



Hybrid Deep Learning and UAV Vision System for Road Surface Defect Detection

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To Cite this Article

N M Ramalingeswara Rao, B.Lowkika, V.Kranthi Kiran, P.Sai Pavan & Ch.Ramanjaneyulu (2026). Hybrid Deep Learning and UAV Vision System for Road Surface Defect Detection, 12(03), 59-67. <https://doi.org/10.5281/zenodo.18880523>

Article Info

Received: 28 January 2026; Revised: 26 February 2026; Accepted: 02 March 2026.

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KEYWORDS	ABSTRACT
Road Defect Detection, UAV-Assisted Pavement Inspection, Hybrid YOLO-Based Detection Framework, Drone Image Analytics, Road Surface Anomaly Identification, Real-Time Defect Localization, Intelligent Transportation Infrastructure Monitoring, AI-Driven Damage Assessment.	Maintains road designing is crucial for the development and Traffic congestion are have to control the transportation. Traditional road damage data storing is labor-intensive and unsafe. Utilizing UAVs and AI offers efficient and accurate solutions. This project aims to hybrid deep learning and UAV vision system to be control to find the road defect detection and reducing manual collection challenges.YOLOv5 and YOLOv7 are used to detects the road damage UAV images, trained and tested on combined Chinese and Spanish datasets. Results show 82.5% precision with both YOLOv5 and YOLOv7, YOLOv8 indicating effectiveness across various damage types. UAVs streamline road defect detection, offering promising applications of infrastructure monitoring and upcoming research on transportation management. High-resolution road images are captured using UAVs and processed using YOLOv5, YOLOv7 and YOLOv8 models to detect and classify surface defects accurately. The system performs preprocessing, feature extraction, and real-time object detection to identify damaged areas under varying environmental and lighting conditions. A backend module is developed to manage image processing and store detection results, enabling scalable and efficient monitoring. The performance of the system is evaluated using standard metrics including Accuracy, Precision, Recall, F1-score, and mAP. Experimental results demonstrate that the proposed approach provides reliable and efficient detection performance, with YOLOv8 achieving the most balanced results among the compared models. The integration of UAV vision and deep learning significantly reduces manual inspection effort and improves monitoring efficiency.

INTRODUCTION

Road Maintenance plays a vital role in transportation safety and economical development for roads. vehicle damage, and accident risks. However, road surfaces wastes over time due to heavy traffic loads, climatic conditions and material aging. Common road damages such as potholes and cracks, if not detected early, can lead to serious safety issues and increased maintenance costs. Traditional road inspection methods are mainly manual or vehicle-based. Actual inspections require field personnel to physically survey roads and record damage details, which is time-consuming, labor-intensive, and prone to human error. Vehicle-mounted inspection systems improve coverage but are costly and limited by traffic conditions and accessibility. Both approaches lack scalability and real-time monitoring capabilities. Recent advancements in computer vision and deep learning have enabled automated visual inspection systems. Deep learning models, especially object detection algorithms, can automatically learn features from images and accurately identify damaged regions without manual intervention. Among these models, the YOLO (You Only Look Once) family has gained attention for its high detection speed and accuracy. *Unmanned Aerial Vehicles (UAVs) provide an efficient solution for large-scale road 1 monitoring by capturing high-resolution images over extensive areas in a short time. UAV-based inspection improves safety by eliminating the need for on-road inspections and enables access to remote or difficult locations. When combined with YOLO-based models such as YOLOv5, YOLOv7 and YOLOv8, UAV systems can perform real-time road defect detection with high reliability. It proposes an road defect detection using UAV images and deep learning models. The system detects and classifies road damages such as holes and cracks, providing accurate visual outputs to support timely and efficient road maintenance.

