Driver Distraction System and Vehicle Speed Controlling Using AI and IOT

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Abstract - Clearly, the road safety business requires more oversight, as over 50 million automobiles are sold annually and over 1.3 million people die in car accidents. India, which accounts for 11% of all road fatalities globally, is a developing country where driver conduct needs special attention. Redirections account for 78% of driver-involved incidents, according to the report. As a result of drivers being preoccupied with other things, such as texting or chatting on the phone, road safety is significantly diminished. A cutting-edge ML model that employs computer vision techniques to reliably detect various forms of driver distractions in real-time is the primary focus of this endeavor. We aim to address this important matter. Using a convolutional neural network (CNN) ensemble, such as the state-of-the-art YOLO model. In order to proactively intervene and avoid accidents, we want to use deep learning and image recognition to categorize distractions. Studying the model's overall performance, scalability, and classification accuracy is crucial for deployment on edge devices. We assess the approach's viability and generalizability by looking at performance indicators like inference time and resource use. We propose a model that, with the help of an IoT model and a microcontroller, can do more than only detect distractions; it can also alert the driver and make the vehicle slow down.

Key Words: Machine learning, YOLO, Convolutional neural networks, deep learning, the IOT model and micro controller.

1.INTRODUCTION

More than half a million cars are sold annually, yet over a million people die in car accidents, so clearly there is a serious problem with road safety in the automotive industry that needs fixing immediately. The problem is especially bad in India because the country accounts for 11% of the world's road accident deaths. Auto insurance claims in the fiscal year 18-19 were Rs. 58,456.932 crores, which is a large amount of the country's gross domestic product each year; expenses add up quickly. Driver error accounts for an astounding 78% of accidents, and most road safety issues, especially in developing countries, have their origins in human behaviour. With the introduction of completely autonomous and networked vehicles, the automotive industry is seeing a sea change toward technologically based solutions. In spite of the current difficulties, this movement is proceeding. Never before has there been a greater chance to address concerns about drivers' safety on the road than with the introduction of this technological advance. Despite the fact that technological progress is pushing the car industry to build safer roads, we must still think about the monetary and social effects of road safety. Tragically, healthcare systems often bear the brunt of automobile accidents, which also cause substantial financial losses. Not to mention the heartbreaking number of lives that are often lost.

Victims, their communities, and the families of the deceased all bear some of the brunt of the impact that traffic accidents entail. Such injuries can have long-lasting effects, limit a person's independence and increase their reliance on others for support. This predicament also has significant financial repercussions because lost production, medical bills, and rehabilitation costs might have a major impact on the national budget.

Rapid urbanization and infrastructure issues are increasing road safety problems in developing nations like India. Because of this, finding solutions to these problems is even more critical if we want to generate growth that lasts. Collaboration between public and private sectors must be fostered if we are to find new ways to lessen the dangers of traffic and promote safe driving practices. Proactive risk management and accident prevention are both made possible by AI-powered technology. When stakeholders use prediction algorithms and real-time data analytics, they can swiftly identify high-risk areas, encourage safer driving practices across a large population, and implement tailored interventions. It is possible to accomplish all of these goals. Along with technical endeavors, programs are put in place to educate and create awareness about the importance of safe driving practices. It is important to adopt a holistic approach that considers community involvement, policy enforcement, and technological advancements in order to promote behavioral changes like putting down electronic devices and following traffic restrictions. To sum up, it's not enough to simply address the technical aspects of road safety; a holistic strategy must also consider the social, economic, and regulatory factors that impact these developments. Constructing roads that are welcoming to all users in terms of safety and inclusion, as well as efficient and equipped with state-of-the-art technology, can be achieved through collaborative efforts involving numerous stakeholders. One way to reduce the chance of accidents and the harm they cause is to adopt a real-time alert system that uses artificial intelligence (AI) to remind drivers to stay focused. One major cause of traffic accidents is drivers who aren't paying attention to the road. This includes drivers who are texting, drinking, or otherwise not paying attention. We propose developing a system that can detect distractions in real-time and alert drivers to possible dangers so they may respond quickly in order to solve this problem. Vehicles equipped with an edge device configuration provide for instant notifications and interactions over the internet of things. Additionally, this paves the way for asynchronous data evaluation and insight extraction. With the use of computer vision techniques, this research aims to build an efficient machine learning (ML) model that can classify the various forms of distractions people face while driving. Furthermore, the model's scalability and performance guarantee a problem-free integration into edge device settings.

