Automatic Overhanging vehicle Detection

[1]Ganga N, [2]K.S. GiriPrasath
M.Sc. Data Science and Business Analysis, Rathinam College of Arts and Science,Coimbatore

Abstract - This study presents an intelligent system that can recognize vehicles for other users of the road automatically. This research provides a novel deep learning and computer versioning method for AUTOMATIC OVERHANGING VEHICLE DETECTION (AVOD). Convolutional neural networks are used by the proposed AVOD system to assess real-time data and effectively recognize overhanging cars. This method locates and identifies overhanging automobiles precisely by using a two-step process that combines object detection and segmentation. Because this research is good at identifying them, it can help prevent accidents and improve traffic management. It can also have a favorable impact on road safety. By combining real-time monitoring and notifications, the method offers a preventative measure against potential traffic problems brought on by overhanging vehicles. This method has the potential to ensure a safer environment and enhance overall transportation efficiency.

Keywords: Overhanging vehicles, Object orientation, image segmentation, traffic management.

I. INTRODUCTION

Road safety is mostly importance to a nation's environment safety. The construction of a high-quality road network directly increases a nation's environmental safety. India, like most developing countries is facing the dilemma of vehicle over hanging. In Hurry-curry of our roads, there's a hidden danger that often goes unnoticed: vehicles carrying loads that extend beyond their usual limits. These overhanging loads are risk to other road user and causes accidents.

This introduction sets the stage for exploring how AOVDS employs algorithms, encompassing deep learning and image processing, to detect these potentially hazardous overhanging vehicle. It's like giving our roads a pair of intelligent eyes that can see beyond the ordinary. imagine a super-smart system that uses advanced neural networks – that's AOVDS with CNN deep learning. It's like giving our roads a brain that can quickly and accurately identify vehicles with overhanging loads, a significant safety concern on our highways. CNN, a powerful type of deep learning, enables AOVDS to process and understand complex visual data. The transformative potential of AOVDS in revolutionizing road safety. By combining technological process with road safety imperatives, AOVDS with CNN deep learning emerges as a pivotal advancement, showcasing the potential to make our roads safer and transportation more secure.

1.1 Related Work

At present, vision-based vehicle object detection is divided into traditional machine vision methods and complex deep learning methods. Traditional machine vision methods use the motion of a vehicle to separate it from a fixed background image. This method can be divided into three categories [1]: the method of using background subtraction [2], the method of using continuous video frame difference [3], and the method of using optical flow [4]. Using the video frame difference method, the variance is calculated according to the pixel values of two or three consecutive video frames. Moreover, the moving foreground region is separated by the threshold [3]. By using this method and suppressing noise, the stopping of the vehicle can also be detected [5]. When background image in the video is fixed, the background information is used to establish the background model [5]. Then, each frame image is compared with the background model, and the moving object can also be segmented. The method of using optical flow can detect the motion region in the video. The generated optical flow field represents each pixel's direction of motion and pixel speed [4]. Vehicle detection methods using vehicle features, such as the Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) methods, have been widely used. For example, 3D models have been used to complete vehicle detection and classification tasks [6]. Using the correlation curves of 3D ridges on the outer surface of the vehicle [7], the vehicles are divided into three categories: cars, SUVs, and minibuses. The use of deep convolutional networks (CNNs) has achieved amazing success in the field of vehicle object detection. CNNs have a strong ability to learn image features and can perform multiple related tasks, such as classification and bounding box regression [8]. The detection method can be generally divided into two categories. The two-stage method generates a candidate box of the object via various algorithms and then classifies the object by a convolutional neural network. The one-stage method does not generate a candidate box but directly converts the positioning problem of the object bounding box into a regression problem for processing. In the two-stage method, Region-CNN (R-CNN) [9] uses selective region search [10] in the image. The image input to the convolutional network must be fixed size, and the deeper structure of the network requires a long training time and consumes a large amount of storage memory. Drawing on the idea of spatial pyramid matching, SPP NET [11] allows the network to input images of various sizes and to have fixed outputs. R-FCN, FPN, and Mask

