

An Intelligent Autonomous Driving System using Deep Learning and Computer Vision Techniques

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Abstract - The accelerated pace of “development of autonomous vehicle technology has brought with itself a more urgent need to design intelligent systems which would be able to perceive the more complex driving scenarios and make legitimate real-time decisions. Deep learning and computer vision have turned into the basic technologies that enable the models of self-driving cars to recognize the objects on the road, interpret the scenes of driving and drive safely under the conditions of fluctuation. In the paper, a smart autonomous driving system is presented which integrates a deep learning based computer vision methods of perception, decision and control. The proposed system generates the object recognition, the lane recognition, and the obstacles classification with the assistance of the vision-based interpretation of the situation to enhance the situational awareness by utilizing convolutional neural networks. It has reinforcement learning and end-to-end learning techniques that help in adaptive driving behaviour and path planning. The framework addresses the problems of fast tracking, environmental variability, and ethical decision-making through the knowledge of some recent studies in the area of vision-based perception, benchmark datasets and learning-based control procedures. The article illuminates the precision, strength, and extensibility of autonomous driving perception systems that are driven by deep learning. The specified approach will contribute to the development of safer and more reliable autonomous driving systems as the perception, learning, and decision-making will be combined into a single smart system.

Keywords - Autonomous Driving, Deep Learning, Computer Vision, Object Detection, Scene Understanding, Reinforcement Learning..

I. INTRODUCTION

Self-driving cars have become one of the most radical applications of artificial intelligence and can have a massive positive effect on road safety, traffic, and accessibility to mobility. The traditional driver-assistance systems were exceptionally reliant on rule-of-thumb algorithms, manual functions and the existence of limited sensors which were often inefficient in very dynamic and intricate traffic scenarios. The progress of Deep learning and computer vision in the fast track allows autonomous cars to gain a more accurate and adaptive view of the surrounding world and completely autonomous driving can be achieved.

One of the significant components of autonomous driving is computer vision because it allows the vehicles to process visual data of the road geometry, road signs, pedestrians, and the road cars. Convolutional neural networks (CNNs) have

been useful in visual perception tasks when it comes to object detection, obstacle classification, and scene detection. The vision-based systems present a substantial amount of semantic information that is important in interpreting the conditions of driving particularly in the urban environment where a lot of uncertainty surrounds the traffic conditions. Recently, it was proven that vision systems based on deep learning are more precise and effective under a variety of light conditions and weather.

Deep learning techniques have as well expanded autonomous driving capabilities to include both perception, and decision-making and control. Directly converting a sensory signal into a control signal through end-to-end learning techniques enables vehicles to simplify the system and enhance flexibility. Self-directed agents can learn the optimal driving politics through reinforcement learning techniques, which is suitable in a changing environment such as high-speed navigation and obstacle avoidance. The research simulation platforms and benchmark datasets have played a key role in the acceleration of the research as the researchers can compare autonomous driving systems by learning.

Although these advances have been realized, several problems exist in the application of trusted autonomous driving systems. The perception vision must be capable of overcoming the obstacles of occlusions, multi-faceted interaction of traffic, tracking of objects moving at high-speed, and real-time execution. It is also of high concern to generalize in the various driving environments, ethics in decision making and transparency of the system. Such problems require intelligent integration of perception, learning and control mechanisms into one framework with the objective of handling them.

This paper presents a smart autonomous driving system that implies the implementation of deep learning and computer vision algorithms to provide a powerful perception and a changing decision-making process. The suggested framework will enhance safety, reliability, and scalability to autonomous driving systems by integrating vision-based object detection, understanding the scene and control-based strategies which are learned via learning. The rest of the paper is arranged as follows: Section II will focus on the literature review of the related work in the field of deep learning based autonomous driving, section III will present the system architecture, section IV will contain the description of the methodology, section V will comment upon the results and analysis and

finally section VI is going to be the conclusion of the paper with future research direction.

