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A Novel Approach for Safe Zone Drive Space of Autonomous Ground Vehicle (Self-Driving Car)

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ABSTRACT

Autonomous or self-driving is one of the important research areas of Artificial Intelligence and Robotics. The current scenario is the most suitable condition for researching autonomous driving for maintaining social distance in public transport like UBER, OLA etc. In this paper we are presenting a novel mathematical [Analytical Geometry] model for safe zone driving space in accordance with lane detection and drivable space. Driving space for autonomous vehicle is an environment of real driving which helps to determine driving decision process. This paper reviews the existing research for more systematic understanding of driving space and formulate a problem that how to reconstruct the driving environment. An analytical geometric model has been proposed to determine the safe zone drive space for self-driving vehicle or Autonomous Vehicle.

KEYWORDS

Autonomous Driving; Analytical Geometry; Safe Zone Drive Space

1. INTRODUCTION

Driving a vehicle is an inherently risky or uncertain activity. This in reality is the most dangerous issue in both robotic and human drivers enabled car, however accidents will happen both in a self-driving enabled car or human-driven enabled car. In theory, with a host of many sensors startsng from computer vision to lidars and radars, self-driving cars should be as good or even little better than human enabled drivers at identifying, detecting and bypassing obstacles, provided there is no sensor failures or issues in the embedding software stack. But teaching or training a car to anticipate pedestrian stepping suddenly onto the roadway leads to many challenges. So, to determine the safe zone drive space is one the research area in autonomous driving or self-driving cars.

Human intuition slows the vehicle speed down while driving in a residential neighbourhood with no sidewalks. Some human drivers go slower than 25 km per hour — just to be on the safe side. It isn't regulations but common sense that prompts this sort of defensive driving. But for a machine, what does "drive cautiously" mean? That's a puzzler for a programmer. "How do you make [being] cautious 'machine interpret-able,' and how do you explicitly define it?" Human drivers can easily intuit these types of events, but to make human intuition adaptable or comprehensible by a computer we need to formalize it mathematically, define it, and pick the number behind the definition — whether the result is deemed a "safe speed" in a certain neighbourhood or a safe following distance for Autonomous Vehicle.

We want self-driving cars to drive cautiously as well as we also expect them to be assertive when necessary. Above all, we expect AVs to drive like human driver. The ideal AVs that don't create hazards and "play well with others." Making an AV both safe and "useful" is neither a theoretical nor philosophical discussion.

This is a technical and practical conundrum with which today's AV designers are wrestling [12] [2].

Fig. 1 Autonomous Vehicle Safe Zone [17]

2. LITERATURE REVIEW

2.1 Review

There are model proposed by many researcher considering the control of autonomous vehicle. Nobody has considered the lane and safe space around the vehicle. Our model gives the intuition about the safe zone drive space around the vehicle as well as the safe lane driving for Autonomous Vehicle. Petrov has given the idea of controlling AVs for two vehicle convoy that tracks the path/trajectory of the front vehicle ahead by maintaining inter-vehicle distance as defined. They consider the angular and linear velocities, as well as the curvature radius of the travelled path by the front vehicle and developed an adaptive controller [9]. Steven Shafer and Douglas A. Reece has claimed a dynamic task analysis computational model for developing a model of driving in traffic. They have implemented a driving program for the vehicle's acceleration and lane use by applying traffic and safety rules as constraint, and perfectly shown where the self-driving car needs to keep attention at each moment while driving decisions are finalized [11].

Distance safe driving seems like an elemental practice, even if the driver is a student. But for a machine to keep cautious, needs training of AV to balance numerous factors. It needs to account its velocity, road friction (is it driving on wet pavement?) and its response time. The main computing important parameter is "What is my assumption of the reasonable worst-case braking of the vehicle I am following?" Xiaobo Qu, Mofan Zhou, Sheng Jin has been proposed a vehicle to vehicle interaction for total travel time optimization and smooth traffic behaviour [18]. Hayoung Kim, Kyushik Min, Kunsoo Huh stated a deep reinforcement learning model for driver assistance system for driving in simulated traffic environment of highway with zero collision and by maintaning high speed by analyzing images and LiDAR data [5]. Pin Wang, Ching-Yao, Arnaud has given an idea of vehicle agent needs to be trained for automated lane change behavior so that under diverse and even unforeseen scenarios to take intelligent decision while changing lane using Deep Q-Learning algorithm [13].

