


Image Filtering Techniques for Object Recognition in Autonomous Vehicles


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Abstract: The deployment of autonomous vehicles has the potential to significantly lessen the variety of current harmful externalities, (such as accidents, traffic congestion, security, and environmental degradation), making autonomous vehicles an emerging topic of research. In this paper, a literature review of autonomous vehicle development has been conducted with a notable finding that autonomous vehicles will inevitably become an indispensable future greener solution. Subsequently, 5 different deep learning models, YOLOv5s, EfficientNet-B7, Xception, MobilenetV3, and InceptionV4, have been built and analyzed for 2-D object recognition in the navigation system. While testing on the BDD100K dataset, YOLOv5s and EfficientNet-B7 appear to be the two best models. Finally, this study has proposed Hessian, Laplacian, and Hessian-based Ridge Detection filtering techniques to optimize the performance of those 2 models. The results demonstrate that these filters could increase the mean average precision by up to 11.81%, and reduce detection time by up to 43.98% when applied to YOLOv5s and EfficientNet-B7 models. Overall, all the experiment results are promising and could be extended to other domains for semantic understanding of the environment. Additionally, various filtering algorithms for multiple object detection and classification could be applied to other areas. Different recommendations and future work have been clearly defined in this study

Keywords: Autonomous Vehicle, Deep Learning, Object Recognition, Image Filtering Techniques, Navigation System

Categories: I.0, I.2, I.3, I.4, I.5, I.6, J.6

DOI: 10.3897/jucs.102428

1 Introduction

Unlike traditional vehicles, autonomous vehicles [Yair, 2022] are land-based vehicles integrating vehicular automation [Francis and Anoop, 2014] that can sense their surroundings and operate securely [Hu et al., 2020a] with minimal or no human intervention [Brummelen et al., 2018]. To achieve this, autonomous vehicles employ a fully or partially automated driving system that enables them to adapt to external situations similar to a skilled driver [Yair, 2022]. The autonomous driving system incorporates a range of sensors to sense its environment, including GPS (Global Positioning System), thermographic cameras, radar, sonar, odometry, LiDAR (light detection and ranging), and IMU (Inertial Measurement Units) [Hu et al., 2020a, Marchegiani and Fafoutis, 2022, Thrun, 2010, Feng and Liu, 2019, Jedrasiak et al., 2013]. Traffic signals are normally detected by video cameras, which could also recognize other vehicles, street signs, and pedestrians. Radar sensors focus on the location and movement of surrounding objects. Meanwhile, LiDAR sensors assess distances, detect road boundaries, and recognize lane markers by bouncing light pulses off the car's environment. Automobiles' wheels are also equipped with ultrasonic sensors to detect obstacles and other vehicles while parking [Schwartz et al., 2018].

Those sensory data are analyzed and interpreted by cutting-edge control systems to build a map of the surrounding environment for planning/executing relevant navigation routes, avoiding obstacles, and recognizing essential signs [Hu et al., 2021]. The systems then issue instructions to the car's actuators, which regulate steering, acceleration, and braking [Yair, 2022]. The program could comply with traffic regulations and avoid obstacles due to its object identification capabilities, obstacle avoidance algorithms, hard-coded rules, and predictive modeling [Friedrich, 2016]. Notably, precise scene perception and accurate localization are critical prerequisites for effective and safe driverless car navigation systems. These 2 functions must accurately obtain and evaluate data gathered about real surroundings [Nguyen and Le, 2013]. To achieve this, multiple primary sensors, such as LiDAR and digital cameras, are installed on autonomous vehicles to collect precise contextual data.

In general, Deep Learning models have been widely applied in autonomous cars [Uçar et al., 2017] with 3 major tasks: segmentation, detection, and classification [Guan et al., 2016, Hien, 2022]. These models incur a variety of data source inputs (e.g., 1-D speech, 2-D pictures or videos, 3-D CAD (Computer-Aided Design), and 3-D LiDAR point cloud) [Wiseman, 2022] which is the primary focus of most research [Bagloee et al., 2016]. However, technological limitations and the high cost of proprioceptive sensors have a significant impact on the implementation of fully self-driving systems [Wiseman, 2022].

- Firstly, one of the most serious concerns is incorrect object detection and classification [Bagloee et al., 2016]. The data generated by various sensors is accumulated and processed by the autonomous system. However, with just a few pixels of variation in an image created by a digital camera, a vehicle may mistake a stop sign for a different sign such as a speed restriction sign, which could be potentially dangerous. If the algorithm similarly wrongly identifies a pedestrian as a traffic light, it would not expect it to move [Pozna and Antonya, 2016]. Therefore, object recognition and classification are critical for research relating to autonomous vehicles and this is the driver of this research.
- Secondly, a majority of objects, including vehicles, street signs, and pedestrians, are identified and classified from image data by digital cameras due to their low cost

and high efficiency [Vivacqua et al., 2017]. Camera-based vision is comparable to that of a human driver and has become the most widely utilized data in perception tasks using 2-D appearance-based representation [Paya et al., 2009]. Nevertheless, poor image quality acquired under extreme conditions (e.g., low illumination, rain, fog/mist/haze, snowstorms, and sandstorms) would adversely affect the performance of deep learning models [Ondrus et al., 2020]. Consequently, there is a need to employ different filtering techniques to enhance the quality of the images to improve the deep learning models.

Those identified gaps have prompted this study to construct and evaluate different Deep Learning models for 2-D Object Recognition in autonomous vehicle navigation system, with the following set of Research Objectives (RO).

RO1: To conduct a critical autonomous vehicle-related literature review by addressing the following Research Questions (RQ).

- **RQ1.1** What are the potentials in the development context of autonomous vehicles?
- **RQ1.2** What are the challenges of autonomous vehicles?
- **RQ1.3** Will the environmental impact of autonomous vehicles be better compared to the current traditional transportation mode?
- **RQ1.4** What deep learning applications and frameworks are currently applied in autonomous vehicles?
- **RQ1.5** How are current deep learning models employed in 2-D object recognition for autonomous vehicles?

RO2: To identify a suitable dataset for preprocessing and analysis.

RO3: To propose a range of filtering techniques for deep learning models in object recognition and classification in 2-D image data, optimizing their performance, with the following RQs:

- **RQ3.1** What are the performance of current state-of-the-art deep learning models for 2-D object recognition?
- **RQ3.2** Is the mean average precision and detection time of object recognition by deep learning models with proposed filtering techniques better compared to the models without them?

RO4: To make evidence-based recommendations and inform future relevant research work.

To address the above research objectives and questions, firstly, a literature review is undertaken to furnish an overview of autonomous vehicles, their limitations, and opportunities, as outlined in Section 2. Relevant research methodologies are discussed in Section 3, followed by an investigation of the performance of current state-of-the-art deep learning models for 2-D image data object recognition in Section 4. The novelty of this research includes proposing varying filtering techniques to enhance digital camera images to achieve a better level of performance (Section 5). Finally, pertinent discussion and evidence-based recommendations are presented in Sections 6 and 7. The findings are promising, and they will lead to more studies in the future, relating to various filtering algorithms for object detection and classification in autonomous cars.

2 Literature Review

2.1 Overview of Autonomous Vehicles

2.1.1 Autonomous Vehicles

In contrast to traditional vehicles, autonomous vehicles [Yair, 2022] (also known as driverless vehicles [Marchegiani and Fafoutis, 2022], self-driving cars [Mike et al., 2017], robocars [Feng and Liu, 2019], or robotic cars [Thrun, 2010]) are land-based vehicles that integrate vehicular automation [Francis and Anoop, 2014], sense their environment and operate safely [Hu et al., 2020a] with no or minimal human intervention [Brummelen et al., 2018]. Autonomous vehicles have been assessed in terms of their environmental [Kopelias et al., 2020], practical [Fan and Xu, 2019], and human lifestyle impacts [Pozna and Antonya, 2016]. It has been deployed in a variety of forms, including shared self-driving taxis [Martinez and Viegas, 2017], and connected vehicle platoons [Hu et al., 2020b].

A car navigation package incorporates a GPS [Rahiman and Zainal, 2013] and a geographic information system (GIS) [Quan, 2019] to collect location data including latitude and longitude coordinates. The positioning system determines the relative vehicle location using an inertial navigation system (INS) [Liu et al., 2020]. Furthermore, an autonomous car is equipped with an electronic map (EM) that saves data on road and traffic infrastructure [Yuan et al., 2018]. Subsequently, the vehicle's position is estimated followed by relevant path planning [Chen et al., 2014].

The three basic channels for environment perception are visual perception, radar perception, and laser perception [Zhu et al., 2017]. Radar perception involves the calculation of the distance via time estimation from which a radar sensor's wave is transmitted and reflected [Dickmann et al., 2016]. Reflection time and reflection signal strength are exploited in laser perception for the creation of cloud data for target points such as position, shapes, and states. Light Detection and Ranging (LiDAR) is used to avert accidents and in emergency braking circumstances. LiDAR systems produce a high number of laser pulses per second. After interacting with nearby objects, these pulses are reflected. Calculations based on the speed of light and the distance traveled by the pulse aid in the creation of a three-dimensional representation [Li and Ibanez-Guzman, 2020].

