SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348 – 8379 / https://doi.org/10.14445/23488379/IJEEE-V9I8P101

Volume 9 Issue 8, 1-7, August 2022

Original Article

Autonomous Path Finder and Object Detection using an Intelligent Edge Detection Approach

Manasa R[1], K Karibasappa[2], Rajeshwari J[3]

[1] *Department of Electronics and Communication Engineering, Dayananda Sagar College of Engineering, Bangalore, Indıa.*

[2] *Department of Computer Science Engineering, Graphics era deemed to be University, Dehradun, Indıa.*

[3] *Department of Information Science Engineering, Dayananda Sagar College of Engineering, Bangalore, India.*

Received: 11 June 2022 Revised: 08 August 2022 Accepted: 15 August 2022 Published: 31 August 2022

Abstract - *This work carried an approach to automatic detection and recognition of road boundary line demarcation as well as detection of other objects available over the road. Maintaining the vehicles over the road and in proper lanes is important for the autonomous vehicle and driver assistance system. The proposed work has applied an intelligent approach to edge detection using the feed-forward architecture of neural networks, which carried the self-adaptive strategy of transfer function slope in their active nodes. The proposed model has used the neural network as a low pass filter, which tries to develop the same outputs as available inputs. Other information from the image, except edges, was generated by the neural network very well. In contrast, the edges carry high-frequency information, and the neural network doesn't develop the output as it is. Hence a complement of the generated output image to the input image delivered the edges in the input image. The recognition of road boundary was detected as two parallel straight or curve lines. Detecting any object in the lane or over the road was done in two phases. In the first phase, the cover region was divided into several parts, and pixel density was estimated in the near region. The statistical information of pixels' distribution in the near and front region is estimated. In the second stage, a support vector machine-based classifier was used to define the object's presence. Such recognition can help control the vehicle's speed to run the vehicle safely. The proposed work has been applied to various real road images, and obtained results were appreciable. This work can be considered one step further toward developing autonomous vehicles cost-effectively.*

Keywords - *Autonomous vehicles, Edge detection, Object detection, Lane detection, and Neural network.*

1. Introduction

Object detection is one branch of computer vision concerned with detecting scenarios of objects that are semantic of a particular class (such as living beings, housing developments, or automobiles) in images and digital videos. Object detection has established itself as a critical part of various critical applications such as video monitoring, face detection and autonomous driving system. With the advancements of the twenty-first century, there's been a surge of creativity and innovative methods that allow users to use detection and classification in a modular form. Detection is a critical vision task that becomes integrated into a wide range of consumer applications. Recently, which included systems and related systems, text recognition on mobile phones, and disease diagnosis via MRI/CT scans. Additionally, autonomous driving relies heavily on object detection. Automated driving relies on their perception of their surroundings to ensure safe and dependable driving. This viewpoint system will utilize algorithms to recognize nearby things, such as pedestrians, autos, traffic signs, and obstructions [1, 2]. Object detection is divided into two subtasks: localization, which helps determine the location of an object inside an image (or video clip), and classification, which assigns the object to a category (such as 'pedestrian, ''vehicle,' or 'traffic light'). A. Two-stage object detectors versus particular object detectors The two steps of two-stage object detectors include region proposal & classification algorithms. Even during the region proposal stage, an object detector proposes many Regions of Interest (ROIs) inside the input data, increasing the likelihood of holding objects of interest. The second stage involves selecting the most favourable ROIs (while eliminating the others) and classifying the objects contained within them. [3] In recent years, autonomous vehicles (AVs) have garnered substantial interest due in part to their potential to increase driver visual comfort and decrease vehicle collision-related injuries. According to statistics, more than three million Americans died in deadly automobile accidents in 2019 2]. Using embedded sensors also, including camera systems, LIDARs, and radars, automated cars may understand their surroundings through the detection of nearby objects and the attempt to make choices in real-time to prevent collisions and maintain safe driving behaviour. Attempting to detect items in the AV area utilizing software-based object detection techniques is one of the key challenges in enhancing AVs' environmental view. Object identification is a vital computer vision task requiring the AV to identify and localize nearby things, such as pedestrians, stoplights, various autos, and barriers. It serves as the foundation for advanced AV functions that as object recognition and tracking, activity recognition, motion detection, and route planning.