Fig. 2 Breaking Space of Various Cars [17]

Manfred Plochl, Johannes ¨ Edelmann has given a driver model for their application and methodical modelling approaches in diverse ways. The importance is given on the automobile (like design and optimization of vehicle components and the overall dynamics of vehicle behaviour) by implementing their approved (mathematical) models [10]. Junqing, John, Jarrod, Bakhtiar has proposed is used for robust single-lane autonomous driving behavior control under uncertainties using a point-based Markov Decision Process (QMDP) algorithm. Three types of uncertainties like perception constraints, sensor noise and surrounding vehicles' behavior have taken into account [14].

The problem gets tricky due to different variants of vehicle manufacturing. As the table below shows, the maximum braking capability of a 2018 Porsche 911GT3 is 12.57 meters per second. In contrast, 1996 Honda Civic brakes at 8.19 meters per second (mps). This is a big difference.

2.2 Deep Learning based Lane Detection

Qin Z, Wang Q, Han T, Gao J, Li X stated a very unique method of multitasking: 1) combining the strong localization ability provided by handcrafted features with semantic information of CNN model and 2) identifying the location of vanishing line. A novel vanishing line prediction for lane fitting model is also proposed for sharp curves and non-flat road [21].

Neven D, De Brabandere B, Georgoulis S, Proesmans M, Van Gool L stated that the lane detection problem as an instance segmentation problem - where each lane forming can be its own instance – which will be trained end-to-end. Before lane fitting they parameterize the segmented lane instances and further propose to apply a trained perspective transformation, conditioned on the image, in contrast to a fixed "bird's-eye view" transformation [22].

Gu X, Huang X, Zang A, Tokuta A, Chen X claims a novel algorithm to combine color images with LiDAR data together. The algorithm consists of a pipeline with two stages. First stage consist of road surface segmentation and with the corresponding color images register LiDAR data. Second stage states that, convolutional neural networks (CNNs) for classifying image patches to lane marking with non-marking training. The algorithms based on handcrafted features being compared with the algorithm to learn a set of kernels for extraction and integration with features from two different methodologies. The pixel-level classification rate in their experiments shows that the algorithm is very robust in different conditions like missing lane, shadows and occlusions [23].

Chen Z, Liu Q, Lian C states an end-to-end lane detection algorithm in which the coordinates the drive scene with lane line points directly, and which could be deployed on the embedded system of NVIDIA PX2. High precision and real-time performance in autonomous driving is the main objective of this algorithm [24].

Bai M, Mattyus G, Homayounfar N, Wang S, Lakshmikanth SK, Urtasun R claims that a novel that LiDAR and camera sensors are producing very accurate estimates directly in 3D space with the advantages of deep neural network. They clearly explained the performance of this approach in both highways and city roads and shown avery accurate results in complex scenarios like heavy traffic (which produces occlusion), fork, merges and intersections [25].

Kumar S, Jailia M, Varshney S First, they states the history of conventional and lane detection deep learning-based methods. Then explain the importance of loss function in the lane prediction. Secondly comparing the experimental results of every technique of deep learning and current CNN Architecture state-of-the-art methods. Third, the existing datasets for lane detection has been summarized, checked the performance evaluation criteria, as well as lane detection based of latest CNN architecture methods are discussed. Finally, taken care of some of the current aspects for deep learning algorithms. [26].

Oğuz E, Küçükmanisa A, Duvar R, Urhan O declared a vision based robust lane detection technique using a novel 1-dimensional deep-learning method has been applied. Challenging complex situations like rain, shadow, and illumination variation in the overall performance of computer vision based techniques. The performance of proposed approach outperforms existing approaches in literature including these challenging situations in terms of detection performance versus processing speed assessment clearly shown by Experimental results. Deep learning techniques which provide high performance has compatibility issues on low-capacity embedded systems, the proposed method has a efficient solution with its lower processing time significantly [27].