Self-driving cars normally use short-range vehicle-to-vehicle communication to connect with their environment and other cars [Shieh et al., 2018]. This form of communication requires a real-time and redundant infrastructure [Hien et al., 2021a]. The concepts of MANETs (mobile ad hoc networks) – the spontaneous establishment of a wireless network of mobile devices – are applied to the transportation domain to produce vehicular Ad hoc networks (VANETs). VANETs are used by connected automobiles to communicate with one another [Sood and Kanwar, 2014]. To facilitate the integration of autonomous vehicles with existing connected vehicle technology, the autonomous vehicle must employ the same communication standard that is currently used for connected vehicle technology [Jiang et al., 2011].

The Society of Automotive Engineers (SAE) outlines a system named SAE J3016 (revised periodically) for 6 levels of driving automation, ranging from Level 0 (completely manual) to Level 5 (completely autonomous), as depicted in Figure 1 [Automotive Engineers, 2021]. At the beginning of Level 3, the autonomous driving system can monitor the driving surroundings. Autonomous cars would first advance through these 6 levels of driver-aid technologies before being able to operate on public roads [Cui and Sabaliauskaite, 2017].

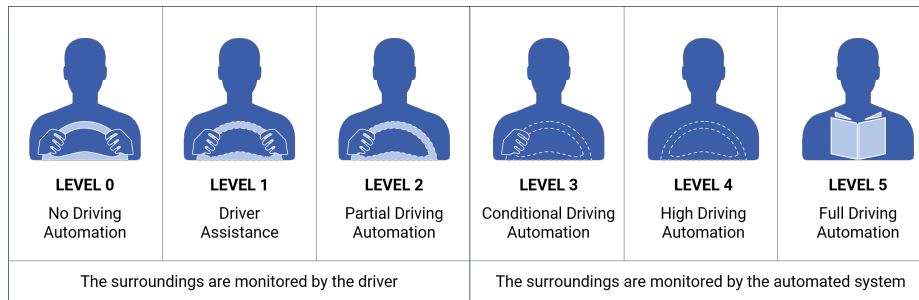


Figure 1: Society of Automotive Engineers (SAE) 6 levels of driving automation.

Numerous efforts to produce a fully autonomous commercial vehicle are in various development phases but self-driving cars are yet to be offered to the general public [Litman, 2017]. Level 3 and above vehicles continue to represent a minuscule fraction of the market [Markets, 2021]. As of May 2022, Tesla is currently at Level 2 because the autonomous system operates without driver supervision only under specific, and constrained situations [Morris, 2021]. However, according to Elon Musk, Tesla is expected to reach Level 4 autonomy in 2022, when critical development milestones of full self-driving (FSD) are accomplished to perform better than a human driver in averting accidents [Fox, 2021]. Moreover, Ultra Cruise and Super Cruise, which are currently offered on Cadillac and Chevrolet automobiles, are classified as Level 2 since the human driver must maintain complete attention anytime [Ulitskaya, 2021]. Audi AI Traffic Jam Pilot, first announced in 2017, is supposed to be the new A8's highlight feature, enabling the driver to assume control of the vehicle driving on the highway [Hartmann, 2017]. However, Audi has scrapped plans to update its premium A8 vehicle with Level 3 autonomous driving in April 2020, citing the need for governments to build a legislative framework before making the technology available broadly [Davies, 2020]. Honda is the first business to offer a legally authorized Level 3 vehicle in March 2021 [Honda, 2021]. Mercedes-Benz is the second company to receive legal approval for a Level 3 that exceeded regulatory conditions in December 2021 [Group, 2021].

Due to current technological infrastructures and regulations, most Level 4 cars are designed for ridesharing within a specific region [DeKort, 2019]. In 2020, Waymo, a subsidiary of Alphabet, becomes the first manufacturer to offer an autonomous taxi trip to the general public within the Phoenix region in Arizona. It is currently categorized as a Level 4 since the driver is not needed in the vehicle despite a remote observer is still required [Lee, 2020]. Magna, a Canadian automaker, has developed MAX4 - a technology that allows Level 4 autonomy for both urban and motorway environments. They are collaborating with Lyft to equip high-tech kits that transform cars into self-driving vehicles [Magna, 2022]. Around the Tokyo 2020 Olympic Village, Toyota has provided a potential Level 4 solution [Davis, 2021]. NAVYA, a French company, has been manufacturing and marketing Level 4 taxis and shuttles in the United States, which operate fully on electrical power with a peak speed of 55 mph [Vijayenthiran, 2018]. The remaining manufacturers are still in the developing phase to launch a Level 4 autonomous vehicle. For example, Volvo and Baidu form a strategic cooperation in 2018 to jointly develop Level 4 electric vehicles for the Chinese robo-taxi sector [Bolduc, 2018]. In terms of Level 5, fully autonomous vehicles are being tested in various parts of the world,

but none is currently accessible to the general public [Mane, 2021].

2.1.2 Potentials of Autonomous Vehicles

Driverless cars are currently being integrated into the product catalogs of all major automotive original equipment manufacturers (OEMs) [Kang et al., 2019]. Furthermore, recent advancements in VANET (Vehicular Ad hoc NETwork) applications and services [Maalej et al., 2018] as well as connected automobile technology [Contreras-Castillo et al., 2017], have prompted companies such as Google [Lee, 2020], car manufacturers (e.g. Tesla [Fox, 2021] and Audi [Group, 2021] to research on self-driving automobile technologies. Other leading manufacturers, including BMW, Ford, Mercedes-Benz, Toyota, Hyundai, Kia, Honda, Nissan, Volvo, Volkswagen, and General Motors, have undertaken programs such as semi-automatic pilot driving, emergency braking, smart parking, and accident alert [Hussain and Zeadally, 2018]. Volkswagen and Microsoft have broadened their cloud-based technology partnership to include autonomous vehicle development [Lawrence, 2021]. This transition will significantly transform how transportation solutions are accessed and utilized in the future, as well as how metropolitan regions are planned, designed, and built to facilitate a cleaner and greener coexistence of different transportation solutions such as automobiles, electric motorcycles, trucks, public transportation, supply vehicles, and bicycles [Kang et al., 2019].

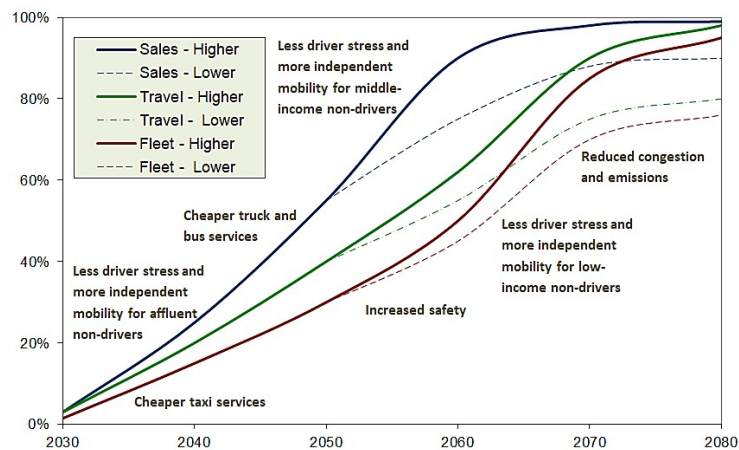


Figure 2: Predictions of Fleet, Sales, Travel, and Benefits of Autonomous Vehicles [Litman, 2017].

With continuous improvement, autonomous cars are steadily gaining acceptance [Wiseman, 2022]. According to ABI Research, by 2025, there will be around 8 million semi-autonomous or autonomous vehicles in operation [Research, 2018]. The Victoria Transport Policy Institute anticipates that half of the new vehicles will be autonomous by 2045, with half of the whole fleet operating autonomously by 2060 [Litman, 2017]. Meanwhile, the COVID-19 pandemic is depleting manufacturers' financial reserves and

threatens to hinder progress in self-driving car research, a sector that Bain predicts will reach a critical point in 2028 [Klaus et al., 2020].

Figure 2 depicts the forecast trend of market penetration and benefits for autonomous vehicles. It is predicted that by 2045, half of the new cars will be autonomous. Level 4 autonomy is expected to alleviate driver stress and boost productivity, but the most advantages associated with Level 5 autonomy would be autonomous pickup and drop-off [Litman, 2017].

Autonomous vehicles would help ensure road safety, reduce traffic congestion, enhance security, and mitigate environmental degradation [Saeed et al., 2016]. Cities may reduce carbon dioxide (CO₂) emissions by up to 80% if they embrace three revolutions (3R) within vehicle technology: electrification, automation, and ride-sharing. By 2050, these three urban transportation revolutions might decrease the worldwide cost of automobiles, infrastructure, and transportation system operations by 40%, depending on the successful deployment of ride-sharing and sustainable energy sources consumption [Lew et al., 2018]. Moreover, autonomous vehicles can increase mobility and accessibility [William and Pande, 2021], as well as optimize land use [Hawkins and Habib, 2019].

