Pothole Detection With Red Light Violation using Deep Learning

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Abstract: *Pothole detection with red light violation using deep learning is a project aimed at developing a system that can automatically detect potholes and red light violations using deep learning techniques. Potholes and red-light violations are major causes of accidents and fatalities on roads, and early detection and prevention of these can significantly reduce the number of accidents. The proposed system uses deep learning techniques to detect potholes and red-light violations from video footage captured by CCTV cameras installed at traffic junctions. The system first employs object detection algorithms to identify vehicles in the video footage. The system then uses semantic segmentation algorithms to identify the road surface and the presence of potholes. The system can also detect the color of the traffic light and identify instances where vehicles violate the red light. The deep learning model is trained on a large dataset of video footage containing instances of potholes and red-light violations. The system can learn to accurately detect these instances by comparing the captured video footage with the training dataset. The proposed system has the potential to revolutionize road safety by providing real- time detection and prevention of potholes and red-light violations. The system can be integrated with existing traffic management systems to provide early alerts to the authorities about potential safety hazards on roads. The system can also be used to monitor the performance of road maintenance and repair activities..*

Keywords: Machine learning, Deep learning, Neural Network, RCNN,FRCNN,YOLOV8

I. INTRODUCTION

In Existing system, we obtained the result on image size 224 using ResNet101 pretrained model and achieved validation accuracy of 94.08%. Here they used YOLO v2 and R-CNN. In each system we find there is limited datasets for training and it has less images for potholes. Several studies have been conducted on deep learning-based pothole detection approaches using various machine learning-based object detection algorithms. A comparative study it has an accuracy of 87% is achieved using the YOLO version 2 object detection algorithm. We analyses the paper perform a comparative analysis upon 4 models that are YOLO-V3, SSD, HOG with SVM and Faster-CNN. The experimental results show that the YOLO V3 model performs least reliable for detection results. The detection of potholes on highway and achieved this with max accuracy with the help of YOLO-V4 deep learning algorithm and trained it with 334 potholes regions on 105 images. Correct detection was made in 504 images out of a total of 576 performance test images, and a success accuracy of 80.5 percent was achieved. The computer vision model library You Look Only Once version 3, also known as Yolo v3, is used in this paper to detect potholes automatically .The main defect is high memory requirements need for YOLOv3 requires . The detection of pothole using RCNN-based models is that they take more time to forecast. Therefore, it is required to develop a new system which is cost-effective for detection. Most of the system have less accurate prediction.

II. LITERATURE REVIEW

Detection of potholes on highway and achieved this with max accuracy with the help of YOLO-V4 deep learning algorithm and trained it with 334 potholes regions on 105 images. Correct detection was made in 504 images out of a

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, September 2023

total of 576 performance test images, and a success accuracy of 87.5 percent was achieved.learned weights for the classification task. Several studies have been conducted on deep learning-based pothole detection approaches using various machine learning-basedobject detection algorithms. A comparative study by Roopak Rastogi . An accuracy of 87% is achieved using the YOLOversion 2 object detection algorithm. Muhammad Harun Assad et al. developed an algorithm that uses YOLO v4 as the baseobject detection algorithm, trained on a custom dataset, and achieved 90% accuracy at 31.76 FPS. Zhang proposed anembedded system for road obstruction detection integrated with CNN using the Montreal Pavement dataset. The model shows thatthe true positive rates for potholes, patches, marks, linear cracks, and crack networks are 75.7%, 84.1%, 76.3%, 79.4%, and 83.1%,respectively. Oche used five binary classification models (Naive Bayes, Logistic Regression, SVM, K-Nearest Neighbors(KNN), and Random Forest Tree) to apply various classifications to data collected via smartphone and car routes. They presented a comparison of machine learning approaches. The Random Forest Tree and KNN achieved the highest accuracy of 0.8889 on the test set. To improve the accuracy of the Random Forest Tree, they tuned hyperparameters and increased accuracy up to 0.9444. The model has shown promising results on different routes and out of sample data. Arbawa proposed a method for detectingroad potholes using the gray-level co-occurrence matrix (GLCM) feature extractor and support vector machine (SVM) as a classifier. They analyzed three features such as contrast, correlation, and dissimilarity. The results have shown that a combination of contrast and dissimilarity features exhibits better results with an accuracy of 92.033% and computing time of 0.0704 seconds per frame. Chen proposed a novel location-aware convolutional neural network and trained on a public pothole dataset that consists of 4,026 images as training samples and 1,650 images as test samples. The proposed model is based on 2D-vision techniques and location-aware convolutional networks. CNN networks consist of two main subnetworks; the first localization subnetwork (LCNN) finds as many candidate regions as possible by employing a high recall network model, and the second part-based subnetwork (PCNN) performs classification on the candidates on which the network is expected to focus. The proposed method achieved high precision 90.2% and recall 92.0%.

