Applications of Computer Vision for Autonomous Vehicles

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Abstract- Autonomous vehicles rely on computer vision to navigate and interact with their environment. With the ability to perceive and understand their surroundings, autonomous vehicles can make decisions and take actions without human input. We have here presented a literature review on the applications of computer vision for autonomous vehicles by initially introducing computer vison and relevant work already present. The object detection task in autonomous cars is then discussed, which entails identifying and classifying items in the vehicle's field of sight. The review is thus concluded with challenges being faced by computer vision and its future in autonomous vehicles including the improvements that can be implemented.

Index terms- computer vision, object detection, autonomous vehicles

I. INTRODUCTION

Computer vision is a subset of artificial intelligence which is inspired by human visual system, that trains machines how to see. it aims to decipher the message behind the pixel, its objectives from a biological science perspective are to develop computational models of the human visual system. Engineering-wise, computer vision tries to create autonomous systems that could carry out some of the functions that the human visual system is capable of (and even surpass it in many cases).

Self-driving automobiles can make sense of their surroundings thanks to computer vision. Cameras record footage from various angles around the car and transmit it to computer vision software, which processes the images in real-time to determine road edges, read traffic signs, and detect other cars, objects, and pedestrians. The self-driving car can then navigate streets and highways, avoid collisions, and safely drive its passengers to their location. [1].

The foundation of artificial intelligence technology is computer vision. AI enables computers to interpret and process the visual data they have gleaned from a variety of sources. Utilizing AI algorithms, it involves intelligent visual understanding. The facial recognition tool is the best illustration of computer vision. It is deployed in autonomous vehicles along with sensor technologies to detect vehicles, pedestrians, and other roadside items. [2].

How does computer vision work?
Computer Vision works in following steps as shown in figure 1:

Figure 1 – Steps involved in working of computer vision [3]

Data-It includes images, even large data sets, can be acquired in real time through video, photos or 3d technology for analysis.

Data Processing-In this step deep learning / machine learning models automate much of this process, but the models are often trained by the first being fed a thousand of labelled or pre-identified images.

Understanding The Data-In this step the object is identified or classified, and the output is achieved.

How Computer Vision working is similar to Humans:

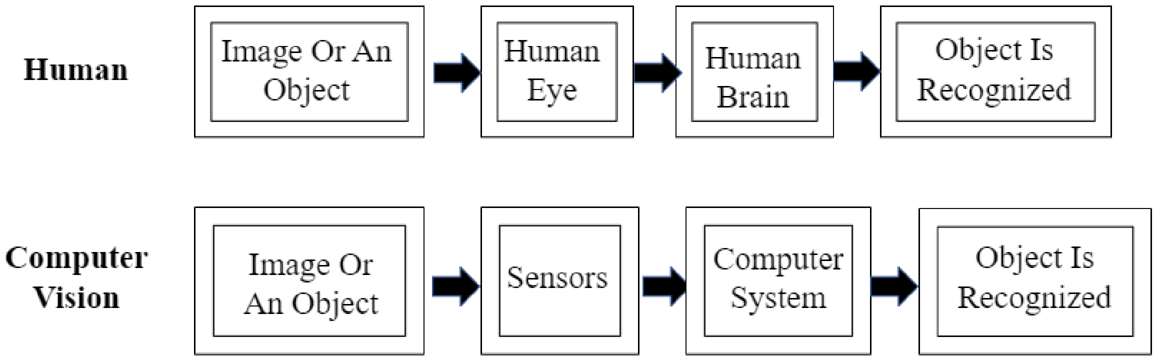

Figure 2 – Similarity of working between humans and computer vision [4]

The goal of computer vision is to enable machines or computers to acquire, interpret, and process visual data in a manner similar to that of human vision, and to derive information of value from this data.