On the consumer side, autonomous vehicles have the potential to relieve vehicle occupants of driving and navigation tasks, lowering stress, and enhancing productivity [Ahangar et al., 2021]. This enables individuals to perform other duties, such as playing and working while commuting or resting during their lengthy and stressful traffic travels [Andrew, 2015]. Furthermore, self-driving automobiles eliminate limitations imposed by driver ability or condition. It provides non-drivers with more autonomous mobility and has the potential to minimize drivers' chauffeuring duties and transit subsidy demands, particularly for the blind, intoxicated, elderly, underage, and impaired people [Hussain and Zeadally, 2018]. A driving test or driving license is no longer necessary since humans do not need to drive [Ilkova and Ilka, 2017]. With fewer traffic accidents and collisions, autonomous vehicles can improve safety while also lowering crash risks and insurance costs. Customers can also benefit from lower costs of taxi and commercial transportation [Saeed et al., 2016].

On the social side, self-driving cars might become a solution to the problem of depleted fuel economy, lessening the environmental burden of existing transportation modes [Litman, 2017]. Moreover, autonomous vehicles may promote commercial car-sharing and ride-sharing, lowering overall vehicle ownership and travel expenses [Mike et al., 2017]. Better control of traffic flow will enhance road capacity and minimize traffic congestion [Grigorescu et al., 2020]. Furthermore, self-driving vehicles may reduce the demand for parking at destinations, leading to less parking costs [Saeed et al., 2016].

2.1.3 Challenges of Autonomous Vehicles

There are numerous technological challenges associated with autonomous cars. The distance traveled determines the system's reliability. If no accident happens, a self-driving car would need to travel approximately 291 million miles to achieve a 95 percent equivalent to a certified human driver [Hars, 2016]. Systems programming will require an in-depth assessment of product development and supply chain [Nastjuk et al., 2020]. Furthermore, AI is now incapable of successfully operating in densely populated metropolitan regions [Ondrus et al., 2020]. Security and data privacy of autonomous cars might be challenging due to mandatory location monitoring and data sharing [Bagloe et al., 2016]. The car's computer, as well as the communication system between vehicles, might be compromised [Andrew, 2015]. Extreme weather, such as rain and snow, as well as intentional interference (e.g., spoofing and jamming), may have an impact on the

car's navigation and sensory systems [Bagloee et al., 2016]. It is crucial to determine the severity of driving lane impediments, such as safely straddling a pothole or debris or avoiding moving animals [Hars, 2016]. The car may be involved in an accident if the main sensor and backup sensors break. High-definition maps may be required for autonomous vehicles to correctly function. Where these maps may be out of date, they must be able to assume sensible decisions. Additionally, some temporary construction zones may not be updated on the maps and databases [Faisal et al., 2019]. Most importantly, for autonomous vehicles to correctly function, existing road infrastructure may need to be upgraded [Gill, 2021].

Furthermore, the development of self-driving automobiles encounters a variety of social obstacles. The high cost of creating and deploying self-driving cars poses as a barrier, raising concerns about end-user affordability [Singh and Saini, 2021]. Furthermore, uncertainty about future regulations and policies may defer the deployment of driverless cars on the road [Saeed et al., 2016]. Transparent as well as unambiguous regulations and procedures that address potential consumers' concerns are essential [Ilkova and Ilka, 2017]. Another important concern is how self-driving cars make a judgment with justifiable behaviors in potentially challenging emergencies [Hussain and Zeadally, 2018]. The development of self-driving automobiles may reduce the need for cheap mobility choices such as walking, biking, and public transportation [Gill, 2021]. Another area of concern is the health consequences preferred vehicle usage over public transportation and walking since less exercise leads to a rise in obesity [Bagloee et al., 2016]. Reliance on autonomous driving results in less experienced drivers when manual driving is required [Andrew, 2015]. Terrorists or other criminals might theoretically employ driverless automobiles as autonomous explosives. As a result, there is a need to build a legal framework and regulatory laws for self-driving automobiles [Andrew, 2015].

Though autonomous cars have made significant advances, there are still constraints that must be appropriately addressed. Despite the potential difficulties of self-driving cars, the common view is that the benefits outweigh the drawbacks [Ahangar et al., 2021]. While autonomous car companies have made great technological advances, people must be prepared to adopt them. To ensure that technology continues to progress, the above-mentioned technological and societal concerns must be addressed.

2.1.4 Carbon Footprint

Undeniably, environmental challenges caused by transportation becomes more severe as urbanization advances [Vos et al., 2021]. Carbon dioxide (CO₂) emissions (the highest contributor to climate change) have continued to rapidly rise, according to statistics from Our World in Data. Humans currently release around 38.02 billion tons of CO₂ each year (data from 2020) [Data, 2022]. Notably, passenger and freight transportation contribute 20% to 30% of world greenhouse gases (GHG) [Straka et al., 2021], while passenger vehicles account for 75% of overall CO₂ emissions [Climate Change, 2019, Hien and Kor, 2021]. Consequently, to address this global challenge, electric cars (EVs) will ultimately replace fuel-powered cars.

a) *The calculation of CO₂ emissions of EVs*

It takes a lot of energy to produce batteries made from materials such as lithium, copper, and refined silicon. Thus, energy consumed for autonomous cars' production, and its associated CO₂ emissions amount to half of its lifecycle emissions (i.e., 6.3

tons of CO₂). For fossil-fuel vehicles, the amount represents only 17% of their lifecycle emissions (i.e., 5.6 tons of CO₂) [Bjørn and Hauschild, 2012]. Additionally, many electric cars are likely to require battery replacement after several years. When emissions of the replaced battery are included, the total CO₂ produced by an electric vehicle jumps to 12.6 tons, compared to 5.6 tons for a gas vehicle. Furthermore, due to the energy required for collecting and recycling metals in the battery, disposal would double the emissions [Verma et al., 2021].

Considering charging, if the energy required to recharge the electric car comes mostly from coal-fired power plants, it will emit about 15 ounces of CO₂ for every 50,000 miles traveled, which is 3 ounces more than a comparable gas-powered car [Bjørn and Hauschild, 2012]. If electric cars are driven for over 67,000 miles with green electricity, they would be greener than gasoline cars. For instance, for a covered distance of 90,000 miles, the EV emits 24% less CO₂ than its gas-powered counterpart, which is equivalent to 8.7 tons of CO₂ [Bjørn and Hauschild, 2012]. Research has shown that EVs driven by the current European energy mix would have a 10% to 24% lower global warming potential than traditional diesel or gasoline vehicles with lifespans of 150,000 km [Hawkins et al., 2012].

b) The actual efficiency of EVs

Though Nissan claims that its EV efficiency is about 100 miles, the actual figure is approximately 58 miles [Woodhill, 2011]. With cold weather or fast driving, this is further reduced to 30 miles. On the other hand, a traditional vehicle could travel 300 to 400 miles. A Nissan's Leaf takes 20 hours to fully recharge on 110V household power. This duration can be reduced to 8 hours by using a 240V charger which costs more. Although there are pricey 480V chargers that can reduce this duration to 4 hours, Nissan has warned against it because of the negative impact of frequent use on the battery's life [Woodhill, 2011]. However, autonomous vehicles and their supply chain have the potential to significantly increase toxicity, freshwater eutrophication, eco-toxicity, and metal depletion [Hawkins et al., 2012].

c) Comparison of the environmental impact of an electric car and a gas-fueled car

When considering the mitigation of natural resource consumption, EVs will be the preferred option [Swedish Environmental Research Institute, 2019]. By 2061, the world will have to transition away from gas-powered vehicles, and coal-fueled power plant industries to renewable energy sources [Jacobson, 2017]. The environmental impact of autonomous cars will be minimal if they are charged with renewable solar and wind energy [Roth, 2021].

The environmental impacts of autonomous vehicles depend on how electricity is generated. If autonomous cars are charged with renewable solar and wind energy [Roth, 2021], they will be fairly clean. The environmental impacts of autonomous vehicles also depend on the lifetime of the vehicle that customers use. The calculation of EVs' CO₂ emissions above estimated that when the electric car is driven for over 67,000 miles with green power, such as renewable solar and wind energy, EVs are greener than gasoline cars.

Overall, with the current context of major electricity production by coal-fired power plants, electric cars may not seem to be a good solution. However, with a long-term vision of using green power, EVs are proven to have real value in terms of being environmentally friendly in the long run. Conditions for doing so include a substantial supply of green

energy, usage phase energy consumption, vehicle lifetime, battery replacement schedules, and the transition from private vehicle use to shared and community use. Therefore, improving the sustainability level of autonomous vehicles necessitates collaboration on minimizing vehicle production supply chain impacts and encouraging clean power sources in electrical infrastructure decision-making.

