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A Review of Machine Learning Techniques Utilised in Self-Driving Cars

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ABSTRACT: Science and technology researchers are currently focused on the creation of self-driving cars. This can have a profound effect on social and economic progress; self- driving vehicles can help reduce auto accidents dramatically and enhance the quality of life of people the world over. Self-driving cars have had a tremendous increase in popularity in the recent past because of artificial intelligence development. However, there is a lot of research work to be done to manufacture fully-automated cars because a self-driving carshas tto be able to sense its environment and operate without human involvement. A human passenger is not required to take control of the vehicle at any time, nor are they required to be present in the vehicle at all.
Currently, self-driving cars are still at level 3 and are not allowed ply the roads due to many challenges which usually cause blurred images, including irregular roads, weather factors (rain and fog).
This paper is a review study on self-driving cars, and will be examining the obstacles that self-driving cars face, as well as how they might overcome them. The paper will provide the researchers with pieces of information about self-driving cars, the challenges they face, the recent methods used to overcome these challenges, and the advantage, disadvantage, and accuracy of these methods. The paper aims to encourage researchers to work on solving the problems that inhibit the evolution of self-driving vehicles.
Keywords: Autonomous driving vehicles, Vehicle detection, Pedestrian detection, Traffic sign detection, Convolutional Neural Network(CNN).

1. INTRODUCTION

The stud of self-driving cars has gained more relevance and attention in recent years. According to figures on traffic, about 94% of crashes are caused by driver errors, such as improper movements and inattentive driving. Human error can be considerably decreased by automating vehicles, because distractive and inebriated driving is avoided. Further, accidents caused by driver error and inattention can be dramatically reduced through the use of autonomous vehicles. This automation is similar to how suitable moves can be programmed into cars to completely avoid a collision. By getting rid of the possibility of driver error, autonomous driving holds the potential to save thousands of lives. Individuals of all ages, including those with impairments—as well as other targeted groups—who are unable to drive themselves will gain from mobility, thanks to autonomous vehicles. Additionally, autonomous vehicles can contribute to more efficient driving, which can minimise operating fuel costs and have less negative environmental impact [1].
The primary contributions of this paper are: (1) A presentation of the main stages of self-driving car development and the challenges facing researchers.
(2) A review of the recent methods (deep learning) used in field self-driving car and their advantages, disadvantages, and accuracy.
(3) A summary of the main concepts of autonomous cars and a highlight of their importance.

The remainder of this paper is structured as follows: Section 2 introduces the levels of automation, while section 3 presents the definition of autonomous cars. Sections 4 and 5 introduce the challenges in this field of research, while section 6 presents the key issues. Section 7 introduces some of the previous works. Section 8 focuses on the main databases used in the field of self-driving cars, while section 9 discusses obstacles detection. Further, section 10 is devoted to comparisons of methods and publications, and section 11 presents the author's opinion on the future of self-driving cars. Finally, section 12 concludes the paper. The rate of publications around autonomous vehicles over time is shown in Fig. 1

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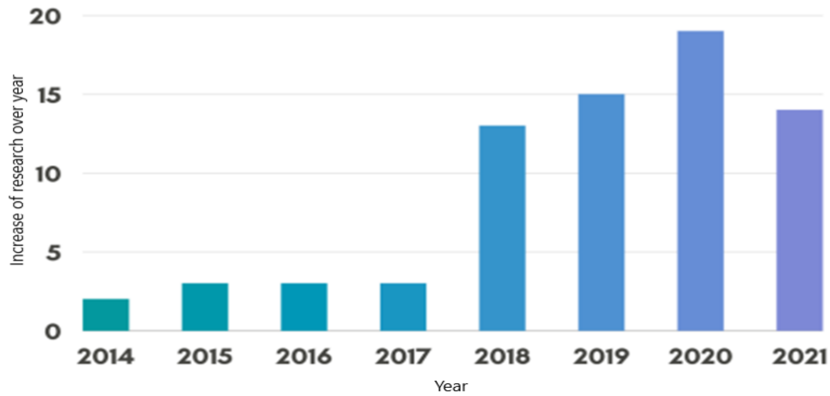

Figure 1. **-Publications over time [2]**

2. Autonomous vehicles

A. Definition

An autonomous vehicle is a vehicle that can drive and travel without human input. Driverless car and robotic car are other names for self-driving vehicles.

