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Pothole Detection in Drivable Area using Deep Learning

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Abstract

In today's world, vehicle traffic is increasing on all types of roads, from single-lane streets to multi-lane highways. This rise in traffic emphasizes the need for improved road safety measures to protect drivers and other road users. Ensuring road structural integrity is essential for preventing accidents caused by road damage, such as potholes, landslides, and uneven surfaces, which are common contributors to traffic hazards. Road conditions often lead to media-reported incidents involving vehicle damage, visibility issues due to weather, suspension system damage, and unnecessary traffic congestion. Addressing these issues, this study presents an efficient solution using deep learning for real-time pothole detection, leveraging the YOLOv5 (You Only Look Once) algorithm. Unlike traditional methods like accelerometer-based, image-processing, or basic machine-learning approaches, YOLOv5 provides greater accuracy and is simpler to implement, yielding a promising mean Average Precision (mAP) of 84.5. Moreover, the performance of YOLOv5 can be enhanced by utilizing high-specification GPUs, thus enabling faster and more accurate pothole identification. This approach holds the potential to benefit both the public and government agencies by providing a highly precise and effective pothole monitoring solution. In addition to real-time monitoring, the proposed system allows for proactive maintenance measures, thereby contributing to safer roads and reducing the likelihood of road-related accidents.

Keywords: Computer Vision, Drivable Area Segmentation, Pothole Detection, Road Safety, YOLOv5.

Introduction

Driving on roads requires attentiveness, logical thinking and understanding of the vehicle's surrounding environment (which is dynamic in nature). Driving a car is not an easy task for humans; it requires correct training procedures for expertise. But recently, the concept of Autonomous driving vehicles has emerged (self-driving cars). This requires the extensive training of AI algorithms to detect, recognize and react to the different physical environmental elements in real-time. According to estimates from the World Health Organization, 1.3 million individuals worldwide lose their lives in car accidents each year (1). Between twenty and fifty million people suffer from non-fatal injuries; many of these people go on to develop disabilities as a result of their injuries. As per annual report of 2022-23 released by Ministry of Road Transport and Highway of India, nearly 1,60,000 persons died by road accidents in the year 2021(2). Inadequate road conditions, careless driving, misdirected signals, etc. are a few factors that contribute to traffic accidents. Out of all these factors, it has been found that poor road conditions caused by anomalies in the road, including potholes, are the most significant contributor to traffic accidents (3, 4). Road imperfections such as potholes can also lead to damage to cars, reduce comfort when traveling, increase usage of fuel, waste of fuel, and other problems. In this situation, real-time observing potholes, detection, and spatial mapping throughout the urban area may offer a somewhat effective way to lower the frequency of accidents. In order to reduce this regrettable situation, the Advance Driver Assistance System (ADAS) is now playing an important role. Autonomous vehicles (AVs) or ADAS require a system that knows where to drive. Numerous technologies, including GPS, LiDAR, and camera sensors, are available for performing this. Numerous techniques for monitoring road conditions have been documented in the literature (5, 6). Additionally, the literature has a plethora of approaches (7–9) for pothole identification tasks. In the realm of image processing and computer vision, Convolutional Neural Networks (CNNs) have