The proposed work aims to make it easier for autonomous vehicles to navigate in specific lanes and to provide a means of detecting an object that appears in their route so that appropriate speed control action can be taken at the appropriate time. A novel approach to edge detection has been used based on low-pass filter properties neural network models. To eliminate irrelevant data, an image-based self-adaptive threshold approach was used. This same image area has indeed been segmented into several sections, with the frontal region used to detect objects in the closer region. The SVM-based classification was used to determine object presence based on the statistical characteristics of the available pixel density inside the ROI.

This paper's work has been divided into several sections. Section 2 discusses related work, while the proposed work is discussed in Section 3. The experimental analysis is discussed in Section 4, and a conclusion is provided at the conclusion, along with recommendations for future work.

2. Related Work

A recent review [4] sought the purpose of this systematic review of the latest work at the intersection of computational and computer vision. Its objective was to shed light on the recent advancements in brain-inspired visual recognition design features underlying the visual, neurological method. Obstacles obfuscate the object image or eliminate all its pixels, likely resulting in inadequate features and complicating object recognition. To address this issue, [5] developed a system for recognizing occlusions in object images using visual memory selection (VMS) designs. [6] develops a concept for illusionary object recognition solutions based on neurobiological and neuropsychological investigations of the primate visual system. In computer vision systems, it is crucial to have excellent detection and classification procedures for features. For object recognition tasks, there are many cutting-edge feature detectors & descriptors available. The researchers of [7] compared the effectiveness of the Shi-Tomasi corner detector to extracted SIFT and SURF features and evaluated Shi-performance Tomasi's once integrated with SIFT and SURF descriptors. [8] described a strategy for distinguishing an object using a multi-mode cable. A machine learning-based classifier was fed a set of speckle patterns transmission through a multi-mode fiber. Deep Learning has several disadvantages inside the object recognition application: first, the activation function's capability for nonlinear modelling is limited; second, the deep learning model needs to perform a large number of related pooling operations, which results in information loss. [9] proposed numerous exponential linear values to truly united and capable of learning parameter forms in the brightness of these limitations. This method incorporates 2 previously understood parameters into the exponential linear unit (ELU), enabling it to represent piecewise linear and exponential non-stationary functional areas. [10] proposed a method for converting deep representations of knowledge gained from object and scene datasets to solve the problem of related image-based factors. [11] discussed the problem of recognizing objects with distinctive edge features. A recognizing method based on the local edge features has been presented for this purpose. Each image was first detected for its edge features, but its descriptor must have been calculated to locate the matching features. Each match has cast a vote for the object's location, scale, and orientation. Utilizing 3 (3D) integrated component photography, [12] studied object detection in low-light conditions. With advancements like machine vision (e.g., artificial eye, unmanned aircraft, & surveillance systems), scene semantic recognition (SSR) technology has attracted significant interest due to its applications in automated cars, tourist navigation, intelligent traffic, & remote aerial sensing. While great progress has been achieved in visual interpretation, numerous challenges remain (i.e. occlusion, backgrounds which are dynamic, lack of labelled data, changes in illumination, direction, and size).As a result, [14] introduces a new SSR framework that thoughtfully subdivides object locations, produces an innovative set of Features, and uses Maximum Entropy to recognize scenes. [15] described the automated recognition of underground objects using light identification and ranging (LIDAR) systems; the objective was to distinguish objects based on their physical/chemical properties. We used laser-induced fluorescence (LIF) spectrometry and an ad hoc signal processing loop to efficiently evaluate the LIF spectral region retrieved at the detected object range. [17] discussed the use of these topographically continual features predicated on the objects' shape features to address this issue. Two types of features, sparse persistence image (PI) and amplitude, are obtained by applying continuous homologous recombination to high feature filters. These are multi-directional simple cubic complexes used to represent the object segmentation maps. [19] proposed the use of a Learning - based Generative Adversarial Computer system (RL-GAN) to start generating recognition-optimized super image representations. While most of the existing fully automated registration plate recognition (ALPR) methodologies are focused on a single license plate (LP) category, there has been little research on multiple or mixed LPs. The manuscript [20] proposed a single neural network based on ALPRNet to detect and recognize LPs with mixed styles. Numerous studies in self-driving vehicles, fields of robotics and intelligent assistance systems have been conducted in recent years. In [22], an optimization solution for learning adaptive system hyper-parameters was investigated to increase object recognition accuracy. The proposed method was developed using a framework for discovering a variety of learning hyperparameters based on an evaluation of a previous CNN model using data from the advanced driver assistance systems (ADAS) device revolution. Numerous approaches to hardware development for object recognition have been explored in [23-26].