Although the concept of an autonomous vehicle dates back to the 1920s, Japan developed the first such car in 1977. A substantial autonomous driving vehicle was developed in the 1980s, with a maximum speed of 31km/h. Self-driving automobiles can assess their surroundings and drive through traffic and other obstacles autonomously with little to no human assistance [3].

Modern traffic issues like accidents and congestion are commonly regarded as having a good chance of being solved through the use of autonomous vehicles. This is because such vehicles possess a complex system with sub-modules for perception, path planning, control, etc. [4].

Almost all level 3 self-driving cars or higher consist of four parts as shown in Fig 2.

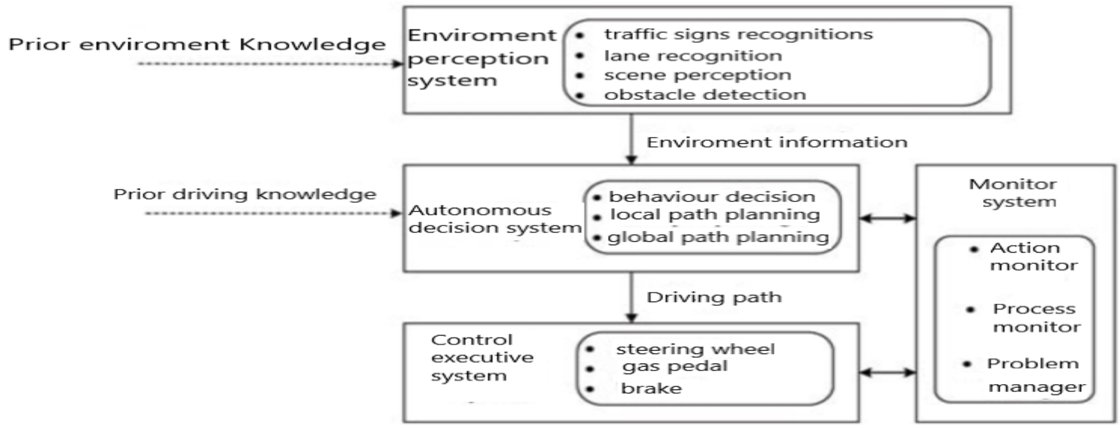

Figure 2. **-The overarching technical architecture for self-driving vehicles equipped with level 3 or higher autonomous systems [5]**

B. The driving automation levels

There are many classifications of autonomous vehicle levels, with the most prominent being the six-tier classification system. The levels in this system are:

- Level 0: No Driving Automation
- Level 1: Driver Assistance
- Level 2: Partial Driving Automation
- Level 3: Conditional Driving Automation
- Level 4: High Driving Automation
- Level 5: Full Driving Automation