The hybrid deep learning and UAV vision System which can be designed for the road damage techniques which can be crucial for advancements which is really happened at the road detection monument. The Deep learning technique which is used to find the major segments which can suitable for road defect to detect their damage on roads. The required Performance evaluation on roads which can play a crucial method

which can be useful for the cracks on roads. This Method of dealing with the Exceptional theory on roads. The Crucial method which can be used to Identify the defect via UAV findings to Establish the recall for the road defect .The Road damage is more occurs on the patches and cracks ..The Traffic conditions will rectify with these type of defecting detection via webpage to be compared to the sectional roads Or other normal detection. This type of deep learning techniques were very useful for this new generations on road defect detection.

RELATED WORKS

Several studies have been conducted in the area of road defect detection using image processing and machine learning techniques. Early research mainly focused on traditional image processing methods such as edge road defect detection, thresholding, and texture analysis to find cracks and surface defects. Although these approaches were simple to implement, which limited their accuracy in real-world environments. With the advancement of machine learning, researchers began applying classical classifiers for road damage classification. These methods required handcrafted features and careful parameter tuning, make them less adaptable for different road conditions and damage types. Recent research has shifted toward deep learning-based approaches due to their superior performance in visual recognition tasks. Convolutional Neural Networks (CNNs) have used widely for road damage classification and segmentation. Several studies outperform the traditional methods by automatically learning complex features from road images. YOLO have been applied to detect road damages with improved accuracy. Among these, YOLO-based models gained popularity due to their real time detection capability and high processing speed. Researchers have successfully used YOLOv5 and YOLOv7 models to detect potholes and cracks from road images with high precision. In recent years, UAV-based road inspection systems have gained attention for their ability to capture high resolution aerial images over large areas. Studies integrating UAV imagery with deep learning models have shown improved coverage, reduced inspection time, and enhanced safety. However, challenges such as varying lighting conditions, camera angles, and image

resolution still exist. The proposed system builds upon these existing works by integrating UAV-based image acquisition with advanced YOLO models for accurate and real-time road damage detection. This approach aims to improve detection robustness while reducing inspection cost and human involvement. .

EXISTING SYSTEM

Existing road defect detection systems have taken from purely normal inspection techniques to semi automated and deep learning-based approaches. Despite these advancements, current methods still face several challenges related to accuracy, scalability, cost, and real-time performance. In the earliest approaches, road damage detection was carried out through manual inspections, where trained personnel visually examined road surfaces to identify defects such as potholes and cracks. While manual inspection allows direct observation, it is extremely time-consuming, labor-intensive, and highly dependent on human judgment. This results in inconsistent reporting and delayed maintenance actions. Moreover, inspectors are exposed to traffic-related hazards, making this method unsafe and unsuitable for frequent monitoring. To improve efficiency, vehicle-based inspection systems were introduced. These systems employ cameras, laser scanners, or vibration sensors mounted on vehicles to capture road surface data. Although vehicle-based methods reduce manual effort and increase inspection speed, they require expensive equipment, trained operators, and are limited by traffic congestion and road accessibility. Real-time analysis remains difficult due to the large volume of data generated. With the rise of artificial intelligence, deep learning-based methods began to replace traditional image processing techniques. Convolutional Neural Networks (CNNs) were initially used for road damage classification and segmentation. However, these methods often lacked real-time detection capability and required high computational resources. Recent existing systems have adopted object detection frameworks such as YOLO (You Only Look Once) for automated road damage detection. YOLOv5 has been widely used due to its balance between detection accuracy and processing speed. It enables real-time detection of road damage from images captured by vehicles or UAVs. However, YOLOv5 still faces challenges in detecting small cracks

and damages under complex backgrounds. YOLOv7 was introduced to improve detection accuracy and speed through architectural optimizations. Some existing systems utilize YOLOv7 to enhance real-time road damage detection performance, especially for high-resolution images. Despite its improvements, YOLOv7 requires powerful hardware and large labeled datasets to achieve optimal results, which increases system cost and complexity. YOLOv8 represents a further advancement with improved training strategies and detection performance. A few recent approaches have started adopting YOLOv8 for road damage detection due to its better accuracy and robustness. However, YOLOv8-based systems are still limited by dataset diversity and deployment complexity, particularly in large-scale and real-time UAV-based applications. Although the integration of YOLOv5, YOLOv7, and YOLOv8 has significantly improved automated road damage detection, existing systems still suffer from limitations such as high computational requirements, limited generalization across different road conditions, and lack of seamless integration with UAV-based inspection platforms. These challenges highlight the need for a more efficient, scalable, and robust system that effectively combines UAV technology with advanced YOLO models for real-time road damage detection.