[1] Xinyu Qi et al. proposed YOLOv4 driver distracted behavior detection algorithm that has been improved and made lighter. There is a replacement of the backbone network with mobile net, and DSC is utilized in order to reduce the amount of model calculation and enhance speed. A SE module has also been included, which results in an increase in accuracy. Comparing this method to the ways that came before it, the results of the tests show that the accuracy of this method is improved by 2%, and the speed is enhanced by 27 frames per second.

[2] Kevin Koch et al. proposed With camera-based sensor technology, this device is the first of its kind to identify drunk driving. It is through this that we directly meet the needs that the HCI community has in practice: All around the world, including in the United States [96], there are policy efforts and regulations that are calling for new technology and interventions to identify drunk driving. This is done with the goal of reducing the amount of harm that is caused by alcohol. Autonomous driving will not be generally available within the next twenty years, according to experts [6, 69], despite the fact that there has been progress made toward fully autonomous driving. Because of this, detection systems that build upon the human-computer interface (HCI) technologies that are already present in vehicles and that make use of the interaction between the driver, the vehicle, and the surroundings are required for the years to come. Our innovative machine learning technology, which makes use of the driver monitoring cameras that are already in place, provides a method that is both cost-effective and scalable for this situation. In order to achieve this goal, our technology offers fresh possibilities for digital interventions that aim to lessen the negative effects of alcohol use, including fatalities caused by trafficking.

[3] Lixiao Gao et al. presented A unique approach to optimize the weighting parameters of DSMPC for PMSMs in vehicle motion control is presented here. The approach that was proposed made use of LSTM networks and fuzzy logic theory in order to obtain optimal weighting parameters for vehicle control under a variety of vehicle control requirements. The efficiency of the proposed strategy was demonstrated by the results of the simulation. An accurate reflection of the drivers' subjective perceptions can be achieved through the use of suitable weighting settings. The utilization of LSTM networks for the purpose of weighing speed and load torque references enables this technology to achieve superior control performances in comparison to the conventional DSMPC framework. In the same way that the torque response was improved, the speed response of PMSMs that had their weighting parameters optimized was also achieved with greater speed and accuracy. The LSTM networks were able to successfully identify the temporal dependencies and offered a dependable foundation for the optimization of the control parameters during the process. After applying the principle of fuzzy logic, the perception labeling of the drivers was successfully attained. The subjective parts of the driving experience were illustrated in a manner that was accurate. Using the weighting factors that have been optimized, the PMSMs of the vehicle are able to respond to the requests that are made by the drivers. Therefore, it is possible to produce a better driving experience and to increase the control performance of the motion of the vehicle. Not only did this technology provide optimization parameters for DSMPC of PMSMs, but it

also addressed the expectations that drivers have for vehicle motion control. Through the process of bridging the gap between PMSMs and vehicles, the study provides the framework for future breakthroughs in control systems that put the driver's experience and preferences at the forefront.

An examination of earlier research that was deemed a Literature Survey is presented in the second part of this publication. The proposed methodology, which lays out the entire plan of action, is detailed in Section 3. Chapter 4 delves into the experimental evaluation, Chapter 5 examines possible modifications, and Chapter 6 concludes the article with a conclusion regarding the present plan.

2. LITERATURE SURVEY

[4] Leyla Shojaeifard et al. Analyzed Based on the findings, it is possible to accurately identify the head's position in three different orientations using a tiny ear-worn device, such as an earable equipped with accelerometer and gyroscope sensors. Due to two factors—first, the data contains far fewer points than a video stream—and second, the machine learning models used are typically lightweight but effective—the methods employed in this study are less resource-intensive than traditional video-based techniques used for head orientation measurements. This data will be valuable in developing apps that teach or remind drivers to keep their heads moving around the road enough to avoid blind areas. Beyond just accurate predictions, our study stresses the significance of data preprocessing and comprehension of the outcomes. We demonstrate how data imbalance is a major cause of erroneous conclusions and offer solutions to fix it. We further demonstrate that, for this particular sensor, the prediction outcomes are unaffected by the window size.