2.2 2-D Deep Learning Object Recognition Models for Autonomous Vehicles

Object detection and classification are the initial steps (after sensor steps) in the perception phase of autonomous vehicles. The data collected from these steps should be merged for data fusion. Next, the data fusion output becomes the input for the decision and planning phase, before yielding output to the control system and invoking relevant actions [Behere and Torngren, 2015]. Therefore, object recognition is the initial and critical step that tremendously impacts subsequent actions in autonomous vehicle systems. This is also the reason why object recognition is the main focus of this study.

Object detection involves the use of bounding boxes for producing object localizations [Wang et al., 2022] and recognizing objects based on their salient attributes [Che et al., 2019]. Single-stage and double-stage detectors are the most often used structures for 2-D object detection in pictures. "You Only Look Once" (YOLO) [Jiang et al., 2022], the Single Shot multi-box Detector (SSD) [Kumar and Srivastava, 2020], CornerNet [Law et al., 2019], and RefineNet [Zhou et al., 2022] are all renowned single-stage detectors. RCNN, Faster-RCNN [Cheng et al., 2018], and R-FCN [Zhang and Chi, 2020] are two-stage detectors that divide the object detection process into two parts: region of interest for object candidates' generation and bounding box classification. In general, single-stage detectors do not perform as well as double-stage detectors, but they are substantially quicker.

Figure 3 shows a comparison of the object recognition algorithms using the Pascal VOC 2012 dataset and their measured mean Average Precision (mAP) with an Intersection over Union (IoU) value of 50 and 75, respectively. The first four techniques on the right are single-stage detectors, whereas the rest are double-stage detectors. Due to their greater complexity, two-stage detectors have a reduced runtime performance in frames per second (FPS) [Grigorescu et al., 2020].

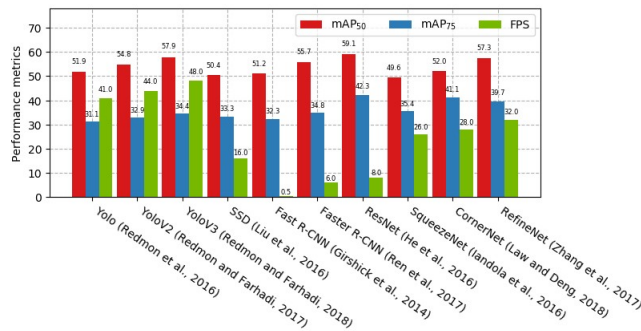


Figure 3: Comparison of object detection and recognition performance of different deep learning models on Pascal VOC 2012 benchmarking dataset [Grigorescu et al., 2020].

It can be seen from Figure 3 that the ResNet model seems to perform the best with the Pascal VOC 2012 benchmarking dataset, compared to other models. Meanwhile, SqueezeNet, SSD, and Fast R-CNN are models that need to be optimized in terms of mean Average Precision. Another comparative analysis has been conducted on the VOC 2012 dataset. The results have been tabulated in Table 1 and depicted in Figure 4.

Model	mAP (mean Average Precision)
R-CNN(Alex)	53.3
R-CNN(VGG16)	62.4
Bayes	66.4
Fast R-CNN	68.4
SutffNet30	70.0
NOC	68.8
MR-CNN & S-CNN	73.9
HyperNet	71.4
OHEM + Fast R-CNN	80.1
ION	76.4
Faster R-CNN	70.4
YOLO	57.9
YOLO + Fast R-CNN	70.7
YOLOv2	78.2
SSD300	79.3
SSD512	82.2
R-FCN (ResNet101)	85.0

Table 1: Comparison of object detection performance of different deep learning models on VOC 2012 Dataset [Zhao et al., 2019].

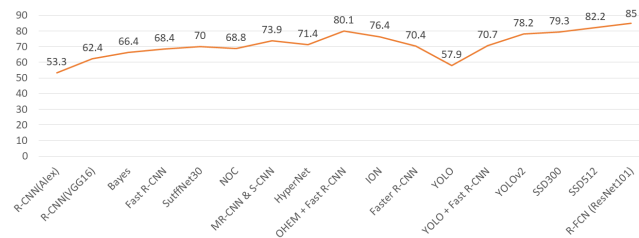


Figure 4: Comparison of object detection performance of different deep learning models on VOC 2012 Dataset [Zhao et al., 2019].

From Table 1 and Figure 4, R-FCN (ResNet101) appears to be the best model when

compared to YOLOv1 and R-CNN(Alex). By experimenting on another dataset – COCO with the latest deep learning models, the comparison results are shown in Figure 5. It evidences that the DyHead model (Swin-L, multi-scale, self-training) is currently the best in terms of Box Average Precision, compared to state-of-the-art models on the COCO test-dev dataset [Code, 2022].

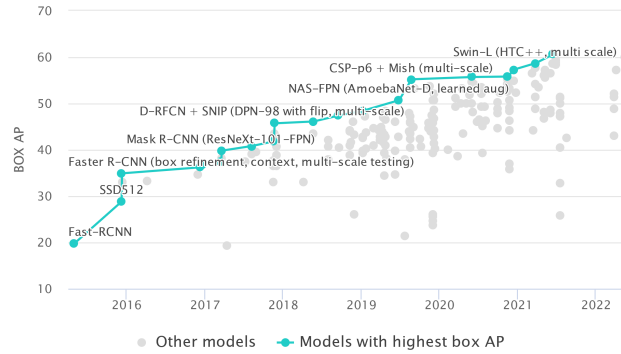


Figure 5: Comparison of object detection performance of different deep learning models on COCO test-dev Dataset [Code, 2022].

3 Methodology

3.1 Macro Methodology

In this study, the chosen dataset for the deep learning experiments on object recognition and classification of image data is Berkeley Deep Drive Dataset (BDD100K). This research follows the data analytics lifecycle (see Figure 6) which is adopted from EMC Education Services [Ultralytics, 2022].

The data analytics lifecycle comprises 6 phases. The initial stage is the Discovery phase which involves the identification of the problem, context, hypothesis, and goals for which the data will be used. The datasets are then processed and compacted into a single spreadsheet in Phase 2 - Data Preparation. The dataset is explored and visualized in Phases 3 and 4 - Model Planning and Building - utilizing 2 levels of data analytics: (i.e., descriptive and inferential statistical analysis). Finally, in Phases 5 and 6, key analytics and prediction outcomes are communicated to inform relevant operations.

Overall, BDD100K is a large-scale driving dataset with diverse types of annotations provided by UC Berkeley, USA. This dataset can be used to recognize 2-D and 3-D objects, segment instances, mark lanes, and determine drivable regions. It is presently the largest dataset for self-driving AI, with over 100,000 videos of over 1,100-hour driving experiences at various times of the day and weather conditions. The BDD100K dataset collects video data using cameras (in collaboration with Nexar). The footage is captured with a Nexar dashcam at 720p and 30 frames per second. The collection includes videos

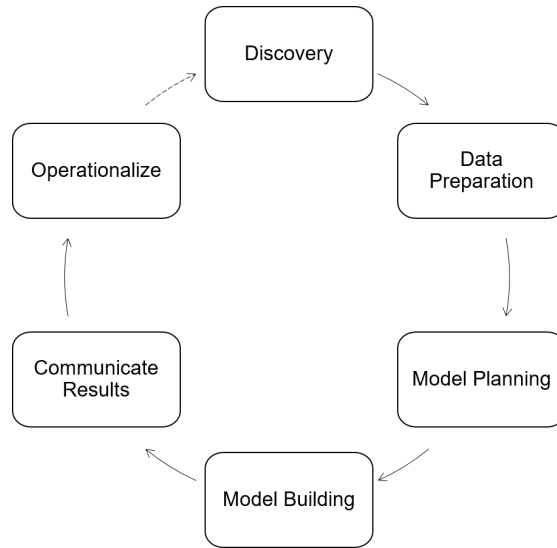


Figure 6: The Data Analytics Lifecycle.

from several cities in the USA, including New York, Berkeley, San Francisco, and the Bay Area.

Frame extraction is performed on 100,000 video clips to provide images with respective bounding box coordinates of the objects, considerably lowering the pre-processing time for this dataset. The frame of each video clip is extracted from the 10th second of the video, allowing viewers to distinguish items. All photographs have a resolution of 1280 x 720 pixels in RGB. A JSON file containing the properties of each video, including the time of day, objects, scene, weather, and their respective bounding boxes, has been given (Table 2).

To reiterate, in the Discovery stage, the problem, context, and objectives for using this dataset are defined. The main aims of the study are to propose different filtering techniques for deep learning models in object detection and classification in 2-D image data. Therefore, only images of the dataset are being used for this purpose. The dataset consists of 100,000 images that are split into 3 subsets: 70,000 images in the training; 10,000 images in the validation; and 20,000 images in the testing.

In Phase 2 (Data Preparation), all the labels are in JSON format. They are converted to COCO JSON format followed by the YOLO format. To ensure that each image matches its label, a search of on-labeled data is conducted for removing images without labels. In the end, there are a total of 80821 remaining images, with 69,863 images in the testing; 10,000 images in the validation; and 958 images in the testing subset.