3. Proposed Work

The proposed solution's detailed process for lane and object detection is depicted in Figure.1. Following image acquisition, the gray-scale transformation was applied if necessary, and pre-processing was defined by dividing an image into a specified lot of small pixels blocks. Normalization was used to convert the pixels' values to those in the range [0 1] so that normalized pixels could be used as input to the neural network. The neural network is often used as a low-pass filter by offering a single node as a hidden layer. With fewer hidden nodes, generalization is impossible, but only lower frequencies information is passed to the output layer. The target has been assumed to be identical to the input image for the output to represent the same image as the input except without the high-frequency signal data inside the original input image. Rough edges were extracted by subtracting the neural network-developed image from the original input image. The rough edges represented the amount of unwanted data removed using the self-adaptive threshold strategy. Estimating the self-adaptive threshold is done using a weighted sum function based on the mean values of the pixel and the standard deviation of each frame. Further refinement of the edges was accomplished by discarding information from the images' side regions to maximize the exposure of the image's central region, which contained the greatest amount of lane information. The refined image was divided into multiple regions, and the pixel's density was estimated to obtain information about the available mean number of pixels and their standard deviation. If there are no objects in the immediate vicinity, the central region of the lane will be devoid of pixels except for those containing lane information. If an object is present, the pixel's density increases, making it a useful parameter for detecting the presence of an object. The linear SVM classifier was used to determine whether the lane contained an object or was empty. The entire procedure is depicted in Figure 1, while the neural network low pass filter design is depicted in Figure 2. The near region of interest is illustrated in Figure 3, where it is assumed that the image is a square matrix and that the internal lines represent the lines that divide the image into various regions. The highlighted region in different colors in Figure.3 is the region of interest, and the pixel's density in this region is estimated. If an object appears in this region, proper precautions must be taken to move the vehicle.

