



Machine Learning Based Logistic Decision Support System for Intelligent Vehicles and Transportation Systems

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Abstract

Recognition and modelling of driver behavior (DB) have lately been crucial in intelligence transportation systems (ITS), human-vehicle, and intelligent vehicle systems (IVS). The evidence that drivers are distracted most often causes accidents and incidents involving vehicles is growing. Using camera sensors in the vehicle or sensors worn by the driver can help detect and prevent drivers from engaging in distracting behaviors like talking on the phone, eating, drinking, adjusting the radio, interacting with navigation systems, or even combing their hair while behind the wheel. However, this system requires a lightweight data processing module and a powerful training module for real-time detection. Data must be collected from certain cameras or wearable sensors to detect distracted drivers and ensure a rapid reaction from the administrator on safe driving. Therefore, this paper suggests a Machine Learning Driver Distraction Prediction Model (MLDDPM) with a decision-support system (DSS) that can alert the driver to possible dangers on the road by analyzing both internal (vehicle parameters) and external (road infrastructure messages) data. This research MLDDPM employed semi-supervised algorithms to reduce the expense of labelling training data for driver attention detection in actual driving scenarios. Two attentive and cognitively distracted driving states were used to assess support vector machines: i) as a supplementary parameter for the aggregate risk assessment of driving and ii) as a parameter for providing the driver with the most appropriate message type on possible road dangers. Finding the optimal approach to driver assistance to guarantee secure transportation is the primary goal of this work.

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1. Introduction

Logistics and transportation are now complementary parts of delivery services. Logistics refers to supervising commodities' internal and external movement from producers to consumers, while transportation refers to the actual movement of things [1]. In logistics, managers are tasked with making decisions beyond transporting goods [2]. These decisions encompass packing, containerization insurance, transportation, compliance with regulations regarding imports and exports, handling freight claims, and working with other stakeholders and supply chain management team representatives to minimize risks [3]. An ever-increasing degree of automation has recently swept the automobile industry. This automation has created new opportunities for human drivers [4]. One kind of driving aid technology is the Advanced Driver-Assistance Systems (ADAS) installed in vehicles such as automobiles, lorries, and others [5]. The two main tenets upon which advanced driver assistance systems (ADAS) depend are that (i) drivers are mentally and emotionally prepared to execute the correct operation at the correct moment and (ii) ADAS can accurately model its environment and make decisions or sound alarms appropriately [6]. The first area that can benefit from driver models is vehicle dynamics, which includes onboard control design, analysis of vehicle dynamics, and overall stability analysis [7]. The second area is intelligent transport systems (ITS), which includes things like traffic flow simulation using control theory models of driver behaviour and modelling driver risk-taking behaviour [8].

Developing and implementing various driver assistance and information management systems has enhanced road safety [9]. Several road safety applications, including lateral and raise surveillance systems, lane-changing assistants, collision warning systems, and various telematic applications on road infrastructure that communicate direct and up-to-date information about traffic between infrastructure and motorized vehicles, have been developed and demonstrated as potential solutions toward this issue [10]. This method only generates warnings in certain driving scenarios and deals with road incidents one at a time [11]. Different methods include real-time low vigilance detection using a variety of measurement factors to promptly and safely inform the driver when his level of attention drops [12-15].

Consequently, this study proposes an MLDDPM enhanced with a decision-support system (DSS) that may notify the driver of potential road hazards by evaluating data from both internal sources (vehicle characteristics) and external sources (road infrastructure messages). Using semi-supervised algorithms, this study MLDDPM was able to lower the cost of labelling training data for attention detection in real driving situations. Support vector machines were evaluated in two different driving states: i) while the driver was fully focused and ii) when they were cognitively distracted. The former was utilized as an additional criterion for the overall risk assessment of driving, and the latter was used to determine the best warning message to provide the driver. This endeavour primarily aims to find the best way to help drivers so that transportation is safe.

2. Literature Survey

Aggressive driving is a major component in traffic accidents, which continue to rank among the top causes of unintentional mortality among humans. The features of aggressive driving related to behaviour are examined in this research based on Meta-Analysis [16]. Most people find that visualizing hostile events is the most effective induction strategy. The outcome may be used as a benchmark for measuring aggressive driving habits. Automotive businesses have developed vehicles equipped with sophisticated features that facilitate various driving activities.