Artificial neural networks (ANNs) are created to mimic the operations of the human brain. The objective is to enable computers to gather, analyze, and process visual data in a manner similar to that of human vision. However, because the brain and eyes are extraordinarily sophisticated organs, current technology cannot come close to matching what the human body is capable of. As much as 50% of the brain's neuronal tissue is directly or indirectly related to vision, and over 66% of our neural activity is devoted to visual processing alone, our brains are considerably more powerful than any computer [5].

II. RELEVANT WORK

Numerous research has been done on the subject of computer vision in autonomous vehicles with different approaches to a particular problem such as object detection, lane detection, etc. Here, a few milestones will be highlighted, which summarises insights on how computer vision is applied in autonomous vehicles.

Troung and Lee [6] carried out experiments on lane detection using computer vision. Their lane detection algorithm detects lane marking lines and can be applied to Autonomous Guided Vehicles or assisted -driving vehicles.

Jeong et al. [7], mentioned that among object detection algorithms, YOLO (You Live Only Once) is the most efficient. Highlighting that the main advantage it has over the others is that it detects objects a thousand times faster than most algorithms, such as Regional Convolutional Neural Network (RCNN) and Single Shot Detector (SSD).

Darapaneni et al. [8] created a model using Fully Convolutional Networks (FCN) and UNET that identified road obstacles. The dataset which was used were sequential images captured from vehicle cameras.

Tseng and Jan [9] proposed a model which combined object detection and semantic segmentation for autonomous vehicles. In their research, FCNs and SSD were used to build the model.

Okuyuma et al. [10] proposed a simulation of an autonomous agent that learns to drive in a simplified environment which had static objects and road signs. Deep Q network was used to train this agent to learn to drive in the environment relying on a camera to detect road features.

Min et al. [11] carried-out research on SAE level 3 autonomous driving for ETRI (Electronics and Telecommunications Research Institute). They used Machine Learning to create a 3D vision-based technique that uses cameras to generate depth maps and detect motion.

Johari and Swami [12] used CNN, SSD, RCNN and RFCN to evaluate object detection performances in different weather conditions.

Behringer and Muller [13] performed tests on German Autobahn and demonstrated that it is possible to guide a vehicle on tight curves and turn-offs using machine vision system in a closed-loop simulation.

Xinxin et al. [14] proposed a low-cost stereo vision system compared to using LIDAR technology in solving lane-level localisation for autonomous vehicles. The system integrates a lane line detection algorithm and evaluates to fit multiple road models.

Choi et al. [15] proposed an algorithm for environment detection which was implemented and tested. They illustrated the detection algorithm showed good performance in detecting lanes, pedestrian crossing, obstacle positions and speed bumps.

III. APPLICATIONS

Computer vision is a key technology in the development of self-driving cars. It allows the vehicle to "see" its environment and make decisions based on that information. Some specific applications of computer vision in self-driving cars include:

- **Object detection and classification**: This allows the vehicle to identify and classify objects in its environment, such as other vehicles, pedestrians, traffic signs, and road markings.
- **Lane detection and tracking**: This allows the vehicle to determine its position on the road and stay within the appropriate lane.
- **Traffic sign recognition**: This allows the vehicle to recognize and interpret traffic signs and signals, such as speed limit signs and stop signs.
- **Pedestrian detection**: This allows the vehicle to identify and track pedestrians and make decisions to avoid collisions.
- **Environmental mapping**: This allows the vehicle to create a detailed map of its environment, including the location of objects and obstacles. This information can be used for navigation and planning paths.

Overall, the use of computer vision in self-driving cars allows the vehicle to perceive and understand its environment, which is essential for safe and efficient operation. In this era that we are living, autonomous cars are no longer a science fiction. There are engineers worldwide, designing self-driving cars by using the computer vision technology. Additionally, computer vision can be used for more advanced tasks such as detecting road conditions and traffic patterns, which can help the car make more informed decisions about its movements. We have a new technology as well, which assist drivers while driving, parking in order to avoid any possible human errors, knows as the Advanced Driver Assistance system (ADAS). This provides a safer environment for the drivers as well for the entire traffic present of road [16].