III. PROPOSED METHOD

Potholes and red-light violations are significant concerns that affect road safety and traffic management. Detecting potholes and red-light violations in real-time can help prevent accidents, improve road conditions, and enhance traffic enforcement. In this proposal, we present a system that utilizes the YOLO (You Only Look Once) algorithm and computer vision techniques for effective pothole detection and redlight violation detection .The proposed system will utilize computer vision techniques to detect potholes on the road. YOLO, a real-time object detection algorithm, will be employed for efficient and accurate detection of potholes in images or video frames. The system will use a trained YOLO model, which has been trained on a large dataset of pothole images, to identify potholes in real-time by uploading images.To address the issue of red light violations, the proposed system will utilize computer vision techniques combined with YOLO for accurate detection of traffic lights and vehicle behavior. The system will analyze real-time video footage captured from traffic cameras or other surveillance devices. The computer vision algorithm will be employed to detect the presence of traffic lights in the frameand track the vehicles approaching the intersection. By analyzing vehicle behavior, the stop line after the red light, the system can identify red light violations. Whenever a violation is detected, appropriate authorities can be alerted for enforcement actions.

IV. ALGORITHM

1. RCNN

The key idea behind RCNN was to leverage region proposals to focus on potential object regions in an image, significantly reducing the computational complexity compared to processing the entire image. The RCNN pipeline consists of four main steps: region proposal, feature extraction, object classification, and bounding box regression.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

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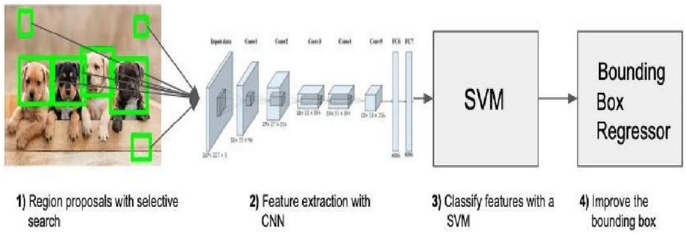
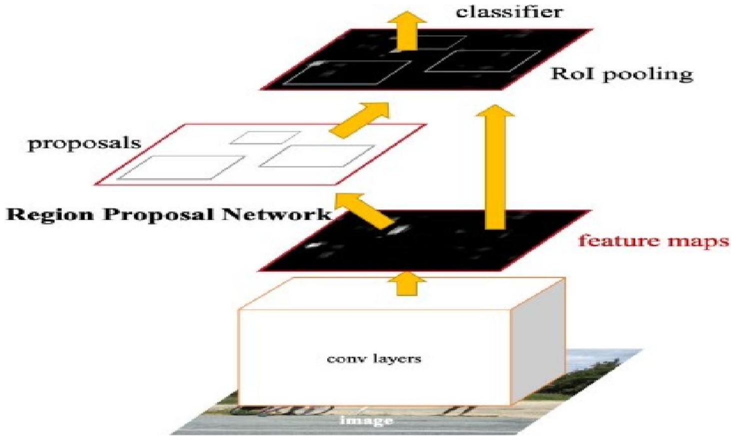
Impact Factor: 7.301