[5] Abdelhak Khadraou et al. presented a novel approach to the categorization and identification of driving distractions. Human Pose Estimation, which can be seen as a feature extractor from the driver's photos, is the foundation of our approach. Random Forest, MLP, SVM, and KNN were the four fundamental classifiers used for the classification. After applying Random Forest, the optimal outcome is achieved. Positive results demonstrating the usefulness of the human pose's keypoints as classification features are achieved. Our long-term goal is to classify the keypoints using Graph Neural Nets (GNNs). Every possible position of the driver can be thought of as a graph. We are also actively pursuing opportunities to apply the process to more datasets.

[6] Xiaobo Liu et al. based ISA system, which is mandated by the European Union in 2021 and 1958, and examines how well existing passenger car speed limit warning systems work in terms of driver convenience and safety. We can deduce the following: The majority of car types come equipped with high-quality speed limit warning systems. The system considers the fact that different types of alarms might make drivers feel varied levels of urgency or displeasure. The system efficiently uses visual and auditory warning to alert drivers to fast behavior while limiting unnecessary interference.

[7] Jiacheng Liu et al. studied The goal is to use a virtual reality (VR) environment and a number of sensors to study how drivers' physiology and behavior are affected by various road scenarios, types of distractions, and driving modes. Our primary results demonstrate that the vehicle's control behavior is considerably affected by the driving mode. As an illustration, the aggressive driving mode involves increased throttle, acceleration, and vehicle speed, whereas the safe driving mode is characterized by less friction and increased head movement. Driving behavior and physiological reactions, such as steering angle and heart rate, are also affected by scene type and distracting conditions. As a whole, drivers exhibit better stability and control when in safe driving mode, and more responsiveness and control when in aggressive driving mode. The significance of building autonomous driving and driver monitoring systems while taking into account the influence of various elements on the physiology and behavior of the driver is emphasized by our work. While this study does shed light on how our bodies and minds react while behind the wheel, it isn't without its flaws.

[8] BRIJ B. GUPTA et al. proposed As the ITS industry evolves, new protocols and standards are required to meet the demands of the present. For this reason, we put out a deep-learning framework for ITS driver behavior identification. The detection of driving behavior within the context of Intelligent ITS and CPS has shown encouraging results in our research. We trained our deep learning model to identify important driving behaviors with a remarkable 94% accuracy rate. These behaviors include yawning, non-yawning, eye closure, open-eye states, and more. In addition to demonstrating the power of deep learning in CPS-based ITS, these findings bode well for improved

transportation efficiency and road safety in the years to come. Our system is able to monitor driver actions in real-time using artificial intelligence, which improves road safety. These results have significant real-world consequences. Our model is ready for real-world use thanks to its excellent accuracy and resilience. A system like this might drastically cut down on accidents caused by drivers who are either too tired or too distracted to pay attention on the road.

[9] Rafael Cirino Gonçalves et al. introduced are now researching how well driver profile data and gaze attributes captured by cameras can forecast SAE Level 2 AV takeover success rates. We hope that our preliminary findings shed light on the formation and regulation of DMS. First, we discovered that predictions of drivers' takeover performance using gaze features alone aren't always accurate. A few gaze parameters—including AVR and total roadside glance time—were predictive, but the best predictors were individual profile characteristics. Driver training, driving experience, and age consistently had higher SHAP values, indicating that these factors have a more significant role in explaining takeover success. Understanding these unique differences in takeover readiness is crucial for ensuring safe handoffs of control and supporting drivers as they adapt to autonomous driving systems. Our first findings and conclusions suggest that regulatory authorities, UI designers, and DMS developers require a more human-centered approach to design that is capable of learning and adapting to individual drivers. In addition to gaze-based measurements for things like visual distraction and fatigue detection, our research suggests that current DMS methods might use systems that can adapt to the specific characteristics of each driver.