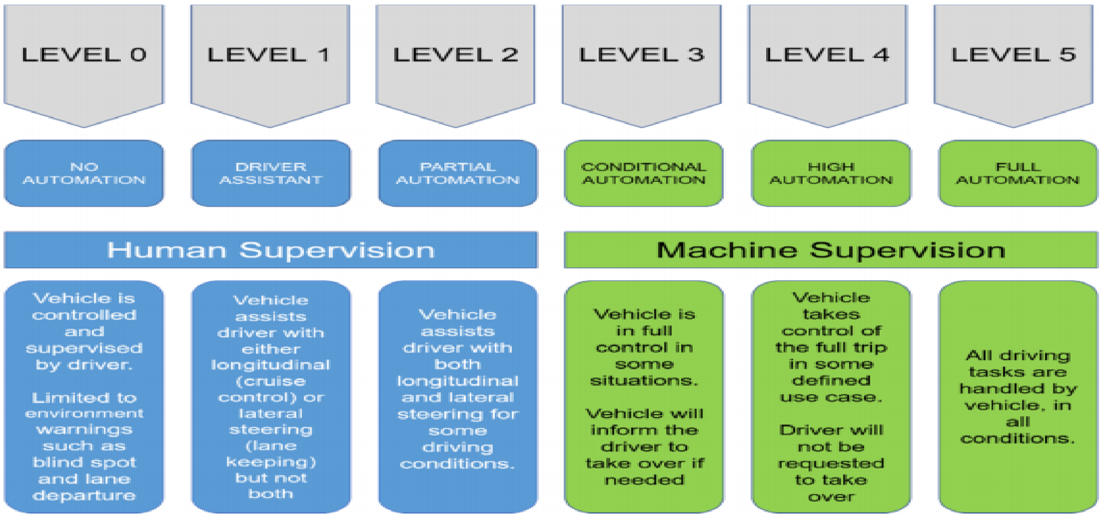

FIGURE 3. - **The driving automation levels [6]**

C. Problems of Autonomous Vehicles

The development of driverless cars capable of moving on city streets could significantly reduce accidents. However, problems lie in developing a perception system that permits driving on roads without altering the existing infrastructure without requiring prior visits, and while taking into account the potential presence of pedestrians and other cars [7].

Two of the most important elements of autonomous cars involve proper and precise recognition of obstructions and maintenance of the vehicle's track. With respect to recognition of obstructions, the vehicle or car should be able to precisely and quickly detect the presence of a barrier and stop itself at a safe distance to prevent collision. Regarding track maintenance, the vehicle needs to be able to follow lane markers and stay within track borders in order remain in its right location [8].

D. The Challenges

Designing self-driving cars involves numerous challenges that must be addressed to ensure safe and effective operation. Some of the key challenges in designing self-driving cars include:

- ❖ Obstacle Detection and Tracking: One major challenge is detecting, localising, and recognising a static or moving obstacle. Obstacle detection and tracking are crucial components of how autonomous vehicles perceive their environment. Additionally, this ability serves as a crucial foundation for autonomous vehicle's decision-making and path planning [9].

- ❖ Distance Measurement: Autonomous vehicles being able to measure the distance between themselves and other vehicles is necessitated by the critical changes that occur on the road. Vehicle speed significantly influences the severity of traffic accidents on the road [10].

- ❖ Weather factors: Given the close relationship between autonomous driving and weather recognition, bad weather is a crucial concern while building autonomous vehicles. Driving under bad weather is more challenging than it is when the weather is good because of conditions like rain, fog, or snow [11].

- ❖ Blurred Images due to Moving Vehicles: Fast-moving vehicles are usually the main cause of blurred images. The blurring effect becomes severe when the vehicle is travelling at an excessive speed [12].

3. Key Issues Related to Self-Driving Cars

Autonomous vehicles, also referred to as self-driving cars, are a complex and rapidly evolving technology that present several key issues and challenges. Some of the key issues related to self-driving cars include:

1. Safety: Safety is the primary concern when it comes to autonomous vehicles. Ensuring that self-driving cars operate reliably and safely in various road and weather conditions is crucial. There have been incidents involving self-driving cars, raising concerns about their ability to accurately detect and respond to unexpected situations [13].
2. Liability and Legal Framework: Liability determination in self-driving automobile accidents is a complicated matter. The legal framework needs to be updated to address questions related to responsibility, insurance, and accident

investigations. Regulators and policymakers must establish guidelines and regulations to govern the operation, testing, and deployment of autonomous vehicles.

3. Ethical Dilemmas: Autonomous vehicles face ethical dilemmas in certain situations where a split-second decision must be made, such as when faced with a potential collision. Determining whether the vehicle's occupants' safety should come before that of other road users is a challenging moral question that requires careful consideration and societal consensus.
4. Data security and Privacy Issues: Self-driving automobiles generate and collect a lot of data, including location data, driving behavior, and personal preferences. A major concern is preventing illegal access to this data and maintaining privacy. Robust cybersecurity measures must be implemented to safeguard the data and prevent hacking attempts.
5. Job Displacement: Professional drivers, like taxi and truck drivers, may lose their jobs as a result of the widespread use of self-driving cars. The use of autonomous vehicles could disrupt industries heavily reliant on human drivers, requiring techniques to address the economic and social effects of job loss and facilitate a transition for affected individuals.
6. Infrastructure Adaptation: The current infrastructure, including roads, traffic signals, and signage, was designed primarily for human-driven vehicles. Adapting the infrastructure to accommodate self-driving cars, including the implementation of supportive technologies like smart traffic management systems, is necessary for seamless integration and optimal performance.
7. Public Trust and Acceptance: Building public trust and acceptance is crucial for the successful deployment of autonomous vehicles. Many people are still skeptical about the dependability and safety of these vehicles. Transparent communication, extensive testing, and clear demonstrations of the benefits and safety features are necessary to gain public confidence.