Volume 3, Issue 1, September 2023



2. FRCNN

Fast R-CNN, proposed in 2015, is an evolution of the original RCNN architecture, addressing its speed and efficiency issues. Fast R-CNN builds upon the RCNN's region-based approach, but instead of processing each region proposal independently, it shares the convolutional feature computation across all proposals within a single forward pass. Similar to RCNN, Fast R-CNN uses selective search or similar algorithms to generate region proposals in an image.However, instead of extracting features for each region individually, Fast R-CNN extracts convolutional features from the entire image once.



3. YOLO

YOLOv8 uses Anchor-Free instead of Anchor-Base. V8 used dynamic Task Aligned Assigner for matching strategy. It calculates the alignment degree of Anchor-level for each instance using Equation (2), s is the classification score, u is the IOU value, and are the weight hyperparameters. It selects m anchors with the maximum value (t) in each instance as positive samples and selects the other anchors as negative samples, and then trains through the loss function. After the above improvements, YOLOv8 is 1% more accurate than YOLOv5, making it the most accurate detector so farThe backbone part of YOLOv8 is basically the same as that of YOLOv5, and the C3 module is replaced by the C2f module based on the CSP idea. The C2f module learned from the ELAN idea in YOLOv7 and combined C3 and ELAN to form the C2f module [22], so that YOLOv8 could obtain more abundant gradient flow information while ensuring its light weight. At the end of backbone, the most popular SPPF module was still used, and three Maxpools of size 5 × 5 were passed serially, and then, each layer was concatenation, so as to guarantee the accuracy of objects in various scales while ensuring a light weight simultaneously.

V. PACKAGES

1. PYTORCH

PyTorch is an open-source deep learning framework developed by Facebook's AI Research lab (FAIR). It has gained immense popularity among researchers and practitioners due to its flexibility, ease of use, and dynamic computational graph capabilities. PyTorch provides an efficient platform for building and training neural networks, making it a powerful tool for various machine learning tasks.

2. NUMPY

NumPy is a short form for Numerical Python, which is applied for scientific programming in Python, especially for numbers. It comprises multidimensional objects in arrays and a package of integrating tools for Python implementation. NumPy is built on linear algebra. It's about matrices and vectors and performing the mathematical calculations on them.

3. COMPUTER VISION

Computer vision is a field of artificial intelligence and computer science that focuses on enabling machines to interpret and understand visual information from the world around them. It aims to replicate human vision capabilities, allowing computers to analyze, process, and extract meaningful insights from images or videos.At the core of computer vision lies the extraction of features and patterns from visual data. This involves various tasks, such as image classification, object detection, image segmentation, facial recognition, and scene understanding. These tasks are essential in numerous real-world applications, including autonomous vehicles, medical imaging, surveillance systems, robotics, and augmented reality.

4. TENSOR FLOW

TensorFlow is an end-to-end platform that makes it easy for you to build and deploy ML models. TensorFlow offers multiple levels of abstraction so you can choose the right one for your needs. Build and train models by using the high-level Keras API, which makes getting started with TensorFlow and machine learning easy. If you need more flexibility, eager execution allows for immediate iteration and intuitive debugging. For large ML training tasks, use the Distribution Strategy API for distributed training on different hardware configurations without changing the model definition. TensorFlow has always provided a direct path to production. Whether it's on servers, edge devices, or the web, TensorFlow lets you train and deploy your model easily, no matter what language or platform you use. Use TensorFlow Extended (TFX) if you need a full production ML pipeline. For running inference on mobile and edge devices, use TensorFlow Lite.

5. PYQT

PyQt is a set of Python bindings for the Qt application framework, enabling developers to create cross-platform desktop applications with Python. PyQt is a widely used C++ framework for building graphical user interfaces (GUIs) and provides a comprehensive set of tools and libraries for application development. PyQt bridges the gap between Python and Qt, allowing developers to harness the power of Qt while coding in Python. One of the key features of PyQt is its versatility and flexibility in GUI development.