AdaBoost Multi-class Support Vector Machine (MSVM) with Cat Mouse Optimizer (CMO) algorithm for Advanced Driver Assistance System (ADAS) intrusion detection [20]. Connected to a smartphone mounted on the dashboard, this gadget may monitor the driver's movements and trigger an alert if they deviate from the road. Jiangxi Bus Company's power supply voltage data is used to gather the experimental data. Lastly, the AdaBoost MSVM with CMO method was used to classify both regular and unconventional driving actions once the low dimensionality features had been retrieved.

Stepwise weight assessment ratio analysis (SWARA) with measurement of alternatives and ranking according to compromise solution (MARCOS) approach to design the FMEA method for outlying roads in the southern Italian region of Cosenza [21]. This research aimed to identify potential dangers and create strategies to reduce traffic accidents; both objectives are important to sustainable development and mobility. Consequently, to enhance road safety, evaluating the regulations and procedures required to decrease human hazards on Calabria's regional road network is crucial.

Functional framework (FF) to vehicles driven remotely for commercial vehicles [22]. The prototype's functioning and efficiency in real-world driving scenarios were verified via empirical research. The working model was

connected to a professional 4G/5G cellular network. This crucial field of study and innovation gained in-depth technical understanding via the design, execution, and empirical assessment.

Deep reinforcement learning-based decision-making model (DRL-DMM) to execute the optimal action-state map for our automated agents while controlling several cars in a multi-agent traffic setting [23]. The proposed model would revamp the mathematical aspects of collision avoidance optimization based on our proposed framework. The survey results will help clear the path for implementing autonomous automated traffic systems by discussing open research topics.

Runtime assurance framework (RTA-IR) guarantees AI controllers of complicated autonomous cars a safe driving experience without sacrificing performance to an unacceptable degree [24]. Based on the Responsibility Sensitive Safety Model (RSS), RTA-IR includes a high-performance but untested advanced controller, two security processors that may be verified, and an assessment module. Experimental evidence shows that RTA-IR outperforms the baseline technique regarding efficiency and safety.

Spatio-temporal point segmentation algorithm (S-TPSA) for performance evaluation methodology for LiDAR sensors in vehicles that can be used in both static and dynamic testing environments [25]. Four extensive environment computations and four vehicle-level tests with dynamical scenarios for testing are conducted using time-series information about the environment from real-world U.S. road fleets to evaluate an automotive-graded LiDAR sensor. Based on our tests, several environmental conditions might reduce the accuracy of LiDAR sensors.

The site selection challenges of electric car-sharing stations (ECSS) are resolved by fuzzy multi-criteria decision-making techniques based on Geographic Information Systems (GIS-FMCDM) [26]. To achieve this, a three-stage solution methodology is devised: (i) using fuzzy analytical hierarchy process (f-AHP) to determine and weight 20 sub-criteria; (ii) using geographic information systems (GIS) to obtain an appropriateness map for possible ECSS; and (iii) using Elimination and Choice Translating Reality (ELECTRE) to sort the level of performance of ECSSs assigned corresponding to the suitability map.

3. Proposed Methodology

Vehicle tracking for logistics optimizes routes, but managing a growing fleet is tough. MLDDPM uses driver analysis to improve vehicle performance, reduce driver stress, and build smarter assistants. This driver behavior modeling, crucial for smart cars and safety systems, helps researchers assess driver assistance, identify skills, and personalize vehicle experiences.