PROPOSED METHOD

The methodology aims to develop an automated and intelligent road damage detection system by integrating Unmanned Aerial Vehicle (UAV) with advanced deep learning based object detection models. The system is designed to reachout the limits of existing manual and vehicle based inspection methods by providing accurate, scalable, and real-time road condition monitoring. The methodology begins with UAV-based image acquisition, where UAVs equipped with high-quality cameras are deployed to capture aerial images of road surfaces. UAVs follow predefined paths to ensure complete coverage of the inspection area. This approach enables safe and efficient data collection over large and hard-to-reach regions without interrupting traffic flow. The collected images are then subjected to data processing to enhance quality and consistency. These steps improve the clarity of road damage features

and ensure compatibility with deep learning models. The dataset consists of labelled images containing various road damage types such as potholes and cracks, collected from publicly available datasets and UAV inspections. After preprocessing, These models perform object localization and classification in a single forward pass, enabling real-time detection. YOLOv5 is used as a baseline model due to its efficiency and stability, while YOLOv7 provides improved accuracy and faster inference. YOLOv8 is incorporated to further enhance detection performance and robustness under complex road and lighting conditions. During the training phase, labeled images are used to train the networks to identify damage patterns. Hyperparameters are optimized to achieve better detection accuracy. The trained models are evaluated using standard performance metrics such as Precision, Recall, F1-score, and mean Average Precision (mAP). Once the optimal model is selected, it is integrated into the road surface defect detection system for inference. When a UAV-captured image is provided as input, the system processes the image and applies the trained YOLO model to detect and classify road damage. The detected regions are marked using bounding boxes and class labels, providing clear visual outputs. Finally, the result visualization and analysis module presents the detection results in an understandable format. The output can be used by road maintenance authorities to identify damaged locations and plan repair activities efficiently. This proposed methodology ensures accurate, safe, and scalable road damage detection, it is suitable for real-world infrastructure monitoring actual and usual applications.

ARCHITECTURE DIAGRAM

The architecture of proposed road damage detection system illustrates the overall workflow and interaction between different system components. It describes how road surface images are captured, processed, analyzed, and visualized using UAVs and deep learning models. The process starts with the UAV Image Acquisition Module, where Unmanned Aerial Vehicles equipped with high-resolution cameras are deployed to capture useful images of road surfaces. UAVs follow predefined flight paths to ensure complete coverage of the inspection area. This module enables efficient, safe, and large-scale data collection without interrupting traffic flow. The captured images are forwarded to the

Preprocessing Module, where image enhancement operations are performed. This includes resizing images to a standard resolution, noise reduction, normalization, and contrast enhancement. Preprocessing improves image quality and obtains the data is suitable for deep learning model input.