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gained prominence, largely attributed to the rapid advancements in Graphics Processing Unit (GPU) technology. CNNs may be trained to learn representative features from photos using many datasets that contain vast amounts of image materials released online, such as ImageNet (10) and KITTI (11) dataset. Deep learning-based approaches are used for pothole recognition (12, 13) due to its capacity to acquire knowledge from unlabeled or unorganized information (14, 15). The ability to have many parameters allows deep structures to be flexible enough to fit extremely complicated data. Using computer vision to detect road surfaces has been the subject of numerous studies. The majority of the ideas centered on enhancing road surface detection from a single image and detecting ground surface with hardware sensors. These methods, however, have a long latency and are insufficient for providing real-time notification notifications to drivers. The proposed project will build AI Architecture with the help of video datasets containing Indian roads that are unlike roads in other countries. They often produce great numbers of potholes and other objects that deliberately cause vehicles to slow down. The idea is to train our Deep Learning model to recognize such objects in real-time, recognize street signs and help avoid these obstacles along with the autonomous car's speed control, in order to increase passenger safety and vehicle maneuverability. The rest of the paper has been organized as follows. An overview of the relevant works has been discussed in the next section. The suggested method is then discussed in section 3, and section 4 offers the assessments, findings, and analysis. The conclusion and next steps are covered in the final section. For autonomous vehicles, a dependable method for identifying road regions is necessary. To solve this issue, several different strategies have been tried in the last few decades. Depending on which sensors are utilized to collect data, these methods can be categorized into four groups: multi-sensor fusion, stereo vision, laser sensors, and monocular cameras. Techniques that utilize monocular vision have been widely employed in road detection. Comparing a visual sensor to other types, it is less expensive, smaller, and easier to install. Additionally, rich visual information can be obtained via a visual sensor having a wide detection range. Comparatively speaking, the ocular sensor might be more covert than other types of sensors. Above all, a visual sensor's structure and workings are comparable to those of the human sensory system. 2D visual scene data, including color, edge, and texture, corner points, and shape, are used in road detection. Segmentation processing typically occurs in the color space of RGB (16), HSI color space (17), or color spaces of other models, when it comes to color cue. In Jau et al.'s work (18), several illumination circumstances were used to compare RGB and HSI color segmentation. As suggested by Finlayson et al., this study builds a shadow-free picture representation using a physics-based illumination constant space (19). Additionally, Maddern *et al.,* created an extra illumination invariant color space via using the spectral characteristics of the camera that produced unprocessed color pictures in order to lessen the impacts of sunlight-induced illumination shift (20). The application of convolutional neural networks (CNNs), which have demonstrated its outstanding effectiveness in this sector, is another ongoing research concern (21, 22). CNNs were initially used to address classification problems (23, 24). Nevertheless, there has been a recent rise in the application of CNN-based techniques for sematic segmentation (25, 26). In order to identify potholes with accuracy and efficiency, researchers examine and evaluate the pothole detection techniques that have been created thus far (27). They also suggest a possible path for future development. The researchers address this problem by utilizing deep learning-based techniques. In this study, a deep CNN with two models and a distinct design based on You Only Look Once version 2 (YOLOv2) was employed as the detector (28). An image processing method for detecting and recognizing speed break and road markings was reported by the researchers (29). To determine if the recommended method identifies speed breakers or performs OCR. To recognize traffic signs, like "STOP" marks by an algorithm for optical character recognition (OCR) was employed. The next step was using a Hough transform to find line marks. As a pre-processing phase, the stop line inclusion tells the algorithm whether to identify stop signs or speed breakers. A Hough transform is employed to identify line marks on road for various speed breakers (30). This is a preprocessing step to find out when OCR or speed breaker recognition is carried out using the suggested technique. The "STOP" marker on traffic signs and other signs are recognized by the OCR algorithm. As a kind of pre-processing, the stop line inclusion tells the algorithm when to identify stop signs or speed breakers. Images were processed using image processing techniques to extract characteristics. The Local Binary Pattern (LBP) was obtained as features so that the Support Vector Machine (SVM), speed breaker detection classifier could be trained. The goal of the research is to stop accidents caused by irresponsible driving and to draw notice to drivers who break traffic laws (31). By eliminating all irrelevant information from a picture other than a road sign and employing shape attributes to identify the sign, this research achieves high accuracy and an efficient sign detection approach. There hasn't been much research done specially to identify the problem of road sign identification on Indian highways (32). Though, authors represented a novel approach to find out the drivable path (33). In order to tackle this pressing issue, a study is being conducted with the following goals in mind: to assess Indian roads; to propose an automated driver assistance system; and to identify and categorize road signs. Road sign recognition and classification is achieved by utilizing the nearest neighbor classifier in conjunction with segmenting colors and modeling shapes using thin spline transformation (TPS). To make driving safer and simpler on Indian highways, an automated driver guidance system is being developed. Recent research on pothole detection using deep learning has made significant strides in enhancing the accuracy and reliability of detection systems. A study on pothole detection under low-light conditions introduces the use of feature pyramid networks, and Grad-CAM for feature extraction (34). Another research focused on real-time pothole detection that demonstrates its effectiveness in practical applications (35). A comparison between Random Forest and Convolutional Neural Networks (CNNs) for pothole detection also underscores the advantages of deep learning models over traditional methods (36).

Methodology

The proposed project will build AI Architecture with the help of image datasets containing Indian Roads that are unlike roads in other countries.

The idea is to train our Deep Learning model to

- Recognize Drivable area
- Recognize Potholes

The proposed work is progressed in the following way-

- Collect image and video samples of Indian roads in sufficient quantity.
- Pass the images/videos through our proposed model to gain depth information
- Pass those information/annotations to determine drive-able area
- Extract necessary features within the frames.
- Detect drive-able area, pot-holes

Figure 1 illustrates the step-by-step operation of the proposed system.

Drivable Area Detection

For creating a segmentation mask, we need to create a custom dataset of images from where we can extract the required feature by manually annotating the Region of Interest (a popular method to create object/region detection models for custom classes, in our case it is drivable area). We used the online Visual Geometry Group (VGG) Annotator website to annotate almost 2500 images (sample screenshot provided). Here, we had to create polygons to mark the particular drivable area inside the chosen images.

After that, we exported the annotations in JSON format (which is supported by Mask RCNN). Figure 2, represents the block diagram of the proposed model for drivable area detection.

