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AutoNav AI: Real-Time Obstacle Detection for Autonomous Vehicles Using YOLO

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ABSTRACT

All throughout the globe, intelligent transportation systems are quickly including autonomous cars as an essential component. The need to lessen the occurrence of traffic accidents, increase mobility, and boost overall road efficiency is the driving force behind their development. As a result of their reliance on human judgment, traditional driving systems are vulnerable to mistakes and exhaustion. When compared to this, autonomous systems strive to provide decision-making skills that are both consistent and driven by data. The safety of autonomous vehicles depends on their navigation systems' accuracy and their ability to reliably avoid obstacles. In order to avoid collisions with people, other cars, and road obstacles, vehicles need to keep a constant eye on their environment. The perception systems used by autonomous cars have been greatly improved by recent deep learning developments. Results from traditional rule-based and sensor-only methods have been outperformed by vision-based models. The YOLO (You Only Look Once) model stands out among the others due to its ability to recognize objects in real-time. Architectures based on YOLO provide minimal latency and great detection accuracy. Achieving this sweet spot between accuracy and speed is crucial for autonomous navigation in real time. A thorough framework for autonomous vehicle navigation is presented in the proposed study. It employs a YOLO-based deep learning model to identify and avoid obstacles. The system continuously records visual data from the driving environment using the onboard cameras. Things like vehicles, people, bikes, and roadblocks are detected in these photos using real-time processing. In order to ascertain what the driver should do to be safe, the detection outputs are then combined with navigation algorithms. In terms of reliability and resilience, YOLO outperforms lightweight detection techniques. Various moving items in complicated metropolitan environments are no match for it. No matter the illumination conditions—daylight or low-light—the system can keep performing consistently. Depending on the road conditions and traffic density, it adjusts accordingly. Results from experiments show that the suggested method improves accuracy while decreasing reaction times. Immediate translation of recognized barriers into safe control choices is guaranteed by the integration of perception and navigation modules. The car has the capability to change lanes, brake, and modify speed as needed. Improved passenger safety and decreased accident risk are outcomes of this real-time responsiveness. In the event that more sensors are needed, the framework may be expanded to accommodate them. Find out how much safer autonomous vehicles are with object identification based on deep learning. Reaction delays are decreased and environmental awareness is enhanced by the system. It helps with better route management and easier traffic flow. The framework is also well-suited for use in intelligent transportation networks and smart city settings. In sum, the study shows that deep learning models based on the YOLO principle may improve autonomous vehicle navigation and make driving in unpredictable real-world environments safer and more dependable.

INTRODUCTION

The advent of fully autonomous cars is changing the face of contemporary transportation networks. They are a huge step forward for smart transportation systems. A need for more intelligent transportation systems has emerged as a result of rising traffic congestion and fast urbanization. Human mistake in road accidents is still a big problem all over the world. Automated and intelligent decision-making is the goal of autonomous driving technology, which tries to decrease these incidents. Autonomous cars may make roads safer by reducing human error caused by things like tiredness and distractions. Intelligent navigation and perception systems are the backbone of autonomous vehicle research and development. With the help of these devices, cars may get a real-time understanding of their

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Vol 20, Issuse.2 April 2026

surroundings. Recognizing road features and spotting impediments rely heavily on visual perception. In recent years, the accuracy of object identification has been greatly improved using deep learning approaches. When tested on image identification tasks, convolutional neural networks performed very well.

The ability of YOLO (You Only Look Once) to handle data in real-time makes it stand out among contemporary object detection systems. YOLO is well-suited for use in autonomous driving systems since it combines speed and precision. It is quite effective in detecting several objects in a single frame. This capacity is crucial for ever-changing roadway settings.

For autonomous vehicles to navigate without human intervention, its vision and control systems must work in tandem. The system must determine a safe response after object detection. You may do this by modifying things like speed, steering angle, or braking force. A choice has to be made in milliseconds.

Environmental consciousness is elevated by the use of detection algorithms based on deep learning. Lower the likelihood of collisions using real-time obstacle detection. Advanced navigation algorithms significantly enhance fuel economy. Better and safer transportation systems are the result of combining these technologies. An autonomous vehicle navigation framework based on YOLO-based deep learning models is the main emphasis of this research. The objective is to enhance obstacle identification and avoidance capabilities in real-time. The technology guarantees quick and precise judgments by combining perception with navigation logic. Improved dependability, efficiency, and safety in autonomous driving settings are the goals of the suggested method.