For creating real time algorithms that support driving activity, researchers working on the ADAS technology use computer vision techniques such as pattern recognition, feature extraction, object tracking, and 3D vision.

Deep Learning and Machine Learning are the two key technologies employed in these applications. Deep learning techniques such as YOLO, SSD, or RetinaNet are used to recognise objects. Before making a decision about what to do next, self-driving cars must be aware of everything that is going on around them, as well as how they are acting and what they might do next. Using object tracking, a path that an object will travel can be predicted. The main problem with tracking is occlusion. There are times when many items being tracked partially conceal one another as a result of interactions between the objects.

It is useful to be aware of what the drivers are doing at the moment, such as if their hands are on the wheel or their heads are pointed in the direction of the road. Pose recognition can be done with both 2D and 3D data. A benefit of using 3D sensors over 2D images is that they can be utilised to overcome problems like overlapping and low lighting, among other things [17].

IV. LITERATURE REVIEW

In this section, the prime focus on the narrow task of object detection in autonomous vehicles, which involves identifying and classifying objects in the vehicle's field of view. A holistic overview of the technologies used in this area is provided, including the various stages of the object detection pipeline and the techniques used at each stage [18], [19].

A. Perception

Perception is the first stage of the object detection pipeline, where the vehicle gathers information about its environment using sensors. In autonomous vehicles, this is typically done using a combination of different sensor modalities, including omnidirectional cameras, visible spectrum cameras, thermal infrared cameras, and lidar sensors.

Omnidirectional cameras provide a 360-degree field of view, which grants enhanced coverage compared to standard cameras with a limited field of view. This reduces the need for extra cameras or mechanically turnable cameras, which can be expensive and complex to implement. There are two main types of omnidirectional cameras: catadioptric cameras, which use a standard camera with a shaped mirror (parabolic, hyperbolic, or elliptical), and dioptric cameras, which use fisheye lenses. However, these cameras can suffer from very high distortion if modelled as a linear projection, and the model needs to account for mirror reflection in the case of catadioptric cameras, or lens refraction for fisheye cameras.

Visible spectrum (VS) cameras are used for daytime perception, and capture images in the same wavelengths of light that the human eye can see. These cameras provide high resolution and good colour accuracy but are limited in low light conditions.

Thermal infrared (TIR) cameras are used for night-time perception and capture the relative temperature of objects in the scene. This allows the vehicle to distinguish between warm objects, such as pedestrians, and cold objects, such as vegetation or the road. However, TIR cameras have lower resolution and colour accuracy compared to VS cameras.

Event cameras, also known as dynamic vision sensors (DVS), are a new type of sensor that captures events instead of images. An event is a location, time, and precise timestamp of when a change in the scene is detected, and these sensors can capture a very high temporal resolution and high volume of events. This allows the vehicle to capture the dynamics of the scene and facilitate dynamic perception and state estimation.

Lidar sensors use lasers to measure the distance to objects in the scene, providing range estimation information. This can be combined with other sensors, such as cameras, to provide complementary information about the scene.

Overall, using multiple sensor modalities provides redundancy and allows the vehicle to better handle occlusions, weather variations, and the weaknesses of individual sensors. For example, lidar and VS cameras can provide information about reflective surfaces, while TIR cameras can provide information about hot objects and warm temperatures.

B. Representation

Once the raw data has been gathered by the sensors, it needs to be processed and represented in a way that is more suitable for object detection. This involves transforming the data into a higher-level representation, which provides a more compact and robust representation of the image.

One way to do this is to use pixel-level representations, which are the most granular representation of the image, but are also the most difficult to work with. This is because they have a large number of variables, and many algorithms can only model local interactions between pixels.

An alternative is to use superpixels, which are a broader generalization of pixels. Superpixels are similar in colour and texture, and respect image boundaries, so the properties of interest remain constant within a superpixel. This provides a more stable and robust representation of the image, while still being computationally tractable.

Another representation that is commonly used is the “stixel”, which is a medium-level representation that aims to bridge the gap between pixels and objects. The goal of stixels is to provide an efficient and compact representation that is also stable and robust.