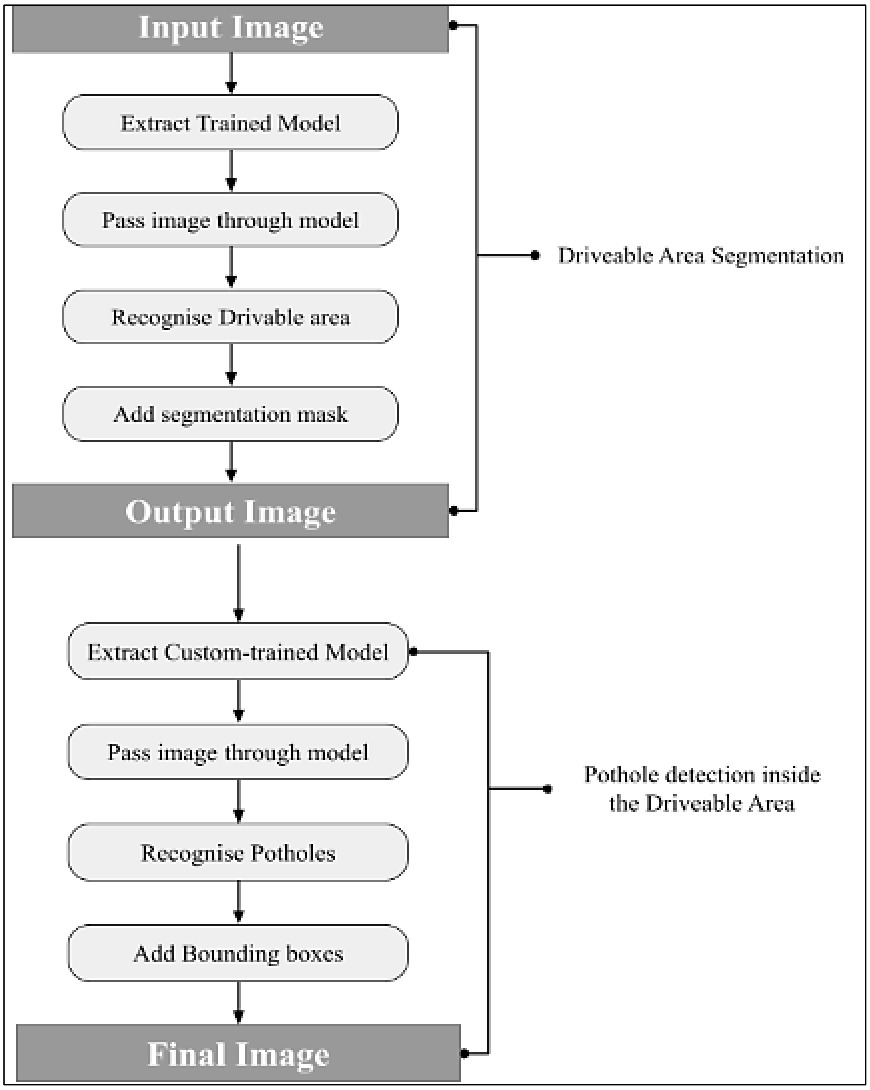

Figure 1: Proposed System Design

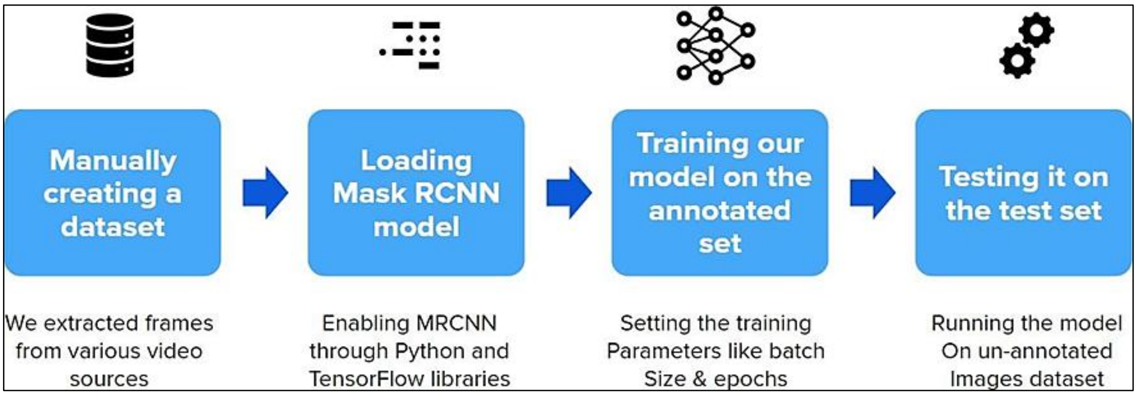

Figure 2: Workflow Diagram of Proposed Method for Drivable Area Detection

The underlying concept of Mask RCNN is essentially Region-based Faster RCNN; this is employed mainly for applying a mask (of a particular color) to the required object of interest in the provided frame. It can also create bounding boxes and color splash effect. Since the goal is to find out the drivable area (region) inside a particular frame, we opted for Mask RCNN. We extracted still frames from various video sources containing Indian roads and created our own custom dataset containing approximately 2500 images. We artificially added sections of potholes inside some of the pictures to add noise and randomize our dataset. After that we annotated 2000 images among that in the VGG Annotator website. The necessary ROI is isolated and it is separated from the background using the mask RCNN. The output feature maps' resolution can be further decreased by propagating them through eight pooling layers and many alternating convolutional layers. Typically, the limited resolution of FCN's direct predictions leads to somewhat hazy object boundaries. These are the FCN architecture's salient characteristics: In order to perform semantic segmentation, the FCN transfers knowledge from the VGG16. A class presence heat map is produced using 1x1 convolution, following the conversion of VGG16's fully connected layers into convolutional layers. By transposing the convolutions (initialized with bilinear interpolation filters) to become higher resolution, the semantic feature maps are up sampled. Throughout the up-sampling process, coarser but better resolution features are introduced from lower layers in VGG16 during the up sampling process, which further reduces the up sampling process. In the next convolution step, skip connections are introduced to make it possible for the next block to take the previously pooled features and extract more abstract, class-specific features. One of the most common applications for fully convolutional neural networks is semantic segmentation. We have used the Tensor Flow module and different Python3 libraries (such as NumPy and SciPy). The annotations corresponding to our custom dataset acts as weights to train the model and detect the ROI and apply mask to it. FCN mainly sends information from VGG16 to do semantic segmentation. The fully connected VGG16 layers form a fully convolutional neural network and in turn, create a low-resolution heat map. These low-resolution semantic heat maps are up-sampled using bilinear interpolation filters. This is mainly performed by the lower layers of VGG16. The multiple pooling layers are used to refine the features extracted from each layer. In this architecture, the pre-trained VGG16 is used as an encoder. The decoding is performed by the layers from layer 7. Padding is used in every layer. The last layer of VGG16 is a 1x1 convolution. By using up sampling from the 11th layer of FCN, we get the actual image back. First VGG16 is loaded into Tensor flow, and a GPU-enabled runtime is used to utilize the tensor cores of the same. The layers of FCN are made in the next step. Here we apply 1x1 convolutions to the encoder and then add decoder layers for the up sampling. Next, we optimize our neural network by using cross entropy and Adam optimizer algorithm. We kept the number of epochs as 5 and batch size as 500. We train the model using load Mask RCNN, layers and optimize functions. Each epoch took approx. 8 minutes to complete, adding to total of approx. 45 minutes for the total model to train.