Tang J, Li S, Liu P states a comprehensive review of lane detection methods using computer vision. The review begins with an introduction that likely discusses the importance of lane detection in autonomous driving and the evolution of lane detection techniques over time. It introduces both traditional lane detection methods and deep learning techniques, suggesting a historical perspective. The existing lane detection methods are categorized into two classes: two-step and one-step techniques. This categorization likely refers to the number of steps involved in the detection process. The review delves into the network architectures used in lane detection, and these architectures are categorized into different groups, such as classification and object detection-based techniques, end-to-end image-segmentation techniques, and possibly a discussion on optimization strategies. The summary mentions the relevance of loss functions in lane detection, indicating that different loss functions may be discussed in the review to improve the understanding of their application in this context. The review likely highlights the strengths and weaknesses of each lane detection process, which can provide readers with insights into the trade-offs involved in choosing a particular method. A short comparison is presented, likely to help readers quickly assess the differences and similarities between key lane detection techniques. The review addresses complex scenarios and challenges in lane detection, such as computational intensity and issues related to generalization, providing a realistic perspective on the limitations of existing techniques.The review concludes by suggesting areas for future research, including semi-supervised learning, meta-learning, neural architecture search, and other potential direction for advancing lane detection technology. [28].

Huang Y, Chen S, Chen Y, Jian Z, Zheng N consists of three parts: (i) This step involves applying an inverse perspective transform to the input images, which helps in converting the view of the road into a top-down perspective. Spatial and temporal constraints of lane boundaries are used to estimate the position of the lane boundaries. This is a crucial step in understanding the layout of the lanes on the road. (ii) CNNs are used for two key tasks. First, they classify the type of boundaries (e.g., solid, dashed) detected in the transformed images. Second, they perform position regression, which helps in accurately determining the precise location of the detected lane boundaries. CNNs are well-suited for image analysis tasks like this due to their ability to learn features from the images. (iii) After detecting lane boundaries and classifying their types, an optimization step is performed to refine the detected lanes. This may involve smoothing the boundaries and ensuring they are consistent over time. Lane fitting is also a part of this process, which involves creating a smooth representation of the lanes. Besides, They also realized the application of our algorithm on embedded platforms and verified the algorithm's real-time performance on real self-driving cars [29].

Qin Z, Wang H, Li X introduce a novel lane detection approach, FastLane, designed to achieve exceptional speed and accuracy, especially in challenging scenarios. FastLane treats lane detection as a row-based selecting problem using global features, reducing computational costs significantly. By incorporating a large receptive field for global features, it excels in handling complex scenarios. Additionally, we propose a structural loss to explicitly model the structure of lanes. Extensive experiments on two lane detection benchmark datasets demonstrate that FastLane achieves state-of-the-art performance in terms of both speed and accuracy. Notably, a lightweight version of FastLane can achieve 300+ frames per second at the same resolution, outperforming previous state-of-the-art methods by at least 4x. [30].

Baek SW, Kim MJ, Suddamalla U, Wong A, Lee BH, Kim JH a benchmarking It appears that you are describing a study or project related to lane detection using deep learning techniques. In this project, different deep learning models were applied to lane detection, and their performances were compared to assess their suitability for optimizing real-time performance and accuracy. Here's a breakdown of the key components and concepts mentioned in your description: Feature extraction modules are parts of a neural network that are responsible for identifying important features in the input data. In this case, lightened feature extraction modules were used to extract relevant information from the input images. Decoder modules are used to reconstruct the spatial information from the extracted features. In this project, different decoder modules were applied. VGG-16, MobileNet, and ShuffleNet are examples of neural network architectures used for the encoder module. These architectures are known for their varying levels of complexity and computational efficiency. Frontend dilation refers to the use of dilated convolutions in the front-end layers of the neural network. This can be used to increase the receptive field of the network and capture more contextual information. UNet is a popular architecture for semantic segmentation tasks, which is commonly used in lane detection. It consists of an encoder-decoder structure. The project includes a benchmarking framework, which is a systematic approach to evaluating the performance of different models. It involves using performance metrics to compare models and select the best one. Perspective loss likely refers to a loss function or concept designed to account for the perspective distortion that occurs in images taken from the front view. This concept is aimed at improving accuracy and operating speed. The TuSimple dataset is a well-known dataset for lane detection, often used for benchmarking and evaluating lane detection models. It contains a large number of annotated road images for training and testing. In addition to the TuSimple dataset, it seems that a local dataset collected and verified in Singapore was also used. This local dataset is likely more specific to the project's target environment and may help improve the model's performance under local [31].