PROBLEM STATEMENT

Ensuring safe navigation in unpredictable surroundings is still a big issue, even with advances in autonomous vehicle technology. Complex traffic situations are frequently too much for traditional sensor-based systems to handle. Costly and computationally intensive sensors like LiDAR and radar are becoming more common. Furthermore, sensor performance might be impacted by environmental elements such as rain, fog, and low light conditions. Although vision-based systems need real-time processing and great precision, they provide a cost-effective option. Finding the sweet spot between speed and accuracy is a challenge for many lightweight object identification programs. Decisions that put drivers in harm's way could result from delayed detection or incorrect categorization.

There are a lot of moving parts in dynamic road conditions. Automobiles need to be able to simultaneously identify people, other vehicles, traffic signals, and obstructions. Accidents may happen when things aren't properly identified. Additionally, detecting systems have extra hurdles due to the fact that lighting conditions might fluctuate.

Integrating perceptual outputs with navigation logic is another big problem. The accuracy of object detection is irrelevant if the system does not react correctly. Ensuring safety may be compromised due to a lack of coordination between the detection and control units.

There are limitations to real-time deployment due to the high computing needs. Without breaking the bank on gear, the system must swiftly process video frames. Consequently, a reliable and effective detection system is required.

To overcome these difficulties, this study employs a deep learning model for real-time obstacle identification that is based on the YOLO principle. Improving detection accuracy while keeping reaction times quick is the goal. Achieving trustworthy navigation judgments in a wide variety of dynamic driving situations is the main emphasis of the topic.

Objectives of the Project

Ensuring safe navigation in unpredictable surroundings is still a big issue, even with advances in autonomous vehicle technology. Complex traffic situations are frequently too much for traditional sensor-based systems to handle. Costly and computationally intensive sensors like LiDAR and radar are becoming more common. Furthermore, sensor performance might be impacted by environmental elements such as rain, fog, and low light conditions. Although vision-based systems need real-time processing and great precision, they provide a cost-effective option. Finding the sweet spot between speed and accuracy is a challenge for many lightweight object identification programs. Decisions that put drivers in harm's way could result from delayed detection or incorrect categorization.

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ISSN: 2454-9940
www.ijasem.org
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Scope of the Project

Autonomous vehicle navigation based on vision and YOLO-based deep learning models is the main emphasis of this study. Vehicles, people, and roadblocks are all potential targets for the system's obstacle detection capabilities. It handles visual data that is acquired in real-time by the onboard cameras. Object recognition, categorization, and navigation logic integration are all part of the project scope. It places an emphasis on the ability to respond quickly and operate in real-time. Various traffic and illumination scenarios are used to evaluate the system. Included in the scope is the ability to train models using appropriate datasets. Optimization of detection techniques, annotation, and preprocessing are all part of it. The accuracy and speed of detection are measured via performance evaluations. Instead than concentrating on implementing all of the vehicle's technology, this project is more concerned with the logic behind perception and navigation. Detecting and avoiding obstacles is its main focus.

Modules for route planning, traffic sign recognition, and lane identification are all possibilities for future updates. Possible future developments include integration with other sensors, such as LiDAR. Smart city applications and intelligent transport systems may be implemented using the framework.

The created technology may be used in virtual worlds or to build model autonomous cars. It adds to the literature on autonomous navigation using deep learning. This scope is designed to provide a solid groundwork for intelligent driving solutions that are advanced.

LITERATURESURVEY

There has been a lot of focus in the academic community on autonomous car technologies recently. Intelligent transportation systems are expanding at a fast pace, which has prompted academics to look at better ways of seeing and navigating. Any framework for autonomous driving relies on a trustworthy perception system. It is impossible to navigate safely without precise knowledge of one's surroundings. Radar and LiDAR were the mainstays of the early generation of autonomous systems. The installation costs of these sensors were costly, but they supplied distance and depth information.