Pothole Detection

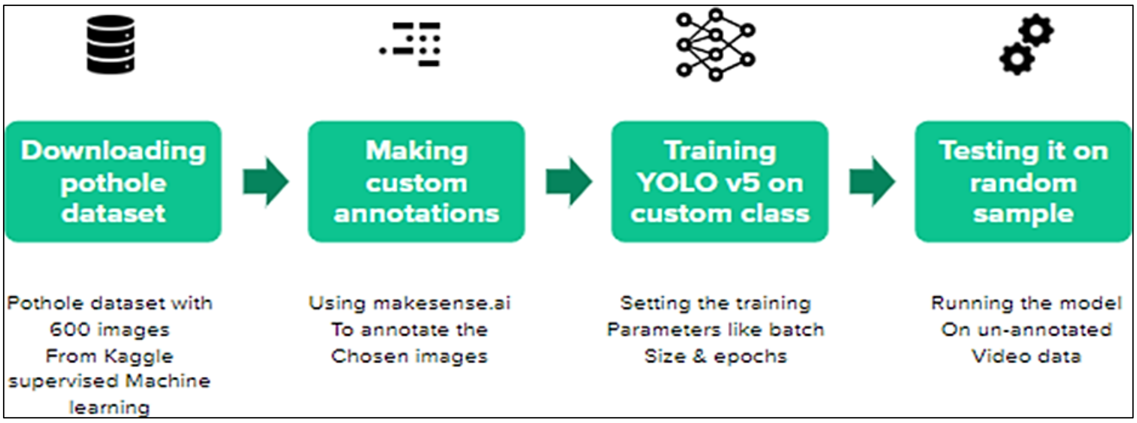

Figure 3: Workflow Diagram of Proposed Method for Pothole Detection

Figure 3 shows the workflow diagram of proposed method for pothole detection. For Pothole detection, we used YOLOv5. Yolo is a very fast and efficient object detection model that can readily recognize 80 different predefined classes of objects inside videos and images. But among those classes, the pothole was not there. So we had to train yolo to recognize just the potholes inside the drivable area output of the area segmentation model of Mask RCNN. For this we have downloaded a public dataset containing 600 images of various potholes from Kaggle. We used almost 200 of those images in makesense.ai to annotate the potholes using a bounding box manually. Sample images of the pothole dataset represented by figure 4 and figure 5 respectively. Again, since we are making our own custom class, this is the recommended method. The more pictures we annotate, the more will be the accuracy of the model.

