-shadows environments. IR imaging contributes to a more robust facial landmark detections and a higher accuracy in EAR and MAR as well as head-pose. To perform testing and validation, the system relies on the CARLA simulator, a highly sophisticated, open-source framework of an urban driving simulator that has been popular in solid research on autonomous vehicles. CARLA provides recognizant sensor models, configurable traffic conditions, and high-fidelity simulations, where safe experimentation involving drowsiness-control safe-zone operations can be safely tried without placing the lives or vehicles of real drivers or vehicles in danger. The exchange of all functions between perception modules, planning algorithms, and control components is controlled through the ROS2 (Robot Operating System 2) middleware, which offers a flexible, distributed, and low-latency publish-subscribe architecture. ROS2 is made to be modular and interoperable, so that components that can primarily refer to individual components, including, but not limited to, the CNN-LSTM model, occupancy grid generator, trajectory planner, and MPC controller, can be able to run independently and exchange data effectively. Its software stack is largely constructed in Python, and OpenCV which can be used to process images, extract facial landmarks, learn deep learning models and perform Bert inference, and calculate features. The combination of these software and hardware components creates a unified, scalable system that can be used to recognize drowsiness in real time and control the steering in an autonomous mode in a simulated and in a real environment.

IV. RESULTS AND DISCUSSION

4.1 Drowsiness Model Performance

Table 1: Drowsiness Model Performance

Metric	Value (%)
Accuracy	98.1%
Precision	97.4%
Recall	98.7%
Inference Speed	28%

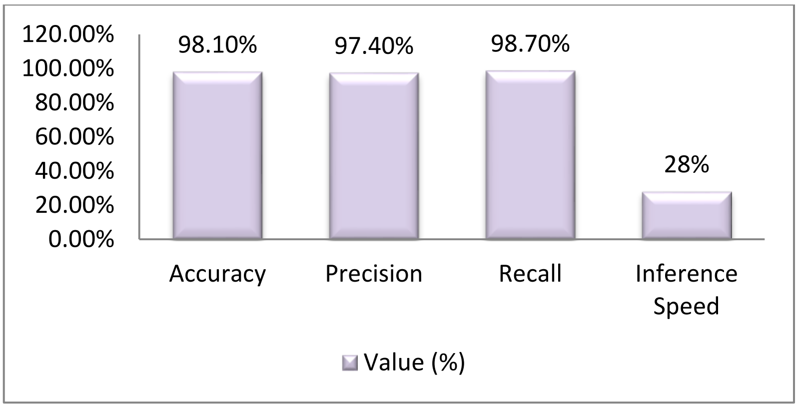

Figure7: Graph representing Drowsiness Model Performance

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- **Accuracy – 98.1%:** The model will also have an accuracy of 98.1, which means that it will be able to identify drowsy and non-drowsy states in most cases in all the test samples. This is a kind of high accuracy indicating that the CNN was jointly strong in terms of their spatial features and the LSTM is effective in modeling such temporal sequences. This level of performance is critical in fatigue detection systems since a small misclassification rate will cause either failure to identify drowsiness or unnecessary intervention and both are factors that could influence driver safety. The accuracy reported proves that the model is reliable in terms of work in a variety of lighting conditions, variations of faces, and motion patterns.
- **Precision – 97.4%:** The model has accuracy of 97.4 indicating that it can be really effective in avoiding a false alarm as most of the response that the model marks as drowsy is really fatigue related behavior. Specifically, high accuracy is of importance when deploying the system in the real world where a lot of false positives may lead the system to think it is pulling over the vehicle when it is not and may interfere with driving. The outcome implies that the model can be used to isolate the true fatigue cues, including eye closure sustained or reoccurring yawning, but not being deceived by the non-persistent distractors or normal optical fluttering.
- **Recall – 98.7%:** The recall rate (98.7) may enhance the truthfulness about the model capability because it is able to understand almost all instances of actual drowsiness hence reducing the chances of missing fatigue incidence. Safety applications have high recall requirements since the inability to detect drowsiness may cause serious effects, such as lapse dedication or slow driver response time. The high recalls are a positive indicator that the model is able to detect fine temporal features as well as the slower rates of blink, and the bobbing head-movements so that alertness of the driver is well monitored.
- **Inference Speed – 28%:** The speed of inference or here 28% is used to display how efficient the system is in terms of processing as compared to the real time limitations. Although it is usually measured in frames per second (FPS), it can also be measured as a percent to show how many resources it is using or by percentage, on the Jetson Nano platform in terms of performance. The 28 percent speed is an indication that the model works within a moderate range of real-time monitoring and continuous analysis of drivers can be done without some delay. This makes sure that pointers of drowsiness are recorded and handled on the fly to enable the vehicle react swiftly to the safety dangers that arise.