In Phases 3 and 4, the analyzed and visualized results of different models are presented in Section 5. Finally, in Phases 5 and 6, relevant findings and discussion are presented in Sections 6 and 7.

a particular forecast. While classification tasks perform well for each grid, separating the bounding boxes for each prediction is more challenging. The third and last grid is to utilize the intersection of union (IOU) to obtain the optimal bounding boxes for a specific object identification task [Alves-Oliveira et al., 2020].

Figure 8 presents the performance of different versions of YOLOv5 and EfficientDet in terms of Average Precision in the validation set and GPU Speed on the COCO Dataset. Results reveal that YOLO models have faster GPU speed for object detection, compared to different EfficientDet models. YOLOv5s is the fastest model amongst the 4 versions of YOLO but with the lowest average precision. In contrast, the YOLOv5x is the slowest model but with the highest average precision among the 4 versions [Ultralytics, 2022].

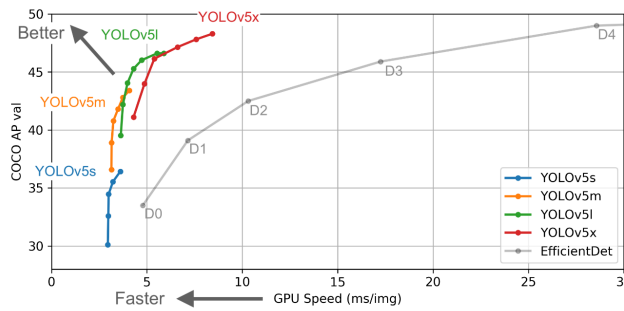


Figure 8: Performance of different versions of YOLO on the COCO Dataset [Ultralytics, 2022].

b) EfficientNet-B7

EfficientNet is an architecture and scaling approach to a convolutional neural network [Hien et al., 2021b] that uses a compound coefficient to consistently scale all depth/width/resolution dimensions (Figure 9). This scaling approach evenly scales network depth, width, and resolution using a predetermined set of scaling coefficients [Hoang and Jo, 2021].



Figure 9: The architecture of EfficientNet [Hoang and Jo, 2021].

As can be seen from Figure 10, EfficientNet models outperform earlier CNNs in terms of accuracy and efficiency [Baheti et al., 2020].

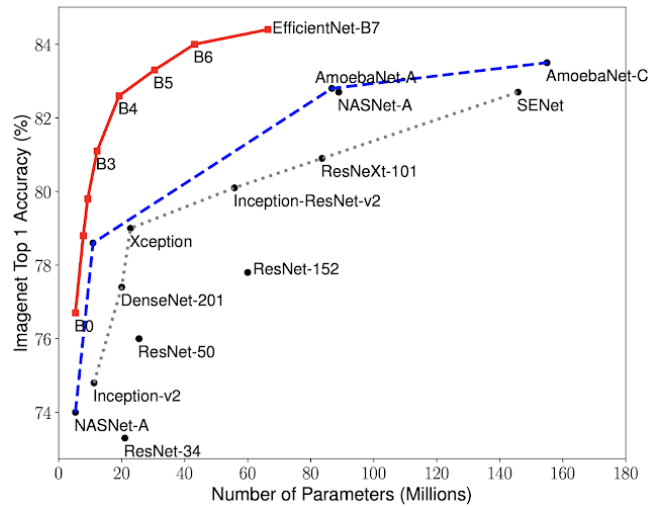


Figure 10: Performance of different versions of EfficientNet [Baheti et al., 2020].

c) Xception

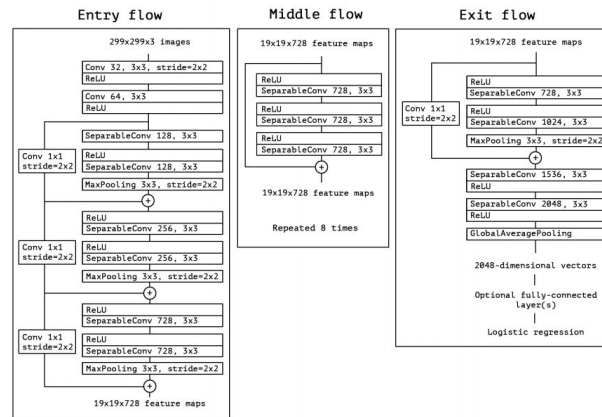


Figure 11: The architecture of Xception [Chollet, 2017].

Xception is a variation of the deep CNN architecture with Depthwise Separable Convolutions. Inception modules in CNN are introduced by Google as an intermediary step between normal convolution and the depthwise separable convolution process. In this context, a depthwise separable convolution may be viewed as an Inception module with an infinite number of towers. However, in a new deep CNN architecture (motivated by

Inception), the Inception modules are substituted with depthwise separable convolutions [Chollet, 2017].

As presented in Figure 11, data is routed repeatedly 8 times through the entry flow and the middle flow, and ultimately, through the exit flow. In most conventional classification problems, the Xception algorithm outperforms VGG-16, ResNet, and Inception V3.

d) MobilenetV3

MobileNetV3 is a tuned CNN for mobile phone CPUs by using a mix of hardware-aware NAS (network architecture search) augmented by the NetAdapt algorithm. The network is a new efficient version of nonlinearities suitable for the mobile environment. It complements search approaches with an innovative powerful network design. The network architecture is depicted in Figure 12, which includes the use of hard swish activation and squeeze-and-excitation modules in the MBCConv blocks [Kavyashree and El-Sharkawy, 2021].

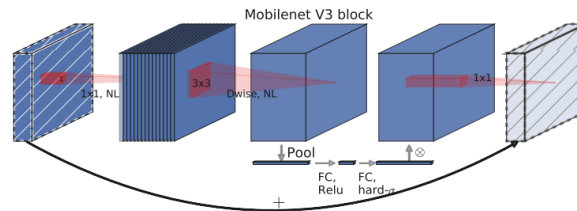


Figure 12: MobilenetV3 Architecture [Kavyashree and El-Sharkawy, 2021].

a) InceptionV4

Inception is an architectural design of a deep neural network that comprises replicated components known as Inception modules. CNN employs these Inception Modules to provide more efficient computation and deeper networks by reducing dimensionality using stacked 1×1 convolutions. The modules are created to address challenges such as computational cost and overfitting. Figure 13 depicts the architecture of Inception-v4 [Szegedy et al., 2017].

3.2.2 Filtering Techniques

a) Hessian Filter

A hybrid Hessian filtering technique can be used to filter 2-D and 3-D images. In 2-D images, the Hessian matrix can be defined as

$$H = \begin{bmatrix} H_{xx} & H_{xy} \\ H_{xy} & H_{yy} \end{bmatrix}$$

which is obtained by convolving the image with the Gaussian kernel’s second derivatives in the x- and y-directions respectively. This filter is suitable for detecting continuous

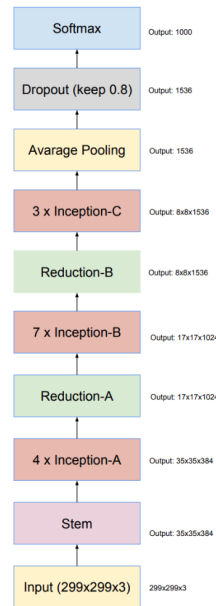


Figure 13: The overall schema of InceptionV4 [Szegedy et al., 2017].

edges, such as wrinkles, vessels, and rivers. It may be utilized to compute a fraction of the entire image that contains such objects. The technique of Hessian is nearly identical to the Frangi filter, but it uses an alternative smoothing method.

Figure 14 presents an application of how a Hybrid Hessian Filter detects the edges of human wrinkles. [Ng et al., 2014]

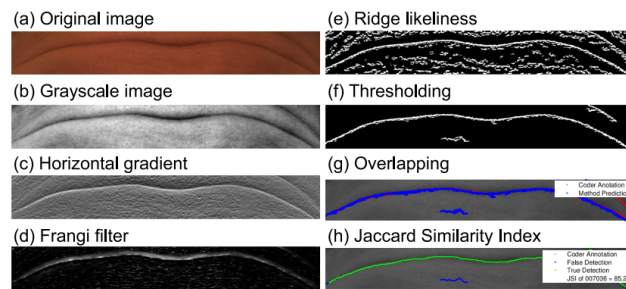


Figure 14: Application of Hybrid Hessian filter for wrinkle detection.

In image processing and computer vision, the Hessian matrix is often used to describe image processing operators. In normal mode analysis, the Hessian matrix can compute

the various molecular frequencies in infrared spectroscopy.

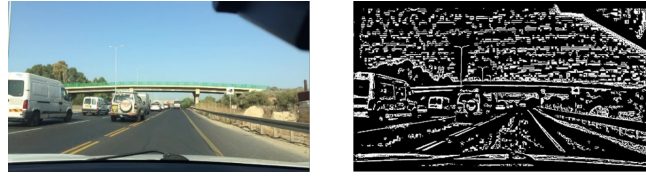


Figure 15: Application of Hessian filter to a driving image.