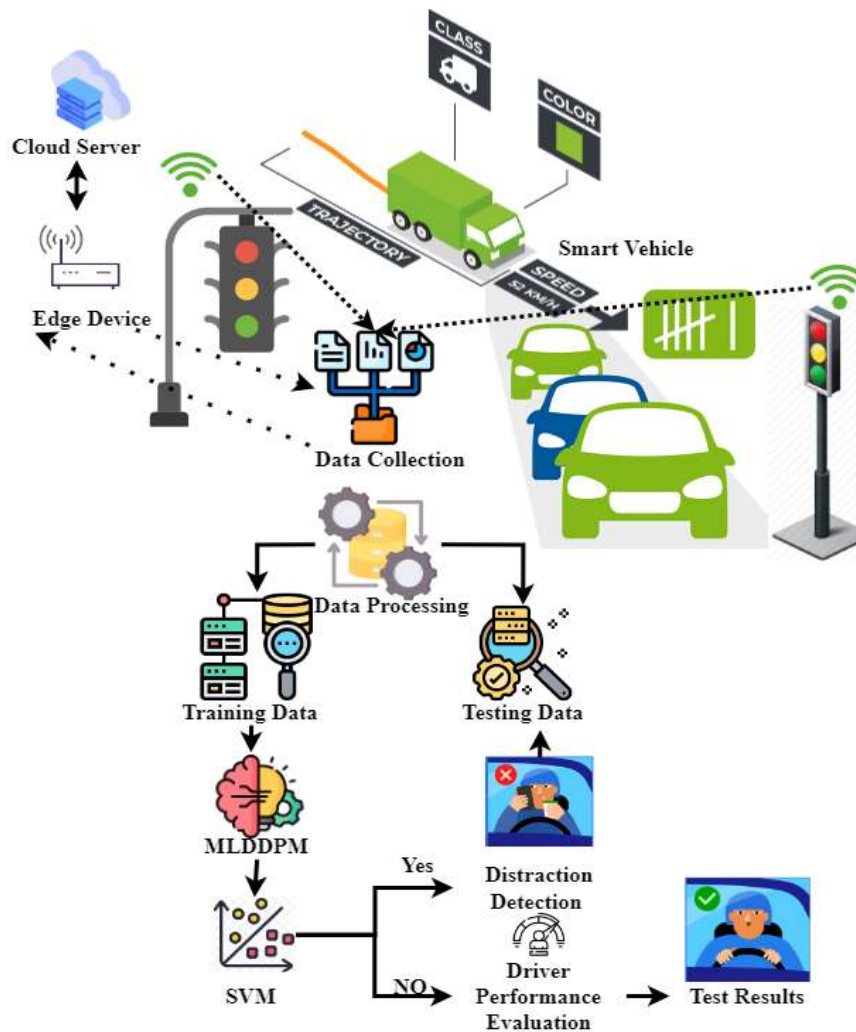


Figure 1: Proposed MLDDPM

The intelligent transport system architecture uses SSA and ELM techniques to identify the logistic-carrying vehicle. This approach aims to make it operate well with the edge-enabled transport architecture. This component is installed in the system's edge server to manage data processing and analysis. Figure 1 displays the various parts of the logistic transportation system model that has been suggested, the MLDDPM. The data-gathering phase involves resource-constrained edge devices temporarily storing the obtained sensory vehicular data (as shown in Fig. 1) before transmitting it to the data-processing phase. The feature selection algorithm takes a subset of the available data as a sample and uses it to generate features. Now that the feature has been chosen, it can be given to the SVM to be classified by logistic type.

The suggested method considers the data sent in by individual cars and the information gathered by the many sensors installed on them. There are four distinct phases to the enormous data collection and processing task before feeding it to MLDDPM. i) Before processing raw sensor data, the data scheduler must be integrated into the system during the first step. In preparation for the data processing phase to receive each sensor's readings, the scheduler adds them to a queue. ii) Data processing, the second step, uses window-based sampling algorithms to process the sensor input. iii) The third step is extracting the sample data's characteristics. iv) In the fourth stage, the produced sample is labelled according to prior knowledge. v) With the last step of the fifth phase, a rule-based decision-support system is integrated to assess MLDDPM performance and control overall system confidence according to that performance. After that, cloud servers save the data for future use in execution and evaluation.

Data Scheduling:

According to the suggested method, the data scheduler handles the incoming data from the logistic vehicle's distant Internet of Things devices. The scheduler receives data from different Internet of Things (IoT) devices via many watchdogs; upon receipt, the data is sent to the scheduler for first-come, first-served processing by the lightweight watchdog algorithms. Scheduling processing of the data follows in the data processing stage. The data scheduler

is an essential component of the suggested approach for managing network traffic; it helps the system receive sensor data simultaneously from several IoT devices in a single-time quantum.

Data Processing:

The data processing component briefly processed each vehicle's data to assemble the data. Verifying the accuracy of all incoming data from different sensors is one of the primary tasks in this part of the process; only valid data will be sent on to the next stage. Over an allotted time frame, sensor readings from each vehicle are combined. The next stage involves mining each vehicle's data for useful traits. One of the most important aspects of processing sensor data is extracting meaningful characteristics. Data gathered from a multitude of sensors is sometimes complicated and non-linear. Unpredictable sensor signals with varying frequencies may be seen due to the dynamic nature of the traffic environment. Data gathered from sensors installed in different Internet of Things devices is not static. This results in M windows representing different areas of the massive signal array, with a fixed window size T within each window for feature extraction. The suggested method lists the characteristics obtained from the different windows below.

