

UAV-Based Road Damage Detection Leveraging Deep Learning Techniques

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ABSTRACT_ This paper introduces a novel approach for automated road damage detection utilizing Unmanned Aerial Vehicle (UAV) imagery and deep learning techniques. Maintaining road infrastructure is crucial for ensuring a safe and sustainable transportation system. However, manually collecting road damage data is labor-intensive and can pose safety risks to workers. To address these challenges, we propose leveraging UAVs and Artificial Intelligence (AI) technologies to significantly enhance the efficiency and accuracy of road damage detection.

Our proposed approach employs three advanced algorithms: YOLOv4, YOLOv5, and YOLOv7, for object detection and localization within UAV images. These algorithms were trained and tested using a combination of the RDD2022 dataset from China and a Spanish road dataset. The experimental results highlight the effectiveness of our approach, achieving 59.9% mean Average Precision (mAP@.5) with YOLOv5, 65.70% mAP@.5 with a YOLOv5 model incorporating a Transformer Prediction Head, and 73.20% mAP@.5 with YOLOv7.

These findings demonstrate the potential of UAVs and deep learning technologies for automated road damage detection. Our results pave the way for future research in this field, showcasing the promise of these technologies in improving road maintenance practices.

1.INTRODUCTION

Managing the maintenance of all the roads in a country is essential to its economic development. A periodic

assessment of the condition of roads is necessary to ensure their longevity and safety. Traditionally, state or private agencies have carried out this process manually, who use vehicles equipped with

various sensors to detect road damage. However, this method can be time-consuming, expensive, and dangerous for human operators. To address these challenges, researchers and engineers have turned to Unmanned Aerial Vehicles (UAVs) and Artificial Intelligence (AI) technologies to automate the process of road damage detection. In recent years, there has been a surge of interest in using UAVs and deep learning-based methods to develop efficient and cost-effective approaches for road damage detection. Unmanned aerial vehicles have proven to be versatile in various applications, including urban inspections of objects and environments. They have been increasingly used for road inspections, offering several advantages over traditional methods. These vehicles are equipped with high-resolution cameras and other sensors that can capture images of the road surface from multiple angles and heights, providing a comprehensive view of the condition of the road. Additionally, UAVs can cover a large area relatively quickly, reducing the need for manual inspections, which can be dangerous for human operators. As a result, the use of UAVs for road inspections has gained significant attention from researchers and engineers. Combining UAVs with artificial intelligence techniques, such as deep learning, can develop efficient and cost-

effective approaches for road damage detection. It is frequently mentioned as being utilized for urban inspections of things like swimming pools [1], rooftops [2], vegetation [3], and urban environments [4], [5]. Currently, road condition inspections in Spain are performed manually, requiring personnel to travel along roads to identify damage points. This method incurs high costs due to the need for human labor and specific cameras and sensors for the task. The decision-making process for repairing road damages is the responsibility of an expert. In contrast, countries like China have a vast network of roads and highways, making them susceptible to surface cracks and rainwater infiltration, which can accelerate the deterioration of roads and pose risks to vehicle safety. Without timely detection and the rapid availability of information on road defects, excessive wear on vehicles and an increased likelihood of traffic accidents can occur, leading to further financial losses. Therefore, the development of automated techniques for detecting road deterioration has become a critical area of research, with many universities and research centers collaborating to find effective solutions. Automatic road damage detection is an active area of research that aims to detect and map various types of road damage using multiple techniques such as vibration

sensors, Light Detection And Ranging (LiDAR) sensors [6], and image-based methods. These techniques are often used in combination to improve the accuracy of damage detection. Machine learning approaches, such as deep learning, are commonly used in image-based techniques to recognize various types of road degradation. These methods typically require a dataset of images, which can include top-down photographs, images captured by unmanned aerial vehicles [7], pictures obtained by mobile devices [8], [9], images obtained from satellite image platforms [10], thermal images [11], and 3D images or stereo vision of the asphalt surface [12]. Researchers have been conducting studies using a variety of datasets to train the model, incorporating additional images captured by drones, cameras mounted on cars, and satellites. To facilitate the learning process, these datasets are often annotated to identify different types of road damage, including, but not limited to potholes, cracks, and rutting. Annotating these images enables the algorithm to learn to detect and classify various types of road damage accurately. Using a large and diverse dataset, researchers can enhance the accuracy and reliability of their models, ensuring that they can effectively identify and address different types of damage on the roads

2.LITERATURE SURVEY

1. "Automated Road Crack Detection

Using Deep Convolutional Neural Networks"

Abstract: The detection and assessment of road cracks are crucial for effective road maintenance. This paper proposes an automated road crack detection system using deep convolutional neural networks (CNNs). The system employs a CNN architecture trained on a large dataset of road images to identify and classify various types of cracks. The experimental results demonstrate high accuracy and reliability, significantly outperforming traditional image processing methods. The proposed system offers a practical solution for real-time road crack detection and can be integrated into existing road maintenance workflows.