At the highest level, 3D primitives such as voxels or point clouds can be used to represent the shape of urban objects in the scene. These representations better preserve the shape of the objects but are also more computationally expensive to work with.

C. Region of interest extraction

After the data has been represented in a suitable form, the next step is to extract regions of interest (ROIs) from the image, where potential objects may be located. There are several techniques that can be used for this, including the sliding window approach and selective search.

The sliding window approach involves shifting a detector over the image at different scales and using heuristics to reduce the search space. This can be computationally expensive, as it requires examining every region of the image, but it can be effective for low to medium resolution detection. However, it can struggle with occlusions and low-resolution inputs.

Selective search, proposed by Uijlings et al. [20] in 2013, is an alternative approach that exploits image segmentation to efficiently extract approximate locations of potential objects. This reduces the search space by focusing on regions that are likely to contain objects and can be more efficient than the sliding window approach.

D. Object classification

Old regime

Once potential objects have been identified in the ROIs, they must be classified into their respective categories. In the past, this has been done using techniques such as linear Support Vector Machines (SVMs) and histogram of orientation (HOGs).

SVMs are a type of classifier that seeks to maximise the margin of all samples from a linear decision boundary. They are effective at classifying linearly separable data but can struggle with more complex data. HOGs, on the other hand, are a type of feature descriptor that represents the distribution of gradient orientations in an image. They are often used in combination with SVMs to improve the performance of object detection. However, both techniques rely on difficult to design hand-crafted features, which can be time-consuming and require expert knowledge.

Another approach that has been used in the past is part-based approaches, which split complex objects into simpler parts and represent their articulation as a composition of these parts. This provides greater flexibility and reduces the number of training samples required. However, these approaches can still be limited by the need for expert design of the parts and the composition models.

Convolutional neural networks

Recently, convolutional neural networks (CNNs) have become a popular approach for object classification in autonomous vehicles. CNNs are a type of deep learning algorithm that are well-suited for image classification tasks and have achieved state-of-the-art performance in many benchmarks.

CNNs consist of several layers of neurons, with each layer transforming the input data into a higher-level representation. The first layer typically consists of convolutional filters, which extract local features from the input image. These features are then transformed by subsequent layers, which can

include pooling layers, fully connected layers, and non-linear activation functions. Finally, the output of the last layer is used to make a classification decision.
One advantage of CNNs is that they can learn the features and the classifier jointly, end-to-end, from the data. This means that they do not require expert knowledge to design the features and can learn to extract the most relevant features for the task at hand. This can provide better performance than hand-crafted features, and is particularly useful for complex and dynamic scenes, such as those encountered in autonomous vehicles.

Another advantage of CNNs is that they can be trained on large datasets, using powerful hardware, such as GPUs. This allows them to learn from a large number of examples and generalize well to new data. This is important for object detection in autonomous vehicles, where the environment can be highly variable, and the number of possible objects is large.

E. Verification and refinement

The final step in the object detection pipeline is verification and refinement of the initial classification. This step takes into account contextual information and additional data from other sensors to improve the accuracy of the detection. This is crucial for ensuring the reliability and safety of the autonomous vehicle.

For example, if the vehicle detects a pedestrian in the road, it may verify the detection by checking for additional evidence from other sensors, such as a heat signature from a thermal infrared camera, or the movement of the pedestrian's body from an event camera. This additional information can help the vehicle confirm or reject the initial detection and make more informed decisions about how to navigate safely.

V. CHALLENGES

Vehicle accidents and road congestion are a routine and common occurrence in many parts of the world. Accidents are caused primarily by human decision and actions such as drunk driving, violation of traffic rules, miscalculating the velocity and direction other vehicles have on the road, weariness, brash driving and much more. Other secondary factors may be due to bad weather conditions, jaywalkers, and improper construction of roads. Deployment of AV’s on public roads is an up-and-coming solution. Current technology features vehicles with Level 2 driving automation. These level 2 AV’s have Advanced Driver Assistance Systems (ADAS) which require limited human intervention, improve vehicle safety, and diminish human error. However, reports about accidents caused by AV’s do occur periodically. Furthermore, AV’s work best in places which have good weather and light traffic conditions. Hence, it is important to address the challenges associated with implementation of computer vision in AV’s to maximize safety, and realize its advantages on a global level.

