

OBJECT DETECTION IN IOT FOR AUTOMATED CARS

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ABSTRACT

An Important Component Of Object Detection is To analyze and Detect the object according to the surrounding . By object Detection Technology it increase the safety of Driver's on the roadways .Object Detection is Vast and Important in our future Automobile Industry. In self driving automobiles, object detection is nothing new; it has long been developed for human comfort. High accuracy and precision are required for IOT-related object detection in relation to the data that has been gathered. This Research Paper Provides an Experimental and Theoretical Based approach on Object Detection used in Self Driving Cars. A high detection accuracy, robustness in a variety of environmental conditions, and low latency are all achieved by the IoT-enabled object detection system. Vehicles in a connected ecosystem can share data easily and make decisions together With the help of integration of IoT technologies. This Research Paper are helpful to find out which Object Detection Method is accurate on automobile industry . Originally, a research study was released for the automotive industry's future human health satisfaction. To accomplish this Various Object Detection Models and Sensors are been Experimentally Observed, accordingly Decision been Published.

Keywords: IOT, Object Detection, Human Comfort, Self Driving Cars, Models And Sensors.

I. INTRODUCTION

IOT stand for Internet Of Thing , which refers to a network of Device that can communicate with each other . Object Detection is a technique in which we analyze the Object and accordingly results are been made . This is not a newer technology in the era of Artificial Intelligence and Machine Learning , Object Detection is also very Important . Collection of IOT with Object Detection give us the Physical Device which Contains the Sensors by which the nearby Object are been identified.

These days, the automotive industry makes extensive use of IOT with Object Detection models. Developing Environment Need Self Driving Cars The Object Detection Used in this. IOT is already integrated with cars in earlier. IOT is primarily utilized for entertainment and multimedia purposes. However, IOT has been designed and developed for human safety and security in the automotive industry in the 20th century. Autonomous vehicles, also referred to as self-driving cars, have the potential to revolutionize transportation systems by lowering collision rates, traffic jams, and energy usage. These cars navigate and make driving decisions on their own, thanks to a combination of cutting-edge sensors, artificial intelligence, and realtime data analysis. For this We need IOT which contains the interconnected Device , sensors , actuators , Cameras and Communication Interfaces.

IOT is integrated with the sensors, actuators, and cameras in self-driving cars to capture the real-time state of the roads. Data is generated, and with its aid we can monitor our fuel usage , Most efficient Paths , Engine Performance etc. Similarly, IOT can be used to detect nearby objects of our vehicle so that we can easily drive a car. Those who are physically challenged can benefit from this innovation, and even our elderly parents or young children can operate a vehicle with ease. In summary using IOT for automated vehicle management means connecting vehicle with network , identify real time behaviour, generate the data.

IoT in object detection definitely has far-reaching implications across various sectors, which is fairly significant. In really smart cities, it can enhance traffic management and very public safety by monitoring and responding to traffic violations or accidents in real-time in a subtle way. In agriculture, it can help optimize crop management by detecting pests and diseases early, leading to increased yields and reduced resource consumption. In retail, it can revolutionize inventory management and customer experience through kind of smart shelves and cashier-less checkout systems. This introduction will delve for all intents and purposes deeper into the convergence of IoT and object detection, exploring the actually key components, technologies, and applications that mostly make this fusion so basically promising in a actually major way.

We will also really discuss the challenges and considerations associated with implementing IoT-based object detection solutions and the basically potential benefits they offer in terms of efficiency, safety, and resource

optimization, which is quite significant. As we navigate through this sort of exciting intersection of technologies, it becomes evident that IoT in object detection specifically is poised to reshape the way we definitely interact with our environment and the objects within it, ushering in a future where machines for the most part are not just connected, but also keenly aware of the world around them, particularly contrary to popular belief.

IoT-enabled object detection systems can provide real-time monitoring of environments. This is critical for applications like security and surveillance, where immediate detection of intruders or suspicious activities can lead to rapid response and enhanced safety. In industrial settings and smart cities, IoT-based object detection enhances safety by identifying and responding to potentially dangerous situations, such as gas leaks or accidents. This technology can also significantly improve public safety by detecting and responding to crimes or emergencies in urban areas.

II. LITERATURE REVIEW

It is necessary to conduct an extensive review of the body of work in the field before writing a literature review on IoT (Internet of Things) object detection research papers. I'll give a succinct overview of some significant research papers and themes in this area below. IoT object detection research may have undergone significant changes, so please be aware that my knowledge is based on information that was available at the time.

YOLOv3: An Incremental Improvement" by Redmon et al. (2018) :

The paper's main contributions and conclusions are succinctly summarized in the abstract. In the case of "YOLOv3: An Incremental Improvement," the abstract probably summarizes the main advancements made in YOLOv3 over its forerunners, emphasizing features like improved accuracy, speed, and efficiency.