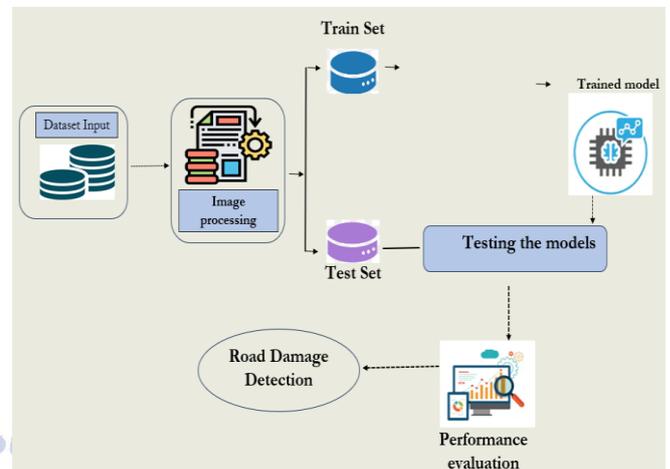


Figure 1: System architecture

After preprocessing, the images are passed to the Deep Learning Detection Module, which is the core component of the system. This module utilizes YOLO-based object detection such as YOLOv5, YOLOv7, and YOLOv8. These models analyze the images to detect and classify road damages like potholes and cracks in a single forward pass, enabling real-time defect detection with high accuracy. The detected outputs are then processed by the Result Visualization Module, where the class labels are drawn on the images to highlight damaged regions. This visual representation helps users easily understand the type and location of road damage. Finally, the Storage and Analysis Module stores detection results for future reference and maintenance planning. The output data can be used by road authorities to prioritize repairs and improve infrastructure management. Overall, the architecture diagram represents a modular, scalable, and efficient system that integrates UAV technology with the new generation deep learning models to adopt the road surface defect detection.

DATAFLOW

The data flow of the proposed road damage detection system explains how information is transferred and processed across different modules from image acquisition to final output generation. The data flow

begins with the UAV Image Acquisition module, where Unmanned Aerial Vehicles capture high-resolution images of road surfaces during inspection flights. These images form the raw input data for the system. Next, the captured images are passed to the Preprocessing module. In this stage, the images undergo resizing, normalization, noise removal, and contrast enhancement. Preprocessing ensures consistency in image pureness and circulates the data for deep learning-based analysis.

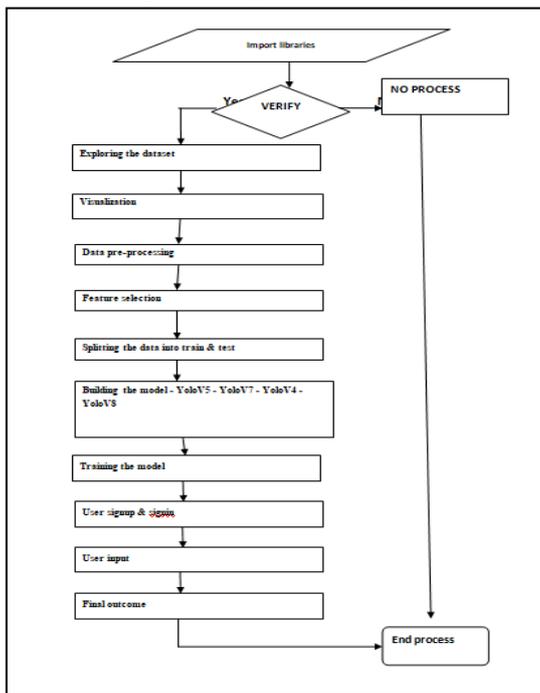
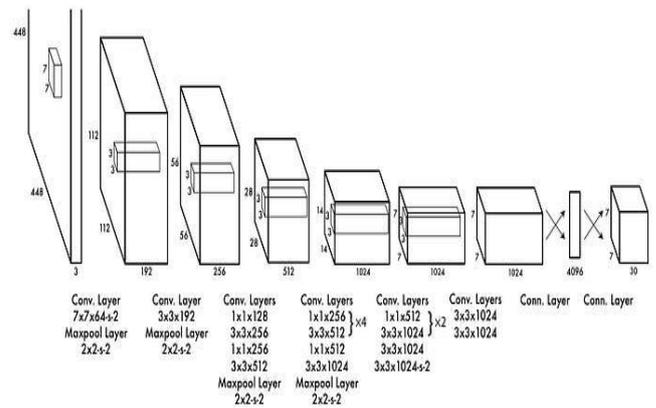