[10] Xiaoyang Liu et al. represented The next sections will walk you through the process of adding tables, equations, and figures to your document. By combining virtual simulation environments with multi-view visual data capture, this study suggested a driver distraction recognition system that uses ResNet50 and the AttenD algorithm. The goal is to detect distracted driving states in real-time. The system successfully detects situations involving distracted driving, according to experimental validation. Optimizing layouts of key control interfaces may also aid in reducing risks of driver distraction, according to the results. Based on the findings, interface design plays a crucial role in reducing driver distraction. Some layouts significantly reduced attention diversion, which improved overall driving safety. Therefore, to maximize driving safety, it is advised that intelligent cockpit designs prioritize the creation of aesthetically pleasing interfaces and include technology that identify distractions in real-time.

[11] YIMING WU et al. proposed an LLM-driven label-auxiliary supervision technique that, when trained with extra label text characteristics, allows the MDER model to outperform its competitors in intelligent vehicular systems' inference tasks. In addition, the label-auxiliary supervision technique is more suited to the computational limitations of intelligent vehicle systems since it only runs during training and reduces computational power consumption when utilizing text-feature models during inference. Also, to improve feature interaction across modalities, we use a cross-modal attention method to fuse features across various modalities. In addition to resolving the issue of traditional MER models' deployment in low-power terminals, the suggested method improves the model's emotional state prediction capabilities by tapping into LLM's strong semantic modeling capabilities. This highlights LLM's promising future in perception and interaction in IoT settings and offers a fresh perspective on multimodal emotion recognition in intelligent driving.

[12] MATTEO FRESTA et al. investigated the practicability of developing a model of cognitive distraction in drivers that is both effective and suitable for use while driving. Here, we demonstrate, based on data collected from 42 participants who took the TQT in a driving simulator, that top-tier DL models optimized for time series processing perform better than shallow ML models. This is likely due to the fact that these models can optimize feature extraction from raw signals using end-to-end ML training. Using a ResNet18 classifier, the results also demonstrate that physiological, eye-tracking, and vehicular signals (collected at a frequency comparable to that of readily deployable commercial fitness monitors) may achieve an accuracy of 78.08% in just half a second.

[13] Hameed Mutlag Farhan et al. introduced an innovative method for detecting a driver-distracted model in the IoT industry by combining the proposed SA-GFRO with the given M-LSTM technique. At first, the various CNN variations were fed the input photographs collected by the IoT. In order to obtain the most effective features for detection, the suggested SA-

GFRO was used in the selection model with these extracted features. Then, the produced M-LSTM was equipped with the most effective features for identifying drivers' distracted actions. Improved detection performance was achieved by fine-tuning the LSTM parameters with the help of the newly-developed SA-GFRO.

[14] Shruti S. Mohite et al. proposed A workable proof of concept (PoC) for combining computer vision with embedded control on a single inexpensive platform is an AI-based system that can identify road signs in real-time and automatically adjust the speed. The system showcases smooth operation and efficient performance in regulated test environments by integrating a Raspberry Pi 4B for picture processing and decision-making with an ESP32 microcontroller for PWM-based speed regulation. Rather than introducing new detection methods, this study primarily contributes to the design, implementation, and validation of a small embedded safety system powered by AI. The system's architectural feasibility and practical usefulness are demonstrated by its real-time deployment of well-established architectures, such as CNN and R-CNN models, on hardware with limited resources. It is recognized that the evaluation was carried out on a small dataset and in controlled circumstances, but the experimental results show promising detection accuracy and response time.

3. METHODOLOGY

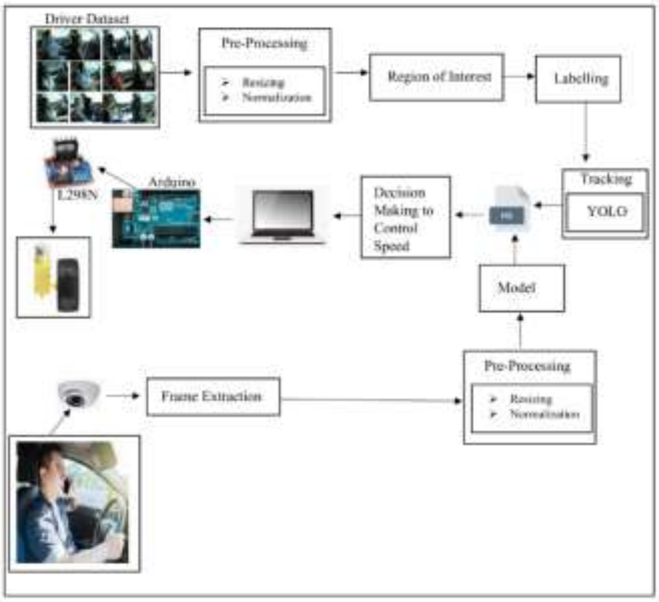

Figure 1: System Overview.