In Figure 15, a driving scene image (on the left) has been applied with a Hessian filter (on the right).

b) Laplacian Filter

In the edge area of an image, the pixel intensity shows a "jump" or a high variation of intensity. Using Sobel Operator to get the first derivative of the intensity, an edge is characterized by a maximum, as illustrated in Figure 16 [OpenCV, 2022].

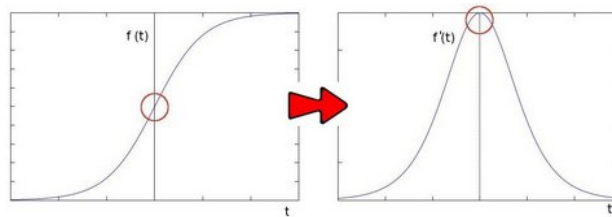


Figure 16: The first derivative of the intensity [OpenCV, 2022].

And while obtaining the second derivate, the value becomes zero, as shown in Figure 17.

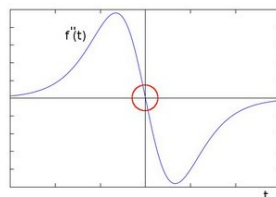


Figure 17: The second derivative of the intensity [OpenCV, 2022].

Therefore, this criterion can be used to detect edges in an image. Since images are 2-D, it is necessary to obtain the derivative in both dimensions.

The Laplacian operator is defined by:

$$\text{Laplace}(f) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

The Laplacian operator is implemented in OpenCV using the function `Laplacian`. Since the Laplacian utilizes the images' gradient, it employs the Sobel operator internally for its calculation.

To apply a Laplacian filter to an image, first, noise needs to be removed from the image by applying a Gaussian blur followed by converting the original image to a grayscale. A Laplacian operator can be applied to the grayscale image and store the output image, as illustrated in Figure 18.



Figure 18: Application of Laplacian filter to a driving image in this research.

c) Hessian-based Ridge Detection Filter

Ridges are eigenvalues of the matrix of second-order derivative of an image, also known as the Hessian matrix. Therefore, it is possible to create a ridge detector function using `scikit-image` to extract local minima ridges. First, noise needs to be removed from the image by applying a Gaussian blur followed by converting the original image to a grayscale. Then the grayscale image can be put into a ridge detector function to output the local minima ridges and save them as a new image presented in Figure 19.

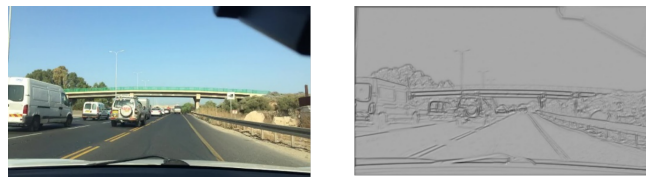


Figure 19: Application of Ridge Detection filter to a driving image in this research.

d) Proposed Filtering Techniques

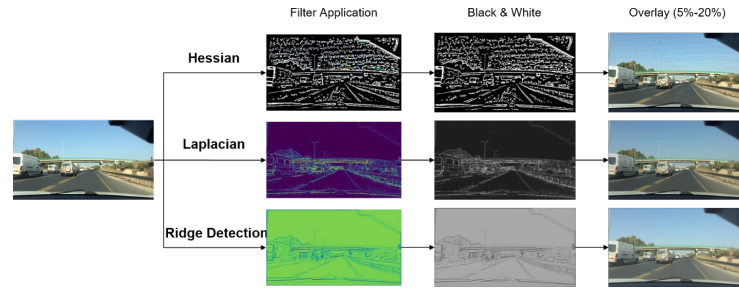


Figure 20: Proposed filtering techniques for object recognition in image data for autonomous vehicles.

In this research, a summary of the proposed filtering techniques for object detection in images (shown in Figure 20) is implemented as follows:

1. One of the 3 proposed filters, including Hessian, Laplacian, and Ridge Detection filters is applied to an input image;
2. The output of (1) is converted to grayscale, retaining only the edges of the image.
3. The grayscale image is then overlaid with the original input image with varying overlaying levels of 5% to 20%. This task includes alpha blending and masking with NumPy.
4. The final image is fed into the deep learning model for object detection.

The critical reason behind this approach is that the final image will have highly sharpened edges.

4 Preliminary Research

In this preliminary research, 5 different deep learning models (YOLOv5s, EfficientNet-B7, Xception, MobilenetV3, and InceptionV4) have been built for object detection in autonomous vehicles with the BDD100K dataset. The results are depicted in Table 3 and Figures 21 to 23.

Table 3 and Figure 21 evidence that YOLOv5s and EfficientNet-B7 models perform the best with the lowest log losses. This result informs a decision for the implementation of the 2 models in the next section.

Regarding the training and inference times, MobileNetV3 has the lowest performance. And in contrast, despite generating one of the best accuracies, EfficientNet-B7 takes the longest time for training and inference. Therefore, EfficientNet-B7 should be taken into consideration for optimization in Section 5. Meanwhile, YOLOv5s has become the best model in terms of accuracy, training, and inference time. This is a promising result and could act as a reference in model decision-making for researchers and manufacturers.

Model	Training time per epoch (s)	Inference time per epoch (s)	Log loss
Xception	3548.529	0.061	0.431
InceptionV4	3704.766	0.074	0.468
MobileNetV3	761.87	0.050	0.538
EfficientNet-B7	6224.268	0.112	0.425
YOLOv5s	2299.266	0.044	0.403

Table 3: Performance of Deep Learning models for object detection.

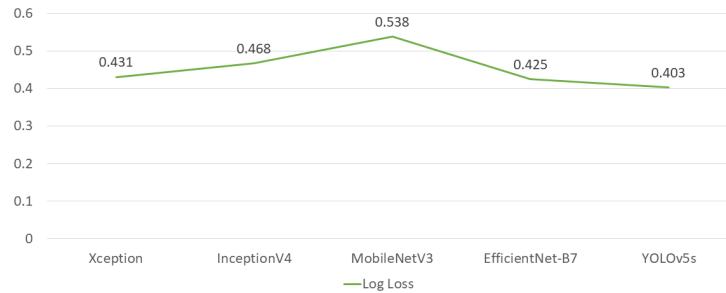


Figure 21: Log losses of the models.

5 Findings and Discussion

5.1 Comparison of Filtering Techniques applying to the YOLOv5s model

Table 4 and Figure 24 have indicated that by using different filtering techniques, the mean Average Precision (mAP) of YOLOv5s models increased remarkably. Particularly, the Ridge Detection filter with 10% overlay, yields the highest mAP increase of 6.69%, from 56.67% to 63.36% (an 11.81% increase of the original mAP), as well as obtaining the highest accuracy and F1 score. This is followed by the Laplacian filter with a 5% overlay and the Hessian filter with a 10% overlay.

Figure 25 plots the mAP values for the Ridge Detection filter with a 10% overlay applied on 1000 test images. The graph shows that the mAP of YOLOv5s with a Ridge Detection filter is higher than the one without Ridge Detection Filter for most of the tested images.

T-test:

A series of 2-tailed t-tests are implemented to evaluate if there is a significant difference between the mean Average Precision (mAP) of object detection using YOLOv5s with and without different filters.

- Null Hypothesis (H0): mAP of model A = mAP of model B
- Alternative Hypothesis (Ha): mAP of model A \neq mAP of model B
- Chosen Confidence Level: 99%, which means the significance level $\alpha = 0.01$.

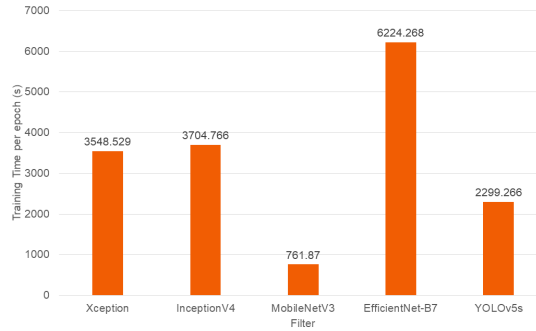


Figure 22: Training time per epoch.

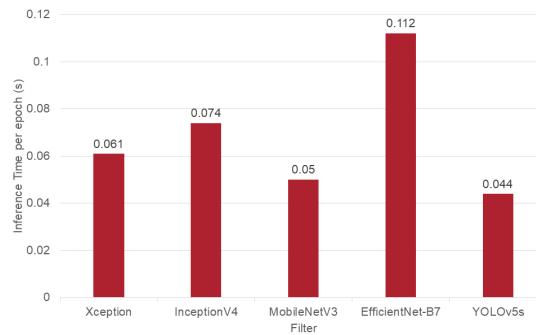


Figure 23: Inference time per epoch.

A series of paired 2-tail t-tests are conducted for the filtering techniques listed in Table 4 and the results are plotted into a heatmap in Figure 26. The value **1** indicates that there is a significant difference in the mAP (i.e., reject the Null Hypothesis) and **0** means there is no significant difference (i.e., accept the null hypothesis).