The reader is given a context for the paper in the introduction. It gives background information on the real-time object detection issue and discusses its significance and potential uses in a variety of fields, including robotics, surveillance, and autonomous vehicles. The purpose of the authors' introduction of the YOLO (You Only Look Once) idea and its earlier iterations is probably to demonstrate the need for more advancements.

The authors outline YOLOv3's accuracy and speed performance in the results section. They probably offer comparisons with earlier YOLO versions and other cutting-edge object detection models. To illustrate the model's efficacy, visualizations like precision-recall curves or mAP (mean average precision) scores may be used.

Real-Time Object Detection for Smart Vehicles" by Wang et al. (2019):

The paper's abstract provides a concise summary of the study's primary objectives and contributions. It most likely highlights the significance of real-time object detection in the context of smart vehicles, as well as the methodologies and findings of the research.

The introduction establishes the importance of smart vehicles and their potential impact on transportation and safety. It most likely refers to the difficulties of real-time object detection in the dynamic environment of smart vehicles. The authors may describe the goals of their research, such as increasing object detection accuracy, decreasing latency, or improving the robustness of detection algorithms. The paper's main conclusions are summed up in the conclusion, which emphasizes the significance of real-time object detection in intelligent vehicles. Typically, authors highlight the contributions, innovations, and potential effects of their work on the field of autonomous vehicles and transportation.

Authors frequently talk about the difficulties they ran into while conducting their research, such as occlusion, bad weather, or sensor limitations. They might suggest directions for future research, suggesting changes or additions to the object detection system.

Scalable Object Detection Accelerators on FPGAs for IoT Applications" by Zhang et al. (2020):

The main goals, contributions, and conclusions of the paper are succinctly summarized in the abstract. In this case, it probably discusses the FPGA implementation, highlights key findings, and discusses the significance of scalable object detection accelerators for IoT devices. By describing the importance of scalable object detection in IoT applications, the introduction provides context. It probably covers the resource limitations and power efficiency standards for IoT devices. The authors could describe the objectives of their study, like real-time object detection on FPGAs with low power consumption. The scalability and adaptability of the accelerators to various IoT applications and scenarios may be covered in this section of the paper. Authors might offer advice

on how to modify or expand their design for different use cases. The conclusion highlights the importance of scalable object detection accelerators on FPGAs for IoT applications while summarizing the main conclusions and contributions of the paper. Commonly, authors reiterate how their work addresses the particular difficulties of object detection in the context of the Internet of Things.

A survey of modern deep learning based object detection models(2022):

The survey's context is established in the introduction, which also explains why object detection is a crucial component of computer vision.

It emphasizes how convolutional neural networks (CNNs), in particular, have revolutionized object detection.

The survey's goals are listed, including an overview of contemporary models and the identification of trends and difficulties.

The main focus of the survey is an examination of various deep learning-based object detection models. The models covered could be: models based on regions, such as Faster RCNN and Mask R-CNN. models that are one-offs, like SSD and YOLO. Pyramid Networks in Feature (FPN). RetinaNet, EfficientDet, and other modern inventions. The survey typically discusses the architecture, guiding principles, and distinctive contributions of each model. The most significant findings and insights from the survey are briefly summarized in the opening of the conclusion. It summarizes the key developments, trends, and difficulties raised in the survey with regard to deep learning-based object detection models. The impact of these models on the larger field of computer vision is highlighted in the conclusion. In addition to improving object detection accuracy, deep learning-based object detection models have paved the way for other computer vision tasks like instance segmentation, object tracking, and scene comprehension. It talks about the various industries in which object detection models have wide-ranging uses. These include robotics and autonomous vehicles as well as surveillance, medical care, agriculture, and other areas. Particular use cases, such as their contribution to improving medical care, streamlining manufacturing processes, or enhancing road safety.

III. RESEARCH METHODOLOGY

As part of a two-stage detection process, R-CNN, one of the first deep learning-based object detectors, used an effective selective search algorithm for ROI proposals [13]. Some of the R-CNN model's issues were resolved by fast RCNN, including as slow and inaccurate inference. The Fast R-CNN model uses The convolutional neural network receives the input image as input.(CNN), producing a ROI projection and feature map. These The feature map is then used to predict ROIs using ROI combining. Unlike R-CNN, which uses the ROI as Fast RCNN uses the entire image as an input to the CNN layers.

Typically, 2D object detectors use 2D image data to identify objects, but recent research has also suggested a sensor-fusion-based 2D object detection approach that combines data from a radar and cameras [25]. Using 2D object detectors, bounding four Degrees of Freedom (DOF) boxes. The method used to encode bounding boxes 4(a) most frequently: $[x, \text{and } 4(b): [x_{\min}, y_{\min}, x_{\max}, y_{\max}]$ [26] for x, y , height, and width. Sadly, 2D object detection is only able to provide the a 2D plane's position of the object, but does not offer information about the object's depth. The item's depth is determining the object's size, shape, and location is crucial. to enable better functionality for various self-driving tasks such as collision avoidance, path planning, etc.