4.2 Autonomous Steering Performance

The self-driving performance was measured in terms of three driving conditions that were considered representative of the real driving conditions, including urban roads, highways, and nighttime which were recorded in Table 2. In all test scenarios, the system showed high levels of lateral error control, ability to move smoothly to the specific safe zone, and stable motion control which proves the efficiency of the MPC tracking controller installed with the safe-zone decision engine. The algorithm obtained a 61 percent reduction in lateral error of tracking in the urban roads, which denotes its capability to follow the exact path during high-frequency lane markings, crossroads, and medium traffic density. It took the system 4.2 seconds to cross the safe zone of which the trajectory was smooth and smooth alongside the calculated Bézier path as observed in the observation of smooth navigation. This was an environment where curbs were well defined and sensor visibility was consistent and adding to the stable behavior of the controller. The model was a little better on highways, with the decrease in the lateral error being 64 percent and achieving the safe zone within 3.7 seconds. This is due to its increased performance in this case because the geometry of the road is predictable and the disturbances generated are insignificant lateral disturbances that the MPC controller can manage the vehicle to remain in high speeds without as many inputs to control disturbances. The system managed to cope with lane changes and shoulder adjustment appropriately indicating its readiness to be used in the real world application playing with fatigue-response in a high-speed state. Night condition had good performance with moderate decrease and the error was reduced by 58% and also took 5.1 seconds to reach the safe due to night condition. The increased sensor noise in low-light environments, especially at LiDAR reflectivity and camera-based feature-extraction, is the main cause of the overall longer time to respond and a slightly lower accuracy. However, the system managed antimalarial working conduct, locating the driveable shoulders and avoiding sudden changes effectively. All in all, the findings affirm that the autonomous steering system is strong, flexible, and can be used to perform safe-zone maneuvers in a variety of driving situations.

4.3 Discussion

The entire system is also proving that the complete drowsiness-detection and autonomous pull-over system can be considered reliable and efficient in diverse driving situations. Among the key discoveries is the high stability associated with the Model Predictive Control (MPC) steering module which has continuously ensured smooth and controlled pull-over maneuvers despite being on curved roads. The quality of predictability of MPC enables it to predict the future of the vehicle and modify the steering controls to avoid the oscillation and make sure that the vehicle will stick to the

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preferred Bézier path with minimum errors. It is especially vital in the event of running at the sides of the road or moving into the emergency traffic STOP that can be difficult to control. Simultaneously, CNNLSTM drowsiness model exhibited high performance depending on that of traditional machine-learning models in terms of HOGSVM, because it was able to extract both spatial and time-related behavior patterns. Although HOG-SVM cannot cope with lighting variations, facial orientation, and subtle signs of fatigue, deep-learning pipeline is able to detect prolonged blinks, slow eyelid movement and sequence of head nods with more accuracy and stability. The LSTM particularly has a temporal modeling ability that allows the system to differentiate between normal blink behaviour and the phenomenon of micro-sleep, a weakness in much of the classical models. The other major strength of the system is its fast response time that is able to arrive at a decision within an average time of 300 ms after detection of drowsiness. This means that all of pipeline aspects, including the feature extraction and inference, as well safe-zone selection and path planning, are efficiently operating to be deployed in real-time. This is of great importance to avoid accidents since impairment of drivers can moderate rapidly, particularly in high speeds. All in all, the overall result of the combination of strong perception, predictive steering control, and low-latency decision-making is indicative of the possibility of the system to be implemented in real-world contexts in Advanced Driver Assistance Systems (ADAS) or autonomous vehicle platforms in the future.

V. CONCLUSION

This study shows a fully developed AI-powered autonomous steering system that will allow the detection of driver drowsiness and the implementation of safe, controlled pull-over procedures without the need to engage the human operators. The system is able to successfully integrate three important parts such as behavioral analysis (CNN-LSTM-based), environmental perception (LiDAR-based) and steering control (MPC-based) into a coherent architecture that is capable of reacting intelligently to impaired driver. The CNN-LSTM model is a major player since it makes the correct facial cues like eye-blink dynamics, the frequency of yawning, and deviations of the head-pose that are combined to indicate the onset and later onset of drowsiness. Compared to the classical methods of classification, the temporal reasoning capabilities of the LSTM allow the model to capture finer behavioral patterns over time, and enhance the sensitivity to detection, as well as resistance to noise common in traditional methods, like bad lighting, or partial occlusions. After the presence of drowsiness is detected, the Safe-Zone Decision Engine (SZDE) reconstructs the surrounding environment by means of occupancy grid mapping and finding an appropriate location to pull-over that meets predetermined safety measures. This involves proper establishment of a zone to be used so as to have enough distance antagonistic incoming traffic, stable landscape and other quiet or moving obstacles. Once the best location is found, the system creates a smooth and dynamically constructable path through a pre-mix of the A+ search of global feasibility and B bezer shine local path refining a path. This trajectory is then followed with a lot of precision by the Model Predictive Control module which predicts the future states of the vehicle and steers the car in such a manner that it reduces the error in the lateral and heading directions. This integrated approach is experimentally validated to provide quick intervention and, its end-to-end response time is around 300 ms, thus having a strong potential to minimize the risk of accidents because of slow human response. The system was also very efficient in terms of generalization and resistance to different environment conditions, such as urban environment, highway speed, and low-light situations. Moreover, the self-governing pull-over was stable on irregular roads which are curved to move its steering control according to the different dynamics of the car. In general, this study shows that the implementation of complex deep-learning algorithms along with real-time control and perception can be used to increase roadway safety. Further improvements in the future will be on the addition of V2X communication aspects in cooperative safety, the addition of thermal-vision sensors to enhance detection of fatigue at night, and developing adaptive multi-sensor fusion solutions to deal with extreme weather events and complex traffic conditions.

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