Addressing these key issues requires collaboration among various stakeholders, including automakers, regulators, policymakers, technology developers, and the general public. As technology advances and these challenges are overcome, self-driving cars could revolutionise transportation, improving safety, efficiency, and accessibility for all [14][15][16].

4. Datasets

Autonomous vehicle technology development relies heavily on the availability of high-quality datasets that capture real-world driving scenarios. These datasets provide crucial training and evaluation resources for autonomous driving algorithms, enabling researchers and developers to build and fine-tune systems that can navigate and understand complex environments.

In this context, a graph has been prepared to illustrate the different types of self-driving car datasets commonly used in the field. The graph categorises the datasets based on their characteristics and the information they provide. Understanding the various types of datasets is important for researchers, engineers, and anyone interested in autonomous driving, as it allows them to select the most suitable datasets for their specific needs and goals. Please refer to the graph illustrated in Fig 4 for an illustration of the types of self-driving car datasets [17].

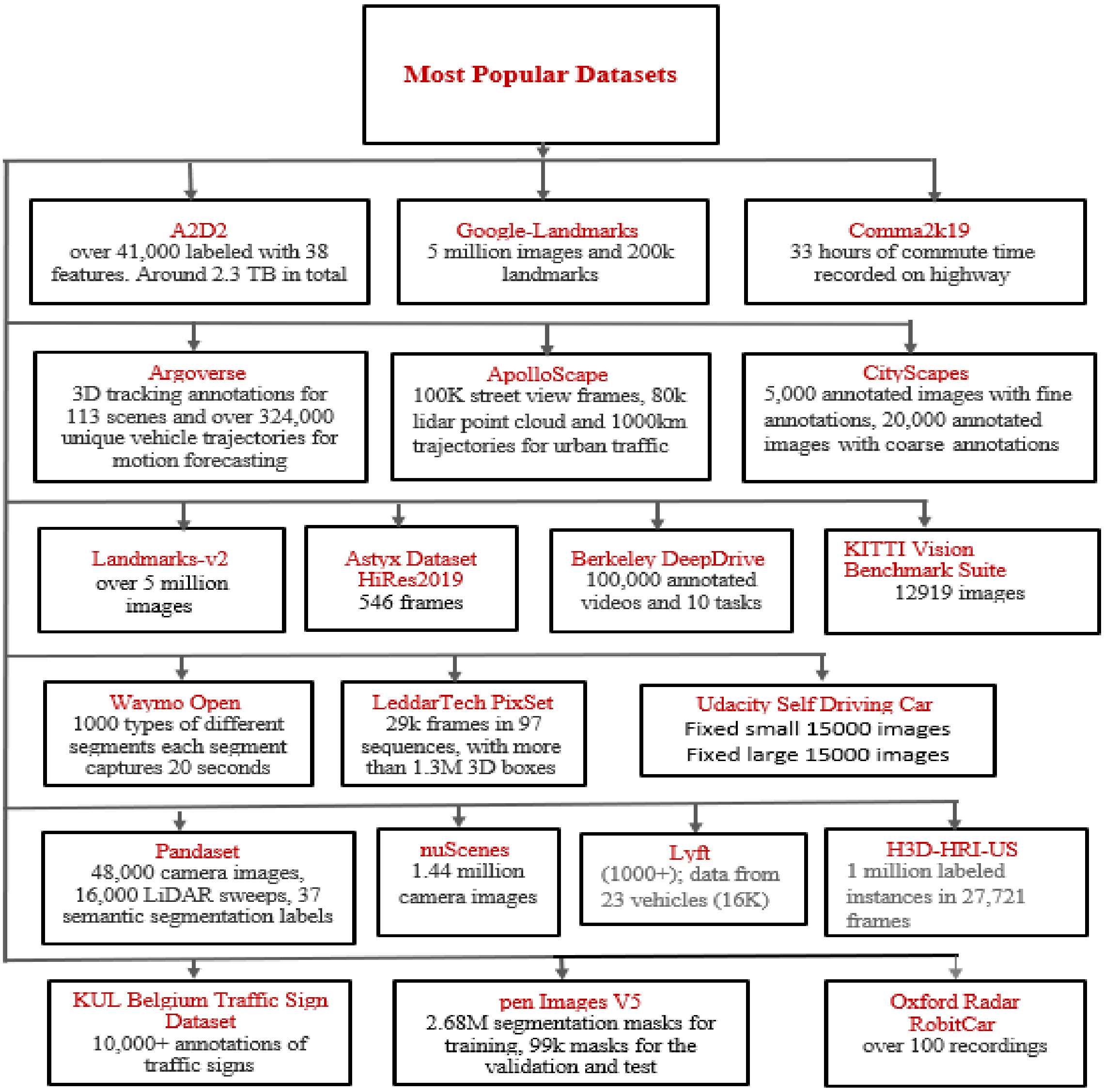

Figure 4. -The most popular database [by authors]

5. Obstacles Detection Based on Deep Learning

Self-anti-collision devices have been created recently to reduce traffic accidents and promote safe driving. Obstacle detection is crucial in these systems, and they must also be able to warn users of the presence of obstacles [18].

