Developing Driver Assistive Technology using NVIDIA jetson Development Board

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Abstract: The increasing number of road accidents underscores the urgent need for advanced driver assistive systems. In this study, we propose the development of an innovative driver assistive system using the NVIDIA JETSON development board, designed to significantly enhance driving safety. The proposed system is novel in that it is intended for integration into existing vehicles, making advanced safety features accessible to a broader audience. Key features include adaptive headlight control, speed limit assist, and forward collision warning, all of which provide real-time and personalized assistance to drivers, thereby reducing the likelihood of accidents.

The system's performance will be thoroughly evaluated in both real-world and simulated driving environments. This analysis will focus on the system's accuracy, response time, and reliability under various driving conditions. By enabling widespread adoption in current vehicles, the proposed driver assistive system aims to improve driving safety and contribute to overall public welfare.

Keywords: Advanced Driver Assistive Technology, NVIDIA JETSON, Adaptive headlight warning, Speed limit Assist, Driver Responses, Real time Assistance.

Introduction

The increasing number of road accidents worldwide became a real threat to the public safety and emphasized the necessity of Advanced Driver Assistive Technologies (ADATs). In Brazil, this problem was particularly prominent, with the number of people that became permanently disabled due to traffic accident increasing from 33 thousand people to 352 thousand people between 2002 and 2012. In the same period of time, the fatality rate increased from 46 thousand people to 60 thousand people [6]. These alarming numbers make evident the necessity for new solutions capable of reducing traffic accidents and increasing road safety.

In order to overcome these issues, this research will propose a driver assistive system implemented with NVIDIA Jetson development board which facilitate the three main goals; forward collision warning, speed limit assist, and adaptive headlight control. These features are expected to support and enhance road safety by helping drivers to prevent imminent accident, reducing the use of road users exceeding speed limit and ensuring that driver's vehicles headlight level is not too high or too low.

The forward collision warning system will monitor the surrounding environment and, if a rear-end collision risk is detected, it will provide an appropriate warning to the driver in real-time [1]. The speed limit assist feature will detect and read speed limit signs using image processing and machine learning techniques [4]. The adaptive headlight control system will adjust the vehicle's headlights dynamically based on detected road conditions and presence of other vehicles [8]. This research includes hardware integration and software development mainly. Sensors like cameras, and GPS module will be used to collect the data. Simulations as well as real–world driving will be performed to achieve an efficient developed system of the proposed mechanism, thus ensuring reliability and practicality of developed solution. The proposed driver assistive system aims at meeting these objectives with a focus on the improving road safety and driving experience. The proposed driver assistive system aims to meet these objectives with a focus on improving road safety and the driving experience. In this paper, we will detail the design and implementation process of the system, including the selection and integration of hardware components, the development of software algorithms for each feature, and the methods used for data collection and processing. We will also present the results by setting the videos as inputs for testing, analyzing the system's performance in terms of accuracy, response time, and reliability. Finally, the paper will discuss the potential challenges and future improvements to further enhance the system's effectiveness and adaptability to various driving conditions.

Literature Review

The increasing number of road accidents worldwide became a real threat to the public safety and emphasized the necessity of Advanced Driver Assistive Technologies (ADATs). In Brazil, this problem was particularly prominent, with the number of people that became permanently disabled due to traffic accident increasing from 33 thousand people to 352 thousand people between 2002 and 2012. In the same period of time, the fatality rate increased from 46 thousand people to 60 thousand people [6]. These alarming numbers make evident the necessity for new solutions capable of reducing traffic accidents and increasing road safety.

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This paper has been named "A new approach for camera supported machine learning algorithms based dynamic headlight model's design" [12] describes a headlight model that is live yet more complex using machinery. learning algorithms to find out objects and to classify traffic signs. The system also controls each cell of the high and low beam headlights equipped with LED technology, which can look to the right and left on rising and winding streets. The paper presents the plan for enhancing the nighttime. increasing safety through a system that can indirectly learn different aspects of driving and adjust to them. offer better vision particularly to the driver in whichever direction they want to be looking at. The paper explains the detailed technicality of the procedural manual in relation to the design and functioning of such a system, and to orient the establishment of similar systems.