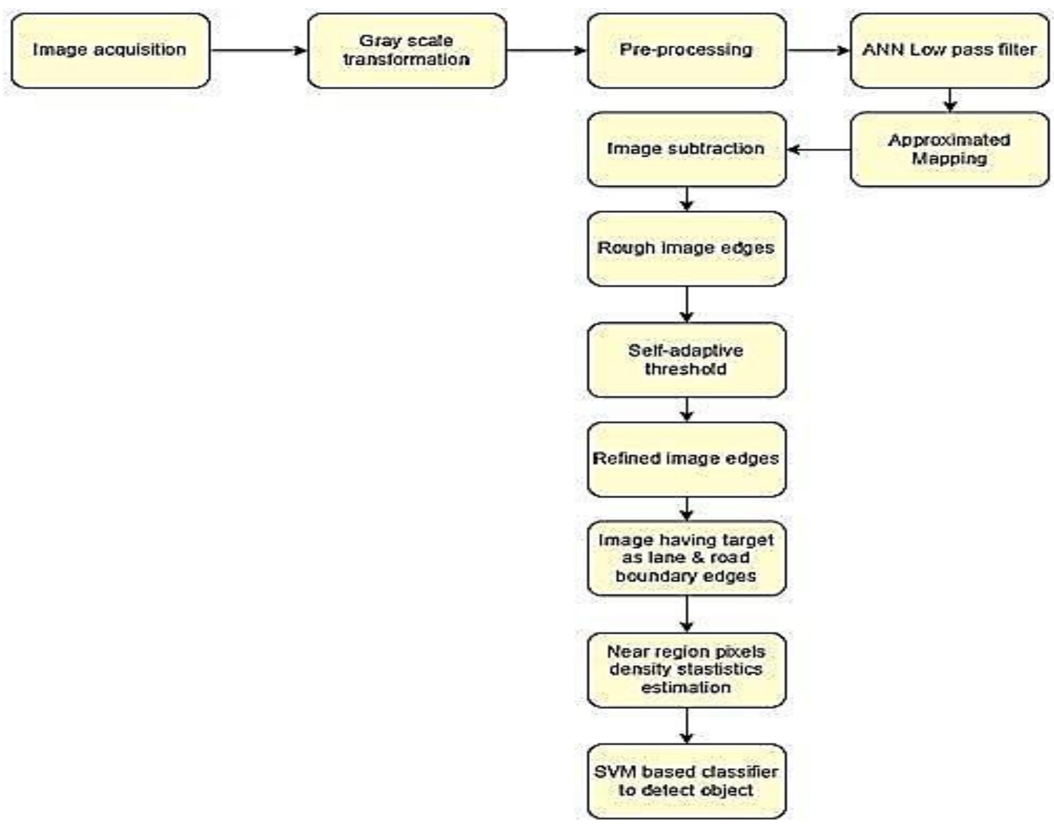

Fig. 1 Complete process flow of the proposed solution for lane and object detection

4. Experimental Results & Analysis

To identify objects and lanes on the road, various real-world images taken from the road were considered for the experiments, each with a different level of complexity. To begin, the greyscale image was divided into 3x3 pixel blocks., More information is lost at the output when there is a larger block size, and less information is passed when the block size is smaller at the local low-frequency level, which is why a moderate size was chosen. Due to the block size, the neural network's size was determined by the [9 1 9] architecture. The active nodes carried the sigmoid transfer function for the uni-model. Five iterations were permitted to minimize the time cost and protect against memorized Learning. Gradient descent-based learning was used with a 0.1 learning rate, and momentum was included to help stabilize the learning process at a 0.1 momentum rate. The adaptive strategy for the slope of the sigmoid function was used, which was updated concurrently with the weight values. Figure.4 illustrates the various stages of image processing, from obtaining rough edges images to fine edges images carrying the region of interest. The entire procedure was developed in the MATLAB environment.