RCNN have improved the feature extraction methods, feature selection, and classification capabilities of convolutional networks in different ways. Among the one-stage methods, the most important are the Single Shot Multibox Detector (SSD) [12] and You Only Look Once (YOLO) [13] frameworks. The MutiBox [14], Region Proposal Network (RPN) and multi-scale representation methods are used in SSD, which uses a default set of anchor boxes with different aspect ratios to more accurately position the object. Unlike SSD, the YOLO [13] network divides the image into a fixed number of grids. Each grid is responsible for predicting objects whose centre points are within the grid. YOLOv2 [15] added the BN (Batch Normalization) layer, which makes the network normalize the input of each layer and accelerate the network convergence speed. YOLOv2 uses a multi-scale training method to randomly select a new image size for every ten batches. Our vehicle object detection uses the YOLOv3 [16] network. Based on YOLOv2, YOLOv3 uses logistic regression for the object category. The category loss method is two-class cross-entropy loss, which can handle multiple label problems for the same object. Moreover, logistic regression is used to regress the box confidence to determine if the IOU of the a priori box and the actual box is greater than 0.5. If more than one priority box satisfies the condition, only the largest prior box of the IOU is taken. In the final object prediction, YOLOv3 uses three different scales to predict the object in the image. The traditional machine vision method has a faster speed when detecting the vehicle but does not produce a good result when the image changes in brightness, there is periodic motion in the background, and where there are slow moving vehicles or complex scenes. Advanced CNN has achieved good results in object detection; however, CNN is sensitive to scale changes in object detection [17, 18]. The one stage method uses grids to predict objects, and the grid's spatial constraints make it impossible to have higher precision with the two-stage approach, especially for small objects. The two-stage method uses region of interest pooling to segment candidate regions into blocks according to given parameters, and if the candidate region is smaller than the size of the given parameters, the candidate region is padded to the size of the given parameters. In this way, the characteristic structure of a small object is destroyed, and its detection accuracy is low. The existing methods do not distinguish if large and small objects belong to the same category. The same method is used to deal with the same type of object, which will also lead to inaccurate detection. The use of image pyramids or multi-scale input images can solve the above problems, although the calculation requirements are large.

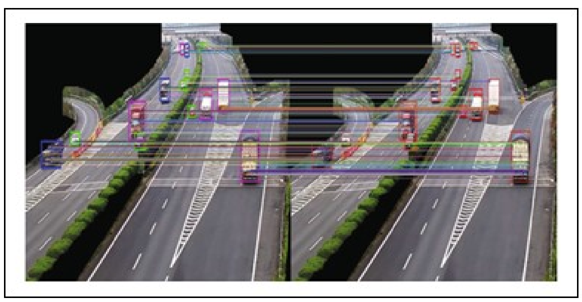


Figure:1 vehicle detection

II. SYSTEM STRUCTURE

This section describes the main structure of the Overhanging vehicle detection First, In this stage, the input image or frame undergoes necessary adjustments to enhance the relevant features for the CNN This might involve deploying noise reduction techniques, scaling, or normalizing pixel intensities. A dataset is generated from annotated photos of driveways with and without overhanging vehicles. These images are used as training data for the CNN model. The system architecture makes use of convolutional, pooling, and fully connected layers to efficiently extract information from the input images and classify them. Relevant elements from the photos should be extracted by the architecture. The pre-processed image data is received by the input layer. Convolutional layers: These layers recognize edges, forms, and textures by extracting spatial elements from the image These layers maintain significant properties while reducing the dimensionality of the data. Fully connected layers classify whether an overhanging vehicle is present in the image by combining the extracted features. The final classification result (overhanging/non-overhanging) is provided by the output layer. When faced with new, unknown input, the network analyzes this training data to find patterns, characteristics, and representations that help it forecast or make judgments.