A. Heavy reliance on machine learning

In order to accomplish high performance, the AV’s need to be trained under a variety of machine learning models, which cover almost all application possibilities. Failing to do so for example, would lead to a situation where a model which was trained to identify a certain object, may not recognize that object anymore due different conditions. So, a fully automated vehicle has to be taught using data sets that provide a complete and precise depiction of all the situations a vehicle can encounter throughout its run. It is simply impractical to expect to have such comprehensive training data sets. Additionally, even for extremely specific training goals, it can be challenging to determine whether a training data set is complete [21].

Vehicles and pedestrians need to be accurately detected by AV’s. Vehicles belong to many different classes (bus, car, truck, etc.), and vehicles which share the same class have a variation in parameters such as size, shape, structure, colour etc. Moreover, these parameters change when viewed from different angles. As for pedestrian detection, they themselves have different height, wear diverse clothing, engage in different poses, carrying different objects, etc. Pedestrians also are dynamic and change directions quickly [22].

B. *Adverse weather conditions*

One of the most critical challenges that AV's must overcome is that the sensors equipped on these vehicles respond poorly under adverse weather conditions such as rain, fog, hail, snow etc. Under heavy rainfall conditions, range of detection of a millimeter wave radar falls by 55% [23]. Under foggy conditions, various type of sensors fail to work as the sensors absorb water droplets, which leads to scattering of electromagnetic waves, thus hampering the functionality of ADAS [24].

C. *Sensor failures*

Majority of the AV's decision-making procedures heavily rely on the data provided by the sensors. Under the unfortunate case of sensor failure, vehicle collision is likely to happen. Sometimes, even if the sensors are performing reliably under real world conditions, several inaccuracies might be present in the sensor collected data provided to the user. For example, the sensor camera is obstructed by objects such as mud or leaves [25].
Successful failure detection and subsequently providing an accurate diagnostic check is an area in which further exploration must be done.

D. *Vulnerability to cyber attacks*

AV's deployed are vulnerable to hackers. GPS systems on vehicles may be exploited by hackers through a method called as 'spoofing', which distances the passenger away from its intended location, or make the passenger arrive at its destination at a later time. Attacks on the vehicle sensors (LiDAR, millimeter wave and ultrasound) could also be performed, thus generating fake virtual obstacles to be sensed by the sensor causing confusion in the decision making processes of the vehicle [26].

E. *Miscellaneous challenges*

AV's are expensive, current technology isn't advanced enough to bring down the costs of AV's to affordable prices. Mass-scale deployment of AV's might translate to many drivers facing the prospect of unemployment. Since AV's are an emerging technology, governments need to enforce new standards and regulations to ensure safe integration with the public [27].

VI. FUTURE WORK

It is anticipated that Autonomous Vehicles will become an essential component of transportation systems thanks to neural networks, decision-making algorithms, and systems with great responsiveness and accuracy.

Only once the driver or passenger could fully and securely trust the car to drive it safely would the incorporation of autonomous vehicles into society be complete. This can be achieved by holding multiple public demos where AVs are put in risky situations and their responses to numerous "unforeseen" events are displayed. [28].

Machine learning and neural networks advancements have the potential to make significant contributions to enhancing driving autonomy's precision. As technology is incorporated into urban fabric, sensors should be capable of interacting with AVs very efficiently, advancing the idea of smart cities and creating the demand for further constrained yet linked areas of the city. This is expected to be aided further by upcoming 6G technologies [29].