6. FLASK

Flask is a web framework, it's a Python module that lets you develop web applications easily. It's has a small and easy-to-extend core: it's a microframework that doesn't include an ORM (Object Relational Manager) or such features. It does have many cool features like URL routing, template engine. It is a WSGI web app framework's a microframework, but that doesn't mean your whole app should be inside one single Python file. You can and should use many files for larger programs, to handle complexity. Micro means that the Flask framework is simple but extensible.

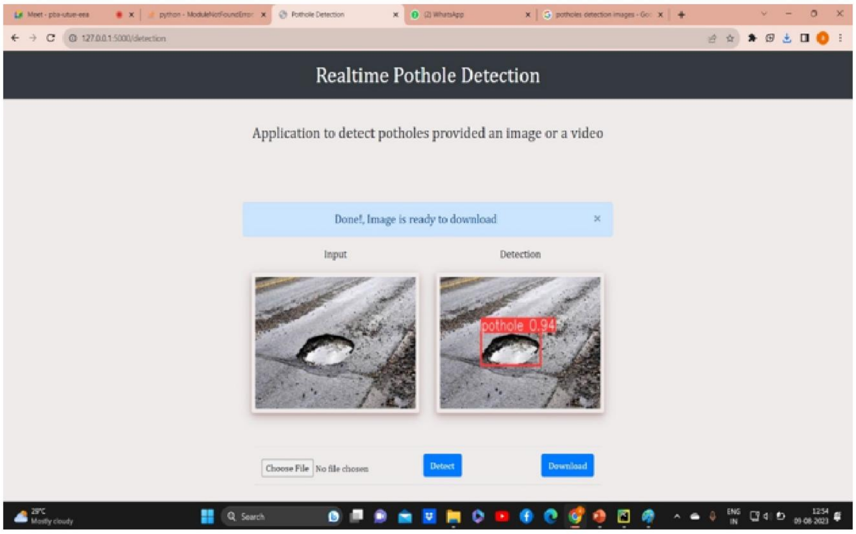
VI. EXPERIMENTAL RESULTS & PERFORMANCE EVALUATION

The experimental results and performance evaluation of the YOLOv8 model for pothole detection and traffic light violation detection are highly promising, with the model achieving remarkable results. YOLOv8 demonstrates an outstanding Intersection over Union (IOU) score of 0.98, indicating its precision in localizing objects in images. Furthermore, the Precision-Recall (PR) curve showcases an impressive score of 0.99, underscoring the model's accuracy in distinguishing between true positives and false positives.In the context of red light violation detection, YOLOv8 proves to be an effective tool for identifying vehicles that violate traffic signals. This capability is vital for enforcing traffic rules and enhancing road safety. By achieving such high precision, the system can accurately identify