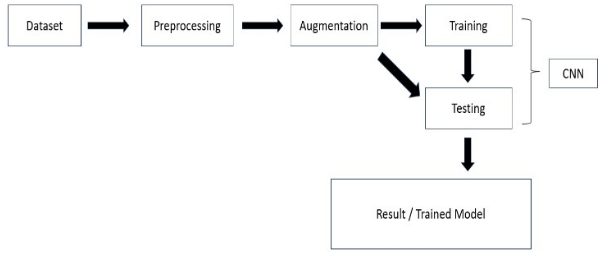


Figure :2

2.1 Overhanging Vehicle Dataset

overhanging vehicle dataset is a specialized collection of data that focuses on instances where vehicles extend beyond the standard dimensions of a road or parking space, creating an overhang. This type of dataset is particularly relevant in urban planning, traffic management, and parking space optimization. It typically includes information about vehicles that overhang, such as the type of overhanging (e.g., cargo overhang, trailer overhang), dimensions of the overhanging part, vehicle make and model, and location data. The dataset may be used for developing Deep learning models aimed at detecting and classifying overhanging vehicles from images or real images, assisting in real-time monitoring and management of traffic flow, enforcement, and ensuring road safety. The insights gained from analyzing an overhanging vehicle dataset can contribute to the development of intelligent transportation systems, helping urban planners and authorities make informed decisions regarding road infrastructure, parking regulations, and overall traffic efficiency in crowded urban environments. Annotated data with precise labels indicating the presence and location of overhanging vehicles is crucial for training the model effectively.

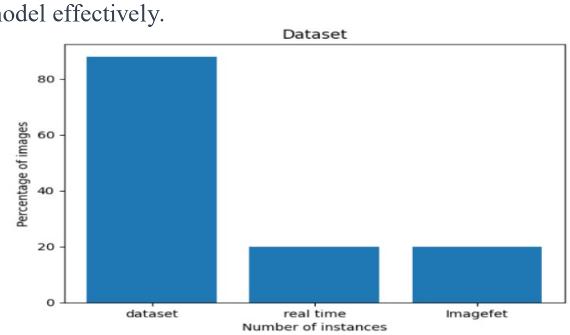


Figure: 3

In Overhanging vehicles, the augmentation and annotation processes are essential elements that greatly enhance the efficiency and accuracy of deep learning models in overhanging vehicle detection. While the annotation procedure involves labelling each image to indicate the presence and number of overhanging vehicles, the augmentation process involves enhancing the dataset by applying various transformations to the original images

a. Augmentation

To provide a more representative and diversified dataset, augmentation entails adding a range of alterations to already-existing photos of parking spaces. Rotation, translation, scaling, flipping, adjusting brightness and contrast, noise injection, random cropping, and color jittering are some of these modifications. adjustments to camera angles, lighting, and vehicle locations. By adding to the dataset, the model gains resilience and improves its ability to generalize to other settings and circumstances Furthermore, by exposing the model to a greater range of variables found in real-world data, augmentation aids in preventing overfitting. By going through this process, the model gains the capacity to precisely identify overhanging vehicles, even in difficult situations, which eventually enhances the system's functionality and dependability in identifying vehicles that cross established limits.

Figure:4

b. Annotation

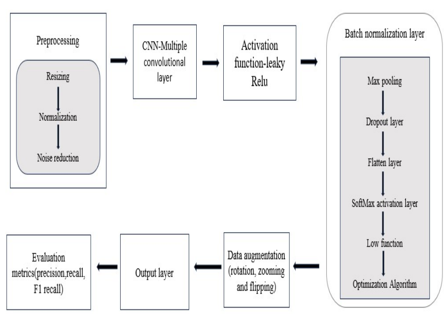
An important and careful phase in preparing data for training deep learning models in overhanging vehicle detection is the annotation process. To accurately identify the existence and depth of vehicles that expand beyond designated vehicles, images must be properly labelled. Generally, annotations involve drawing the lines that define the limits of vehicles that hang over the images, which gives the training algorithm specific ground truth data. To guarantee the accuracy and dependability of the annotated dataset, this procedure necessitates consistency and close attention to detail. Annotations can also contain extra metadata, which gives the model more context when it's being trained. Examples of this content include the kind of vehicle, its direction, and the extent of overhang. Convolutional neural networks (CNNs) are trained on annotated datasets in order to precisely identify and sort and categorize overhanging vehicles in different real-world situations. Through thorough annotation of images, the model gains the ability to recognize delicate visual cues connected to vehicles which are overhanging, enabling it make accurate inferences. As a result, improving the efficacy and dependability of overhanging vehicle detection systems through annotation is crucial for enhancing environment management's level of safety and efficiency.