1. Sign Road: Automatic sign road detection is a significant issue in a computer vision system because it holds immense potential for many intelligent car features, including automated driving, robot navigation, and driver support systems. Changing views, motion blur, lighting, and other factors cause a lot of variances in sign road photos, making reliable detection challenging [19].
2. Traffic Signs: Speed restrictions, the presence of warnings, and other important real-time traffic information are all provided via the signs as shown in Fig 5. Traffic signs are made up of standardised objects that are easily recognisable, thanks to their consistent size, colour, and shape [20].

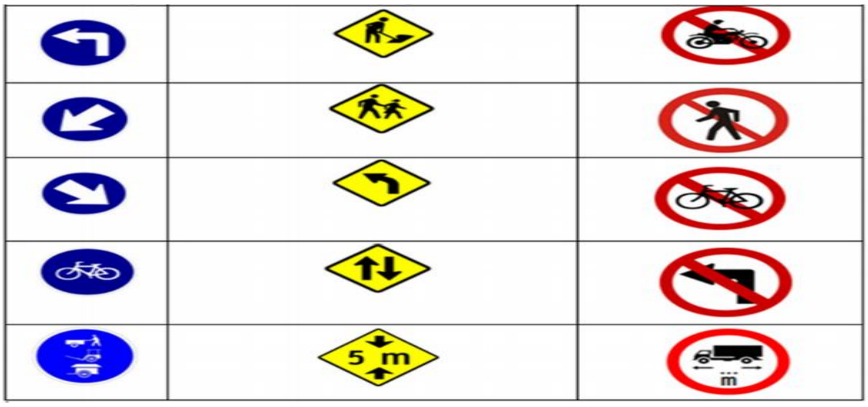

Figure 5. **-Sign Road [21]**

3. Traffic Lights: For driverless vehicles, recognising information about ambient traffic signals (Fig 6) is a necessary challenge [22].

Figure 6. **-Traffic lights [23]**

4. Pedestrian Recognition: Many vision-based applications, from object tracking to video surveillance to, more recently, autonomous driving depend on the ability to recognise pedestrians (Fig 7). In the conventional single-dataset training and evaluation environment, pedestrian detection has attained very good performance owing to the quick growth of deep learning in object detection. [24].

Figure 7. **-Pedestrian [25]**

5. Vehicle Identification: An effective algorithm to produce potential zones for the classifier and the actual classifier make up the architecture of a vehicle identification system (Fig 8) [26].

Figure 8. -Vehicles on the road [27]

6. Road Lane Detection: Roadside lane (Fig 9) detection is crucial for autonomous vehicles as they help to identify the exact lane that the car is in. Notably, autonomous vehicles are complicated, slow, and prone to failure on roads with poor conditions. Statistics show that lane drift or lane change is one of the major contributors to automobile accidents [28].