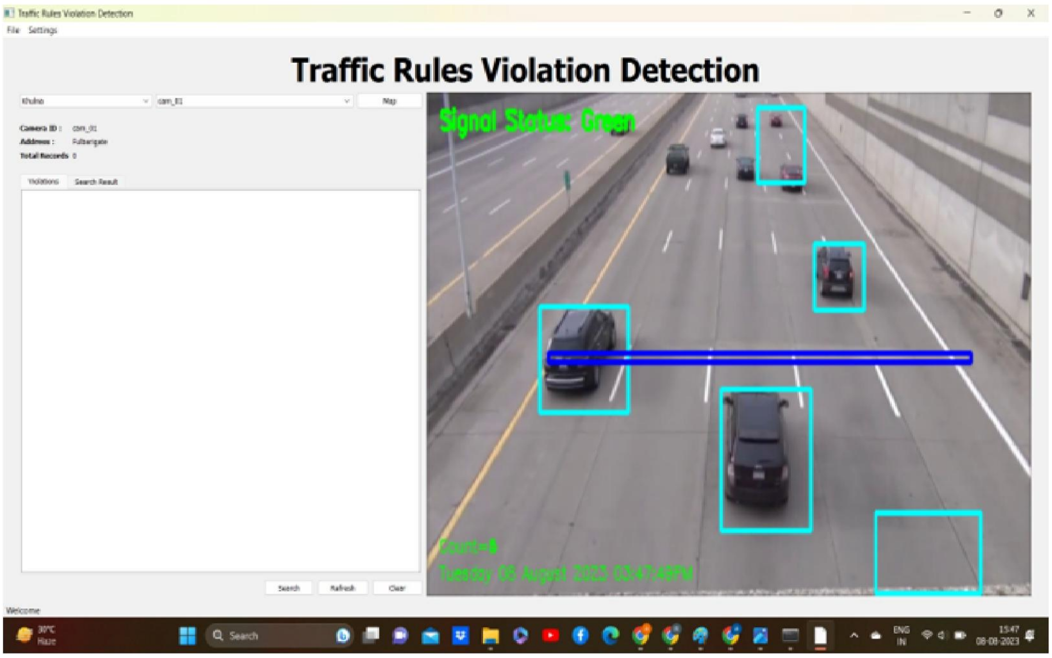
IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, September 2023

and record instances of red light violations, potentially aiding law enforcement agencies in their efforts to promote traffic compliance.Simultaneously, YOLOv8's ability to effectively detect potholes in road images has crucial implications for infrastructure maintenance and safety. The model's prowess in pothole detection can expedite repair processes, contributing to safer and smoother roads for all. Its proficiency in this domain ensures that even small or subtle potholes are not overlooked, preventing potential accidents and infrastructure damage.