More research will be required to create more cognitive systems and achieve a higher level of autonomy. The development of autonomous cars will go toward an abstract, human-like level of sophistication. More effort will be required to improve the challenging interaction between autonomous vehicles and other traffic participants, including both robots and humans. Information on the actions and intentions of other road users must be obtained for this purpose. Off-road terrain today is typically just rural, such as narrow trails through a forest or field. There is a lot of work to be done for categorization and path planning in complete 3-D for real-world off-road terrain, such as dealing with overhanging obstructions and drastically variable soil conditions [30].

VII. CONCLUSION AND MAIN FINDINGS

In conclusion, the technologies used in computer vision for autonomous vehicles are constantly evolving, and there are many different approaches and techniques that can be used for object detection. By understanding the various stages of the object detection pipeline, and the techniques used at each stage, it is possible to design and implement effective systems for enabling autonomous vehicles to navigate safely in the real world.

The main findings of this literature review indicate that key areas of research in this field include the development of robust and accurate object detection and recognition algorithms, as well as algorithms for scene understanding and interpretation. Additionally, research has focused on the use of computer vision to enable autonomous vehicles to better understand and respond to changing road conditions. The future of computer vision in autonomous vehicles looks bright, and we can expect to see many exciting developments in this field in the coming years. Overall, the use of computer vision in autonomous vehicles has the potential to enhance the capabilities and safety of these systems and could play a critical role in the future of transportation.

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REPORT

Group – 25

➢ *Teamwork and execution*

The group worked together tirelessly by conducting meetings online and meetings in the university group study rooms as shown in Figure-1.

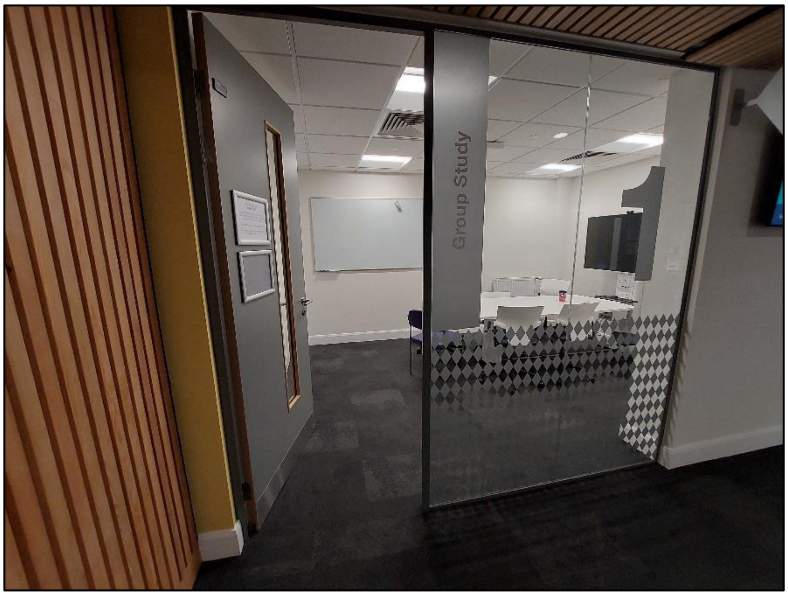

Figure 1 – One of the Group Study rooms used in 502 Teaching Hub

We prepared our plan of action thoroughly and worked on it very hard by sticking to the deadlines. The submissions were done within the given timeframe.