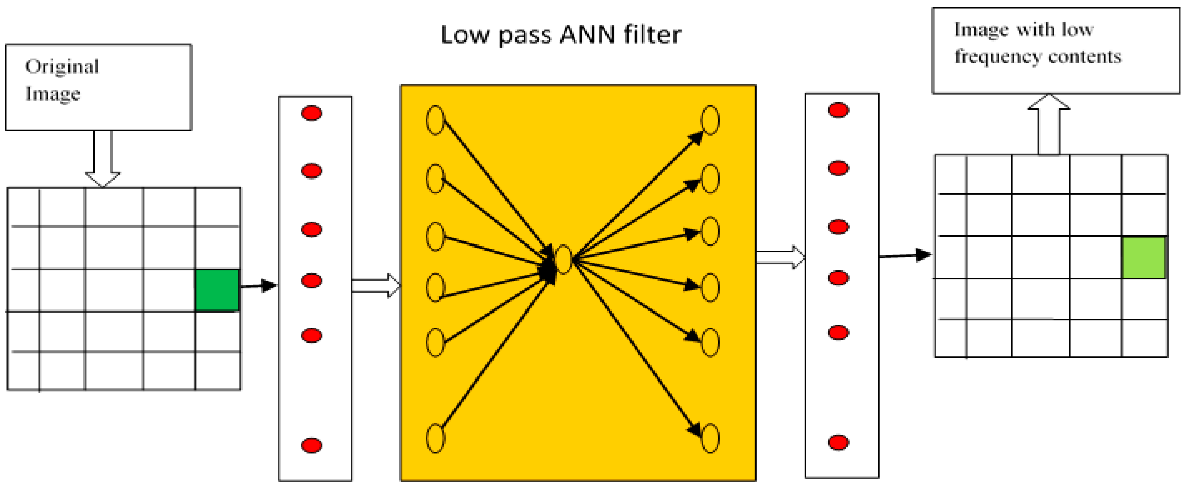

Fig. 2 working modules for NN low pass filter

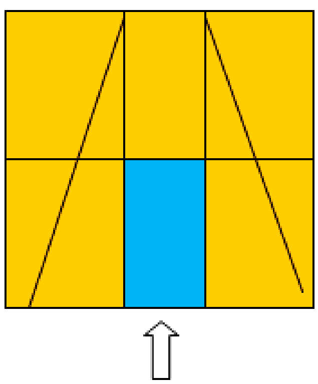

Fig. 3 Region segmentation and region of interest(ROI)

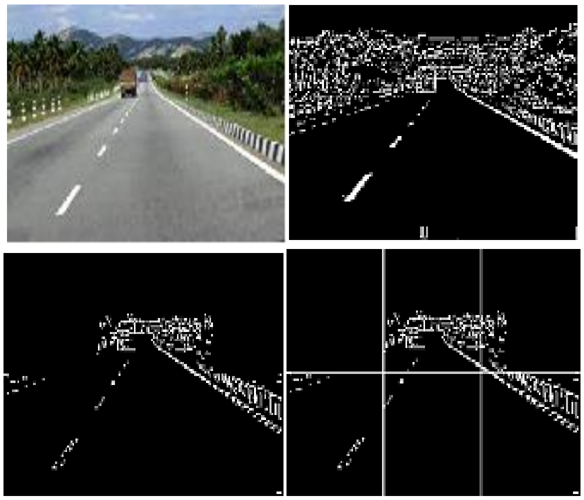

Fig. 4 (a) Original image (b) rough edge image (c) refined edge image (d) region of interest