1. POTHOLE DETECTION



2. REDLIGHT VIOLATION



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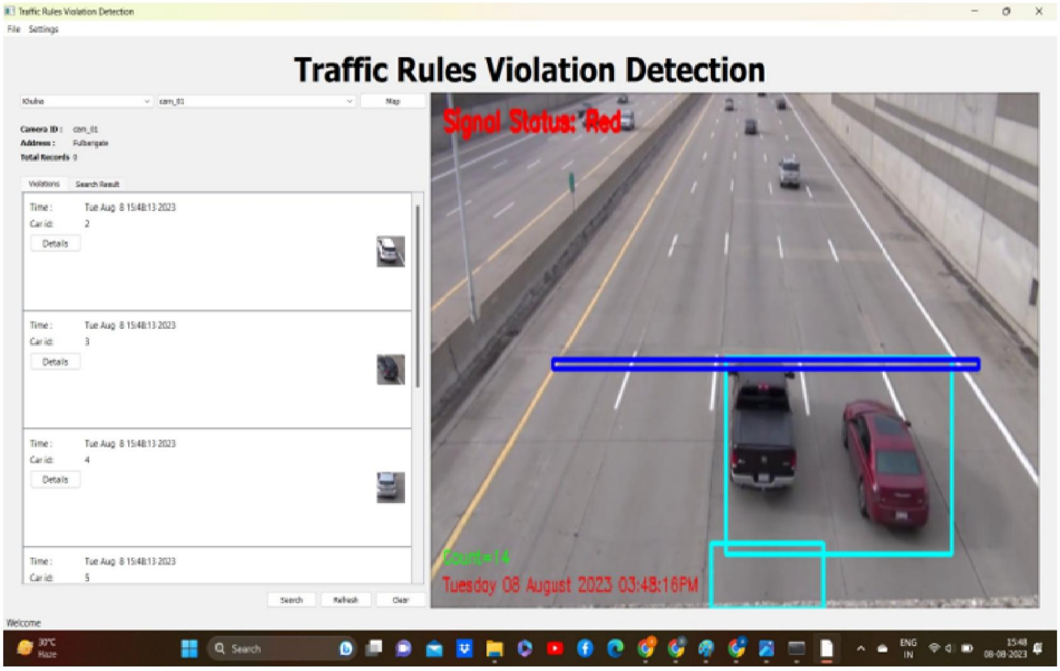
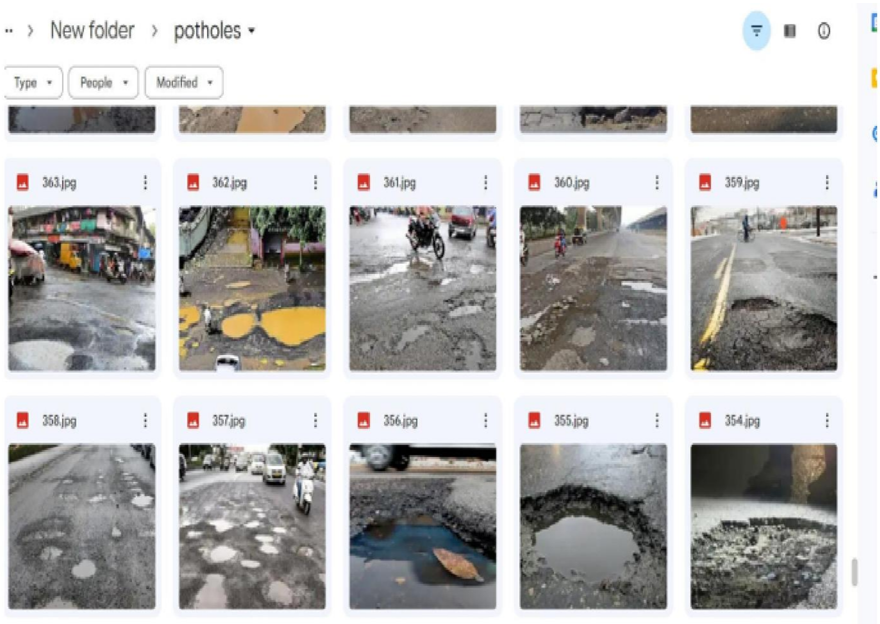
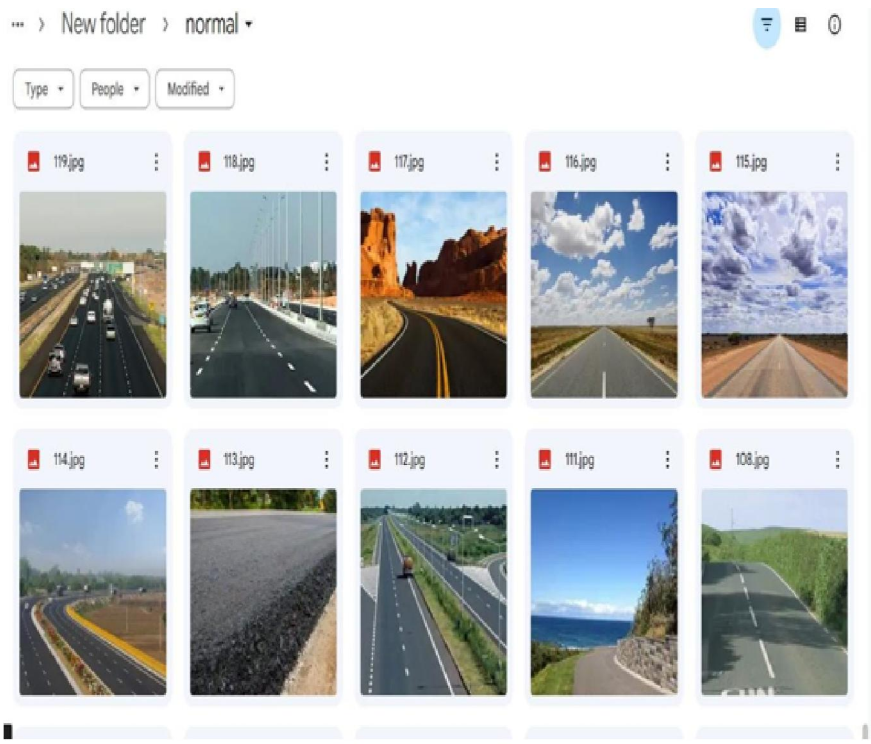