i) Semi-Supervised Algorithm (SSA)

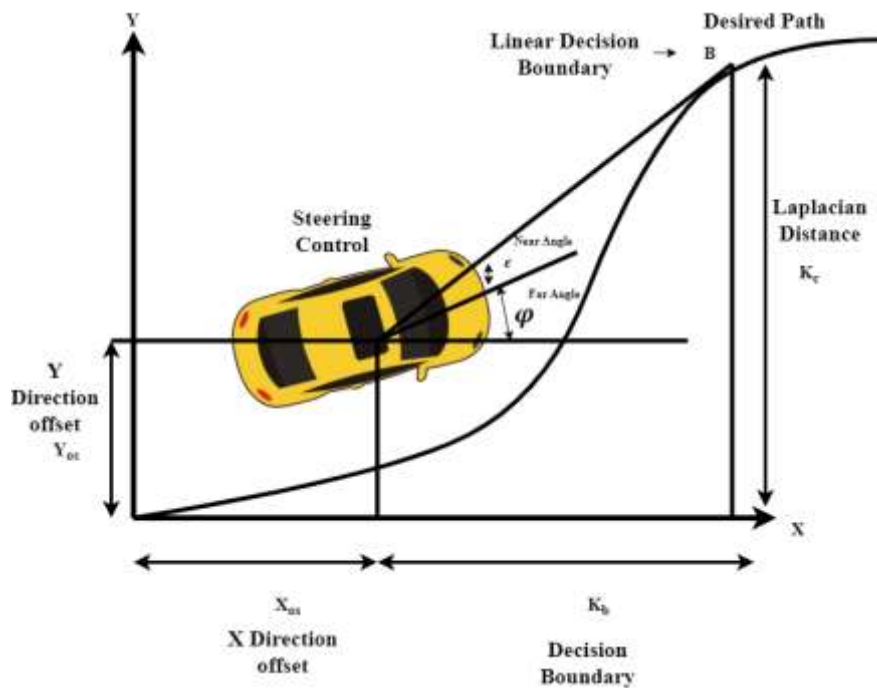


Figure 2: Driver Steering Monitoring

A driver model with aim point distance, response delay, and steering angle simulates curve driving actions, aiming for minimal deviation from planned paths and mimicking real driving. Simulated lane changes and wind gust responses test its accuracy, demonstrating the usefulness of driver models for analyzing driver-vehicle reliability. A control-oriented model using musculoskeletal, visual, and physiological factors further enhances realism by calculating steering torque based on angles and force feedback, represented by a state-space equation accounting for input delay.

$$\dot{y}(s) = By(s) + Av(s - \vartheta_q)$$

$$x(s) = Dy(s) + Cv(s) \tag{1}$$

As found in equation (1) state-space structure has been calculated. A more straightforward and readily integrated cybernetic driver lane maintenance model is now available with driving assistance systems. Nevertheless, driver model structures and decision goals may differ due to the complexity and unpredictability of driving scenarios. The goal of doing more research on driver models, sophisticated mathematical approaches, and advanced control theory is to develop a model that can be used in many scenarios. For instance, to better understand nonlinear driving behaviour, it may be helpful to employ more complicated mathematical representations.

One way to identify and classify a driver's limit-maneuver approach to management is by looking at their steering wheel angle's discrete Fourier transform coefficients (DFTC). The direction of the steering wheels' inclination's M -point DFTC is provided as

$$Y_l = \sum_{m=0}^{m-1} y_j f^{(-i(2\pi j/M)lm)}, \quad l = 0,1,2, \dots, M - 1 \quad (2)$$

Frequent domain identification (FDI) techniques can determine the operator's transfer function and thus the parameters of a multiloop car-following model with a single direct pushing function. Throughout the experiment, variables $U(\varepsilon)$ representing relative velocity and $V(\varepsilon)$ representing acceleration pedal position may be measured. Spectral analysis methods may figure out the transfer function \hat{G}_c^k of an automobile car- behaviour following:

$$\hat{G}_c^k = \frac{\hat{t}_{dv}(\varepsilon)}{\hat{t}_{dv}(\varepsilon)} \quad (3)$$

As deliberated in equation (3) transfer function of an automobile car following behaviour has been expressed. Finding a visually appealing MLDDPM of curve driving requires careful consideration of the model's structure. Characteristics that need to be determined and evaluated with the utmost precision.