Figure 25 shows that mAP of most of the filtering techniques is significantly different from each other. Most importantly, the mAP values of the YOLOv5s model with all filtering techniques are significantly different from those that are without any filter.

Figures 25 and 26 evidence that the mAP of object detection for deep learning models with filtering techniques is better compared to the models without them. Remarkably, the total object detection time could be reduced up to 43.98% by using the Ridge Detection filter with a 5% overlay.

Overall, object detection in the YOLOv5s models with 3 proposed filters (i.e., Hessian, Laplacian, and Hessian-based Ridge Detection) outperforms those without any filter. In this experiment, the Ridge Detection Filter appears to be the best-performing filter.

5.2 Comparison of Filtering Techniques applied to the EfficientNet-B7 model

Using the same methodology of Section 5.1, the results when comparing different filtering techniques applied to the EfficientNet-B7 model are presented below.

Filter	Mean Average Precision (%)	Accuracy	F1 Score	Pre-process Time (ms)	Inference Time (ms)	Non-maximum Suppression Time (ms)	Total Time per Image (ms)
No Filter	56.67	57.21	57.87	36.83	326.70	3.15	363.53
Hessian 20%	57.10	57.33	58.02	102.78	215.38	3.98	318.16
Hessian 10%	60.58	60.48	61.22	38.25	168.05	1.75	206.30
Hessian 5%	59.65	59.62	59.61	48.30	298.70	3.53	347.00
Laplacian 20%	57.56	58.03	59.08	37.20	167.63	1.78	204.83
Laplacian 10%	59.51	60.35	61.34	73.25	161.65	1.95	234.90
Laplacian 5%	62.43	62.06	62.91	112.45	158.78	1.53	271.23
Ridge Detection 20%	60.32	60.73	61.24	37.90	163.80	1.55	201.70
Ridge Detection 10%	63.36	63.08	63.53	39.23	167.85	2.85	207.08
Ridge Detection 5%	59.74	59.67	59.92	39.65	164.00	1.75	203.65

Table 4: Comparison of Filtering Techniques applying to the YOLOv5s model.

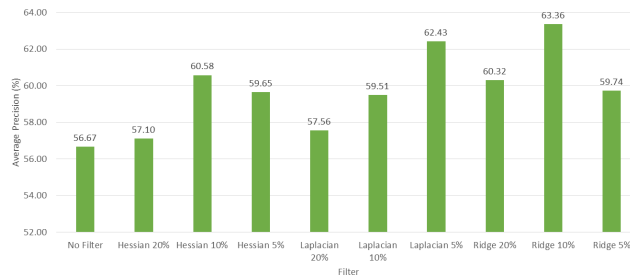


Figure 24: Mean Average Precision of Object Detection in YOLOv5s with different filtering techniques.

Table 5 and Figure 29 prove that with different filtering techniques, the mAP of EfficientNet-B7 models has increased considerably. Especially, the Laplacian filter with a 5% overlay has the highest mAP increase of 1.05%, from 42.46% to 44.76% (an increase of 5.42% from the original mAP), as well as obtaining the highest accuracy and F1 score. This is followed by the Ridge Detection filter with a 10% overlay and the Hessian filter with a 5% overlay.

Figure 30 also shows the mAP of EfficientNet-B7 with Laplacian filter with a 5% overlay is higher than without the filter for most of the 1000 tested images.

Figure 31 indicates that the mAP of the EfficientNet-B7 models with all filtering techniques is significantly better than the ones without filters (except for the Laplacian filter with 20% overlay).

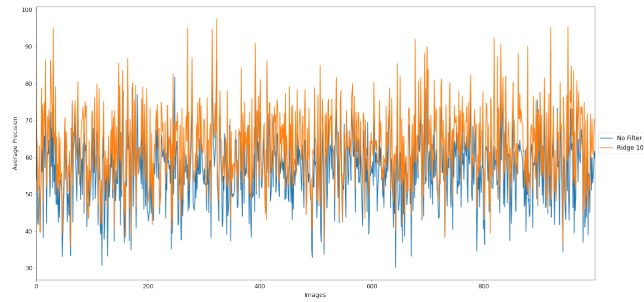


Figure 25: Means of Average Precision of YOLOv5s model with and without Ridge Detection Filter (10% overlay).

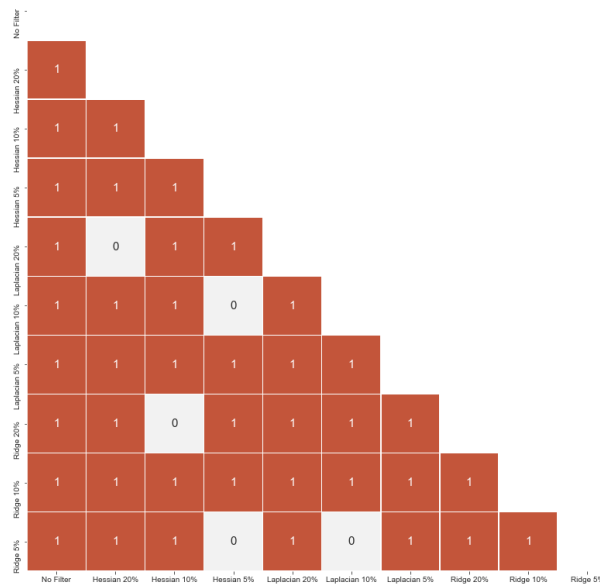


Figure 26: T-Test on mean Average Precision for the different filtering techniques on the YOLOv5s model.

Figure 32 also proves that the mean processing time for object detection by deep learning models with proposed filtering techniques is better compared to the ones without them. Notably, the total detection time could be reduced by up to 21.02% by using the Ridge Detection filter with a 5% overlay, shown in Figure 33.

In general, object detection in the EfficientNet-B7 models with 3 proposed filters (i.e., Hessian, Laplacian, and Hessian-based Ridge Detection) outperforms those without any filter. And in this experiment, the Laplacian Filter becomes the best-performing filter among the rest.

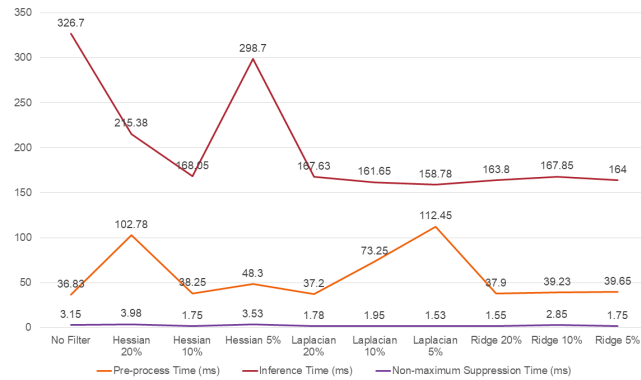


Figure 27: The pre-process, inference, and non-maximum suppression times of object detection in YOLOv5s with different filtering techniques.

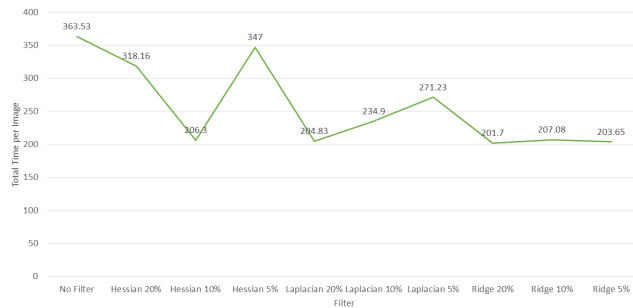


Figure 28: The total object detection time in YOLOv5s with different filtering techniques.

6 Conclusion

The preliminary research of this study aims to build 5 different Deep Learning models, YOLOv5s, EfficientNet-B7, Xception, MobilenetV3, and InceptionV4, which are commonly used for 2-D object recognition. The findings reveal that YOLOv5s and EfficientNet-B7 models perform the best among the 5, with the lowest log losses. While MobileNetV3 has the lowest performance, it delivers relatively satisfactory training and inference time, as well as the lowest energy consumption. On the other hand, despite holding one of the best performances, EfficientNet-B7 consumes the longest time for training and inference; and incurs the highest energy consumption. Meanwhile, YOLOv5s has become the best model in terms of performance. This result could act as a good benchmarking, leading to a decision for optimizing YOLOv5s and EfficientNet-B7 models in this study.

This research primarily proposes 3 filtering techniques, Hessian, Laplacian, and Hessian-based Ridge Detection filters, for 2 deep learning models (YOLOv5s and EfficientNet-B7) in 2-D object recognition, optimizing their performance. Applying

Filter	Mean Average Precision (%)	Accuracy	F1 Score	Pre-process Time (ms)	Inference Time (ms)	Total Time per Image (ms)
No Filter	42.46	42.98	43.62	50.27	1417.64	1467.91
Hessian 20%	43.68	44.04	44.16	50.21	1140.07	1190.28
Hessian 10%	44.54	43.91	44.68	52.16	1129.73	1181.89
Hessian 5%	44.55	45.07	45.29	50.09	1178.97	1229.06
Laplacian 20%	42.98	43.33	43.95	48.40	1132.60	1181.00
Laplacian 10%	44.05	45.44	44.76	50.99	1263.43	1314.42
Laplacian 5%	44.76	45.42	45.52	56.88	1451.26	1508.14
Ridge 20%	44.32	44.15	44.76	53.61	1541.04	1594.65
Ridge 10%	44.72	45.06	45.12	49.22	1325.21	1374.43
Ridge 5%	44.54	44.31	44.77	47.17	1119.69	1166.86

Table 5: Comparison of Filtering Techniques for the EfficientNet-B7 model.