Figure 1 shows the suggested approach for identifying Driver Distraction when an individual is present. The following phases provide a comprehensive overview of what is involved in this process.

Step 1: YOLO V8 Driver Image Training — The system is making use of the image to successfully identify the distraction in the image. Identifying the distraction in the image is the initial stage in the technique before an alarm can be generated for the person. To successfully execute person recognition for the distraction, the driver distracts identification module use the Yolov8 technique. Training this model is a prerequisite to using it for driver distraction detection.

Installing the Yolov8 model's ultralytics and downloading the roboflow dataset are the first steps in the training process. To link roboflow to your application, you'll need an API key. To obtain the driver distraction detection dataset, go to https://universe.roboflow.com/roboflow-universe-projects/driverdestraction-detection-ca3o8. In order to retrieve the directory's file list, the downloaded dataset is thoroughly examined. The number of files in the directory can then be extracted using the file list. For training, there are 3,148 files, and for testing, there are 450 images.

The yolov8 model can be started for the yolo task of person recognition after the roboflow data and driver distraction datasets have been successfully integrated and shuffled. The detection model is being started with the trained weights. The dataset was trained for 200 epochs with 640 X 640 image size and 32 batch size. After training the yolov8 model, the project runs are saved as a zip file in the provided directory. Below, in table 8.2, you can find a description of the Yolov8 model.

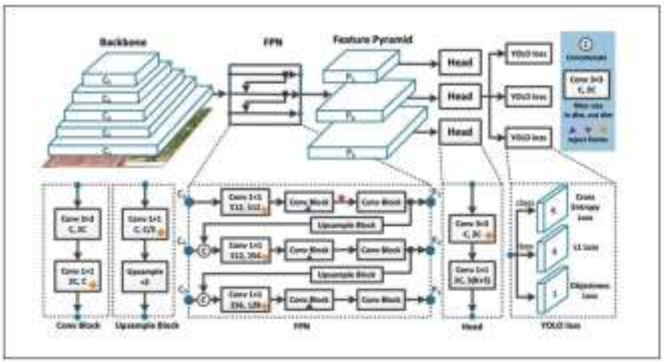

Figure 2: Model Summary for YOLOv8

A Convolutional Neural Network (CNN) variant, the YOLOv8 is its offspring. To improve the accuracy of person recognition, it employs the CNN approach's components in a novel and efficient way. To prevent overfitting and regularize the model, the Yolo design uses 24 convolutional layers with different parameters, a max pooling layer, and a number of dropout and batch normalizations. At last, the model reaches its zenith with two fully connected layers.

The channels are max-pooled after the first convolutional layers decompose and reduce them; the kernel size is 2x2 and the stride is 2. Every layer of this model uses the same max pooling layers. With each succeeding convolutional layer, the kernel size increases to handle the influx of new data. Specifically, these layers make use of the RELU activation function. Except for the fully connected layers, which use a linear activation function to create the.pt file, Yolo8's trained data file, every layer's activation function is the same. Next, we'll use this.pt file to notify the designated driver to reduce speed.

Step 2: Testing the model for Distraction: In this stage, the Python software uses the Droid Cam app, which is compatible with both laptops and mobile phones, to record video and, by extension, frames from the mobile phone's camera. The file containing the trained model's results.The.pt file is utilized to find the driver's upper left rectangular positions in the live streaming frames, which are then used to detect them. By keeping an eye on the frames' stability, this IoT position can issue a verbal warning to the driver to reduce the speed of their car. The model in question is based on an ESP 32 microcontroller and features a DC motor.