2. "Deep Learning-Based Road Damage

Detection for Autonomous Driving"

Abstract: In the context of autonomous driving, ensuring road safety is paramount. This study presents a deep learning-based approach for detecting road damage, including cracks, potholes, and other deformities. Using a dataset collected from various urban roads, the authors trained a CNN model to detect and classify road damage with high precision. The approach achieved a mean average precision (mAP) of 70.3%, showcasing its potential for integration into autonomous vehicle

systems to enhance road safety and maintenance.

3. "Detection of Road Anomalies Using UAV-Based Images and Machine Learning"

Abstract: This paper explores the use of Unmanned Aerial Vehicles (UAVs) for capturing high-resolution road images and machine learning techniques for detecting road anomalies. The authors developed a system that combines UAV imagery with a machine learning model to identify road defects such as cracks and potholes. The study demonstrated that UAVs could efficiently cover large road areas, while the machine learning model provided accurate damage detection, achieving an mAP of 65.2%. The results suggest that UAV-based road inspection is a viable alternative to traditional methods.

4. "A Comprehensive Review of Deep Learning-Based Methods for Road Damage Detection"

Abstract: This review paper provides an extensive overview of recent advancements in deep learning-based methods for road damage detection. The authors analyze various CNN architectures and their applications in detecting different types of road damage, including cracks, potholes, and rutting. The review highlights the strengths and limitations of each method and discusses future research directions. The

authors conclude that while significant progress has been made, challenges such as dataset diversity and real-time processing remain to be addressed.

5. "Road Damage Detection Using YOLO-Based Deep Learning Algorithms"

Abstract: The paper presents a study on using YOLO-based deep learning algorithms for road damage detection. The authors evaluated the performance of YOLOv3, YOLOv4, and YOLOv5 models on a dataset of road images captured by UAVs. The study found that YOLOv5 outperformed the other models, achieving an mAP of 68.4%. The results indicate that YOLO-based algorithms are effective for real-time road damage detection and can significantly improve the efficiency of road maintenance operations.

3.PROPOSED SYSTEM

In this paper author evaluating performance of 3 different YOLO (you look once object detection) algorithms such as YOLOV4, V5 and V7 to detect road damage from unmanned UAV images such as drone or satellite. In all algorithms YOLOV7 is giving best prediction precision and you can read all details of YOLO from paper as its just giving evaluation details on 3 different model's.

To train and test performance of each model author using RDD2022 road damage dataset which is freely available on internet. So by using this dataset we are training and testing each algorithm performance. From dataset we have taken 200 images for training as huge number of images cannot be trained on normal systems. Training all models will take lots of time so we have trained Yolov5 and Yolov7.