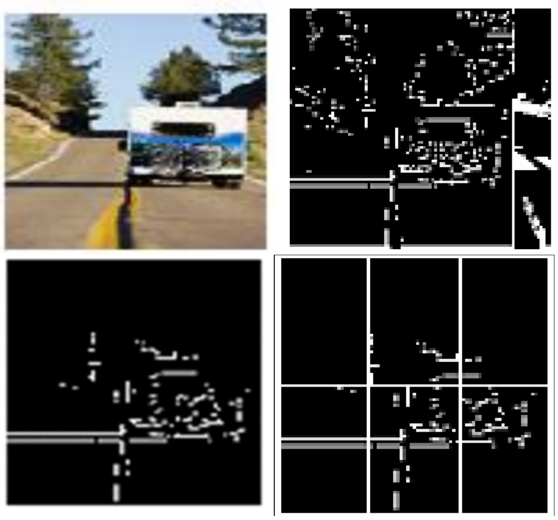

Fig. 5 Road with obstacle

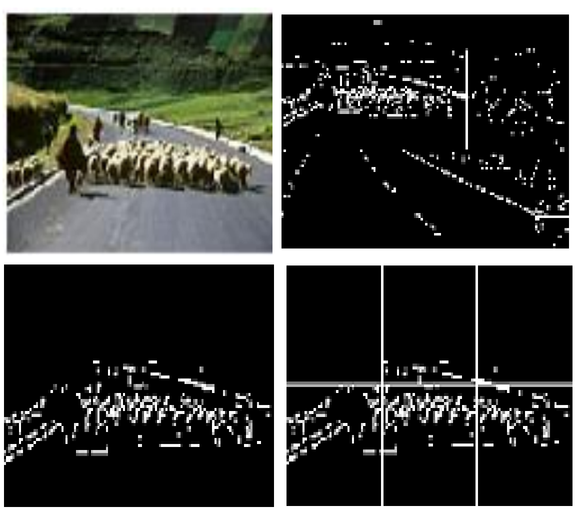

Fig. 6 Road with obstacle

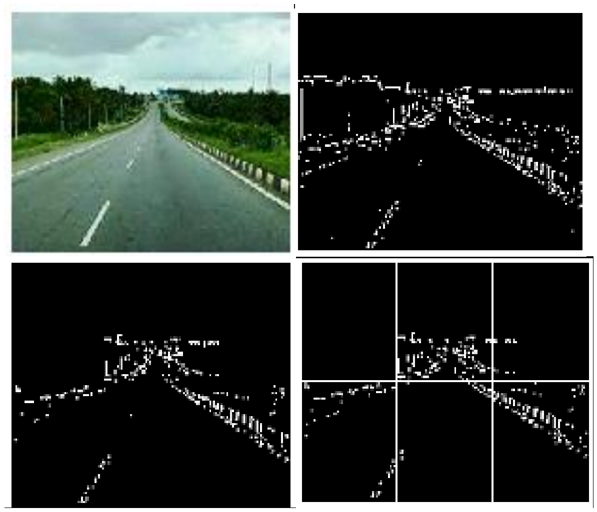

Fig. 7 Road without obstacle

There were 29 images, 10 of which carried objects over the road, while the remaining were devoid. From Figure.4 to Figure.7, the proposed solution's behavior is readily apparent. It is clear from Figure. 5 and Figure. 6 that the region of interest had a high pixel density, whereas the region of interest in Figure.7 had a lower pixel density. The mean and standard deviation for these images have been calculated and are shown in Table 1.

As with Table 1, the pixel density parameters for each image were extracted, and SVM was used to classify the images into two distinct categories: images with an object over the road and images without an object over the road. There were 19 images considered for training purposes and 11 images considered for testing purposes. The SVM demonstrated excellent performance, with an accuracy of 82 percent in detecting objects. Figure.8 illustrates the details of the performances. Table 1. The obtained pixel density in the region of interest

Table 1. Details of Performance

Images	Mean no. of pixels	Std.Dev
Image in Figure.4	0.8459	1.9662
Image in Figure.5	4.9487	5.6333
Image in Figure.6	5.4310	2.4287
Image in Figure.7	0.7816	1.2798

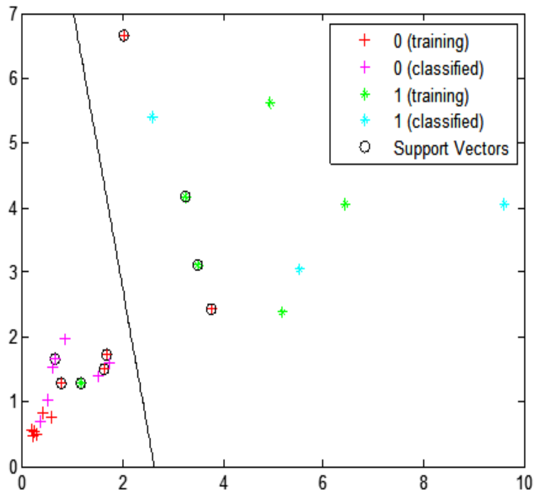

Fig. 8 SVM classification characteristics over training and test data

4.1. Edge detection Comparison with Laplacian and Canny method

The approach to achieve the image edges was applied to Lena's image to compare against different types of existing approaches like the Laplacian method and the Canny method. It was observed that the edges were not very clear, and more noise existed over the edges with the Laplacian and Canny methods. The proposed method has delivered crisp edges without morphological operations and doesn't need any process parameter adjustment.