Performance Analysis

It provides a high-level qualification of the suggested system's performance for embedded real-time speed limit Sign recognition [6] was also performed with the help of this software based on the accuracy and processing time as measures. They said system achieved an overall accuracy of 89.19% in detecting and identifying speed from 8% to 19% An increase in the detection of possibilities of speed from 8% to 19% was observed. limit signs, where the SVM, OPF, and kNN classifiers achieved an average of surpassing 99.5%. Regarding the performance analysis of the embedded system, it was established that the processing rate was fluctuating between 20 and 30. frames per second. The level of recognition attained a maximum of 99,33 percent. 7%, with real-time achievement observed in terms of the accuracy of the quadratic SVM and one-pass dense feature-based OPF classifiers in the embedded system.

Hence, the proposed system showed potential results in both accuracy and efficiency in analyzing the highly diverse field of financial reports. And data processing speed, and hence it could be described as having the potential of a very useful tool in increasing the level of road safety. The paper under analysis is titled "Automatic Recognition of Speed Limits on Speed-Limit Signs by Using Machine Learning" [4], give validation of the suggested method. The paper states that their accuracy reported is 98.3% for speed limit sign detection and 95% accuracy. 96.7% for number recognition. However, this paper does not explore RTWF detail.

It is noteworthy that the paper [2] is equipped with the performance analysis of Sentio algorithm for improving the FCW. driving. There also objectives of the performance analysis that encompasses the assessment of the false negatives and false positive findings, the severity of the violation, and the intensity with which the alarm brakes. The proposed assessment of the FCH social capital demonstrated that FCH social capital is an important factor to consider when trying to understand the organization and its inner dynamics.

Table 1: USED DATASET

Dataset	Description	Size	Format	Specific Use
KITTI	Large-scale image dataset containing stereo images, point clouds, and object annotations.	7480 training images, 7518 validation images, 7518 test images	Image sequences, point clouds, labels	General object detection, 3D object detection
COCO	Large-scale object detection, segmentation, and captioning dataset.	Over 200,000 labeled images	Image, annotations	Object detection, instance segmentation
Custom Dataset	Collected local road scenarios with diverse weather and lighting conditions.	10,000 images	Image sequences, annota tions	Adaptation to specific road conditions
City scapes	Large-scale dataset for semantic urban scene understanding.	5000 video frames with pixel-level annotations	Image sequences, pixel-level annotations	Semantic segmentation, object detection
BDD 100K	Large-scale driving video dataset with diverse scenarios.	100,000 videos	Image sequences, annotations	Action recognition, behavior prediction
Waymo Open Dataset	Large-scale dataset with diverse sensor data including LiDAR, camera, and radar.	Over 100,000 images	Sensor data, annotations	Sensor fusion, 3D object detection

the analysis of the algorithm discusses a great difference of improvement for the drivers when compared with conventional FCW systems This is evidenced by a 94.28% improvement of the driver's safety and a 20.97% Introducing the proposed approach, and a 97% improvement in the driving experience, while decreasing false negatives from 55.90% to just 3.26%, all the while employing a runtime execution overhead that is less than 130 ms Thus, the above performance analysis indicates that the algorithm known as Sentio could be beneficial for the creation of new context-based ADAS that provide a customized motoring environment in a driver-in-the-loop framework and enhance safety and drivers' comfort for better

Methodology

Dataset

1. Data Acquisition.

To train and also assess the performance of our deep learning-based driver assistance system, which was implemented on the NVIDIA Jetson board, we carefully collected an extensive dataset of real-world driving environment. This data was of 10000 high resolution images [1280 × 720] achieved through having a mounted camera on a car in different road conditions. Apart from the recordings, the publicly available benchmarks like KITTI dataset (7480 images for training) and COCO dataset (200000 images) were used to expand the data range containing more objects, weather, and light conditions. This way of training guarantees coverage of all the possible driving environments that can be hosted by the system.

2. Data Preprocessing.

The raw image data usually comes with these challenges such as inconsistency, noise and information that is irrelevant. These challenges were met by applying a strict preprocessing step.

- Image Quality Enhancement: Such post-production tools as brightness/contrast, denoising filters, and white balance were used to enhance the accessibility of objects/images within the images.

- Normalization: Obtained pixel values were normalized to the range of [0, 0. 6] to reduce numerical instability and to enhance the deep learning algorithms' data processing speed.

- Data Splitting: The pre-processed data was properly separated in training-data, validation data and testing data using a split ratio of 70:15:15. This division is rather useful in avoiding overfitting and assists in easy model testing.