Figure 2: System Data Flow

After preprocessing, the images are forwarded to the Deep Learning Processing module, which utilizes YOLO-based object detection models such as YOLOv5, YOLOv7, and YOLOv8. The models analyze the input images to identify and classify road damages such as potholes and cracks. Bounding box and class labels are generated as output from this module. The detection results are then sent to the Visualization module, where bounding boxes and labels are superimposed on the original images. This step provides a clear visual representation of detected road damage, making it easier for users to interpret the results. Finally, the processed output data is transferred to the Storage and Analysis module. The results are stored for future reference and used for maintenance planning and decision-making by road authorities. Overall, the data flow ensures a systematic and efficient transfer of information across modules, enabling accurate and real-time road damage detection.



ALGORITHM

The proposed road surface defect detection uses a YOLO-based deep learning algorithm to identify and classify road surface damages from UAV images. The algorithm follows a systematic process from image acquisition to final damage detection and visualization

YOLOv5:

YOLOv5 is an object defect detection model that uses a singular convolutional to predict the multiple bounding boxes and their corresponding class probabilities in an image. YOLOv5 is implemented as a deep learning model for detecting road surface defect in UAV images

YOLOv7:

YOLOv7 is an upgraded version of the YOLO (You Only Look Once) object detection model, incorporating improvements in architecture and training techniques to enhance detection performance..

YOLOv8:

YOLOv8 is a state-of-the-art object detection model that builds upon previous versions of YOLO by incorporating advancements in architecture design and training methodologies to achieve superior performance in object detection tasks. YOLOv8 is integrated into the project as a Hybrid deep learning and UAVs vision system for road surface defect detection.

RESULTS AND DISCUSSION

The proposed Hybrid Deep Learning and UAV Vision System was evaluated to measure its effectiveness in detecting road surface defects such as potholes and cracks. The system was tested using UAV-captured images and the RDD dataset under different environmental and lighting conditions to ensure robustness.

Performance has analyzed using Normal evaluation metrics including Accuracy, Precision, Recall, F1-score, and mean Average Precision (mAP). Among the evaluated models, YOLOv5 provided stable baseline performance with satisfactory detection accuracy and moderate inference speed. YOLOv7 demonstrated improved precision and recall, indicating better detection of smaller and partially visible defects. YOLOv8 achieved the most balanced performance across all manners, showing higher F1-score and mAP values, which reflects its contains to minimizes the both false positives and negatives .

The Accuracy graph shows consistent improvement from YOLOv5 to YOLOv8, indicating enhanced model learning and better feature extraction capability. Precision values remained high across all models, demonstrating reliable defect classification. Recall performance confirmed that advanced models such as YOLOv7 and YOLOv8 were more effective in detecting difficult or partially occluded damage areas. The F1-score results further validate that YOLOv8 maintains an sequential balance between precision and recall.

The integration of UAV imaging significantly improved coverage efficiency symbolic to traditional normal inspection methods. The system successfully reduced inspection time and enabled large-scale road monitoring without traffic disruption. Additionally, the backend implementation ensured smooth image processing and structured storage of detection results. Overall, the experimental results confirm that combining UAV vision with advanced YOLO-based deep learning models provides an accurate, scalable, and efficient solution for automated road damage detection. Future improvements may focus on real-time GPS mapping, damage severity estimation, and cloud-based deployment for smart city applications.

Table 1: Performance evaluation

Algorithm Name	Precision	Recall	F1-Score	Accuracy
YoloV5	82.5	59.055556	57.713607	57.5
YoloV7	82.5	59.055556	57.713607	57.5
Extension YoloV8	85.0	83.888889	82.093838	82.5