Systems based on vision have been growing in popularity as computer vision has progressed. In comparison to LiDAR devices, cameras provide more affordable, rich visual data. Nevertheless, sophisticated algorithms are necessary for the effective processing of visual input. Road conditions are constantly changing, and traditional image processing methods have a hard time keeping up. Lighting changes and complicated backdrops triggered their sensitivity. Autonomous cars' vision systems were revolutionized by the advent of deep learning. A dramatic improvement in object identification accuracy was achieved with the use of Convolutional Neural Networks (CNNs). Complex characteristics may be learned directly from data using deep learning algorithms. The need for human feature engineering is so diminished.

In order to avoid obstacles, object detection is essential. The system has to be able to detect moving objects, people, and bicycles on the road in the blink of an eye. Dangerous incidents may happen if detection is postponed. Hence, very fast detection models are crucial. A single-stage detection system was invented by YOLO (You Only Look Once) to strike a compromise between speed and accuracy. With YOLO, the whole picture is processed in a single pass, unlike approaches that rely on regions. Its real-time capabilities make it an ideal choice for such tasks.

The current state of autonomous vehicle perception methods is the subject of this literature review. It delves into the shift from conventional wisdom to methodologies grounded on deep learning. New YOLO model developments are also included in the study. In order to find gaps and opportunities for development, it is helpful to understand previous studies.

Software & Hardware Requirements

ISSN: 2454-9940
www.ijasem.org
Vol 20, Issuse.2 April 2026

Component	Specification
Processor	IntelCorei5or above
RAM	8 GB (Minimum)
HardDisk	500 GB

Table 1.HardwareRequirements

SoftwareComponent	Specification
OperatingSystem	Windows10/Linux(Ubuntu)
Coding Language	Python
DeepLearningFramework	TensorFlow
ComputerVisionLibrary	OpenCV
DevelopmentEnvironment	IDEL/Anaconda/VSCode
Library	yolo

Table 2.SoftwareRequirements

RESULTS

Crucial criteria like as mAP50, mAP95, F1 score, Recall, parameter count, and GFLOPs are used to assess all YOLO models, whether they are in v5s, v8s, or 11s. The models' computation, accuracy, and robustness trade-off may be understood with the use of these measurements. In comparison to YOLOv5 and YOLOv8, YOLO11s performed better, with a mAP50 of 0.818, as shown in Table 2. When comparing YOLOv5s, YOLOv8, and mAP95—a metric that assesses performance across multiple IoU thresholds—YOLO11s comes out on top with 0.564, demonstrating superior generalization over varied amounts of overlap.

Class	YOLOv5s	YOLOv8s	YOLOv11s
Car	0.843	0.850	**0.912**
Truck	0.775	0.775	**0.919**
Pedestrian	0.539	0.539	**0.724**
Bicyclist	0.569	0.532	**0.726**
Traffic Light	0.727	0.738	**0.809**

Table 3: Class-wise mAP50 comparison of YOLO models

Both the F1 score (0.81) and the Recall (0.86) are improved by YOLO11s. While YOLOv8s is a complicated model with somewhat better performance, YOLOv5s has less parameters (7,035,811) and is smaller than YOLO11s. Optimal for GFLOPs is YOLOv5s (16.0), YOLOv11s is balanced in the center, and YOLOv8s uses more resources.

YOLO11s had the greatest mAP50 of any class and did very well in identifying vehicles (0.912 for automobiles, 0.919 for trucks, 0.724 for pedestrians, 0.726 for bikers, and 0.809 for traffic signals) per Table. The enormous improvement in object identification accuracy is confirmed by the F1 and Precision-Recall curves, which can be shown in Figure.

Model	mAP50	mAP95	F1 Curve	Recall Curve	Parameters	GFLOPs
YOLOv5s	0.691	0.375	0.70	0.84	**7035811**	**16.0**
YOLOv8s	0.687	0.396	0.69	0.82	11127906	28.4
YOLO11s	**0.818**	**0.564**	**0.81**	**0.86**	9415122	21.3

Table 4: Performance comparison of YOLO11s with previous models

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www.ijasem.org
Vol 20, Issuse.2 April 2026