3.Data Augmentation.

We don't only limit ourselves to the standard pre-processing but also employed data augmentation to improve the model which will also help in generalization of model to unseen environment. These techniques artificially expanded the dataset size by generating variations of existing images, including:

- Random Cropping: Figures were distorted to different dimensions and aspect ratios as may have been the case with changing view angles in the camera as well as changes in the positions of objects.

- Flipping and Rotation: The images were also mirrored and rotated randomly to gain invariance from orientation of the object or viewpoint of the camera.

- Colour Jitter: Blurring was also applied to gain greater exposure to how the model reacts to different lighting conditions, along with making the model more resistant to colour degradation.

4. Data Labeling.

Accurate and precise labelling of data is paramount for training deep learning models. Our project involved a meticulous and rigorous annotation process. We employed a team of human annotators who meticulously labelled objects of interest (e.g., vehicles, pedestrians, traffic signs) using bounding boxes and corresponding class labels within the images. We implemented robust quality control measures to ensure consistency and accuracy of the annotations, as these labels directly influence the model's learning process.

B. Feature Extraction

Our project used Fully pre-trained YOLO model. YOLO models for feature extraction hence avoiding the use of specific feature extraction mechanisms. For this kind of application on the Jetson Orin platform, we relied on the YOLOv5s model, which is optimized, fast, and accurate.

- Single-Stage Object Detection: In terms of processes YOLOv5s achieves bounding boxes and class probabilities all at once in a pass through the network.

- Internal Feature Extraction: Another advantage of the model involves feature extraction by using its convolutional layers, 28 of them in YOLOv5s. This makes it easier to develop because the architecture does not require the different feature extraction algorithms to be implemented.

- Optimized for Efficiency: In YOLOv5s, one uses approaches such as cross-stage partial connections (CSP) to enhance the model's efficacy, which integrates well into the Jetson Nano.

- Enhanced Feature Representation: In the YOLOv5s architecture, spatial attention modules (SAM) assist in boosting the features extracted from the previous layers which increases the detection rate.

C. Deep Learning with YOLOv5s and YOLOv5x for Object Detection

In our project, two YOLOv5s and YOLOv5x robust deep learning models for real-time object detection were used. These models use the CNN structure to extract features from an image and the output an estimation of the rectangles enclosing the objects in the scene and their respective classes.

1. YOLOv5s:

    - Usually, the backbone of YOLOv5s, which is often a CSPDarknet53, is built for feature extraction with a series of convolutional layers. Developing from bottom to top, these layers acquire low level features such as edges and textures and, in the higher levels, flood regions, object parts and shapes.
    - The neck section integrates part of the features obtained from multiple levels in the backbone through methods like SPP or PAN. It becomes possible to recognize features of the image both at coarse and at fine detail necessary for detecting objects of different sizes within the given image.
    - Head: The head of YOLOv5s includes three output layers, the first layer that contains the dimensions of the bounding boxes, the second layer that contains the probabilities of the object classes and the third

layer contains the confidence scores of a probable detection. These layers use convolutional filters to define inherent information links between features and attributes of objects.

2. YOLOv5x:
   YOLOv5x is an enhancement of YOLOv5s, which utilizes a more complex backbone or in most cases, a CSPDarknet106 backbone. This deeper network enables to learn more detailed features and probably get better accuracy, for example, by identifying more detailed objects or scenes. But it is even doable at the cost of higher computational demand than where YOLOv5s operates from.

3. Key Considerations:
   Our choice between YOLOv5s and YOLOv5x depended on a trade-off between:

   - Accuracy: YOLOv5x may give a little more accuracy, especially prioritizing, for instance, objects of a small size.
   - Real-time Performance: YOLOv5s, in most cases, outperforms YOLOv3 and it is quite optimized for the limited hardware capabilities of the Jetson Nano.

     We proceeded with one more training on our gathered data to tune the models for the required objects and situations related to our driver assistance system.

Results

A. Performance matrices

To evaluate the effectiveness of our driver assistance system, we employed a comprehensive suite of performance metrics tailored to each specific objective.