Lee DH, Liu JL a novel approach to lane detection and path prediction in the context of autonomous driving using a modified version of the UNet architecture called DSUNet (Depthwise Separable UNet). Here's a breakdown of the key points mentioned in the passage: UNet is a popular architecture for semantic image segmentation. It is commonly used for tasks like identifying objects and boundaries within images. DSUNet is a modification of the UNet architecture that utilizes depthwise separable convolutions. Depthwise separable convolutions are a type of convolutional layer that reduces the number of parameters and computation, making the network more efficient. The goal of this work is to perform both lane detection and path prediction for autonomous driving applications. Lane detection typically involves identifying and tracking lane markings on the road, while path prediction aims to anticipate the future trajectory of the vehicle. In addition to using DSUNet for lane detection, the authors also integrate a path prediction algorithm with a convolutional neural network (CNN) to create a simulation model known as CNN-PP. The CNN-PP model is used to assess the performance of the CNN qualitatively, quantitatively, and dynamically. This likely involves evaluating the model's predictions both in terms of visual quality and numerical metrics. DSUNet is highlighted as being significantly more efficient and faster during inference compared to the original UNet. It is 5.12 times lighter in terms of model size and 1.61 times faster. The performance of DSUNet-PP is compared to UNet-PP in a dynamic simulation environment. DSUNet-PP outperforms UNet-PP in terms of mean average errors related to predicted curvature and lateral offset. In addition to simulation, DSUNet-PP is also tested in a real car on real roads, and it outperforms a modified UNet in terms of lateral error.[32].

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3. PROPOSED MODEL

In this paper we have designed a mathematical model for safe zone drive space of Autonomous vehicle [SaveNet (Safe Autonomous Vehicle Environment Network)].

There are three types of models given by many researcher for AV's drivable space. These are Grid space, Feature space and Topological space [15].

In our proposed model we are considering the feature space for the construction of safe zone driving space for Autonomous Ground Vehicle. Obstacles are shown by their coordinate position and geometric shapes while the space boundary is fit into an analytic formula. The whole space is described and constructed geometrically in comparison discrete description in grid space. The feature space is described by geometric figures composed of angles, edges, and curves, and some researchers also consider the speed of the obstacles. Here we have described the whole space by a analytical geometry model.

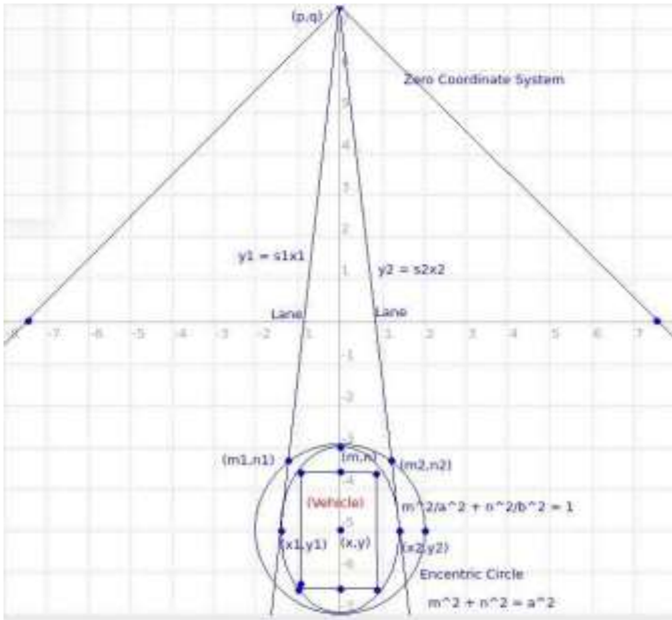

Fig. 3. Autonomous Vehicle's Safe Zone Drive Space Model

In Figure 3 the model has been described.

Vehicle center point: (x, y)

Point (m, n) lies in ellipse and circle centered at point (x, y).

The vehicle is represented by an ellipse: m2/a2 + n2/b2 =1.

The encentric circle of the ellipse: m2 + n2 = a2.

Zero point of the coordinate system: (p, q).

Two tangent from (p, q) to ellipse are y1 = s1x1 and y2 = s2x2 touched at point (x1, y1) and (x2, y2).

The bisector of lane lines and the ellipse intersect at point (m, n).

The two lane intersect the circle at point (m1, n1) and (m2, n2).

From the above mathematical model if we can learn four points as described by the model (x1, y1), (x2, y2), (m1, n1), (m2, n2) then we can identify the lane mathematically and draw graphically also.