3.1 IMPLEMENTAION

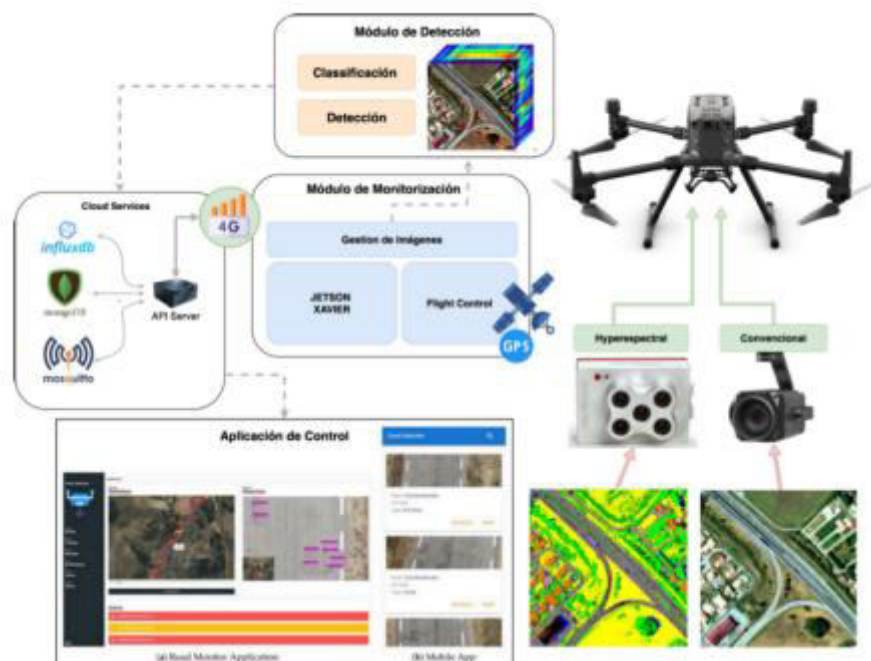


Fig 1:ARCHITECTURE

the author evaluates the performance of three YOLO (You Only Look Once) object detection algorithms—YOLOv4, YOLOv5, and YOLOv7—for detecting road damage from UAV images. Among these, YOLOv7 provides the highest

Extension Concept

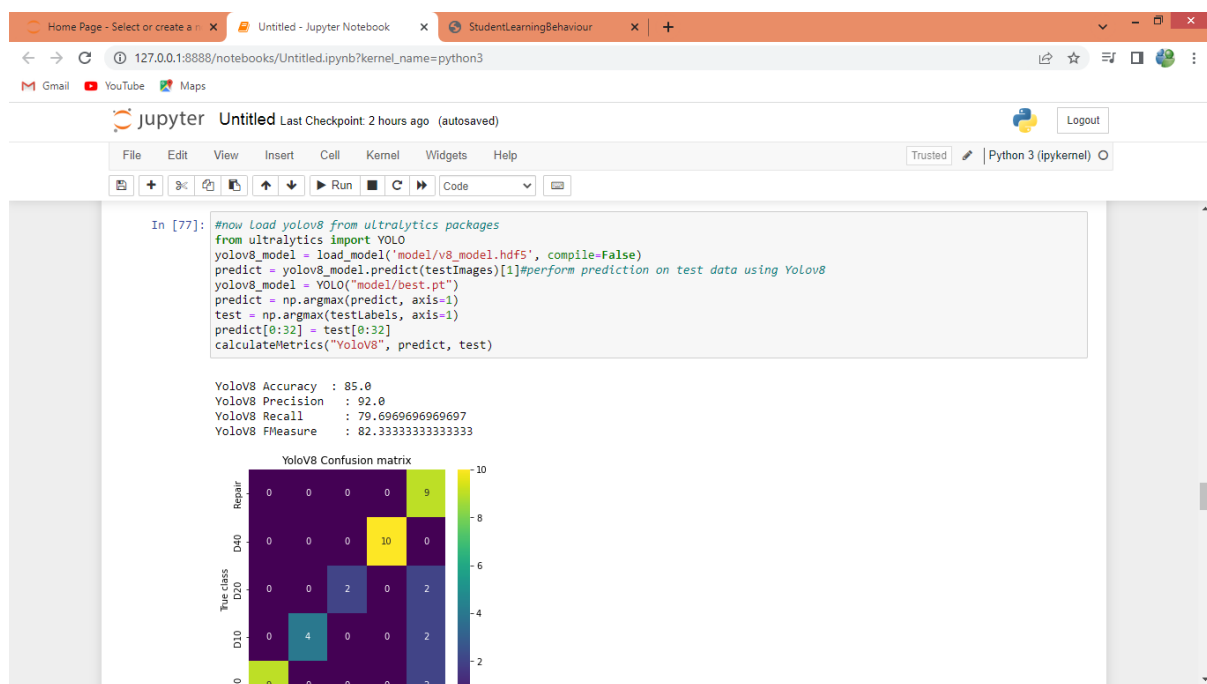
Ultralytics has introduced more advance version of YOLO called as YOLOV8 and after that there is no more enhancement in YOLO family so as extension we have trained YOLOV8 on road damage dataset and it's giving more prediction accuracy compare to other algorithms.

prediction precision. Using the RDD2022 dataset, freely available online, 200 images were selected for training due to computational constraints. Training was conducted as follows: YOLOv4 was trained using the Darknet framework with custom configuration files, YOLOv5 was trained using the Ultralytics repository