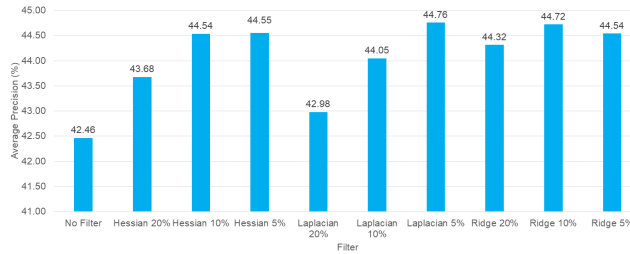


Figure 29: Mean Average Precision of object detection in EfficientNet-B7 with different filtering techniques.

to the BDD100K image dataset, those filtering techniques boosted the mean Average Precision (mAP) of the YOLOv5s and EfficientNet-B7 models remarkably.

- In the YOLOv5s model, the Ridge Detection filter with a 10% overlay brings an increase of the mAP to 11.81%, from 56.67% to 63.36%. Slightly lower than that, the Laplacian filter with a 5% overlay and the Hessian filter with a 10% overlay also reached satisfactory results. A series of 2-tail t-tests are also implemented and has confirmed that all filtering techniques have significantly different mAP compared to the model without filters. Additionally, the mAP of most of the filtering techniques is also significantly different from each other. The mean detection time of object recognition with proposed filtering techniques is better compared to the models without them. Remarkably, the total object detection time could be reduced up to 43.98% by using the Ridge Detection filter with a 5% overlay. Therefore, the 3 proposed filters have enhanced the YOLOv5s model resulting in better performance in object recognition compared to ones without filters.
- In the EfficientNet-B7 model, the Laplacian filter with a 5% overlay increased the

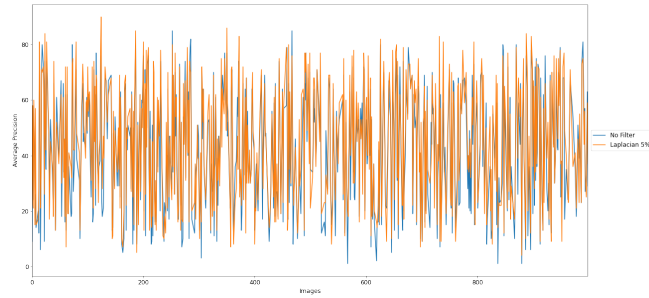


Figure 30: Compare the means of Average Precision of the EfficientNet-B7 model without and with Laplacian Filter with 5% overlay.

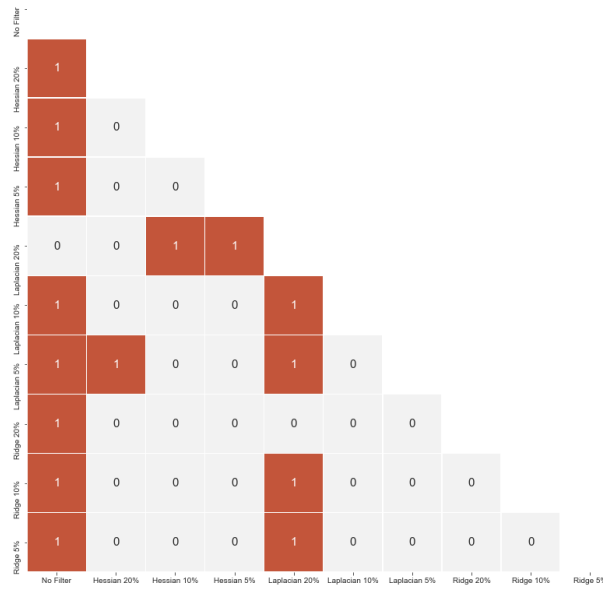


Figure 31: T-Test on Average Precision among different filtering techniques on the EfficientNet-B7 model.

mAP to 5.42%, from 42.46% to 44.76%. Moreover, the Ridge Detection filter with a 10% overlay and Hessian filter with a 5% overlay also delivered promising results. A set of 2-tail t-tests has indicated that all filtering techniques have a significantly different mAP compared to the model without filters, except for the Laplacian filter with a 20% overlay. Furthermore, the proposed filters can also help reduce the mean detection time. Particularly, the total detection time could be reduced up to 21.02% by using the Ridge Detection filter with a 5% overlay. Again, the 3 proposed filters have enabled the EfficientNet-B7 model to outperform its performance when not

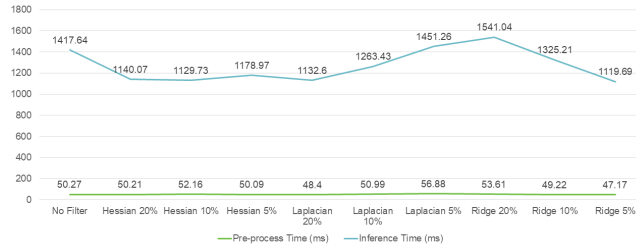


Figure 32: The pre-process, and inference time for object detection in EfficientNet-B7 with different filtering techniques.

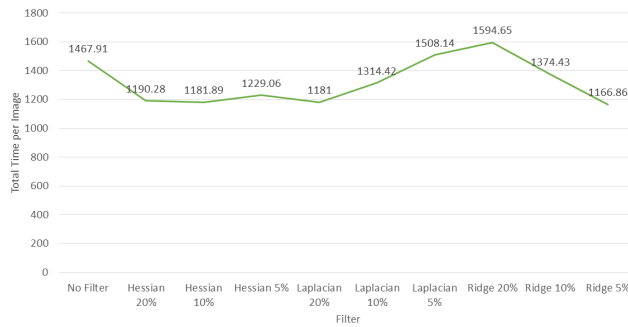


Figure 33: Total detection time for object detection in EfficientNet-B7 with different filtering techniques.

using filters for object recognition.

Despite substantial efforts that have been conducted in the past [He et al., 2022, Wang et al., 2021, Cai and Vasconcelos, 1483], this study has proposed high-efficiency filtering techniques for object recognition and classification for autonomous vehicles. These results may lead to more future studies relating to filtering algorithms for object detection and classification in autonomous cars.

7 Recommendations and Future Work

One of the notable findings from the Literature Review section is that autonomous vehicles are currently yet to be an environmental-friendly solution in transportation, however, they will become an indispensable and greener solution in the long-term vision. Scientists and manufacturers are recommended to use green power for manufacturing and operating autonomous vehicles, optimize the vehicle lifetime, schedule battery replacements, and conduct the transition from private vehicle use to shared and community use. Improving the sustainability level of autonomous vehicles necessitates collaboration on minimizing vehicle production supply chain impacts and encouraging clean power sources in electrical infrastructure decision-making.

Based on the findings of the Preliminary Research, the YOLOv5s and EfficientNet-B7 models are recommended for object detection and classification in the navigation system of autonomous vehicles, instead of the Xception, MobilenetV3, and InceptionV4 models. Particularly, the YOLOv5s model is recommended to be deployed for autonomous vehicle navigation systems since it holds a good balance of precision and detection time.

In the main research section, the proposed Hessian, Laplacian, and Hessian-based Ridge Detection filters have significantly improved the performance of YOLOv5s and EfficientNet-B7 models. Therefore, these image-filtering techniques can be applied in further research to reduce motion blurs and mitigate some of the limitations of image data in autonomous vehicles. Furthermore, while constructing massive deep learning systems, developers should employ energy-tracking tools to reduce the ICT sector's carbon impact. This approach also provides a better consumer experience in terms of how long the batteries in technical products last. This is since the impact of deep learning would be considerably bigger than that demonstrated in this study when a program of a few thousand lines of code is produced.

Future research may gear towards evaluating more deep learning models, and not only in object detection and classification models in autonomous vehicles. Further development of different filtering techniques should be implemented such as optimizing the filters, using different overlaying techniques, or proposing more filtering approaches. Future work also tends to propose different filtering techniques in 3D object detection in LiDAR point cloud data. To enhance the analytical report, a full evaluation of how deep learning affects power use and emissions in a program should be undertaken using more parameters, such as memory utilization. More profiling tools as well as footprint audit tools can be used in later studies to extract more accurate auditing data.

Acknowledgements

This study is supported and implemented under the framework of the Erasmus Mundus Joint Masters Degree (EMJMD) in Green Networking and Cloud Computing (GENIAL) program (610619-EPP-1-2019-1-FR-EPPKA1-JMD-MOB).

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