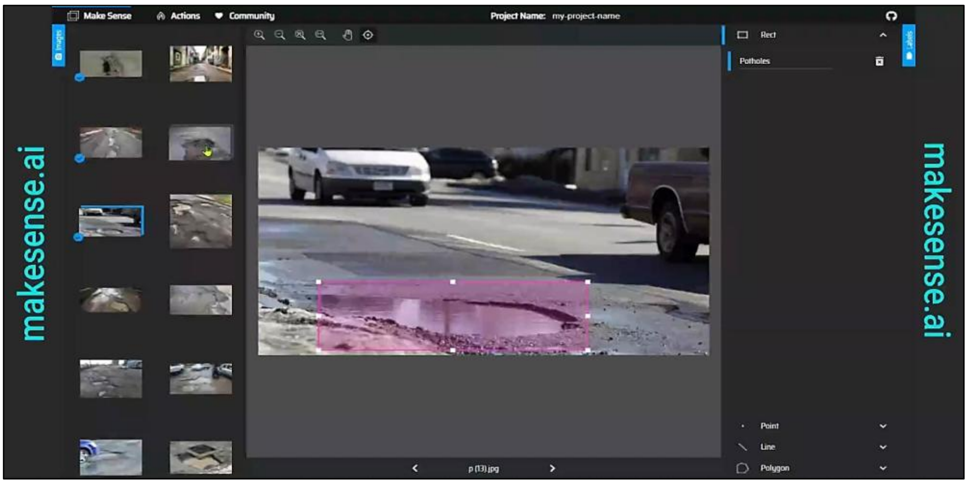

Figure 4: Annotating Potholes Dataset

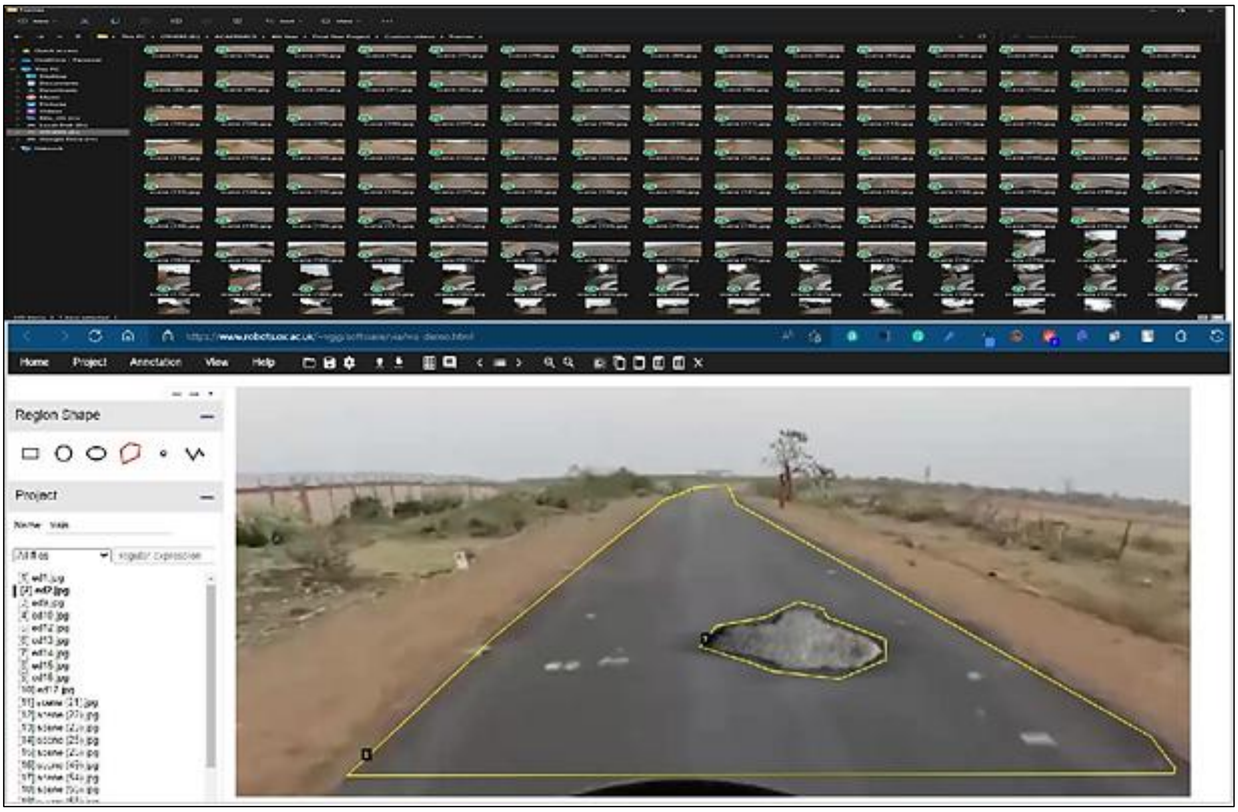

Figure 5: Screenshot of Road Area Dataset Used and the Annotator Website

Then after annotating, we exported the annotations file in YOLO format, since we will be using that in YOLOv5. Next we made changes in the YOLO yaml file that contained all the 80 default classes - removed those and added one class called 'potholes'. In Google colab, we added the images and their corresponding annotation file in the runtime, tweaked the epoch and batch number and trained our custom class YOLOv5 model.

Results

To detect the drivable area, we have made our custom dataset of 2500 images by capturing snapshots from videos and annotating them, VGG Image Annotator (ox.ac.uk) used. The description of the custom dataset is provided in Table 1.

Table 1: Custom Road Dataset

Category	Sub-category	Percentage	Number of Images
Lighting Variations	Bright sunlight	25%	625
	Cloudy	20%	500
	Shadows	15%	375
	Nighttime	15%	375
	Low-light (dusk/dawn)	10%	250
	Artificial lighting (e.g., streetlights)	5%	125
Weather Conditions	Dry	40%	1,000
	Wet (post-rain)	20%	500
	Rainy (active rain or water splashes)	15%	375
	Foggy	10%	250
	Snowy/slippery (optional, if relevant)	5%	125
Surface Types	Asphalt (smooth)	20%	500
	Asphalt (cracked)	20%	500
	Concrete	15%	375
	Gravel	10%	250
	Heavily potholed (various sizes)	25%	625
Camera Views	Top-down views from vehicles	60%	1,500
	Side perspectives (capturing depth)	30%	750
	Angled or oblique views (for generalization)	10%	250
Resolution	High resolution (1920x1080 or similar)	100%	All images

Training dataset – 2000 images, testing dataset – 500 images. After the training is completed, we run random images and videos through the trained model to detect the potholes inside the frames. This YOLO model saves the output images/videos in its root directory from which we can extract the same. The setting is as follows: epochs - 150, batch size - 20, image size – 640. As we can see, the model's accuracy is 84.5% according to the mean average precision (mAP) graph. Raw image of the road, segmented mask, corresponding annotation and corresponding result has been depicted in figure 6 A, B, C and D. The accuracy of machine learning models conventionally depends directly on the epoch numbers and inversely on the batch size. Now, as the training process progresses, the training loss reduces, and the accuracy increases. The same pattern can be seen in the above figure. Here, the accuracy of the model can be observed through mAP (mean average precision) graph. Here, the class loss is zero because this model contains only one class.