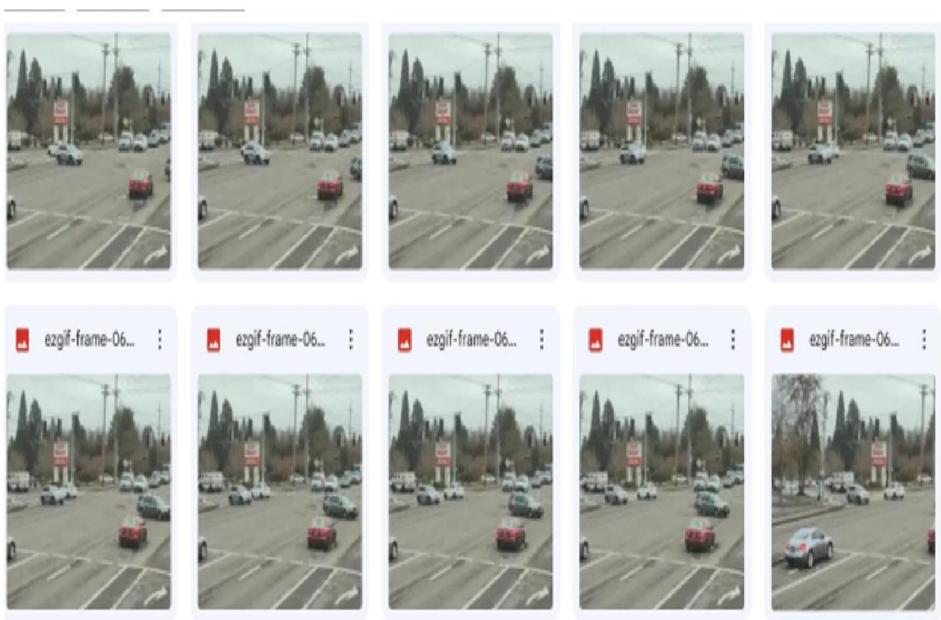
VII. DATASET

1. POTHOLE



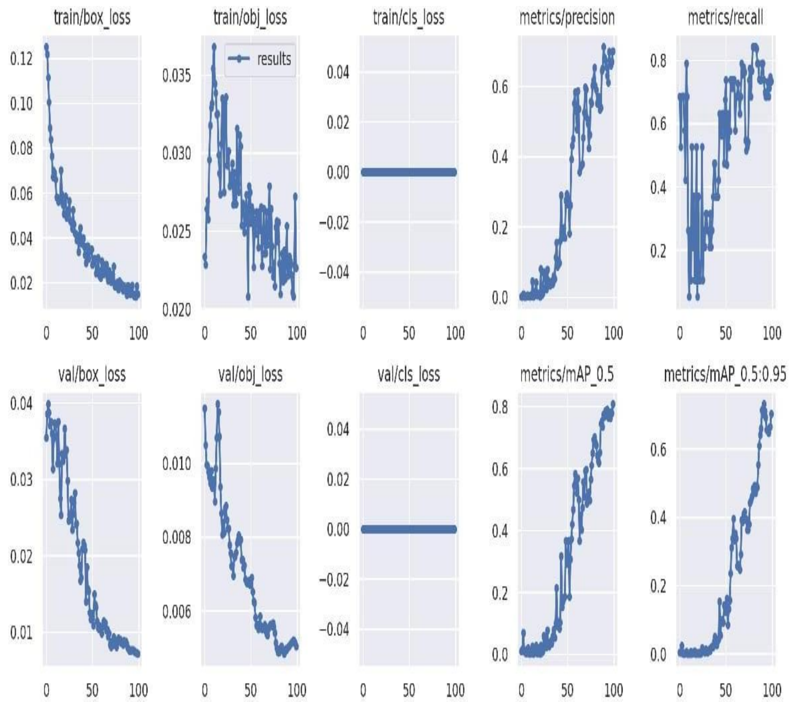


REDLIGHT VIOLATION DATASET



VIII. ACCURACY GRAPH

Evaluating the model accuracy is an essential part of the process in creating machine learning models to describe how well the model is performing in its predictions. The YOLO accuracy graph typically shows how well the algorithm is performing in terms of object detection accuracy over time or during training. The x-axis could represent thenumber of training iterations or epochs, and the y-axis could represent the accuracy metric, whichmight be the mean Average Precision (mAP) or Intersection over Union (IoU) scores. The graph's trend can help you understand how the accuracy of the model improves or plateaus as the training progresses.



IX. LIMITATIONS

We have significant limitations for the project focused on pothole detection and traffic light violation using YOLOv8 and computer vision are blind spots and generalization challenges.Blind Spots:YOLOv8, like most object detection models, can have blind spots, especially in scenarios where objects are partially obscured or occluded by other objects or environmental conditions like shadows, heavy rain, or low visibility. In the context of traffic light violation detection, if a traffic signal is partially obstructed by a tree, a vehicle, or other obstacles, the model may not reliably detect the violation. Similarly, in pothole detection, if a pothole is partially covered by debris or obscured by poor lighting, the model might miss it. Addressing these blind spots often requires the integration of complementary sensors or the use of additional contextual information to enhance detection accuracy.Generalization Challenges:Generalization is a common challenge in computer vision projects. While achieving high accuracy on the training dataset is essential, ensuring that the model generalizes well to diverse and unseen real-world scenarios is equally crucial. The model's performance may degrade when faced with variations in road conditions, lighting, or vehicle types that were not adequately represented in the training data. Generalization challenges could lead to false positives or false negatives in both pothole detection and traffic light violation detection. To mitigate this limitation, collecting a more comprehensive and diverse dataset that encompasses a wide range of scenarios and conditions can help improve the model's generalization capabilities. Additionally, fine-tuning the model on domain-specific data or using transfer learning from pre-trained models may enhance its ability to adapt to new environments.