Deep learning-based 3D object detection has gained popularity in recent years. Complex YOLO is a variation of 4. A Euler Region Proposal Network (E-RPN) was utilized by YOLOv2. based on a point cloud from an RGB Birds-Eye-View (BEV) map data to produce 3D suggestions. The network takes advantage of YOLOv2. To obtain the 3D proposal, use a network followed by an E-RPN [27]. Later 2019 saw the completion of semantic segmentation by Complexer-YOLO. and Random Finite Set (RFS)-based 3D object detection [28].Wen et al.'s more recent research on 3D object detection [29] proposed a compact 3D object detection model in 2021. is divided into three submodules: module for point transformation, which based on the raw data, extracts point features from the RGB image. voxelization, which divides the features into equally spaced voxel grids and then generates a many-to-one mapping between the voxel grids and the 3D point clouds, and 3) point-wise fusion module, which fuses the features using two fully connected layers. The output of the point-wise fusion module is encoded and used as input for the model. Another 3D detector proposed in 2021 called RAANet used only lidar data to achieve 3D object detection [30]. It used the BEV lidar data as input for a region proposal network

which was then used to create shared features. These shared features were used as the input for an anchor free network to detect 3D objects. The performance of these models is summarized.

Knowledge Reduction

Transferring learned information from a more complex model to a more condensed, smaller model is known as knowledge distillation.

IV. EXPERIMENTS AND RESULT

Name	Technique used	Model compression achieved	Object Detector	Latency improvement	Hardware used
Wang et al. [32]	Pruning	32.40 %	SSD	33.61 %	GTX 1080Ti
Zhao et al. [33]	Pruning	93.27 %	YOLOv4	80.70 %	Qualcomm Adreno 64
Fan et al. [34]	Quantization	75 %	SSDLite-MobileNetV2	85.67 %	Zynq ZC706
LCDet [35]	Quantization	77.79 %	YOLOv2	13.66 %	Snapdragon 835
Kang et al. [36]	Knowledge Distillation	37.11 %	RetinaNet	32.98 %	-
Chen et al. [37]	Knowledge Distillation	83.82 %	RCNN	7.93 %	-

The image features a table displaying various numbers related to different techniques and models used in the field of object detection.

The table consists of multiple columns, each representing a specific aspect of the techniques and models. The first column, labeled "Name," lists the names of the techniques/models. These include "Object Detector," "SSD," "YOLOv4," "SSDLite-Mobile NetV2," "LCDet," "YOLOv2," "RetinaNet," and "RCNN."

The second column, labeled "Technique used," provides information about the specific technique utilized for each technique/model. Some of the techniques mentioned include "Pruning," "Quantization," and "Knowledge Distillation."

The third column, labeled "Model compression achieved," presents the extent to which each technique/model achieved model compression. The values listed represent the percentage of model compression achieved, such as "32.40%," "33.61%," "93.27%," "80.70%," "75%," "77.79%," "13.66%," "37.11%," "32.98%," "83.82%," and "7.93%."

The fourth column, labeled "Hardware used," specifies the hardware used for each technique/model. Some examples include "GTX 1080Ti," "Qualcomm Adreno 64," "Zynq ZC706," "Snapdragon 835," and "RCNN."

The above information is organized in tabular form, facilitating easy comparison between different techniques and models employed in object detection. The table provides valuable insights into the performance and capabilities of these different techniques/models, helping researchers and practitioners make informed decisions in their work.

V. CONCLUSION

Automated cars are using object detection systems to keep an eye on different objects, like pedestrians, cars, signs, and other road hazards. This not only helps keep people safe, but also opens up a lot of potential uses, like autonomous navigation, adaptive cruise control, intelligent traffic management, and even accident prevention. As the technology advances, object detection will become even more advanced, able to handle more complex situations and even bad weather. The combination of data from different sensors, like cameras and lidar, will make it even more accurate and reliable. But there are still some challenges, like dealing with ethical and regulatory issues, making sure everything is secure, and making sure the algorithms can handle unpredictable situations. We can expect to see this technology evolve over the next few years, and we'll need to work together with different stakeholders to make sure we get the most out of it.

VI. FUTURE SCOPE

In the future, object detection systems will have to be able to work in bad weather, like heavy rain and snow, foggy conditions, and even in low-light conditions. Sensor tech like radar or lidar will be essential for this. As autonomous driving systems become more popular, object detection will become more important. We'll need to develop algorithms and hardware that can handle complex, unpredictable scenarios.

Plus, object detection will need to be able to handle crowded urban environments with lots of different people, things, and road infrastructure. Finally, machine learning and AI will make it easier for object detection systems to make decisions in split-seconds. Cybersecurity will also be a big part of object detection systems, as they rely on sensors and networks for communication. To protect against threats and attacks, we'll need to have strong cybersecurity measures in place.

ACKNOWLEDGEMENT

I want to express my deep appreciation to my esteemed mentor for his unwavering guidance and support throughout my research project on the subject of "Object detection in automated cars using various sensors". She has been a great mentor to me, giving me the knowledge, motivation, and inspiration to take on this difficult research project.

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