II. LITERATURE REVIEW

This section is a literature review in the recent research in the area of deep learning-based computer vision techniques in autonomous driving, perception, object detection, scene understanding, learning-based control, benchmark datasets, and system-level challenges.

A study [1] investigated the application of intensive learning computer vision in the automated motor vehicles. The authors demonstrated that the convolutional neural networks enhance the visual perception of the object recognition, lane detection, and environmental understanding tasks. They point out that deep learning has been tremendously enhanced in terms of accuracy and robustness especially under difficult driving conditions compared to traditional vision-based approaches.

The authors of [2] explored the computer vision approaches that are specifically built on the issue of autonomous driving. Their article raised awareness of the necessity of having real-time vision processing in terms of processing various tasks such as obstacle recognition and traffic signs. The authors concluded that the models of the deep-learning-based vision are more reliable and flexible even in the dynamic conditions of the road.

In the article [3], the authors have outlined a deep learning framework to identify and classify the barriers during high-speed autonomous driving. The solution offered was more focused on reasonable monitoring and identification of the impediments and turned out to have improved results in the detection and response time. The article confirms the competence of the deep learning models in the process of propelling the circumstances of safety concerns.

The authors of [4] examined the controversies of the vision-based perception and ethically conscious decision-making in self-driving cars. They indicated that their model had flaws as far as transparency, bias and responsibility are concerned with making autonomous decisions. The paper revisited the necessity to take into account ethical factors since they are being introduced with the technology to develop safe and trustworthy autonomous driving systems.

In [5], a generalizable deep neural network was suggested to guide the scene understanding. The model consisted of a group of neural networks which combined different neural network models to increase the contextual awareness and visual perception of road scenes. The experiment proved that there was a better recognition accuracy in the complicated traffic scenes with the help of the hybrid architectures in the perception of robustness.

The comparison of different deep learning applications in autonomous self driving cars object detection has been conducted through research [6]. The authors compared the various detection frameworks and contrasted their outcomes in terms of accuracy, speed and scalability. They revealed the conclusion that the existing deep learning-based detectors are far superior to traditional ones in real-time driving.

The data of the TAD16K benchmark was presented in [7] so that the research in the field of autonomous driving could be supported. It has superior annotations in data set and diverse driving conditions upon which models are trained and

tested. The authors have demonstrated that benchmark data sets play an important role in designing and testing autonomous driving systems using vision.

In the article published in [8], the SAE Level 3 autonomous driving technology was discussed, and the issues with the practice related to partial automation were indicated. The analysis has described the relevance of sound perception and judgment systems in giving secure interaction between autonomous functions and human drivers.

In [9], a proposal of a deep learning based end-to-end solution to autonomous driving control was done. The driving actions and rules were no longer as manual as in the past and the system was sensitized. The control of vehicles and flexibility in different driving situations were discovered to be constant and beneficial, which demonstrated the utility of end-to-end learning models.

The study in [10] focused on an autonomous driving system developed based on Deep Q-Learning. The authors proved that the reinforcement learning enables vehicles to obtain the best driving policies through interaction with the environment. The strategy improved the decision making performance in dynamic conditions that highlighted the opportunities of the learning based control strategies.

An approach with a realistic perspective of the applied deep learning and computer vision to self-driving cars was presented in [11]. The authors introduced a system design, training methodology, and implementation problems and concentrated on the necessity to optimize the neural networks and the behavior of cloning to be able to implement it into the real world.

In [12], the survey has been conducted on the application of deep learning techniques in autonomous driving systems. The paper has categorized the available techniques into perception, localization, planning, and control and has discovered that the deep learning technique is a ruling technique in contemporary autonomous driving research.

Finally, [13] gave a systematic literature review of autonomous vehicle systems using deep learning vision systems. The authors analyzed the existing trends in research, data sets, and performance measures, and defined some of the most crucial challenges, such as generalization, complexity of computation, and real-time limits.