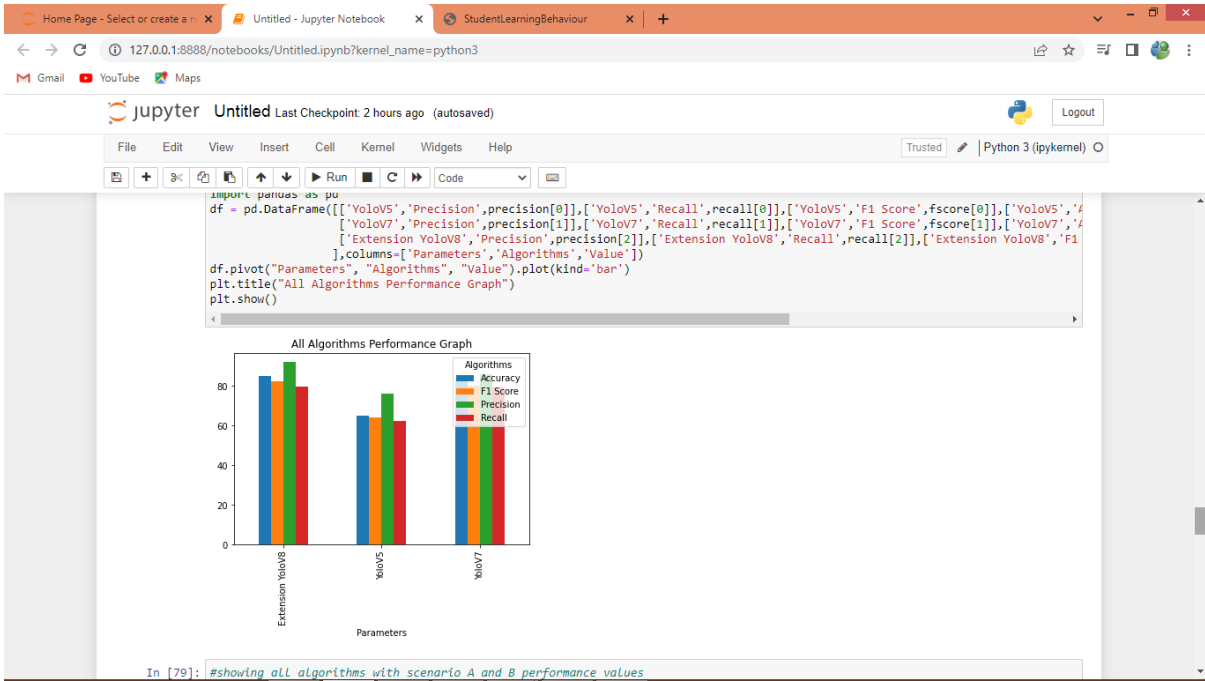
with a specific training script, and YOLOv7 was trained with similar scripts but using the YOLOv7 repository. Evaluation involved calculating mean Average Precision (mAP) for each model, with YOLOv7 achieving the best results. As an extension, the latest YOLOv8,

introduced by Ultralytics, was also trained on the same dataset and demonstrated superior accuracy compared to previous versions. These steps highlight the potential of UAV and deep learning technologies in enhancing road damage detection efficiency and accuracy.