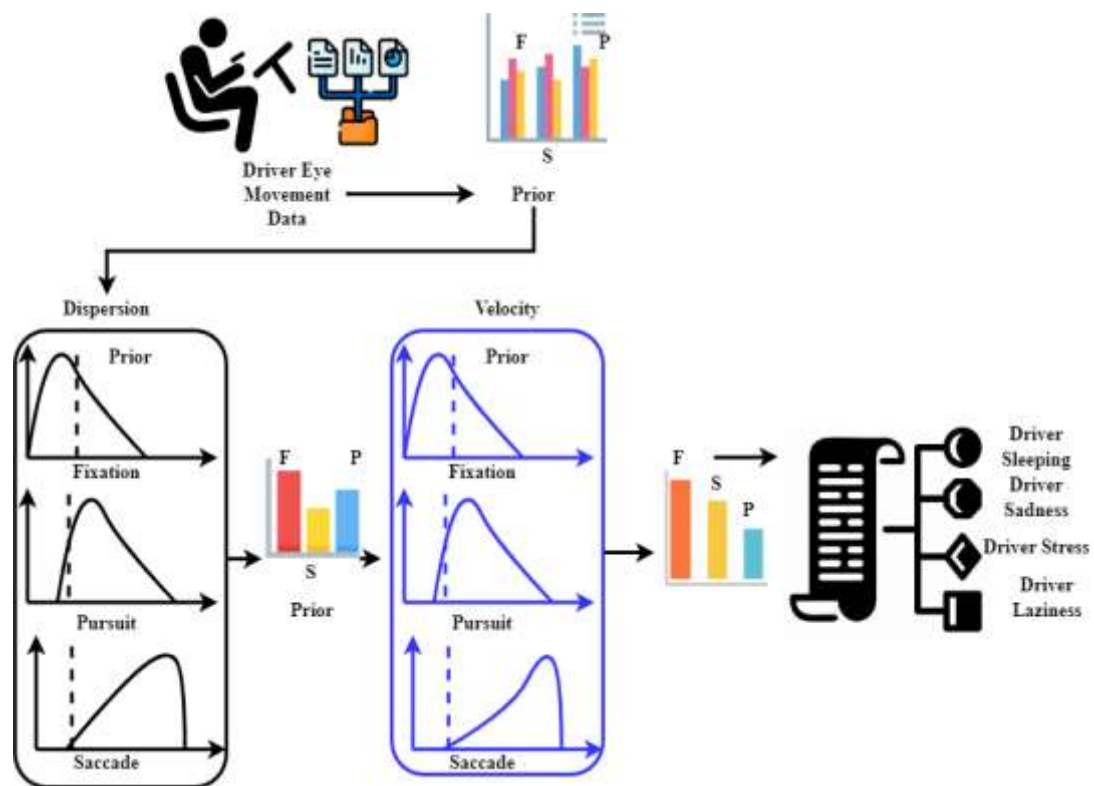


Figure 3: Driver Eye Tracking

Seeing Machines' eye tracker (60 Hz, headgear/chin rest) precisely monitors gaze (5-degree accuracy) without disturbing drivers. Analyses differentiate fixations, pursuits, and saccades based on gaze probability and speed. Ten eye movement measurements, including fixation length, pursuit duration, and gaze direction, are used to assess cognitive distraction's impact, focusing on fixations and pursuits for unobtrusive cognitive attention monitoring.