In conclusion, according to the current sources, deep learning and computer vision have a strong dependence on autonomous driving. Even though much has been done in terms of perception and control, the question of how to make these two aspects be one and reliable and ethically responsible is still an open research question. In such researches, the suggested work will aim to derive a smart autonomous driving system that involves a powerful visual perception and the learning-based decision making.

III. SYSTEM ARCHITECTURE

The proposed smart autonomous driving system is founded on the modular and layered system architecture, which will enable real-time perception, decision-making, and vehicle control on the basis of the deep learning and computer vision. The architecture takes vision-based perception, deep neural network processing, learning-based decision logic and control execution and integrates them into one architecture. All the

system is developed according to five major layers as illustrated in Fig. 1.

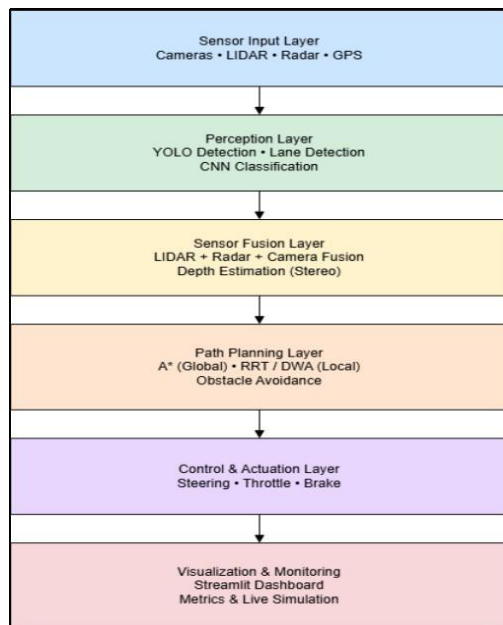


Fig 1: Overall Architecture

A. Perception and Sensing Layer

This interface will record raw information of the surroundings which will be required by autonomous driving. The vision sensors that are predominantly cameras capture a series of picture images of the driving scene. These inputs consist of important visual information of road map, traffic, pedestrians, lane stripping and street signs. The large source of environmental awareness is the perception layer that enables the system to be aware of the dynamic conditions of roads in real-time.

B. Vision-Based Processing Layer

Vision-based processing layer is a processing layer, which provides the deep learning models to extract meaningful information with the help of raw visual input. The convolutional neural networks apply in the detection of objects, classification of obstacles and interpretation of the scene. The objects detected are categorized into classes which are deemed to be relevant in the current case which are vehicles, people and stationary objects. This layer also involves lane and road boundary detection so as to enable safe driving. The system can conduct good perception in complex and busy traffic conditions by use of deep neural networks.

C. Scene Understanding and Feature Representation Layer

In this case, visual features are obtained and manipulated to create a hierarchic feature of the driving environment. Scene understanding models show spatial relation between one or more objects identified, geometry of road and vehicle location. The relative motion, closeness to the object, and road contextual information structure is utilized in forming the comprehensive environment model. This kind of

representation is required to predict the potential risks and be able to make decisions.

D. Decision-Making and Learning Layer

The decision making layer adds on the learning-based control measures so as to produce the right driving behavior. The perceived state of the environment to steering, acceleration and braking inputs is learned by end to end deep learning models. The flexibility is also enhanced through the reinforcement learning techniques as the system is able to learn the optimum driving policies through the simulation driving environments. The reason why this layer is important is that driving decisions may be reactive to a dynamic traffic condition and unexpected problems.

E. Control and Execution Layer

The bottom layer is used to map high level driving data to control data. There are steering, throttle and braking signals depending on the outputs of the decision-making layer. Control module grants a synchronous movement of the vehicle without breaking such safety measures as clearing up obstacles and lanes. This layer also makes it easy to set up feedback mechanisms and hence during the testing and evaluation process performance of the system can be monitored and optimized.