Fig. 9 (i) Lena Image

(ii) Obtained Complementary Image

(iii) detected edge

(iv)Final image edge after cleaning by the proposed method

(v) Image edges with Laplacian Canny method

(vi) Image edges with method

5. Conclusion

The application areas for object recognition have expanded significantly during the current technological development era. Over the years, development has become more reliant on object recognition. As a result, a solution is required that is both simple and effective. The proposed object detection work utilized an intelligent-based edge detection approach to determine a vehicle's safe path over a road by identifying the road boundaries. The detected lane region was further investigated to determine if there was any nearby object. The pixel density-based approach is extremely efficient, and the object confirmation was achieved using the SVM approach. The proposed work has a wide range of potential applications in the field of autonomous vehicle development. There are several avenues for further investigation of the work. The region-based pixel density can determine the object's type and approximate separation distance from the mode of action. Additional useful information, such as roadside sign-board recognition, can be integrated to expand the scope of facilities.

References

[1] R. Chen, Et Al, "Learning Lightweight Pedestrian Detector with Hierarchical Knowledge Distillation," IEEE Icip, 2019.

[2] Automated Vehicles for Safety, Nhtsa Report, 2021.

[3] V. Kukkala, Et Al, "Advanced Driver Assistance Systems: A Path Toward Autonomous Vehicles ", IEEE Consumer Electronics, Sept 2018

[4] Yang, X., Yan, J., Wang, W. Et Al, “Brain-Inspired Models for Visual Object Recognition: An Overview,” *Artif Intell Rev*, 2022. Https://Doi.Org/10.1007/S10462-021-10130-Z

[5] Jin, M., Yu, L., Zhou, K. Et Al, “Occlusion Tolerant Object Recognition Using Visual Memory Selection Model,” *Appl Intell*, 2022. Https://Doi.Org/10.1007/S10489-022-03253-5

[6] Kietzmann, T.C., Lange, S. & Riedmiller, M, "Computational Object Recognition: A Biologically Motivated Approach," *Biol Cybern*, vol. 100, no.59, 2009.Https://Doi.Org/10.1007/S00422-008-0281-6

[7] Bansal, M., Kumar, M., Kumar, M. Et Al, "An Efficient Technique for Object Recognition Using Shi-Tomasi Corner Detection Algorithm," *Soft Comput,* vol.25, pp.4423–4432, 2021. Https://Doi.Org/10.1007/S00500-020-05453-Y

[8] Takagi, R., Horisaki, R. & Tanida, J, "Object Recognition Through a Multi-Mode Fiber," *Opt Rev*, vol. 24, pp.117–120, 2017. Https://Doi.Org/10.1007/S10043-017-0303-5

[9] Fp., Liu, Je. & Bai, L, "Object Recognition Algorithm Based on Optimized Nonlinear Activation Function-Global Convolutional Neural Network," *Vis Comput,* vol. 38, pp.541–553, 2022. Https://Doi.Org/10.1007/S00371-020-02033-X

[10] Wang, L., Wang, Z., Qiao, Y. Et Al, " Transferring Deep Object and Scene Representations for Event Recognition In Still Images," *Int J Comput Vis*, vol. 126, pp.390–409, 2018.Https://Doi.Org/10.1007/S11263-017-1043-5

[11] Lu, T., Peng, L. & Zhang, Y, "Edge Feature Based Approach for Object Recognition. Pattern Recognit*," Image Anal*, vol.26, pp.350–353, 2016. Https://Doi.Org/10.1134/S1054661816020243

[12] O'connor, T., Markman, A. & Javidi, B, "Overview of Three-Dimensional Integral Imaging-Based Object Recognition In Low Illumination Conditions with Visible Range Image Sensors," *Sn Appl. Sci*, vol.2, no.1724, 2020. Https://Doi.Org/10.1007/S42452-020-03521-4

[13] Youngseok Lee, Yeppeun Lee, Changhyun Jeong, "A Study on the Correlation Between Driving Behavior and Driver's Take-Over Time of Level 3 Automated Vehicle on Real Roads," *International Journal of Engineering Trends and Technology*, vol.69, no.2, pp.112-117, 2021, *Crossref*, https://doi.org/10.14445/22315381/IJETT-V69I2P216

[14] Jalal, A. Ahmed, A. A. Rafique and K. Kim, "Scene Semantic Recognition Based on Modified Fuzzy C-Mean and Maximum Entropy Using Object-To-Object Relations," *In IEEE Access*, vol. 9, pp. 27758-27772, 2021, Doi: 10.1109/Access.2021.3058986.

