

Vehicle Detection in Foggy Weather using Deep Learning.

Miss. Nimse Shweta¹, Miss. Phaphale Apeksha², Miss. Thorat Mayuri³, Miss. Walave Prajakta⁴
Prof. S. A. Thanekar⁵

Students, Department of Computer Engineering^{1,2,3,4}

Professor, Department of Computer Engineering⁴

Amrutvahini College of Engineering, Sangamner, Maharashtra, India

Abstract: Vehicle detection is the key to driverless technology. For safety, driverless technology requires extremely high accuracy and real-time for vehicle detection in different situations. Foggy weather can cause such problems as blurred image information and the loss of image details, which may pose great challenges to the vehicle detection based on images and videos. Deep learning-based object detection methods have achieved promising results on the conventional datasets. The existing methods either have difficulties in balancing the tasks of image enhancement and object detection, or often ignore the latent information beneficial for detection. In this project we are using YOLO based algorithm for vehicle detection in foggy weather conditions.

Keywords: Deep Learning, YOLOV3, Vehicle detection, Foggy weather

I. INTRODUCTION

Deep learning is a subset of machine learning that is essentially a three- or more-layered neural network. These neural networks seek to imitate the behaviour of the human brain, albeit with limited success, allowing it to “learn” from enormous volumes of data. While a single-layer neural network may still produce approximate predictions, more hidden layers can assist optimise and tune for accuracy [1] Many artificial intelligence (AI) apps and services rely on deep learning to boost automation by executing analytical and physical activities without human interaction. Deep learning technology is at the heart of both common products and services (such as digital assistants, voice-enabled TV remote controls, and credit card fraud detection) and upcoming technologies (such as self-driving automobiles). Deep learning neural networks, also known as artificial neural networks, try to simulate the human brain by combining data inputs, weights, and bias. These components collaborate to effectively recognise, categorise, and characterise objects in data. Deep learning neural networks, also known as artificial neural networks, try to simulate the human brain by combining data inputs, weights, and bias. These components collaborate to effectively recognise, categorise, and characterise objects in data. Convolutional neural networks may also substantially cut calculation time by utilising GPU for computation, something many networks do not do. Image processing is the process of changing or improving photographs in order to obtain a new outcome. Optimising brightness or contrast, boosting resolution, obscuring sensitive information, or cropping are all examples. With the continual development and widespread use of deep learning and computer vision technology, cite vision-based vehicle target recognition has emerged as the primary technological approach for detecting road traffic targets. Current relevant research results can provide good detection effects in a traditional traffic setting. However, in a foggy environment, atmospheric light is scattered by water vapour and particles in the air, which causes an increase in the whiteness of the image collected by the camera, a reduction in image contrast, and a lack of image details, which significantly raises the difficulty in object detection, particularly on the highway where foggy weather is common due to the influence of geographical characteristics and local climatic conditions Furthermore, the camera’s high position and the rapid speed of traffic flow may make traffic target recognition more difficult. Vehicle recognition is a topic that has lately gained prominence as autonomous cars have gained traction. To ensure that self-sufficient automobiles can safely operate in settings with people in them, the vehicle must be able to recognise and maintain a strategic distance from the vehicle in both long and short ranges, day and night, while keeping movement in mind [2] According to a survey conducted in 2016-17, the majority of accidents

occur due to intense fog, which impairs driver visibility. Furthermore, evidence demonstrates that snowfall causes more accidents and reduces visibility. As a result, the driver was unable to see the car ahead or the impediment ahead. [3] Presents a pure computer vision solution for improving vehicle detection accuracy, which means that driving in extreme weather conditions such as fog can be achieved without the need for other expensive equipment such as LiDAR. They have used the BDD100K data source, involving different practical application scenarios, using the MSRCR algorithm for preprocessing, and using the YOLOv4 model for training, resulting in a vehicle detection model with improved accuracy. To perform domain adaptation for the actual foggy scenario [4] suggested a domain adaptable road vehicle target recognition approach. They employed the cycle-GAN approach to distinguish between foggy images and real image conditions, to detect vehicles. So our goal is to provide a novel technique to obstacle recognition that is based on moving objects. This method is more beneficial for recognising the various and minute barriers in which fog covers the item, allowing driver aid and gaining greater safety.

II. GOALS AND OBJECTIVES

- To investigate and compare various object detection techniques in deep learning domain.
- To design and implement a IA-YOLO approach to improve object detection in adverse weather conditions
- To develop better vehicle detection system in foggyweather condition and compare it with existing techniques.