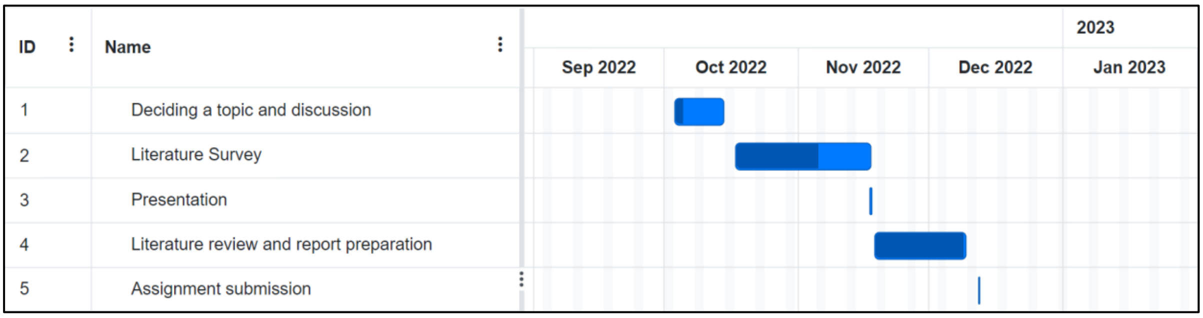

Figure 2 – GANTT Chart describing the plan of action

The tasks were divided equally among the members of the group, and everyone made significant contributions to the same.

➢ *Challenges faced*

After the allotment of the group members, the initial challenge we faced was trying to get in contact with our group members. There were many methods of communication available to us such as Outlook, Microsoft Teams, etc. The problem was trying to figure out which group member would be most reliant on/most active on what method of communication. Initial methods to try to bring everyone on to a centralized form of communication took quite some time as members did not check their communication platforms that frequently. Hence, many communication requests were outright ignored or took a while to receive a prompt response.

One of our initial team leaders failed to mention about his discontinuation of studies, due to personal reasons. Hence, his sudden withdrawal from the group, threw our whole team into disarray. Our topic selection had to begin from scratch because of the absence of our team leader. Recovery from this did took a while and our team morale was a bit low.

The next set of challenges faced by us was that since most of the members in our group were from non-computer science background, we had limited knowledge about the topic. So, the selection of our topic was an arduous task. We were required to submit an initial draft of our presentation before Week 4. We sought the help of our demonstrators on the drop-in sessions available every Tuesday to get feedback on the status of our assignment. They suggested to us that our topic was too generalized, and we needed our topic selection to be more in-depth. Our initial topic was 'Application of Computer Vision'. Their feedback made was constructive for two reasons. The first reason was we engaged in a master's level course and so selection of a state-of-the-art computer science topic was of prime importance. The second reason was, as we mentioned above, that most of the team members were from non-computer science background, we decided to play it 'safe' by selecting a generalized topic. In order to gain knowledge, and seed the thinking of a computer scientist, we were required to get out of our comfort zone. So, our topic was changed to 'Application of Computer Vision for Autonomous Vehicles'.

To discuss the topic, we were required to meet in person. We felt we could engage in more meaningful conversation and dissemination of ideas by meeting face-to-face rather than virtually. Since our group members were from different courses of computer science, which meant that booking a Group Study room was a challenging task, as the timetables differed from person to person. Variation in timetables meant that every meeting had to be effective in the limited time available to us. Due to the presence of assignments required to be submitted by other modules meant that the submission of task divided among each group member was often submitted well after the deadline, which was personally decided among us.

➢ *Solutions*

We were required to attend the theory lectures regularly, in order to understand how to search for papers through different mediums, such as IEEE Xplore, Science Direct, Springer, Google Scholar, Research Gate, etc. Deciding upon a common referencing software provided another dilemma, as selection of a citation style manager required to be extremely user friendly. We decided to go along with Zotero.

We also decided to thoroughly exploit the drop-in sessions by getting constant feedback about the status of our assignment. This helped us gauge what stage were we at and what tools we needed to implement to improve our assignment. They helped us provided provide a key outline of how our literature review was supposed to be.

The technologies used in autonomous vehicles was researched, and the findings was pared down to focus on the narrow task of object detection. The results were collated from the readings and an extensive outline was prepared. It was then converted into an essay, and thoroughly reviewed, edited, and proofread to ensure the submission was of a high quality.

➢ *Conclusion and Remarks*

Overall, our group members behaved in a professional and ethical manner, respecting the needs of others. We believed it is important that all voices are heard, hence we always made sure that no member was left out when any meeting was scheduled. Having good collaboration and fostering a professional and ethical environment made our assignment a success.