[15] S. Matteoli, G. Corsini, M. Diani, G. Cecchi and G. Toci, "Automated Underwater Object Recognition By Means of Fluorescence Lidar," *In IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 1, pp. 375-393, Jan. 2015, Doi: 10.1109/Tgrs.2014.2322676.

[16] Yeon Taek Oh, "Study of Wall Climbing Robot Structure and Driving Torque Analysis," *International Journal of Engineering Trends and Technology*, vol.69, no.9, pp.251-256, 2021, *Crossref*, https://doi.org/10.14445/22315381/IJETT-V69I9P230.

[17] E. U. Samani, X. Yang and A. G. Banerjee, "Visual Object Recognition In Indoor Environments Using Topologically Persistent Features," *In IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7509-7516, 2021, Doi: 10.1109/Lra.2021.3099460.

[18] P. Mahalakshmi, R. Vallikannu, "New Miniature Dual Mode Rat-Race Coupler Design for Autonomous Vehicles," *International Journal of Engineering Trends and Technology*, vol.70, no.1, pp.212-215, 2022.

[19] Y. Xi Et Al., "See Clearly In the Distance: Representation Learning Gan for Low Resolution Object Recognition," *In IEEE Access*, vol.8, pp.53203-53214, 2020, Doi: 10.1109/Access.2020.2978980.

[20] Q. Huang, Z. Cai and T. Lan, "A Single Neural Network for Mixed Style License Plate Detection and Recognition," *In IEEE Access*, vol. 9, pp. 21777-21785, 2021, Doi: 10.1109/Access.2021.3055243.

[21] M.Karthikeyan, S.Sathiamoorthy, "Deep Reinforcement Learning for Computerized Steering Angle Control of Pollution-Free Autonomous Vehicle," *International Journal of Engineering Trends and Technology*, vol.69, no.4, pp.204-208, 2021. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V69I4P228.

[22] D. -P. Tran, G. -N. Nguyen and V. -D. Hoang, "Hyperparameter Optimization for Improving Recognition Efficiency of An Adaptive Learning System," *In IEEE Access*, vol. 8, pp. 160569-160580, 2020, Doi: 10.1109/Access.2020.3020930.

[23] N. Wang, Et Al. Nas-Fcos: "Efficient Search for Object Detection Architectures," *Int J Comput Vis*, vol.129, pp.3299–3312, 2021.

[24] X. Zhang Et Al., "Skynet: A Hardware-Efficient Method for Object Detection and Tracking on Embedded Systems", *Proceedings of Machine Learning and Systems*, vol.2, pp.216-229, 2019.

[25] Y. Zhu Et Al, "Acceleration of Pedestrian Detection Algorithm on Novel C2rtl Hw/Sw Co-Design Platform," *IEEE Icgcs*, 2010.

[26] Y. Ma Et Al, "Algorithm-Hardware Co-Design of Single Shot Detector for Fast Object Detection on Fpgas, " *IEEE/Acm Iccad*, 2018

[27] Shanthi, T., Selvakumar, C., & Prabha, S. U, "Design of Fuzzy Logic Controller for Speed Control of Dc Motor Fed From Solar Pv System," *SSRG International Journal of Electrical and Electronics Engineering*, vol.4, no.3, pp.5-9.

[28] Nair, Remya Ravi, and Ramaprasad Poojary, "Image Denoising Using Decision Tree Based Method," *SSRG International Journal of Electronics and Communication Engineering (SSRGIJECE)*, vol.3, no.6.

[29] Hemalatha, P., Lakshmi, C. H., & Jilani, S. A. K. Real Time Image Processing Based Robotic Arm Control Standalone System Using Raspberry Pi," *SSRG International Journal of Electronics and Communication Engineering (SSRG-IJECE),* vol.2, no.8, 2015