III. DATASET USED

The DAWN (Detection in Adverse Weather Nature) dataset is made up of real-world images taken in a variety of unfavourable weather circumstances. This dataset focuses on abroad traffic environment (urban, highway, and motorway) as well as a wide range of traffic flow. The DAWN dataset is made up of 1000 images from real-world traffic situations that are separated into four weather conditions: fog, snow, rain, and sandstorms. This data aids in assessing the impact of inclement weather on the functioning of vehicle detecting systems. Images in the DAWN dataset are gathered using the Google and Bing search engines during a visual search that includes a list of query keywords (for example, foggy, haze, mist, nasty winter weather, blustery weather, heavy snow hits, sleet rain, sandstorm, duststorm, hazardous weather, adverse weather, traffic, motorway, vehicle). [5] We also used the COCO dataset, which has around 328K pictures. These images are divided into 80 categories and include about 1.5 million object instances. COCO holds information in a JSON file that is organised into info, licences, categories, photos, and annotations. [6]

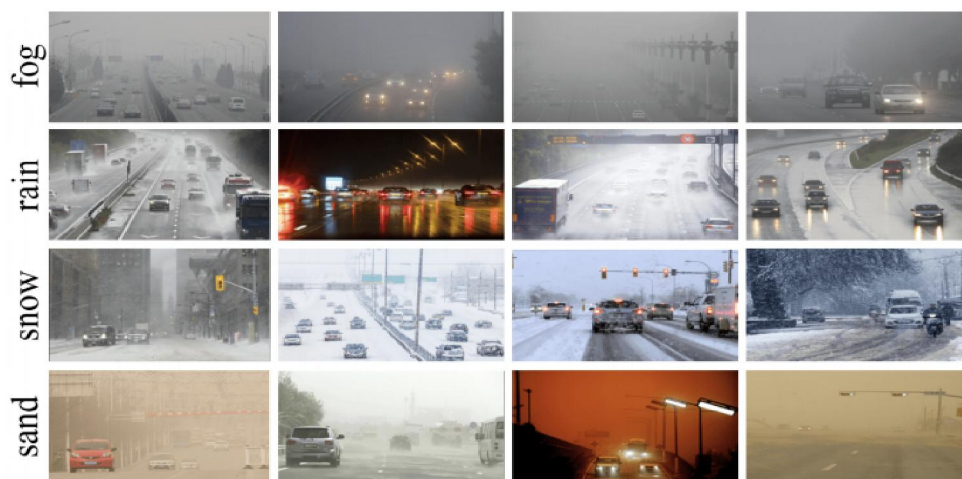


Fig. 1 Sample images of the DAWN dataset illustrating four cases of adverse weather conditions

IV. PROPOSED METHODOLOGY

1) Image preprocessing

Grayscale Image Formation:

It helps in simplifying algorithms and as well eliminates the complexities related to computational requirements. It makes room for easier learning for those who are new to image processing. This is because grayscale compressors an image to its barest minimum pixel.

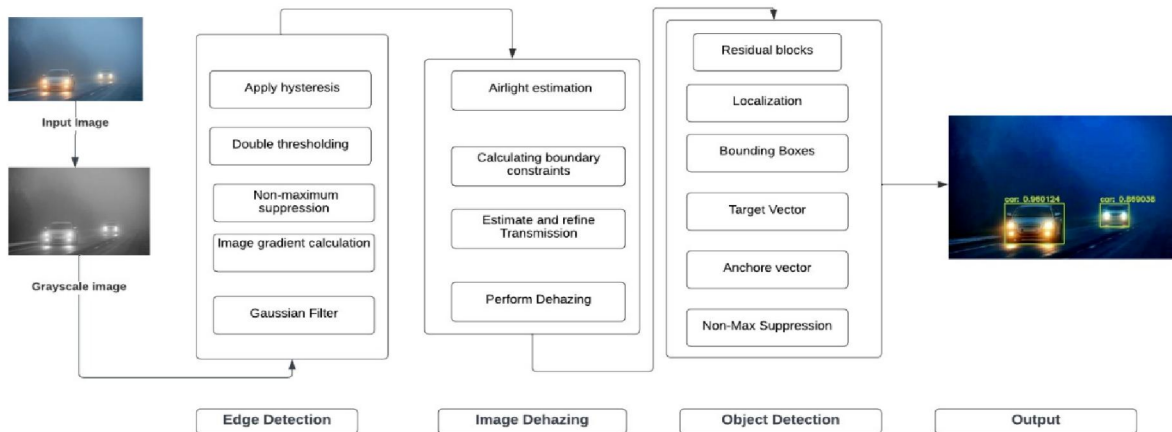


Fig.2. Architecture Diagram

Edge Detection: The Edges detection algorithm is mainly used for the edges detection as well as for generating the ground truth of the image. In our proposed system we have used canny edges detection algorithm for detecting the edges of the image CED uses a multistage algorithm to detect edges. The process is as follows:

Apply a Gaussian Filter: The original picture is smoothed using a Gaussian filter to eliminate image noise that may cause false-positive edge detection. Gaussian filters replace each pixel in a picture with a weighted average of neighbouring pixels. The pixels are weighted in a way that resembles a normal distribution (thus the name 'Gaussian'), with greater neighbour pixels having lower weights. The number of neighbours included inside the average is flexible, and the smoothness of the picture after filtering is determined by the size of the region averaged across.

Calculate the image gradient: The image gradient is calculated by convolving the source image with a derivative filter and getting the first-order partial derivatives, which comprise the (image) gradient vector representation. A prospective edge is simply identified by the values containing the fastest rates of change, therefore the derived values with the largest magnitude are candidates for possible edges.

Apply non-maximum suppression: Non-maximum suppression is a technique for removing unnecessary edge candidates. It works by iterating through all pixel values, compared the current value to the pixel value in the positive and negative gradient directions, and eliminating the current value if it does not have the greatest magnitude in comparison to its neighbours.

Apply double thresholding: Using a low and high threshold value, double thresholding is used to divide the remaining edge pixels into three groups. If the value of an edge pixel exceeds the high threshold value, it is classified as a strong edge pixel, If the value of an edge pixel is less than the high threshold value but larger than the low threshold value, If the value of an edge pixel is less than the high threshold value but larger than the low threshold value, it is classified as a weak edge pixel with a chance of being an edge. If the value of an edge pixel is less than both the high and low threshold values, it is classified as having a very low likelihood of being an edge and is suppressed.

Apply hysteresis: The CED algorithm concludes with hysteresis. It chooses which values from the weak edge category should be added to the final edge detection image. The process simply determines whether a weak edge pixel is linked (neighbored by) a strong edge pixel. If this is the case, the weak edge is included; otherwise, it is eliminated.

2) Image dehazing:

The main objective of our project is to remove fog parameter from image dataset. for removing fog from image image-dehazerpacakage.

The algorithm can be divided into 4 parts:

Airlight estimation

Calculating boundary constraints

Estimate and refine Transmission

Perform Dehazing using the estimated Airlight and Transmission [7]

3) Object detection using YOLO v3:

You Only Look Once (YOLO) is a leading-edge, real time item-detecting technology. To retrieve the locations of all objects among the image, their classes, and associated confidence probabilities, you simply enter the image and run an inference. Previous detection techniques applied models to images of various sizes and locations. YOLO takes a whole image, splits it into regions, then predicts bounding boxes and probabilities for each region using a single neural network. Each picture's information is the N items it includes, and each object has five bits of information, namely the object's centre location (x, y), height, and width. Every object has five bits of information: it's centre location (x, y), height (h), width (w), and class. YOLO splits the input image into $S \times S$ grids, with each grid in charge of identifying items in its own grid. If the coordinates of an object's centre location fall inside a grid, the grid will be accountable for detecting that object.[3] Object detection is a phenomenon in computer vision that involves the detection of various objects in digital images or videos. Some of the objects detected include people, cars, and animals. Object detection consists of various approaches such as fast R-CNN, Retina-Net, and Sliding Window detection but none of the aforementioned methods can detect object in one single run. So there comes another efficient and faster algorithm called YOLO algorithm.

a) Key concept

i) Residual blocks: In Residual Block First, the image is divided into various grids. Each grid has a dimension of $S \times S$. Normally, we use dimensions 3×3 , 13×13 and 19×19 . There are many grid cells of equal dimension. Every grid cell will detect objects that appear within it.

ii) Localization: The term 'localization' refers to where the object in the image is present. In YOLO object detection we classify image with localization i.e. a supervised learning algorithm is trained to not only predict class but also the bounding box around the object in image.

iii) Bounding boxes: A bounding box is an outline that highlights an object in an image. Every bounding box in the image consists of the following attributes: Bounding box center (bx, by) Height (bh) Width (bw) Class (for example, person, car, traffic light, etc.). This is represented by the letter c.