Figure 9. -Road lane [29]

Obstacle detection is crucial for accident prevention in self-driving cars. It enables early warning on and reaction to potential obstacles, classifies them, estimates distance and speed, and assists in path planning. Self-driving cars employ redundancy and have a 360-degree awareness, operate efficiently in adverse conditions, and maintain constant vigilance. They can learn from past encounters, apply emergency braking, and contribute to improved traffic flow, thereby reducing accident risks significantly.

- ❖ Compare the recent papers that focus on obstacles detection as shown in Table 1.

Table 1. - Comparing recent research in obstacle detection

No.	Obstacles	Research name	Principles of work	Accuracy
1	Sign Road	Real-time small traffic sign detection with revised Faster-RCNN [30].	Researchers are interested in developing a method for identifying tiny traffic signs in real time through a redesigned Faster-RCNN. To extract the characteristics of tiny traffic indicators in particular, first employ a small region proposal generator. That is to say, delete using ResNet's pool4 layer of the VGG-16 and dilatation since the generator's stride is too large. Second, to strengthen the system's ability to find the location of small traffic signs, combine the faster-redesigned	According to the testing data, the approach increases mean average precision by a difference of 12.1% when compared to the first object detection technique.

			RCNN's architecture with Online Hard Example Mining (OHEM).	
		Performance enhancement techniques for traffic sign recognition using a deep neural network [31]	It has been suggested to use unique pre-processing and optimisation approaches to create modern traffic sign recognition technology. Yolov3, a powerful and effective deep neural network, has been tweaked to create the traffic sign detector.	98.15%
		Traffic-light sign recognition using capsule network [32]	The suggested model is effective at classifying different traffic sign types and recognising colour differences. This is the first time that a class of traffic-light signs has been successfully identified using CapsNet as a tool for scene interpretation. Capsule networks address spatial interactions significantly more precisely and with less training data than well-known convolutional neural networks.	98.72%
		Simultaneous detection and tracking using deep learning and integrated channel features for ambient traffic light recognition [33]	They employ deep learning-based object tracking and detection like CNN and ICFT, which are designed to determine the location and colour of traffic signals..	96.2 %
2	Traffic Lights	Traffic light detection and recognition based on haar-like features [34]	The suggested technique uses training photos that include a traffic light and the surrounding background and uses Haar-like features to identify the traffic light. In the suggested approach, the possible traffic light regions are examined using SVM before the traffic light is finally identified by subdividing the region. The suggested system can identify traffic lights despite colour changes brought on by external factors like angles and lighting.	Not found
		Traffic light recognition for complex scene with fusion detections [35]	Aim to create a model that integrates prior features and statistic learning. It is a crucial technique for enhancing the detection of tiny luminous objects in blurry images from which it is challenging to extract features. Traffic light recognition (TLR) techniques and the fusion detection	Not found

			model for many traffic signal types are examples of references.	
		A Bayesian approach to traffic light detection and mapping [36]	Proposed mapping traffic signals by a Bayesian technique. It has performed better than previous research, according to evaluations on two benchmark datasets. Traffic light parameters like colour, shape, and height are proven to substantially increase the accuracy of the suggested technique in addition to the spatiotemporal consistency requirement.	The precision and recall rates for the KITTI benchmark and the precision and recall rates for the LARA benchmark are 98:66% and 94:65%, respectively.
3	Pedestrians:	Optimised MobileNet + SSD: a real-time pedestrian detection on a low-end edge device [37]	Offers a concatenation feature fusion module for incorporating contextual information to improve the identification accuracy of pedestrians. Propose a concatenation feature fusion module for incorporating contextual data to the Optimised MobileNet + SSD network.	80.4%
		A robust system for real-time pedestrian detection and tracking [38]	Keeps their eyes on pedestrians. A single-video camera-based real-time detection and tracking system was developed. Using the Gaussian mixture model, the moving object was extracted from an image series that had been segmented using the mean-shift method in the pre-processing module. To lessen the detrimental effects of the shadow on the identified objects, shadow removal was utilised. The method was evaluated using actual traffic videos from several websites . The test's findings demonstrate the system's dependability on and the overall accuracy of the above.	85%.
		Strengthening the effectiveness of pedestrian detection with spatially pooled features [39]	A straightforward yet superior solution to the pedestrian detection problem, and is superior among cutting-edge technologies. The new characteristics are constructed using spatial pooling and low-level visual characteristics.	The ETH benchmark and the INRIA benchmark, decreased the typical miss percentage from 41% to 37%, the TUD-Brussels benchmark from 51% to 42%, and the Caltech-USA benchmark from 36% to 29%,
		Fast multi-feature pedestrian detection algorithm based on histogram of oriented gradient using discrete wavelet transform [40]	Suggest a pedestrian recognition feature and method that combines the discrete wavelet transform (DWT) and the histogram of the oriented gradient (HOG). To increase the speed of detection, the region of interest (ROI) is determined using the magnitude of motion. The specified multi-feature is learned in the final stage to determine whether a	resulting in a speed-up factor gain of 27.21%.