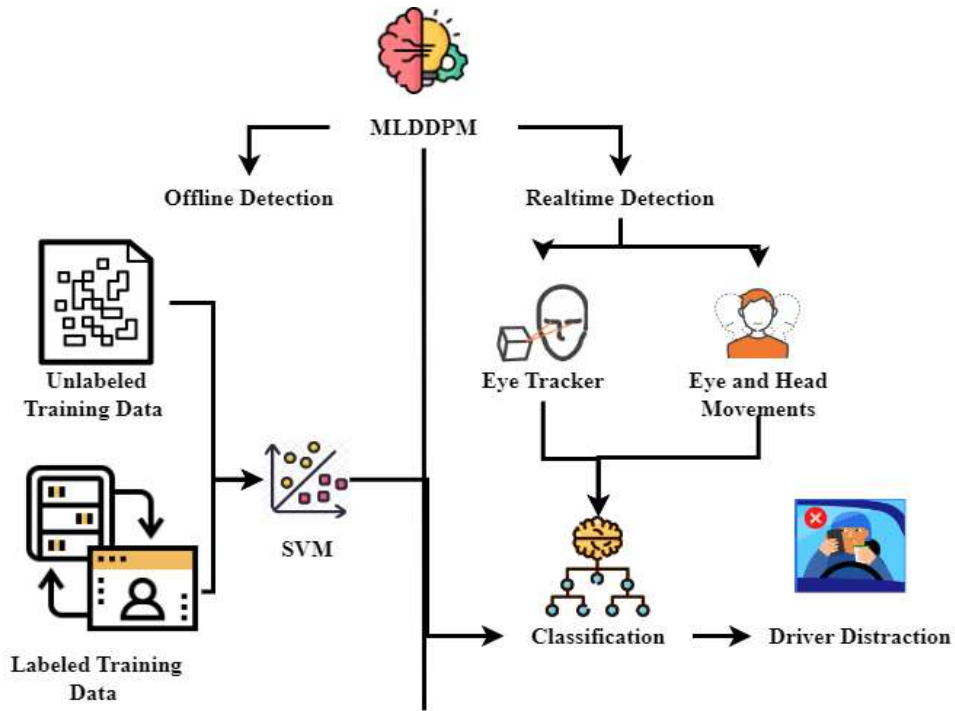


Figure 4: Semi-Supervised Learning Algorithm (SSA)

This research expands on previous work by proposing new semi-supervised detection methods (SSA) for driver distraction using eye/head movements and various metrics. It tests their effectiveness with more participants and verifies their robustness to diverse settings and training data.

4. Numerical Outcomes

The study demonstrates that several driver models have been created from diverse viewpoints using different identification techniques. It indicates that the distinctive attributes of a driver's behaviour, competence, or condition vary throughout driving tasks and scenarios. Developing an MLDDPM that can adequately characterize every driver's behaviour in various driving activities and scenarios is critical. Introducing and building sophisticated mathematical approaches that may swiftly and accurately describe driver competence and behaviour is possible. Thirdly, driving traits and sophisticated control theory should work in combination.

i) Accuracy Ratio (%)

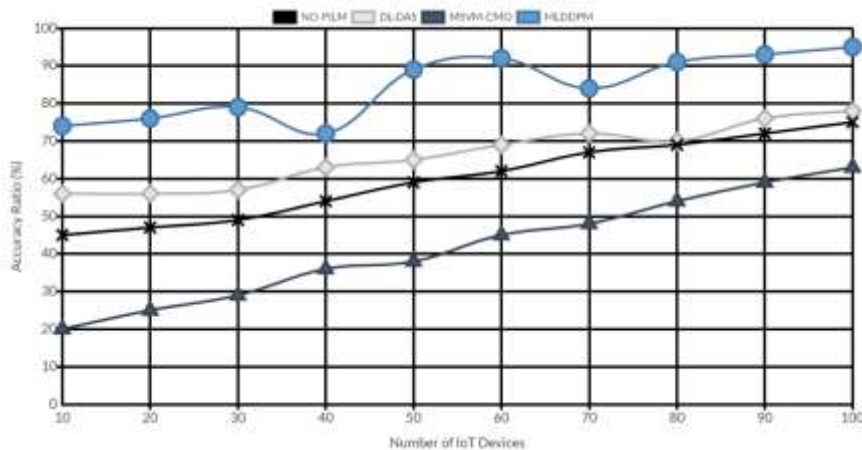


Figure 5: Accuracy Ratio (%)

Figure 5 deliberates the accuracy ratio. This paper's findings provide optimism regarding SSA-based driver distraction detection utilizing data on actual driving situations, including drivers' gaze and face movement information. The ELM improves detection accuracy while reducing labelling costs by using unlabeled data. The most accurate results were obtained by SS-ELM, which reached 97.2%. They found that the models performed well when we tweaked the hyper-parameters. As the amount of unlabeled data sets grows, the advantages of SSA approaches become more apparent. As a result, we may enhance the performance of driver models by learning more about the data structure without formally labelling them. The models' high accuracy also implies that, even in a realistic driving situation, the dominant characteristics in monitoring driver distracted states might be their eye and head movements.