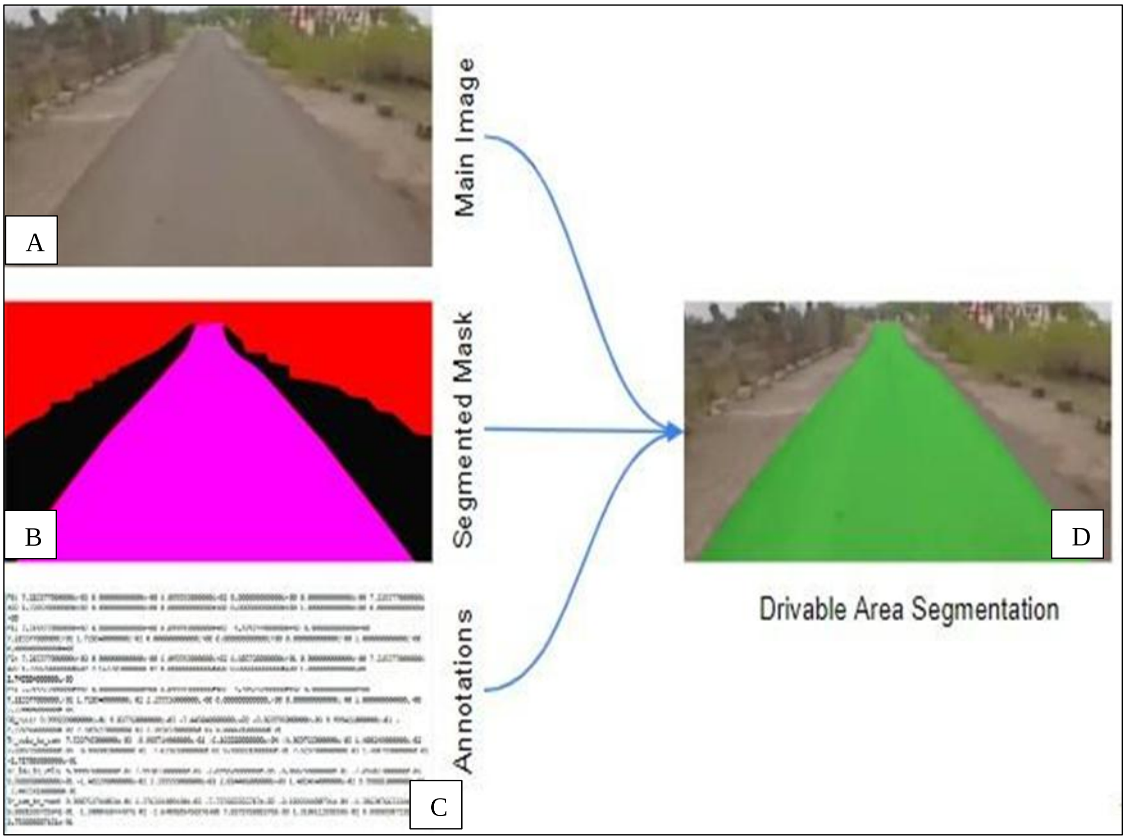

Figure 6: Segmented drivable area A) Raw image B) Segmented Mask C) Annotation D) Corresponding Result

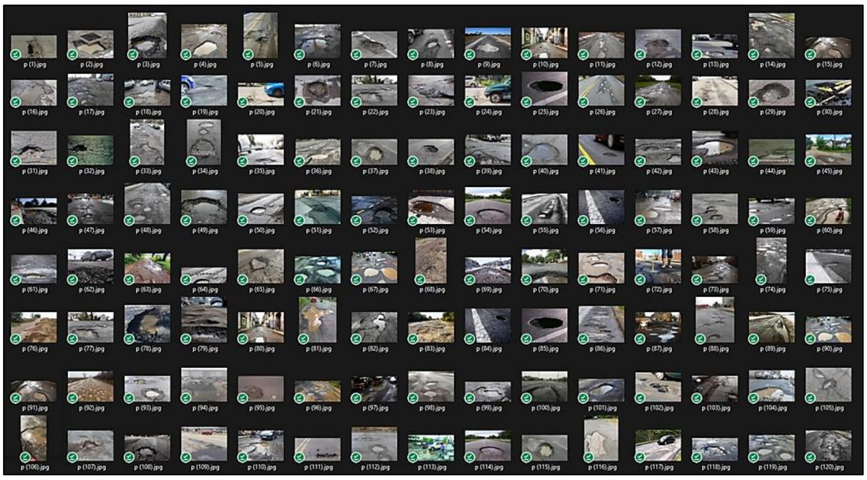

Figure 7: Screenshot of Pothole Dataset

To detect the potholes, we have used Dataset from Kaggle which we had to annotate manually in Makesense.ai. Volume of the dataset as follows: Training dataset – 480 images and testing dataset – 120 images. Few potholes from the dataset have been presented in figure 7. Sample image of pothole detection with bounding box has been presented in figure 8.