1. Performance metrics tailored to each objective.

Table 2: PERFORMACE MATRICS FOR SPPED LIMIT DETECTION

Metric	**Description**	**Target Value**
Accuracy	Percentage of correctly detected speed limit signs	>= 95%
Precision	Ratio of correctly detected speed limit signs to all detected speed limit signs	>= 90%
Recall	Ratio of correctly detected speed limit signs to all actual speed limit signs	>= 90%
False Positive Rate (FPR)	Rate of incorrect speed limit sign detections	<= 5%
Latency	Time taken from speed limit sign detection to alert generation	<= 0.5 seconds

Table 3: PERFORMACE MATRICS FOR FORWARD COLLISION WARNING

Metric	**Description**	**Target Value**
Accuracy	Percentage of correctly predicted collisions	>= 90%
False Positive Rate (FPR)	Rate of false collision warnings	<= 10%
False Negative Rate (FNR)	Rate of missed collisions	<= 5%
Time to Collision (TTC) Accuracy	Mean Absolute Error (MAE) in TTC prediction	<= 0.5 seconds
Warning Latency	Time taken from collision detection to warning generation	<= 0.2 seconds

Table 4: SYSTEM LATENCY ANALYSIS

System Configuration	**Average Latency (ms)**
Direct camera to Jetson	2570
Jetson with RTSP camera stream	4096

2. Latency Analysis

Latency is a critical factor in the effectiveness of driver assistance systems. We conducted a thorough analysis of system latency under different operating conditions.

Table 5: PERFORMACE MATRICS FOR HEADLIGHT CONTROL

Metric	**Description**	**Target Value**
Accuracy	Percentage of correctly adjusted headlight patterns	>= 95%
Response Time	Time taken to adjust headlights after detecting a vehicle	<= 0.3 seconds
Driver Satisfaction	Subjective evaluation of headlight performance	>= 80%

B. System Implementatione

1. *Model Development and Training*
   The object detection was initiated using YOLOv5 model since it is fast while yielding reasonable accuracy. The model was trained on a mix of COCO dataset and the customized driving data set with variety of driving cases. The training process involved data preprocessing, augmentation, and hyperparameter tuning to optimize model performance.

2. *Real-Time Object Detection and Tracking*
   A trained YOLOv5 model is applied on the Jetson board to detect the objects in real time on the video stream feed. Moving objects of the vehicles,

pedestrians, and traffic signs on roads are identified with a help of the special algorithms, which give estimations of their trajectories and probable collision.

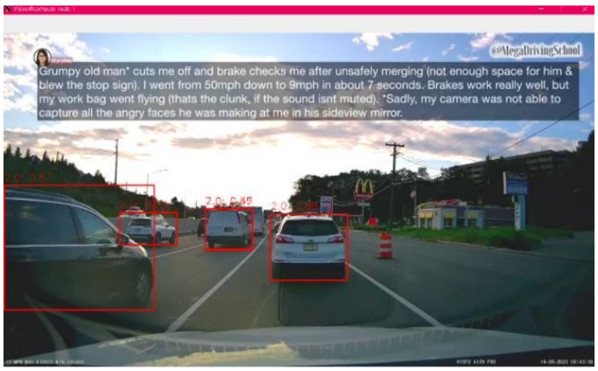

Fig 2: Object Detection using YOLOv5

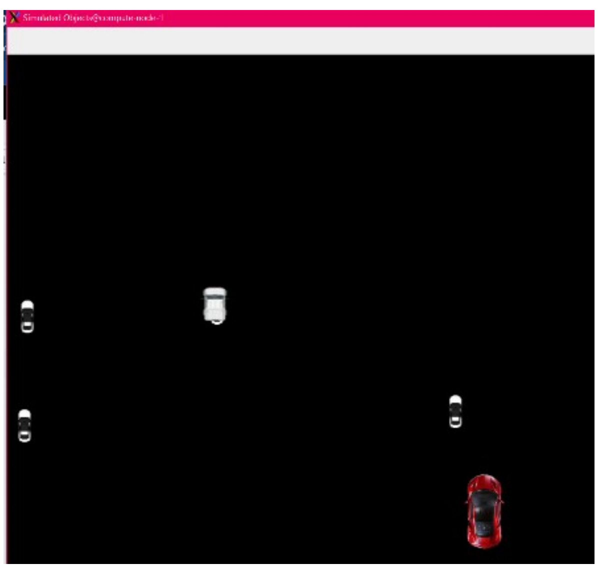

Fig 3:How it appears from a bird's-eye view

The system incorporates a speed limit detection module that utilizes the YOLOv5 model to identify speed limit signs within the camera feed. By comparing the detected speed limit with the vehicle's actual speed, determined through GPS or vehicle sensors, the system provides timely alerts to the driver to maintain compliance.