ii) **Error Rate (%)**

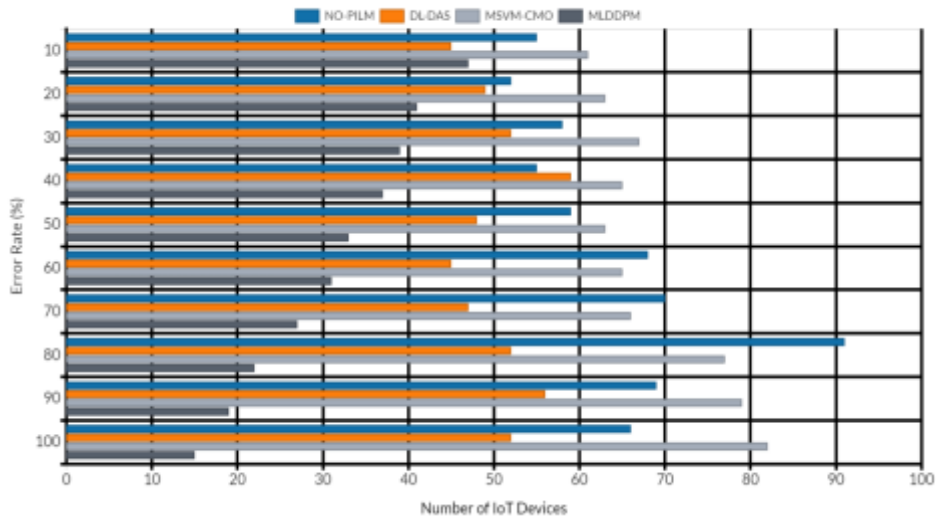


Figure 6: Error Rate (%)

Figure 6 examines the error rate. The SVM models can fit nonlinear connections as well as linear ones. In contrast, logistic models can only fit linear relationships. Secondly, theoretically speaking, logistic methods aim to reduce training error, while support vector machines (SVMs) aim to minimize the upper limit of the generalization error. In SVM, the penalty coefficients for manifold regularization and experimental training error are denoted by λ and C , respectively. This minimizes the output weights. For a wide and continuous area, the performance does not seem too sensitive to changes in the regularization settings. Convolutional neural networks (SVMs) minimize a squared sum of three terms: the output weights' norm, the empirical error during training labelled data, and the manifold normalization term considering both labelled and unlabeled data.

iii) Decision Making Ratio (%)

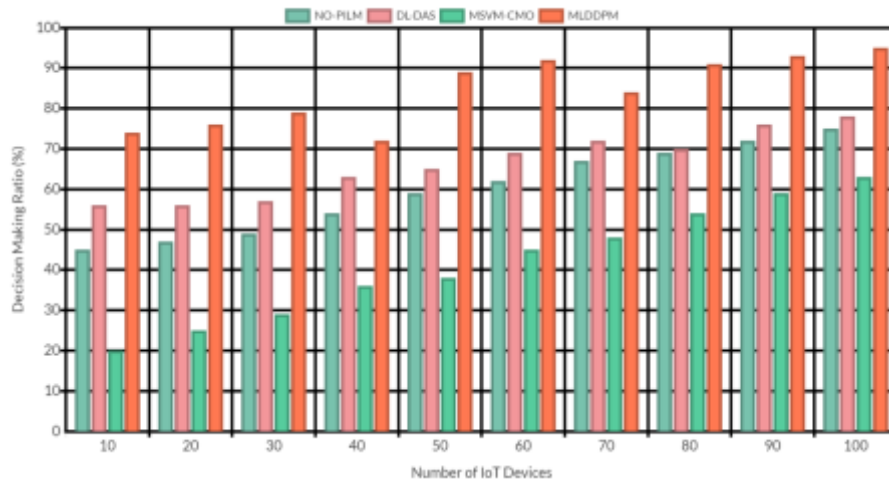


Figure 7: Decision-Making Ratio (%)

Figure 7 discusses the decision-making ratio. A novel strategy for enhancing transportation and vehicle models' ability to make intelligent logistical choices was introduced in this research. This section configures MLIDSS by confirming that driving performance is important for logistic decision support systems. It discusses the characteristics and results of driving with three distinct kernel functions, evaluates their efficiency with support vector machines (SVMs), and applies this information to logistics operations. This research proposed a framework and essential components based on simulation modules for an integrated decision support system (DSS) using ML algorithm to assist service providers with smart logistics DSS while keeping a focus on them. The logistics transportation system is kept smooth by the ML algorithms, which predict distractions from drivers in real time. This research evaluates driver disruption using the drivers' model support vector machine (SVM) and existing DSS systems, as drivers are an element of logistics.

iv) Performance Ratio (%)