Figure 8: Pothole detection

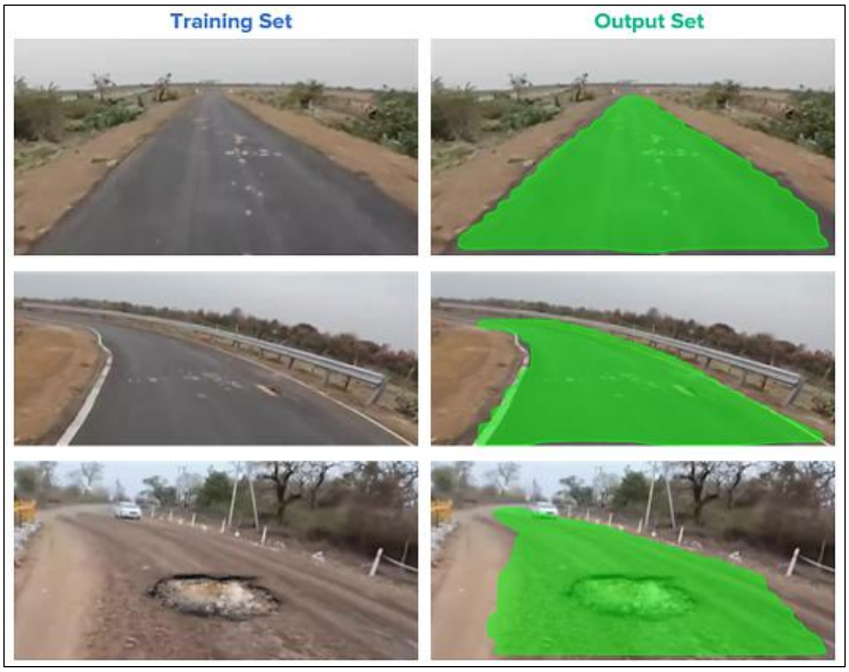

Figure 9: Sample Test Result

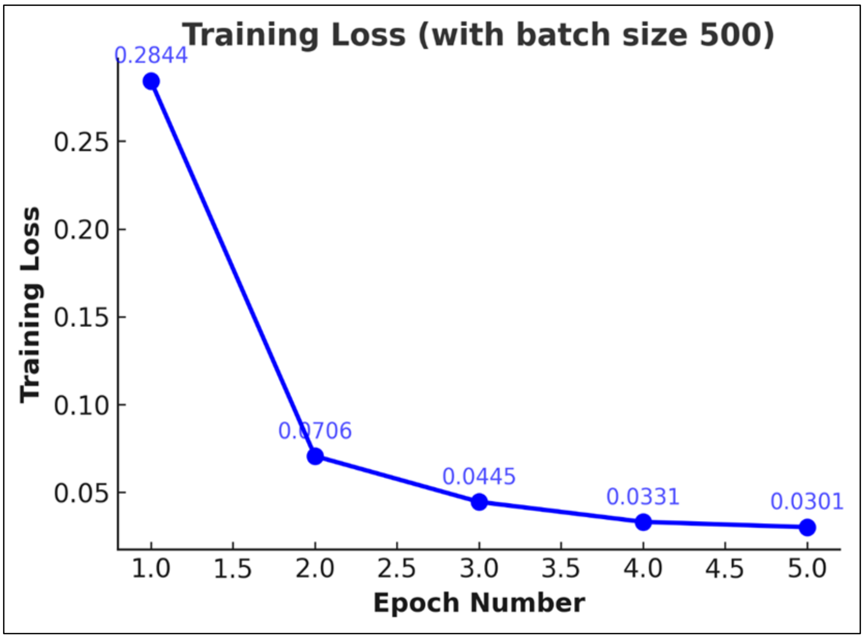

Figure 10: Training Loss graph

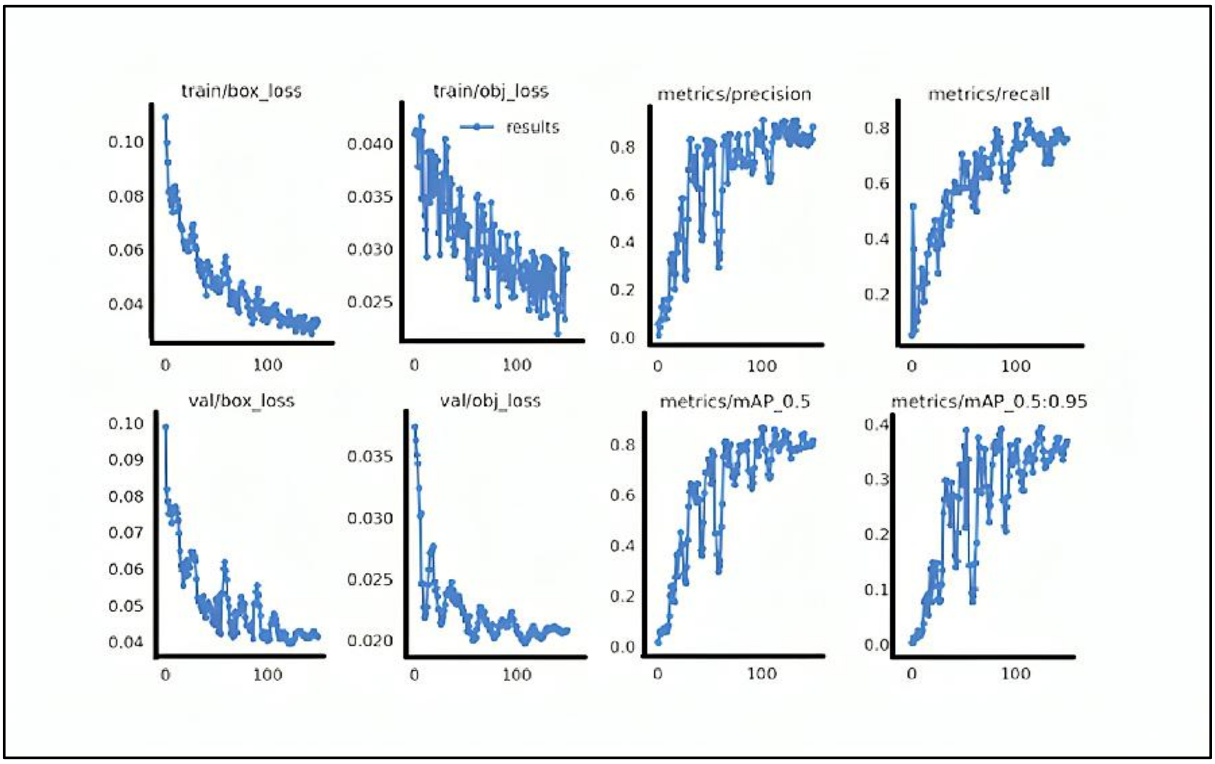

Figure 11: Accuracy Metrics from the YOLOv5 Model

Figure 9 shows sample test result after detecting potholes within drivable area. Epoch number vs. training loss is depicted in figure 10. It shows at epoch 5 training loss converge. Accuracy metrics from the YOLOv5 model represented in figure 11.

Discussion

Notwithstanding the obstacles, the adoption of autonomous driving technology may prove advantageous in many ways and be well-received in the Indian market. Because it allows for a higher standardization of driving conditions, it may enhance road safety. Drivers will save time and fuel thanks to autonomous vehicles. Especially during routine commutes, since they will be connected to real-time traffic data, parking space availability and on-road conditions. This will likely lead to an increase in fuel and parking efficiency. The proposed pothole detection system improves road safety by reducing accidents, preventing vehicle damage, and enhancing navigation for autonomous vehicles and vulnerable road users. It optimizes infrastructure maintenance by enabling automated, proactive road repairs, improving resource allocation, and providing data-driven insights for urban planning. Environmental benefits include reduced fuel consumption and emissions due to smoother roads. Additionally, the system enhances public satisfaction and fosters civic engagement through crowdsourced reporting, contributing to safer, cost-effective, and sustainable transportation networks. AI for road safety and autonomous driving raises ethical issues such as accountability in accidents, bias in data impacting fairness, and privacy concerns from road data collection. It may cause job displacement and challenges in transparency. Balancing safety with innovation and ensuring equitable access are critical. Addressing these concerns promotes responsible, trustworthy, and inclusive AI deployment in transportation systems.

Conclusion

The semantic segmentation technique by the FCN and VGG 16 is used in this research to propose a novel instance segmentation approach for road scene interpretation to find out drivable area. To acquire the precise contour and subsequently collect object classification results to segment the road region thoroughly, an FCN and VGG 16 are used to classify each pixel in the image. Mask RCNN and YOLO v5 technique is used to detect the potholes within the drivable area. Thorough testing shows that the proposed methods not only considerably increase the level of drivable area extracted but also improve the integrity and accuracy of edge contour detection for each object.