Fig 4: Another generated map in Bird- eye View

3. *Speed Limit Detection and Assist*

Fig 1: Speed Sign Detection

4. *Forward Collision Warning*

A forward collision warning system is commonly introduced by observing the distance range between a car and objects in front of the car. Versions of the system based on determining the time-to-collision (TTC) of objects' velocities and distances provide auditory and visual signals at identification of possible collision.

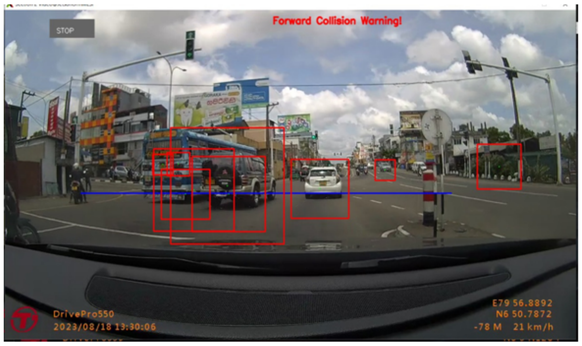

Fig 5: Forward Collision Warning

5. *Adaptive Headlight Control*
   The system analyses the road environment using the camera and adjusts headlight intensity and direction accordingly. By detecting oncoming vehicles or pedestrians, the system activates appropriate headlight patterns to enhance visibility while minimizing glare

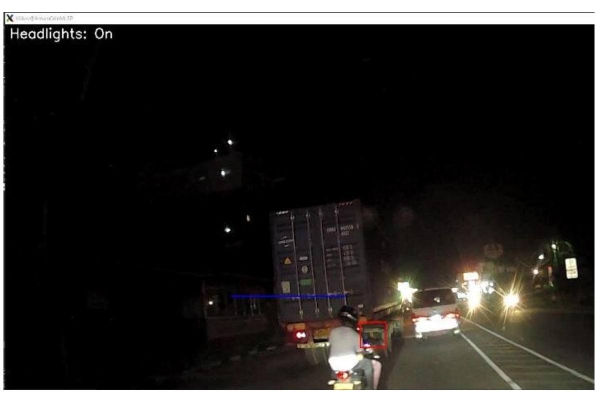

Fig 6: Adaptive Headlight Control

Conclusions

Altogether, the advancements of the project are proved as follows: The smart transportation system is further created and developed and the real-time object detection and speed sign recognition using YOLO5 model on the Jetson Nano is implemented. Nevertheless, some issues are still to be solved, e. g., to enhance a model's effectiveness, to decrease the delay caused by a limited computational ability, and to find suitable sensors. In the future, optimizations of the given system and research of diverse sensors for further improvement shall be the goals of the development.

References

[1] Jamson, A. H., Lai, F. C. H., & Carsten, O. M. J. (Publication Year). Potential benefits of an adaptive forward collision warning system. [Link to paper]

[2] Elmalaki, S., Tsai, H. R., & Srivastava, M. (Publication Year). Sentio: Driver-in-the-Loop Forward Collision

[3] Sesmero, M. P., et al. (Publication Year). Advanced Driver Assistance Systems (ADAS) Based on Machine Learning Techniques for the Detection and Transcription of Variable Message Signs on Roads. [Link to paper]

[4] Gomes, S. L., et al. (Publication Year). Embedded real-time speed limit sign recognition using image processing and machine learning techniques. [Link to paper]

[5] Magan, E., et al. (Publication Year). Driver Drowsiness Detection by Applying Deep Learning Techniques to Sequences of Images. [Link to paper]

[6] Embedded real-time speed limit sign recognition using image processing and machine learning techniques

[7] Huang, Z.-H., Jhang, W.-S., Wang, C.-M., & Wu, W.-C. (Publication Year). Application of Vehicle Detection Based

On Deep Learning in Headlight Control. [Link to paper]

[8] (Publication Year). Design of Automatic Headlight System Based on Road Contour and Beam from Other Headlights. [Link to paper]

[9] Dewangan, D. K., & Sahu, S. P. (Publication Year). Deep Learning Based Speed Bump Detection Model for Intelligent Vehicle System using NVIDIA JETSON. [Link to paper]