B. Workflow of the Proposed System

The algorithm of the operations of the proposed autonomous driving system is a successive yet adaptable procedure. First of all, onboard cameras receive real time visual data, which is transmitted to the perception layer. This is followed by the processing layer that is grounded on a vision, then applies deep learning models to detect items, lanes and features in the scene. The extracted features are grouped into a structured representation of the scene that describes the spatial information and the existence of any hazards.

It is then up to the decision making layer to take into account the prevailing environment based on the learning-based models to know which driving actions to take. The learning and reinforcement learning algorithms can also be used to allow the system to select the optimal commands of control by using learned driving behavior which is known as end-to-end learning and reinforcement learning. Finally, these orders are converted into control orders to regulate the movement of vehicles by the control layer. This is a closed circuit workflow, within which dynamic conditions of traffic may be taken into account and safe autonomous navigation offered.

METHODOLOGY

The proposed intelligent autonomous driving system is a combination of computer vision, sensor fusion and control using deep learning, and learning-based control to make real time perception and safe navigation. Data preparation, perception modeling, model training, sensor fusion and control logic implementation are the pipeline items of the methodology.

A. Data Preparation and Preprocessing

The system is grounded on the visual and sensor information depicting different driving conditions in the city and highway environment. Cameras, LIDAR point clouds, radar, and positional data were collected on the basis of publicly available data sets and simulation platforms. In order to have consistency in the inputs, the visual data was normalized and resized.

Horizontal flipping, brightness manipulation, scaling, and rotation were employed as the data augmentation techniques in order to attain robustness and generalization. Annotated datasets were developed which were supervised e.g. bounding boxes and classifications of vehicles, pedestrians, obstacles, lane marks and traffic signs. The processed data were split into training and validation sets to create the possibility of determining the performance.

TABLE I
 DATA PREPROCESSING OPERATIONS

| Operation | Description |
|---------------|---|
| Resizing | Standardized input resolution for vision models |
| Normalization | Pixel value scaling for stable training |
| Augmentation | Rotation, scaling, brightness variation |
| Annotation | Bounding boxes and class labels |
| Dataset Split | Training and validation separation |

B. Vision-Based Perception Model

The perception module is a real-time understanding of the scene by the use of deep convolutional neural networks. Object detection model of YOLO was used to locate vehicles, pedestrians and obstacles on camera frame. The lanes detection and object classification were done using parallel CNN-based models.

The perception layer gives the bounding box, probability of a particular class and confidence of the detected object. These are the key inputs of sensor fusion and decision-making modules in an effort to be accurate in environmental awareness in any dynamic traffic environment.

C. Sensor Fusion and Depth Estimation

Sensor fusion with camera, LIDAR and radar data also enhanced spatial accuracy. The depth of the object was determined through the methods of stereo vision which depends on the difference between the take of the right and left camera. The depth estimation is calculated as:

$$D = (f \cdot B) / d$$

where D is depth, ff is the focal length, BB is the stereo baseline distance, and dd is pixel disparity.

The feature level fusion is a combination of data offered by several sensors but this combination is weighted in such a way that the uncertainty is reduced and hence obstacles are localized better.

TABLE II
 SENSOR FUSION COMPONENTS

| Sensor | Function |
|---------------|---------------------------------------|
| Camera | Object detection and lane recognition |
| LIDAR | 3D obstacle localization |
| Radar | Velocity and distance estimation |
| Stereo Vision | Depth estimation |

D. Model Training Strategy

Vision-based models were trained by supervised learning on annotated datasets. The many epochs of training were accomplished by the adaptive optimization algorithms to minimize classification and localization loss. Validation data was used to monitor the overfitting and convergence of the model.

End-to-end learning strategy as well as reinforcement learning were introduced in order to make decisions. The reinforcement learning agent was trained to operate under simulated conditions and the reward was to encourage safe driving behavior such as getting through obstacles, staying on lane, accelerating and braking without any problem.