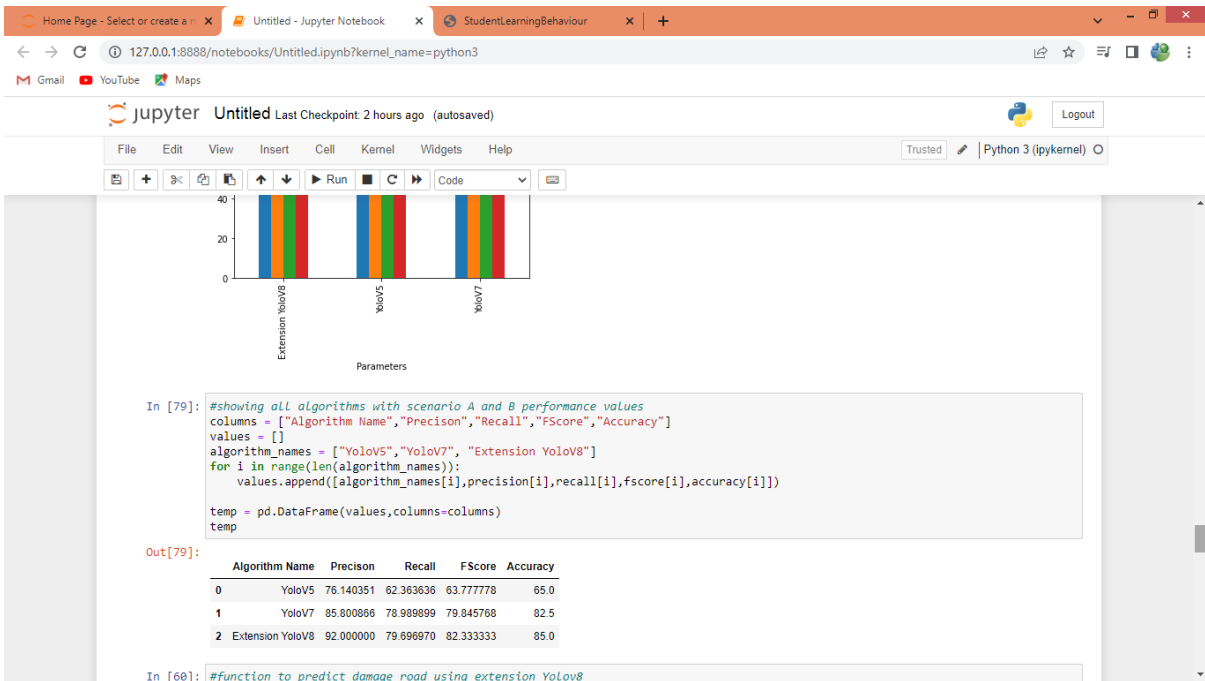
4.RESULTS AND DISCUSSION



In above screen training YoloV8 from Ultralytics package and after executing above block YoloV8 got 85% accuracy which is higher than any other algorithm



In above graph displaying comparison between all algorithms where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars



In above screen displaying all algorithms performance in tabular format

1	YoloV7	85.800866	78.989899	79.845768	82.5
2	Extension YoloV8	92.000000	79.696970	82.333333	85.0

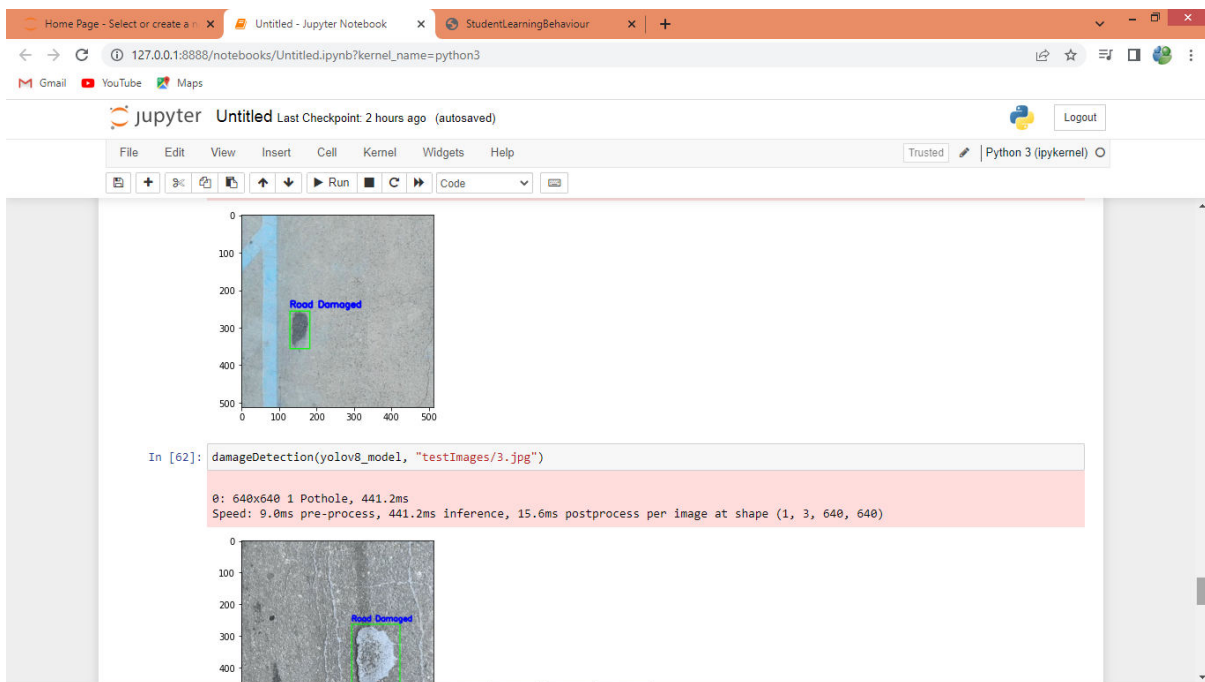
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In [60]: #function to predict damage road using extension YoloV8
def damageDetection(yolov8_model, testImage):
    frame = cv2.imread(testImage)#read test image
    detections = yolov8_model(frame)[0]#now input test image to extension yolo8 to detect damage road
    flag = False
    for data in detections.bboxes.data.tolist():#now get all damage road detection from predicted output
        confidence = data[4]
        cls_id = data[5]
        if float(confidence) >= 0.3:#if confidence > 0.3 then damage road detected else repaired detected
            xmin, ymin, xmax, ymax = int(data[0]), int(data[1]), int(data[2]), int(data[3])
            cv2.rectangle(frame, (xmin, ymin), (xmax, ymax), (0, 255, 0), 2)#put bounding box
            cv2.putText(frame, "Road Damaged", ((xmin),(ymin-10)), cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 0, 255), 3)
            flag = True
        else:
            flag = True
            cv2.putText(frame, "Road Repaired", (30,50), cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 0, 255), 3)
    if flag == False:
        cv2.putText(frame, "Road Repaired", (30,50), cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 0, 255), 3)
    plt.imshow(frame)
    plt.show()