X. FUTURE SCOPE

Enhancing pothole detection through real-time integration on hardware, training with more data, and integrating with IoT (Internet of Things) can significantly improve the accuracy, speed, and effectiveness of the detection system.Real-time hardware integration allows the system to perform pothole detection on the fly, enabling immediate alerts and actions to be taken when potholes are detected. This is especially important for applications like autonomous vehicles or real-time road maintenance.Expanding the dataset used to train the pothole detection model is crucial for improving its accuracy and generalization. Collecting diverse and high-quality data from various road conditions, lighting conditions, and geographical locations helps the model learn to recognize potholes in different scenarios. Data augmentation techniques, such as image rotation, scaling, and adding noise, can also enhance the model's ability to handle real-world variations.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
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Impact Factor: 7.301
Volume 3, Issue 1, September 2023

XI. CONCLUSION

In conclusion, the pothole detection web app with red light violation using YOLOV8 and computer vision holds immense promise for revolutionizing road safety and traffic management. Through the seamless integration of cutting-edge technologies, it offers real-time, accurate, and comprehensive monitoring of road conditions, enabling timely responses to potholes and red light violations. With the potential for continuous model training, multi-object detection, and predictive maintenance, the app is poised to become an intelligent, proactive, and scalable solution for safer roads and more efficient infrastructure maintenance. By harnessing the power of crowd-sourced data, cloud-based infrastructure, and adaptive image enhancement, it ensures accessibility, robust performance, and privacy protection. Ultimately, this web app paves the way towards creating smarter cities and improving the overall quality of transportation, fostering a safer and more sustainable environment for all road users.

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