We can easily calculate whether a point (x1, y1) lies on the ellipse or outside and inside according to (x1 2/a2 + y1 2/b2) equal to, greater than or less than 1. This helps us to generate a warning message about the obstacle that comes within the safe drivable region. The major axis of ellipse having distance a help us to calculate a distance of 2a if front of the vehicle for safe drivable space.

There are many researchers who have proposed their mathematical model for self-driving car is given in table I. With the help of computer vision and machine learning we can graphically represent a lane which is not actually present in the image. However virtual lanes can be drawn using digital geometry and computer graphics. There can be various kinds of lane marking possible or the lane may not be present in the roads. In this scenario our model helps to find the virtual lane of autonomous vehicle for safe zone drive space.

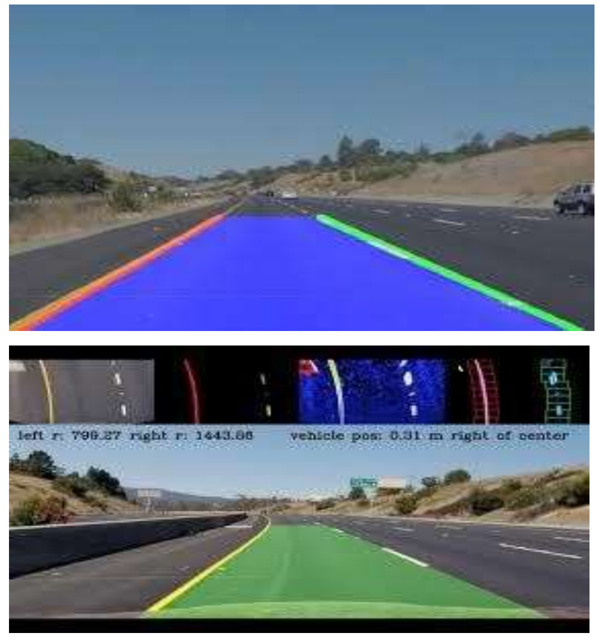

Fig. 4 Autonomous Vehicle Lane Pattern [1]

Table.1 Comparative analysis with another mathematical model of autonomous vehicle

Model Name	Method
Driving Space for Autonomous Vehicles [15]	Learning Based and Rule Based Decision
Autonomous Vehicle Convoy [9]	Learning the Linear, Angular velocities and Radius of Curvature of the path from lead vehicle
Responsibility-Sensitive Safety (RSS) [12]	Measuring Longitudinal Distance and Probabilistic
Ulysses [11]	Dynamic Task Analysis
SaveNet (Our Model)	Fitting Ellipse and Learn coordinate point around the vehicle and Lane

Table. 2 Lane detection accuracy by various ai based learning model on tusimple dataset

Algorithm	Accuracy	FP	NP
ResNet-18 [4]	92.69%	0.0948	0.0822
ResNet-134 [4]	92.48%	0.0918	0.0796
ENet [8]	93.02%	0.0886	0.0734
LaneNet [6]	96.38%	0.0780	0.0244
EL-GAN [3]	96.39%	0.0412	0.0336
SCNN [7]	96.53%	0.0617	0.0180

Using computer vision and video analytics and LiDAR sensor data fusion we will get the obstacle around the autonomous vehicle to keep it in a safe zone. From the image and video analytics we can generate the radius of curvature of the lane in turning road point. There are few software available in the market for controlling autonomous vehicles. The advantage of our model **SaveNet** is a very simple analytical geometry computation. This mathematical model help us to find out any kind of obstacle around and in front of the vehicle. The model helps to find the lane if there is no lane present in the road. The robustness and simplicity for controlling Autonomous Vehicle in our model create a uniqueness compared to other model.