			candidate window contains a pedestrian or not using the training data and the support vector machine (SVM) technique.	
		Fast moving pedestrian detection based on motion segmentation and new motion features [41]	Created a pedestrian detection system based on motion analysis. By separating dynamic and static objects, they employed motion segmentation to find potential pedestrian areas. Similar to previous segmentation methods, their algorithm required a lot of operation.	Results on the Daimler mono moving pedestrian detection benchmark show a log-average miss rate of 36 % in the FPPI range [10−2, 100].
4	Vehicles	Feature selection and classification methods for vehicle tracking and detection [42]	Proposed that local binary patterns and support vector machines (SVM) be coupled to monitor rectangles between thresholds with a confidence value for classification. Using the classifier provided by the Enhanced Convolutional Neural Network (ECNN), another classifier that causes interference involving vehicles and moving items is eliminated.	93.63%
		A fast and effective video vehicle detection method leveraging feature fusion and proposal temporal link [43]	By strengthening the semantic information, choosing and propagating the detection boxes, and averaging the scores, they suggest the novel tracking TDO-based object recognition post-processing method with feature-fused SSD. The missed and erroneous detections brought on by static detectors are significantly decreased by their TDO technique. The suggested method outperforms the static detector because it considerably improves the consistency of video vehicle detection findings.	The studies on their labeled highway dataset reveal that their method's mean average precision (mAP) is 70.5%—surpassing the basic detector by 8.2%, according to the results. Our feature-fused SSD can run at a rate of 27.1 frames per second (fps), demonstrating capabilities for real-time detection
		Vehicle recognition system based on customised HOG for automotive driver assistance system [44]	An optimisation vehicle detection method built upon a personalised histogram of oriented gradients (HOG) was proposed and examined. Two essential points can be used to summarise the work. First, the conventional HOG settings were re-optimised to achieve the best results for car detection. Second, amplification factors were assigned to each bin based on how much they contributed to the extraction of automobile attributes.	97.28%
		A novel particle filter implementation for a multiple-vehicle detection and tracking system using tail light segmentation [45]	Proposed a technique for tracking and detecting multiple vehicles. Vehicle candidate creation and window adjustment both include the use of vehicle tail light detection. A back propagation neural network is trained using eight orientations and five scales. Numerous vehicle occlusions and incidents of temporarily missing	84%

people are looked into by the tracking sub-system.

- ❖ Many papers have been published in journals in the last five years, indicating the importance of this field. Fig 10 summarises the number of papers published according to the type of obstacles try to detect.

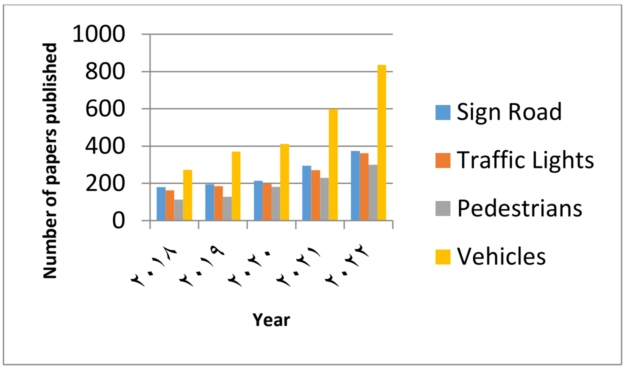

Figure 10. -Number of research papers published in journals during the last five years for each obstacle detection

6. Comparisons

Many algorithms have been proposed for the detection of road obstacles. Most of the algorithms proposed recently used deep learning due to its ability to detect obstacles accurately. The deep learning techniques that were utilised to find the barriers are listed in Table 2.