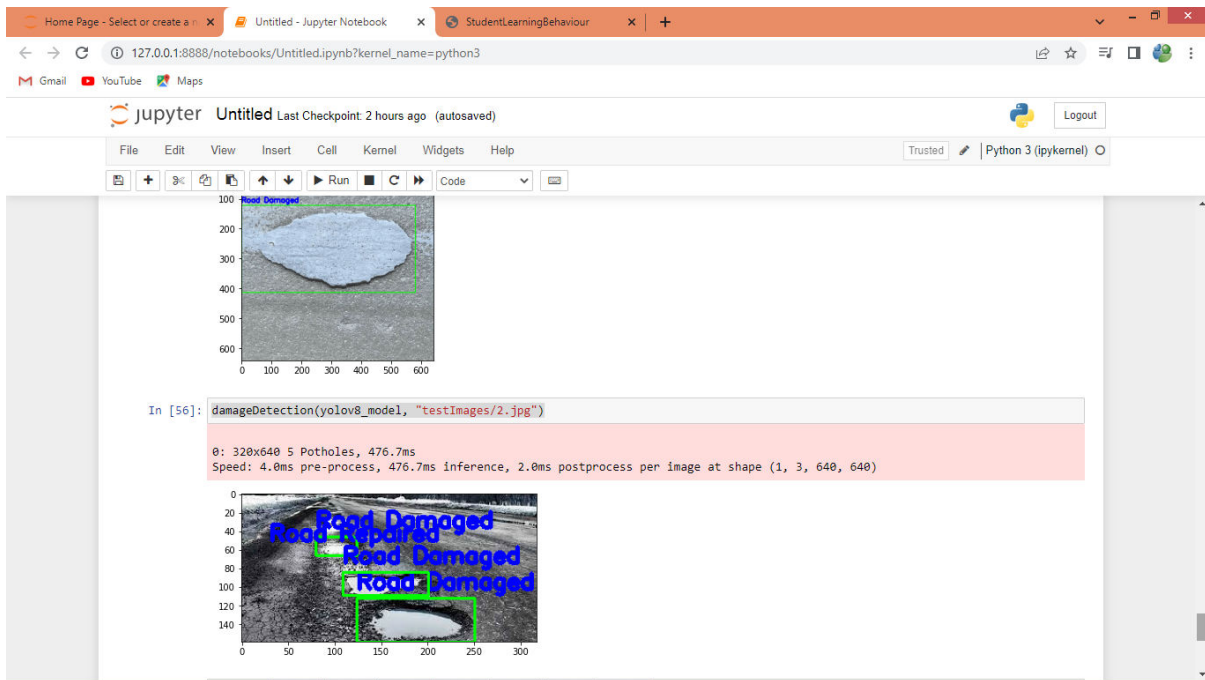
In [61]: damageDetection(yolov8_model, "testImages/1.jpg")