Figure 6: annotation

2.4 Overhanging vehicle detection Using DL

The training process involves splitting the dataset into training and validation sets, initializing the model with pre-trained weights when applicable, and fine-tuning it based on performance metrics on the validation set. Continuous monitoring of loss and metrics guides adjustments to hyperparameters. Post-processing steps, such as non-maximum suppression, refine the detection results by eliminating duplicate bounding boxes. Model evaluation on a separate test set assesses its effectiveness, and further refinement may be undertaken based on identified areas for improvement. Once satisfied with the model's performance, it can be deployed for real-world applications, considering optimizations for inference speed if necessary. Continuous monitoring and periodic retraining with new data contribute to maintaining accuracy and adapting the model to evolving conditions. The process involves an iterative approach, refining

Figure 7: CNN



data and model parameters to achieve optimal performance in the task of overhanging vehicles detection.

Testing a model for overhanging vehicles detection is a critical phase that evaluates the model's performance. generalization on unseen data. Following the training process, a separate test dataset, distinct from the training and validation sets, is employed to rigorously assess the model's ability to accurately identify overhanging vehicles. The test set contains real-world examples, allowing the evaluation of the model's performance in diverse scenarios beyond those encountered during training.

III RESULT

Convolutional neural networks (CNNs) are a crucial part of the total system and can be used as an efficient way to identify overhanging vehicles automatically in order to prevent accidents. CNNs are trained on a variety of datasets using extensive picture recognition techniques to reliably recognize visual characteristics connected to overhanging vehicles. Whenever a camera system has been integrated and positioned in important locations, like tunnels, bridges, and crossroads, it can identify. overhanging equipment or goods that may indicate an overhanging vehicle in real-time video analysis. This technology makes identification accurate and quick, even in complicated traffic situations. Moreover, additional sensors, such Lidar, can be added to the CNN-based approach to improve awareness of depth and detection accuracy of overhanging vehicles. Next, The CNN's real-

time output is subsequently integrated into a larger system that offers communication warnings, allowing for immediate notification to law enforcement, traffic control systems, and neighboring vehicle. This all-encompassing strategy, which combines state-of-the-art CNN technology with a multisensor configuration, guarantees a reliable and proactive way to lessen the dangers connected to overhanging vehicle collisions. For the system to remain effective, regular updates, maintenance,

and coordination with pertinent parties are essential.

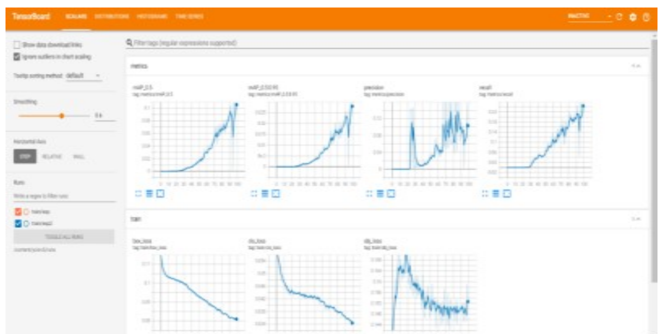


Figure:8 Output of Overhanging vehicle and Accuracy score

IV. CONCLUSION

In conclusion, automatic overhanging vehicle detection systems represent a significant leap forward in enhancing road safety and traffic management. These systems leverage advanced technologies, including deep learning algorithms, to identify and address potential hazards posed by overhanging vehicles. Despite their promising capabilities, it is imperative to acknowledge the existing limitations, such as susceptibility to adverse weather conditions, challenges in complex urban environments, and concerns regarding privacy and cost. The continuous refinement of detection algorithms, leveraging diverse and representative datasets, is crucial for overcoming these limitations and improving the overall reliability of the systems. Additionally, addressing privacy concerns through transparent policies and ethical considerations is paramount for widespread acceptance and responsible deployment.

As these systems evolve, collaboration between technology developers, regulatory bodies, and communities is essential to strike a balance between safety, privacy, and practicality. The ongoing commitment to research, development, and the incorporation of user feedback will be instrumental in ensuring that automatic overhanging vehicle detection systems fulfill their potential as valuable tools in creating safer and more efficient transportation networks.

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