Table 2. - A list of deep learning techniques for obstacle detection

No.	Algorithms	Description	Pros	Cons
1	Convolutional Neural Network (CNN) [46] [47] [48].	A convolutional and pooling layer feed-forward network, CNN is particularly effective at identifying relationships between picture pixels.	Not affected by image alteration	Deep structures are required for locating appropriate hyper-parameters.
2	YOLO (You Lock Only Once [49].	When YOLO applies a single CNN over the entire image, the image is further divided into grids.	1. YOLO employs a single CNN for object classification and localisation. 2. Yolo is incredibly quick due to its architecture.	Tiny and close items are challenging to find.
3	Faster-RCNN [50].	A deep convolutional network called Faster-RCNN is employed for object detection.	Faster-RCNN can foresee the locations of many objects with accuracy and speed.	It takes multiple runs over a single image to extract all the items with Faster-RCNN.

7. The Obstacle object-detecting performance metric

Various algorithms have been created to detect objects from videos or photos. Metrics can therefore be used to assess how well these algorithms function. Numerous methods in the past evaluated an algorithm's correctness or its speed or accuracy [51]. Analysing object detection techniques like Fast R-CNN, SSD, YOLO, etc. involves using a metric called Mean Average Precision (mAP) [52].

- ❖ Mean Average Precision (mAP)

Recall values between 0 and 1 are used to calculate the average precision (AP) values. The AP for each class after interpolation makes up the mAP for a given set of detections. The area under the precision/recall (PR) curve for the detections is what determines this per-class AP [53].

- **Recall:** The capacity to make correct distinctions between all forecasts (TP+FN) and true positives (TP) is measured by your recall, as demonstrated in Equation (1).

- **Precision:** A gauge of precision is the ability to identify true positives (TP) from all positive predictions (TP+FP), as demonstrated in Equation (2).

Equations (3) and (4) define mAP as the average AP of all classes and AP as the accuracy of a single class [54].

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{AP} = \int_0^1 \text{P}(\text{r})\text{dr} \tag{3}$$

$$\text{mAP} = \frac{1}{N}\sum_1^N \text{APi} \tag{4}$$

The mAP formula is built upon the sub-metrics listed below:

❖ Confusion Matrix

In order to create a confusion matrix, we need the following four attributes:

- True Positives (TP): The model correctly locates a label and matches it to the data.
- True Negatives (TN): The model neither predicts the label nor is a part of the ground truth.
- False Positives (FP): These are labels that the model anticipated but are absent from the ground truth (Type I Error).
- False Negatives (FN): These are labels that, albeit not what the model projected, are nevertheless a part of reality (Type II error).

❖ Intersection over Union (loU)

When there is an Intersection over Union, the ground truth box coordinates and the predicted bounding box coordinates overlap. The projected bounding box coordinates are more similar to the real box coordinates when loU is higher [55].

8. The Future of Self-Driving Cars

By the end of 2022, researchers had produced level 3 self-driving cars, but these are not allowed on roads in Germany and the United States. Some experts are optimistic that level 4 self-driving cars will be produced by 2024 or 2025. However, this may be delayed due to high costs and legislation-related considerations.

Accelerating the production of level 4 autonomous vehicles may begin in the taxi and transport industries where the Return on Investment (ROI) is highest. This could possibly reduce costs, making level 4 available for all and paving the way for the emergence of level 5.

9. Conclusion

Obstacle detection and tracking are crucial for the smooth and safe operation of autonomous vehicles, enabling them to identify and avoid obstacles. It ought to also be able to identify how far the impediment is from the car. In recent years, researchers have paid great attention to autonomous vehicles and how to solve the problems faced by this type of vehicles. Deep learning is a valuable tool in this field of research due to its high performance.

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CONFLICTS OF INTEREST

None

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