Key Autonomous Vehicle Software Platforms: USA

	Waymo Driver	Cruise	Argo AI	Aurora Driver	Aptiv
AV start	2009	2013	2016	2017	2015
AVs in-use	600+	250+	150+	50+	120+
Employees	1,500 range	2,000 range	700 (7/2019)	400+	700 (AV only)
AV rides	120K+ in Phoenix	Employees only	Tests only	CA permit 1/2020	110K+ Las Vegas
AV road miles	20M+; 1M/month	2M+	No public data	0.2M+	[illegible]
Virtual miles	15 B+; 1B/month	No public data	No public data	Millions/day	No public data
Partners	Waymo One; Nissan-Japan; Renault-France; UPS-goods AVs	GM; Honda; Softbank	Ford; VW; Walmart & Lyft; Domino-Postmates	Hyundai; Fiat Chrysler; Byton; Amazon	Lyft; Hyundai JV; BMW; Intel-Mobileye
AV use-cases	Robo-taxi; Goods delivery; Autonomous trucks	Robo-taxi; Flexible route AVs; Goods delivery?	Robo-taxi; Goods delivery; Flexible route AVs	Robo-taxi; Autonomous trucks; Flexible route AVs	Robo-taxi; Flexible route AVs; OEM-specific
Test areas	Phoenix, AZ; California; GA-MI-TX-WA; 25+ cities total; AZ-NM-TX (trucks)	San Francisco; Detroit, MI; Plan: New York	Pittsburgh & Detroit; Miami, FL; Washington DC; Palo Alto, CA; Austin, TX	California; Pittsburgh, PA	Las Vegas, NV; Boston, MA; Singapore; Pittsburgh, PA
L4 ready	August 2019	2021-22	2021	2022	2021-22

Fig. 5 Autonomous Vehicle's Software stack [16]

We have proposed only the mathematical model and yet to be implemented physically with state of art embedded system infrastructure using Machine Learning and Computer Vision. In our model we have detected the vehicle around the ego vehicle using YOLOv8[19] object detection model and identifying the coordinate point to calculate the closeness of other vehicle in our system. In literature there are models given with the lane detection accuracy for autonomous driving in the below table II.

3.1 Basic Idea of Object Detection

The basic idea of detection in SAVE-net involves identifying and localizing objects around the ego vehicle to create a safe driving zone estimation as well as plotting a pair of straight line as lane around the ego vehicle. We have chosen the YOLOv8 model for this particular problem, and its selection offers several advantages:[19]

a. Real-time Object Detection: YOLOv8 (You Only Look Once version 8) is known for its real-time object detection capabilities. It can process images and detect objects in a single pass, making it suitable for applications where low latency is crucial, such as safe driving.

b. High Accuracy: YOLOv8 builds upon the earlier versions of YOLO (You Only Look Once), which have a track record of achieving high accuracy in object detection tasks. This accuracy is vital for identifying and localizing objects accurately for safe driving zone estimation.

c. Versatility: YOLOv8 is a versatile model that can detect a wide range of objects, including vehicles, pedestrians, and other relevant elements in the driving environment. This versatility is essential for comprehensive situational awareness.

d. Efficiency: YOLOv8 has been optimized for efficiency, making it feasible to deploy on resource-constrained platforms, which is essential for practical applications in vehicles.

3.2 YOLOv8 Object Detection Algorithm

The algorithm behind YOLOv8 is a single-stage object detection algorithm. This means that it predicts bounding boxes and class probabilities for objects in an image in a single pass of a convolutional neural network (CNN).[20]

The YOLOv8 architecture is divided into two main parts: the backbone and the head. The backbone is a CNN that extracts features from the input image. The head is a neural network that takes the features extracted by the backbone and predicts bounding boxes and class probabilities for objects in the image.

The YOLOv8 backbone is a modified version of the CSPDarknet53 architecture. This architecture consists of 53 convolutional layers and employs cross-stage partial connections to improve information flow between the different layers.

The YOLOv8 head consists of multiple convolutional layers followed by a series of fully connected layers. The convolutional layers in the head are used to fuse features from different levels of the backbone. The fully connected layers in the head are used to predict bounding boxes and class probabilities for objects in the image.

To predict bounding boxes, YOLOv8 uses a grid anchor mechanism. The image is divided into a grid of cells, and each cell predicts three bounding boxes for different object sizes and aspect ratios. The bounding boxes are predicted in the form of four coordinates: the top-left corner x-coordinate, the top-left corner y-coordinate, the bottom-right corner x-coordinate, and the bottom-right corner y-coordinate.

To predict class probabilities, YOLOv8 uses a one-hot encoding scheme. Each cell in the grid predicts a probability for each class of object. The class with the highest probability is assigned to the bounding box predicted by the cell.

YOLOv8 is trained using a supervised learning approach. The training data consists of images with labeled objects. The model is trained to predict bounding boxes and class probabilities for the objects in the training images.