iv) Target label Y: Target label y for this supervised learning task is explained as PC. Pc is the probability of presence of particular class in the grid cell. $Pc \in [0, 1]$. (i.e., $Pc=0$ means that object is not found. $Pc=1$ means 100% Next, if there is an object then our next concern is the definition of bounding box by 4 parameters i.e., Bx, By, Bh, Bw where (Bx, By) defines the mid-point of object and (Bh, Bw) defines the height and width of bounding box. Also, if $Pc = 0$ then there will be n number of C which represents the classes of objects present in the image.

v) Anchors / Priors: One of the problems with object detection as it is so far is that each of the grid cells can detect only one object For example the image on right side has 2 objects in it; car, pedestrian Mid Point of both falls in same grid cell. So algorithm won't be able to output 2 detections, There comes an idea of anchor boxes, with anchor boxes, we can predefine two different shapes called, anchor boxes or anchor box shapes and now we can be able to associate two predictions with the two anchor boxes.

vi) IOU-RANGE: The IOU of two boxes can have any values between 0 and 1. In case there are 2 boxes that do not intersect, the area of their intersection would be 0, and therefore the IOU would also be 0. In case there are 2 boxes that completely overlap, the area of the intersection would be equal to the area of their union, and therefore the IOU would be 1. An Intersection over Union score greater than 0.5 is normally considered a "good" prediction.

IOU = Intersection (area of overlap)/union.

V. RESULT

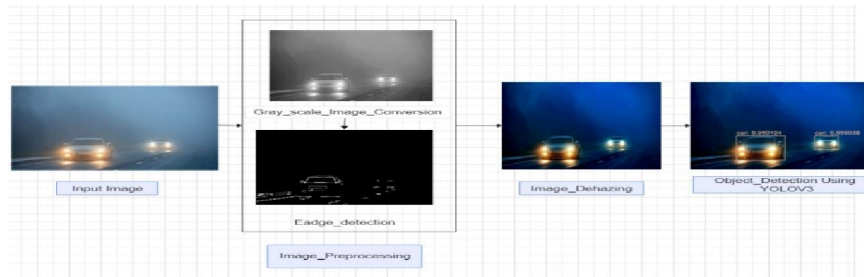


Fig.3. Overall Process

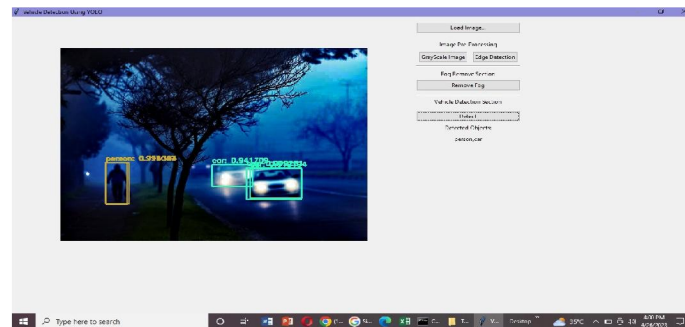


Fig.4. Output Image

VI. CONCLUSION

The insufficient accuracy of vehicle detection technology in foggy weather, this system uses only computer vision to improve the accuracy of vehicle detection. It is a great challenge to detect vehicles under various foggy climatic scenarios. we proposed a vehicle detection and tracking approach in adverse weather conditions that achieves the best trade-off between accuracy and detection speed in various traffic environments. Also a novel dataset called DAWN is introduced for vehicle detection and tracking in adverse weather conditions (e.g. heavy fog). The unique characteristics of the new dataset, DAWN, give us a chance to examine aspects of vehicles detection that have not been examined before in the literature, as well as issues that are of key importance for autonomous vehicles technology and its safety applications. Aiming at the problem of traffic target detection in real road traffic environment with a computer vision in foggy environment, this system proposes a domain-adaptive road vehicle target detection method based on YOLO Algorithm Firstly, Aiming at the insufficient accuracy of vehicle detection technology in foggy weather, this system uses only computer vision to improve the accuracy of vehicle detection. We used the DAWN dataset, involving different practical application scenarios, preprocessing, and using the YOLOv3 model for training, resulting in a vehicle detection [8] model with improved accuracy. The results show that the model improves the accuracy in foggy weather. This makes sense for the availability of driverless vehicles in foggy weather at less cost.

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