The feasibility of real-time implementation in embedded systems for autonomous vehicles is achievable with careful optimization of deep learning models, efficient hardware utilization, and integration of sensor data, balancing accuracy and speed for robust deployment in autonomous driving systems. While the deep learning models show good performance under standard conditions, they may struggle with variations in lighting, weather (rain, fog), and road surfaces (wet, reflective, or shadowed areas). Future research will focus on developing a deep instance segmentation architecture to improve multi-object recognition and tracking, segmentation accuracy, quantitative analysis, and comparison of other detection techniques. Specifically investigation on advanced data augmentation techniques and adaptive models to improve robustness under low-light, rainy, and foggy conditions.

Abbreviations

YOLO: You Only Look Once, mAP: Mean Average Precision, ADAS: Advance Driver Assistance System, AV: Autonomous Vehicle, GPS: Global Positioning System, LiDAR: light Detection and Ranging, CNN: Convolutional Neural Network, GPU: Graphics Processing Unit, AI: Artificial Intelligence, OCR: Optical Character Recognition, LBP: Local Binary Pattern, SVM: Support Vector Machine, VGG: Visual Geometry Group, RCNN: Region-based Convolutional Neural Network, FCN: Fully Convolutional Network,

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Authors Contribution

S. Chandra was instrumental in identifying the research topic and designing the study, as well as in drafting the manuscript and overseeing data collection. Dr. K. K. Dubey was crucial in developing the questionnaires and conducting the data analysis. Dr. G. Agarwal and Dr. N. Chakraborty, together they collaborated closely throughout the research process, ensuring the study was thorough and effectively communicated their findings. This partnership exemplifies their shared commitment to advancing knowledge in their field.

Conflict of Interest

The authors of this work state that they have no conflicts of interest about its publication. Ethics Approval Not applicable.

Ethics Approval

No ethical clearance certificate is applicable for present study. The authors of the submitted paper did not receive support from any organization.

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