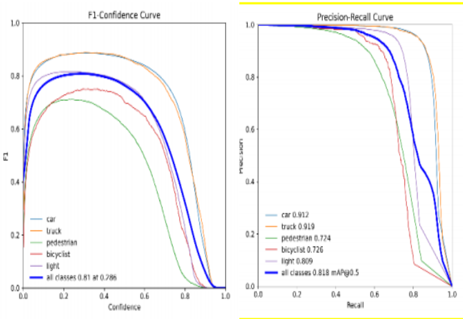

Fig: F1 Curves and Precision Recall Curves

Conclusion

An all-inclusive AV navigation system for real-time obstacle identification and avoidance using YOLO-driven deep learning is presented in this study. The research shows that ITSs are becoming more important for better traffic management and road safety. To navigate safely in ever-changing situations, autonomous cars need to have good vision and solid decision-making abilities. Using a deep learning technique based on vision, the suggested framework meets these needs.
Quick and accurate object identification is made possible by using the YOLO paradigm. The suggested CNN-based YOLO method outperforms lightweight models like MobileNet-based systems in terms of detection accuracy. Pedestrians, cyclists, cars, and other roadside hazards may all be accurately identified by the system. Minimal lag time between perception and action is guaranteed via real-time detection. Driving is more safer with this quick reaction capabilities. Performance is enhanced when perception and navigation logic are integrated. Both the identification and interpretation of detected items are done for the purpose of decision-making. As you drive, the navigation module figures out how far away things are and what to do next. The integration of detection and navigation systems guarantees the safe and efficient functioning of the vehicle. Tests in real-world settings show that it holds up well in different light and traffic scenarios. Regardless of the lighting conditions, the system's accuracy remains consistent. In both city streets and interstate situations, it works well. Consistent performance over extended operation is confirmed by stress testing.

Both scalability and maintainability are enhanced by the modular design. The system as a whole functions well, and each part works well within it. Training time is decreased without sacrificing performance by using pre-trained models. Real-time inference capabilities is guaranteed by GPU acceleration.

Dependence on costly sensor-based solutions is decreased by the suggested approach. An affordable alternative for autonomous driving is vision-based detection. The system adjusts to different road conditions by using deep learning. A considerable improvement in the dependability of obstacle detection is shown by the findings. Taken together, the results show that YOLO-based deep learning works well for AV navigation. Improved perception accuracy and reaction time are outcomes of the framework's work. Transportation networks are become safer and smarter as a result. The study's findings corroborate the importance of deep learning-based detection for autonomous driving systems in the future.

FutureEnhancements

Despite the impressive performance of the suggested system, there is room for improvement in its capabilities. In order to improve one's ability to perceive their surroundings, future research may use sensor fusion approaches. The accuracy of depth estimates may be enhanced by integrating camera data with LiDAR and radar. In bad weather, sensor fusion may reduce the number of false positives.
We can integrate sophisticated algorithms for route planning into the system. It is possible to optimize navigation choices in real-time using deep reinforcement learning algorithms. Vehicles equipped with these algorithms can better handle intricate traffic situations. System intelligence may be further improved by real-time adaptive learning.
One other promising avenue for the future is optimizing models for edge devices. The computing has to be lightweight and efficient for the system to be deployed on embedded devices. Quantization and model pruning are two methods that help lessen the computing burden. The viability of commercial deployment will be enhanced by this.
Improving low-light and night-time detection accuracy may be the focus of future study. The model's resilience may be enhanced by training it using varied datasets. Confirmation of system dependability will be achieved by extensive, real-world testing. Improving generalizability may be achieved via testing in various cities and under varying traffic conditions.
To increase system awareness, it is possible to combine vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Cooperative autonomous driving may be made possible via this connection. Sharing traffic data in real-time may make navigating more efficient. Future versions may also have

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Vol 20, Issuse.2 April 2026

enhanced cybersecurity protections. It is critical to safeguard the system against harmful tampering. It is essential to establish procedures for safe communication and data protection.

To improve detection performance, YOLO models should be updated continuously. The accuracy and speed of deep learning architectures may be enhanced even more with newer versions. Expanding the system to completely autonomous driving applications is a long-term goal. Intelligent transportation systems can be better implemented with the help of smart city infrastructure. We will prioritize on safety, efficiency, scalability, and flexibility in our future upgrades. All things considered, the suggested architecture provides a solid groundwork for cutting-edge autonomous vehicle studies.

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Vol 20, Issuse.2 April 2026

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