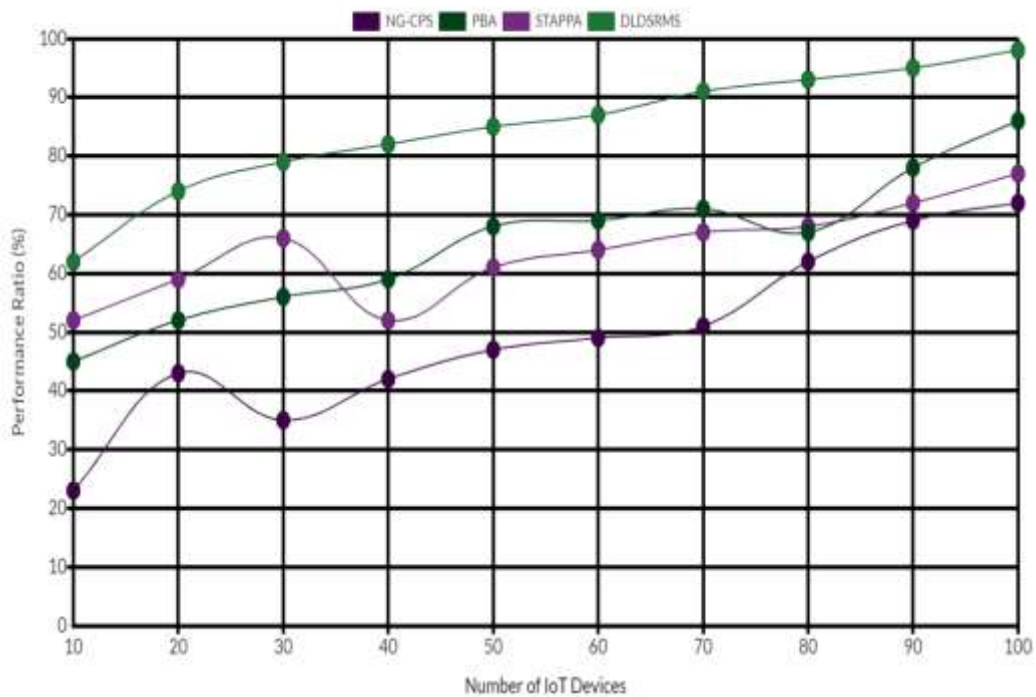


Figure 8: Performance Ratio (%)

Figure 8 and equation 15 explain the performance ratio.

$$C' = \Phi^{-1}(HIT) - \Phi^{-1}(FA)$$

$$\gamma = e^{\left\{ \frac{|\Phi^{-1}(FA)|^2 - |\Phi^{-1}(HIT)|^2}{2} \right\}} \quad (15)$$

To assess model performance, accuracy (correctly identified cases), sensitivity (C' , distinguishing distracted drivers), and response bias (γ , model's tendency) are crucial. Sensitivity is calculated as $\Phi^{-1}(\text{Hit Rate}) - \Phi^{-1}(\text{False Alarm Rate})$, where Hit Rate is true positives/(true positives + false negatives) and False Alarm Rate is false positives/(false positives + true negatives). Response bias is calculated as $e^{(\Phi^{-1}(\text{False Alarm Rate})^2 - \Phi^{-1}(\text{Hit Rate})^2)/2}$. A higher C' indicates better distraction detection, while γ values of 1, less than 1, or greater than 1 signify unbiased, liberal (overestimating distraction), or conservative (underestimating distraction) models, respectively. These metrics, borrowed from signal detection theory, enable a more precise evaluation by isolating sensitivity to distractions from model bias.

5. Conclusion

Robust training and lightweight data processing modules are necessary for ITS's real-time detection capabilities. For the administrator to respond quickly to concerns about safe driving, data must be gathered from specific cameras or wearable sensors that may identify distracted drivers. So, to help drivers stay safe on the road, this study proposes an MLDDPM with a decision-support system (DSS) that can analyze data from both internal sources (vehicle characteristics) and external sources (road infrastructure messages). Researchers at MLDDPM used semi-supervised algorithms to reduce the cost of labeling training data for detecting drivers' attentiveness in real-world driving situations. Using two different driving states—one in which the driver is fully focused on the road and the other in which they are distracted—support vector machines were evaluated for two purposes: (i) as an additional parameter for the overall risk assessment of driving and (ii) as a parameter for giving the driver the best possible warning about potential hazards on the road. This endeavour primarily aims to find the best way to help drivers so that transportation is safe.

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