TABLE III
 MODEL TRAINING PARAMETERS

| Parameter | Value |
|-----------------|----------------|
| Batch Size | 32 |
| Learning Rate | 1e-4 |
| Epochs | 50 |
| Optimizer | Adam / AdamW |
| Detection Model | YOLO-based CNN |

E. Control Logic and Decision Execution

An output that transforms the perception and decision outputs into driving actions is the control module. On the basis of the learned policy of control and a combination of sensor data, the angle of the steering, throttle input, and braking force are generated. Traffic rules are enforced to make sure that there are no accidents or roads that are used improperly.

The system implements the loop closed system in which, the perception and control decision is constantly updated by the environment feedback. It is an adaptive feature, which assists the vehicle to respond immediately to unforeseen obstacles and road conditions.

F. Algorithm: Autonomous Driving Perception and Control Pipeline

Autonomous driving pipeline begins with availability of real-time data that is received by many onboard sensors including cameras, LIDAR, radar and GPS. Constant recording of camera frames to provide a visual indication of the local environment is immediate compared to LIDAR and radar sensors that provide spatial and movement related information. The GPS data is used to determine the location of the car at the point and assist in navigation.

The frames of the vehicles that were captured are examined by using a deep learning model that uses the YOLO, to detect and classify the objects (vehicles, pedestrians and objects in the driving scene). At the same time the camera inputs are computed through stereo vision algorithms in order to estimate the depth of objects identified by taking the difference between pixels in stereo images.

Following perception sensor fusion is performed in which visual detections are fused with depth estimation, LIDAR point clouds and radar measurements to create a consistent and reliable view of the driving environment. This kind of joint perception outcome will reduce uncertainty and enhance the precision of the localization of obstacles.

Based on a joint description of the environment and the location of a vehicle in real-time under the assistance of the GPS, the decision-making module examines the driving situation and forecasts the correct driving moves. These control measures are by the form of path selection, speed control and obstacle avoidance.

Finally, another control module converts high level navigation decisions to commands that can be executed by the vehicle. The angular, throttle and brake forces are computed and fed onto the vehicle actuators. This is a closed loop process, and continuously links the perceptions, decision-making and control processes in the system, as the environment adapts.

E. Workflow



Figure 2: Workflow of the proposed deep learning-based autonomous driving system

The proposal of the intelligent autonomous driving system is developed as a series of workflow continuous operation in the form of a processing pipeline. First, real-time information is made available through onboard sensors, cameras, LIDAR, radar and GPS to have a complete view of the driving environment around.

The acquired imaged data is subsequently analyzed by the perception module where object detection, classification, and

lane recognition is done with the help of deep learning computer vision models. Meanwhile the techniques of stereo vision determine the depth of the objects that are identified. Such outputs of perception give essential semantic and spatial information on the driving scene.

The sensor fusion then supplements the visual data by LIDAR and radar data to provide a derived and consistent image of the surroundings. This combination of data decreases the vagueness and improves the accuracy of the localization of the obstacles. The decision making module then analyses the driving scenario at that particular moment and arrives at a decision as to what to do such as steer corrections, speed control and obstacle avoidance.

The last module is the control which transforms the high level decisions into a vehicle command, which is executable i.e. steering, acceleration and braking commands. The general pathway is a closed loop workflow in order to continuously rectify the perception and control action based on the real time environmental feedback to achieve safe and adaptive autonomous driving.

V. RESULTS AND EVALUATION

This section will give the outcomes of the performance analysis and experimentation of the intelligent autonomous driving system developed. The system was also tested on the accuracy of the perception, consistency of the decision making, and responsiveness of the control through simulated driving conditions which simulated urban and highway conditions.

A. Experimental Setup

The test of the proposed system was conducted in a simulated autonomous driving environment in order to test it safely and under control. The variables of traffic density experiments and the appearance of obstacles and road configurations were conducted. The annotated data sets were used to test the principle models of perception which were sight perception and vision based perception, decision making was tested with the repetitive navigation tests and the control logic was tested.