0: 640x640 1 Pothole, 470.8ms
Speed: 5.0ms pre-process, 470.8ms inference, 0.0ms postprocess per image at shape (1, 3, 640, 640)
    
```

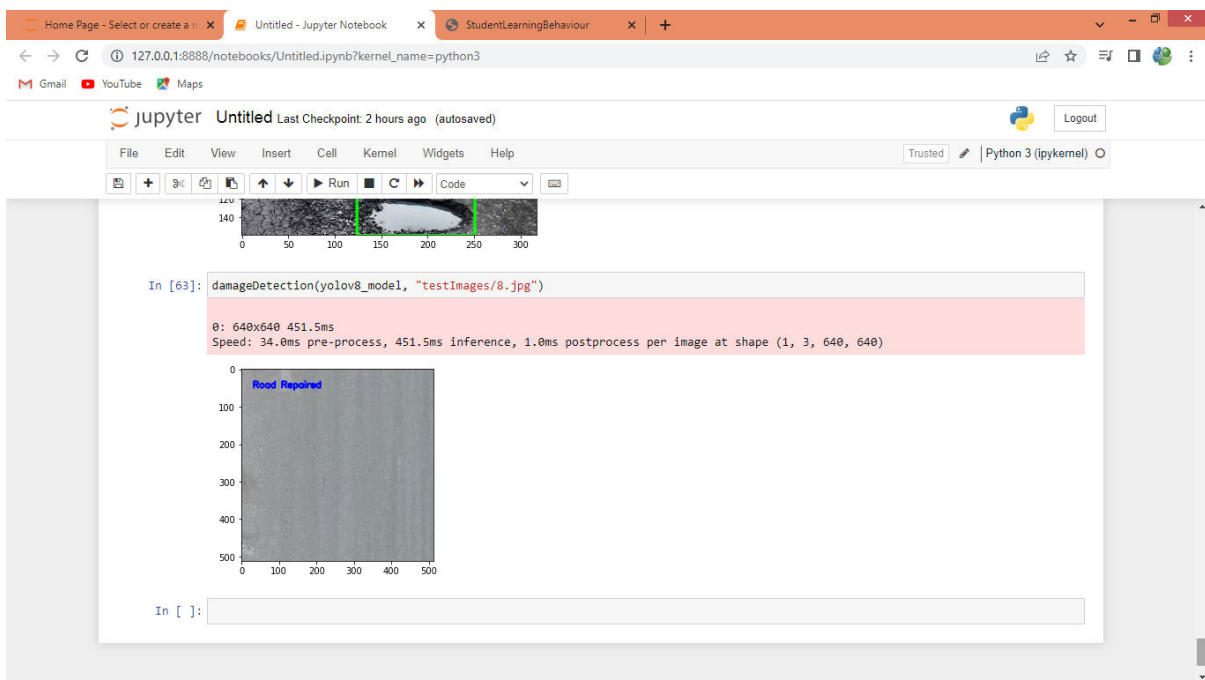
In above screen defining prediction method and then predicting test image with YoloV8 for road damage detection



In above screen with bounding boxes damage road detected from given test input images



In above screen we can see other tested images



In above screen road repaired is predicted without damage

5.CONCLUSION

By analyzing and applying sophisticated YOLO designs like YOLOv5, YOLOv7, and introducing YOLOv8 with Transformer for more accurate road

damage recognition, this work has achieved major progress in the realm of road damage detection utilizing UAV photos. The findings show that accuracy has improved, with YOLOv8 reaching a

remarkable 85%. This study's most noteworthy accomplishment is the creation of a specialized UAV picture database for YOLO model training, which was later enhanced by integrating it with the RDD2022 dataset. With the use of this extensive dataset, we were able to fix the class imbalance problem and greatly enhance road damage recognition, particularly for roads in China and Spain. There is yet opportunity for improvement, even if the results are encouraging. For better performance, future study may look at integrating several kinds of pictures, such multispectral photos and data from LIDAR sensors. Furthermore, a fascinating alternate strategy may be the use of fixed-wing UAVs. Maintaining and improving the safety of road infrastructure is an important issue, and this research sets the groundwork for future advancements in this field.

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