4. RESULTS AND DISCUSSION

Using the NetBeans integrated development environment, the proposed technique for detecting driver distraction, and obstacles has been implemented in the JAVA computer language. A laptop with an Intel Core i5 CPU, 1 TB of storage, and 8 GB of RAM served as the development machine. The video stream was captured and the frames were inputted into the system using an open-source library called open CV.

In order to achieve the precision that the system achieves, it is necessary to evaluate the performance of the proposed methodology for diamond distraction. Accurate application of adaboost and decision tree approaches for precise outcomes can only be determined through the experimental procedure. The experimental procedure has been designed to utilize precision and recall methodology for this goal.

Performance Evaluation based on Precision and Recall

Among the most practical and reliable metrics for evaluating a system's efficacy is the precision and recall performance parametric. Applying recall and precision to the suggested methodology yields reliable performance measurements that can help evaluate the accuracy of the offered strategy.

The experimental procedure pulls detailed information about the performance of the driver distraction detection, alcohol, and obstacle detection approaches using precision and recall. While recall gives the system's absolute accuracy in identifying driver distractions, the precision approach basically finds its performance relative to a given parameter.

Given below are equations, which are utilized to conduct the thorough experimental assessments and determine the parameters.

A = The number of correctly identified Driver Distractions

B= The number of incorrectly identified Driver Distractions

C = The number of Driver Distractions not identified

So, precision can be defined as

$$Precision = (A / (A+ B)) *100$$

$$Recall = (A / (A+ C)) *100$$

Table 1 below shows the results of the rigorous testing of the suggested method, which employs the aforementioned equations to attain the recall and precision levels indicated.

No. of expected Distractions	The number of correctly identified Driver Distractions (A)	The number of incorrectly identified Driver Distractions (B)	The number of Driver Distractions not identified (C)	Precision	Recall
35	110	15	13	88	89.43089431
59	100	10	11	90.90909091	90.09009009
88	70	9	9	88.60759494	88.60759494
121	49	6	4	89.09090909	92.45283019
138	29	3	5	90.625	85.29411765

Table 1: Precision and Recall Measurement Table for the performance of Driver Distraction Detection

Figure 2: Comparison of Precision and Recall for the performance of Driver Distraction Detection

The system for detecting driver distraction has been subjected to extensive testing or has been given multiple trials. The input was the different numbers of expected distractions that needed to be analyzed, and the corresponding result is shown in table 1 above. The data in this table is subsequently used to generate the plot graph seen in figure 2 up top. Based on the results, it's clear that the driver distraction method works well and produces minimal mistakes. Adaboost and decision tree have been used accurately to execute this detraction strategy, as indicated by the recall and precision values of 89.17 and 89.44, respectively.

5. CONCLUSIONS

There has to be an improvement everywhere, but notably in developing countries like India, where drivers are accountable for 11% of all road fatalities. More accidents involving drivers occur when their attention is diverted. Driving becomes far less safe when one is distracted, such when one is chatting on the phone or engaging in other social activities. In order to address this critical issue, we developed a robust ML model that employs computer vision to identify and categorize driver distractions in real-time. Using cutting-edge models like YOLO and CNN ensembles. Our goal is to reduce accident occurrences through the application of deep learning and image recognition to identify and classify potential hazards. Deploying the model to edge devices requires testing its speed, scalability, and classification accuracy. This study does just that. We can learn about the method's feasibility and possible widespread adoption by looking at performance metrics like inference time and resource use. Our proposed model has an Internet of Things (IoT) and microcontroller component that might identify danger, notify the user, and reduce response time.

To make it more reliable in real-world driving situations, future updates to the suggested driver distraction detection system can incorporate multimodal data including eye-tracking, steering behavior, and vehicle telemetry. Optimizing deployment on low-power edge and microcontroller-based devices can be achieved by exploring more efficient deep learning models and model compression approaches. Automated braking and lane control in dangerous conditions are possible thanks to the system's extensibility, which allows for real-time interface with ADAS. Furthermore, by utilizing data from various driving conditions and federated learning, model performance may be continuously improved while user privacy is preserved. Adding the ability to identify emotional states, lethargy, and exhaustion will further improve road safety and accident prevention.

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