Once the model is trained, it can be used to detect objects in new images. The model takes an image as input and predicts bounding boxes and class probabilities for the objects in the image. The bounding boxes and class probabilities can then be used to visualize the detected objects in the image.

YOLOv8 is a fast and accurate object detection algorithm that is well-suited for real-time applications. It is also relatively efficient, making it feasible to deploy on resource-constrained platforms.

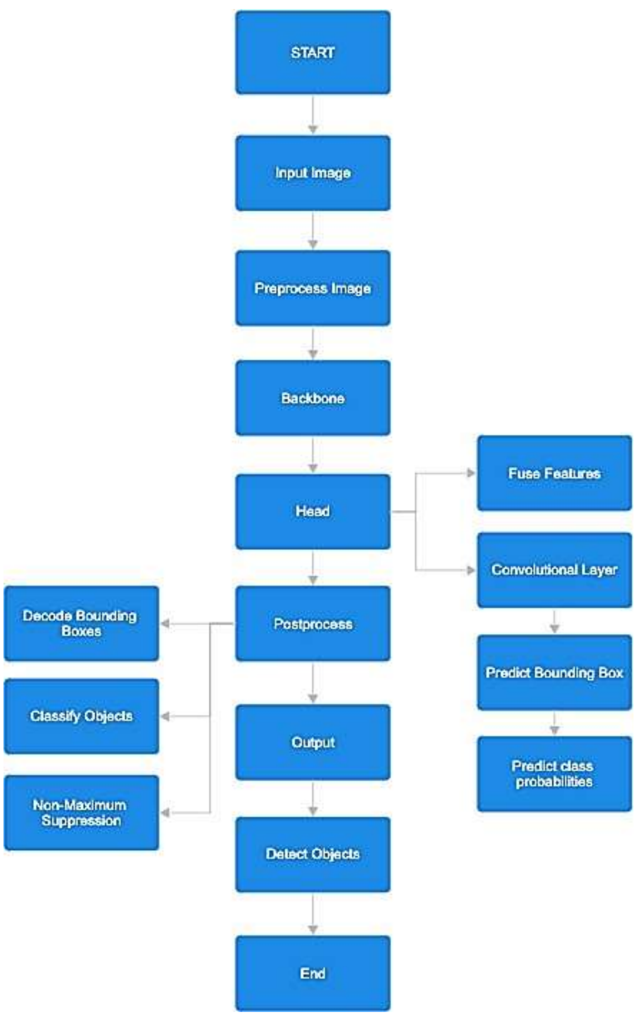

Fig. 6 YOLOv8 Object Detection Algorithm [16]

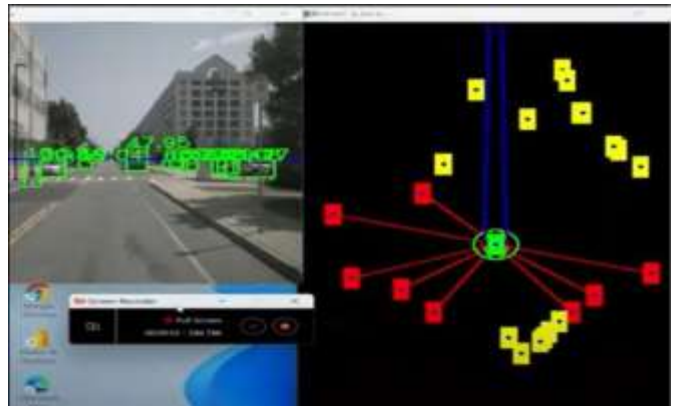

Fig.7 Resultant image of our model after detecting the close vehicle

4. CONCLUSION

Here we have shown only the mathematical model for safe zone drivable space of autonomous vehicles. We have to implement the AI-based model to learn each and every coordinate point to compute the drivable space for autonomous vehicles. With the help of Computer vision and Artificial Intelligence along with Machine Learning, many researchers have implemented lane detection models. In this paper, we have used an analytical geometry approach for lane detection and safe zone drive space of autonomous vehicles. The future scope is to implement this analytical geometry model using state of AI techniques and Machine learning algorithms. However Virtual lane can be drawn with the help of digital geometry and computer graphics where there is no lane marking. In India, there is no lane marking in most of the highways. Our model works well to generate a virtual lane with the help of above said mathematical model.

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