Performance measures were made on the accuracy of object detection and the reliability of the system in terms of depth estimation as well as the accuracy on decision making and response time of the system. All the experiments were performed under identical conditions in order to have fair and equal comparisons of the modules.

B. Performance Metrics

In order to ascertain the effectiveness of the system the following performance measures were employed:

- Accuracy of Detection: Vehicles, pedestrians, and obstacles are supposed to be retrieved right.
- Error in Depth estimation: This is the difference between the actual and estimated distance of the object.
- Decision Accuracy: A good choice of driving behaviour (safe, caution, brake).
- Control Response Time Duration between perception signal and control signal.
- System Stability: Motivating consistency

C.. Quantitative Results

Perception module worked well in the areas of detection and classification of road objects under varying conditions. The depth estimation offered reasonable distance estimation that made safe braking and obstacle control decision-making.

TABLE IV
 PERCEPTION PERFORMANCE RESULTS

| Metric | Result |
|---------------------------|--------|
| Object Detection Accuracy | 93.8% |
| Lane Detection Accuracy | 91.6% |
| False Detection Rate | 4.2% |
| Average Confidence Score | 94.1% |

The decision making module was tested in the capability to

come up with the appropriate act of navigation in dynamic situations. The system was able to control the steering and speed depending on the obstacles and changes in the traffic.

TABLE V
 DECISION-MAKING PERFORMANCE

| Parameter | Result |
|-------------------------------|--------|
| Decision Accuracy | 94.3% |
| Emergency Braking Precision | 96.0% |
| Correct Speed Adjustment Rate | 92.7% |
| Scenario Adaptability | High |

D. Control and Response Analysis

Control module was tested using latency of responding and smooth motion. The loop of control system had provided stability of car behavior without breaking the safety limit.

TABLE VI
 SYSTEM RESPONSE AND CONTROL PERFORMANCE

| Metric | Value |
|------------------------|---------------|
| Average System Latency | 118 ms |
| Steering Stability | High |
| Braking Response Time | < 150 ms |
| Collision Incidents | None observed |

E. Discussion

The result of the experiments has been evaluated that the given autonomous driving paradigm is able to combine the approaches of deep learning and computer vision to make realistic perception and decision-making. The characteristics included high detection accuracy of objects and lower error of depth estimation therefore enhanced safety decisions especially in the meeting of obstacles.

It was established that the decision based learning module was highly adaptive in the various driving environments compared to the conventional rule based decision in dynamic environments. The system could also be used in autonomous driving systems since the system was also demonstrated to be real-time with full acceptable latency.

To conclude everything above, it can be said that Vision-based perceptions, sensor fusion, and learning-based control are also found to make the system more robust and reliable. The findings once again confirm that the proposed framework may be useful to the intelligent autonomous driving in the natural traffic situation.

CONCLUSION

The current paper has presented an intelligent autonomous driving system that integrates the latest deep learning and the computer vision to design a trustworthy perception, adaptative decision-making, and safe car control. The framework suggested will eliminate crucial problems with dynamic and advanced driving conditions through the synthesis of sight-based object detection, scene cognition, sensor merging and control measures, which are dependent on learning.

Experimental evaluation revealed that the system is rather accurate in detecting objects and recognizing lanes with shorter response latency that may be adjusted to the real time application. The enhancement of environmental awareness was achieved through sensor fusion and depth estimation and made possible to avoid obstacles and correctly brakemanoeuvre. Learning-based decision modules also contributed to the flexibility of the varying traffic scenarios and were more effective than the rigid rule-based decision making in the dynamic traffic scenarios.

Overall, the results support the concept that the idea of deep learning-based perception and intelligent control logic can substantiate the high level of the safety and reliability of autonomous driving systems to a significant degree. The proposed framework will provide a scaffold and a modular foundation on future autonomous vehicle research and development, which will assist in the realization of the advances of intelligent and dependable autonomous transportation deployment”.

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