Typical Drone Images



Figure 3: RDD China Drone

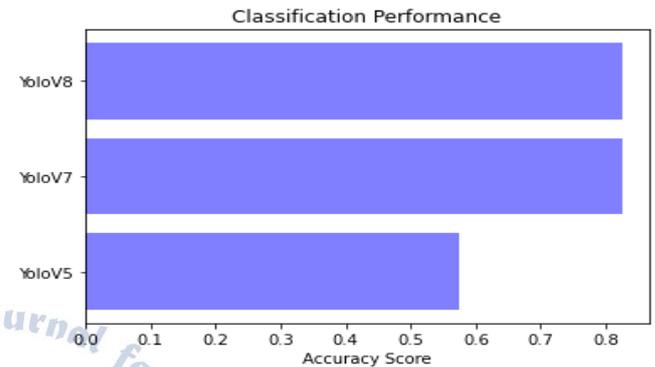


Figure 4: Comparison of Classification Accuracy for different YOLO Models

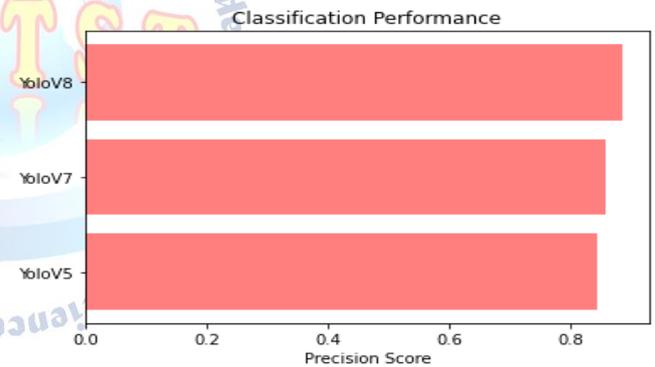


Figure 5: Comparison of Classification Precision for different YOLO Models

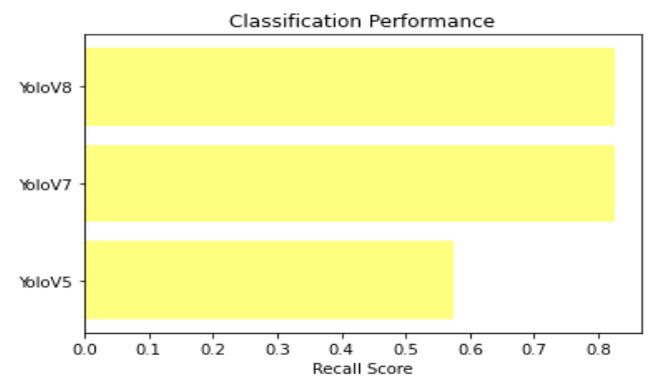


Figure 6: Comparison of classification Recall for different YOLO Models

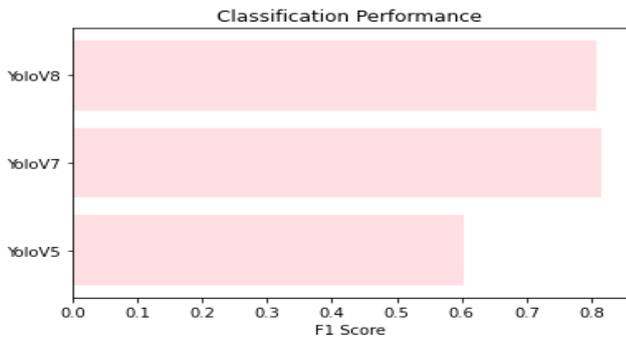


Figure 7: Comparison of classification F1 Score for different YOLO Models

Name	Date	Type	Size	Length
.ipynb_checkpoints	19-01-2024 15:58	File folder		
model	19-01-2024 15:58	File folder		
RDD2022_China_Dr...	19-01-2024 15:58	File folder		
static	19-01-2024 15:59	File folder		
templates	19-01-2024 15:59	File folder		
testImages	19-01-2024 15:59	File folder		
app	28-11-2023 23:29	Python File	5 KB	
best.pt	28-11-2023 23:42	PT File	13,982 KB	
rcnn	01-08-2023 13:36	Python File	6 KB	
RoadDamage	01-08-2023 15:54	Chrome HTML Do...	1,383 KB	
RoadDamage.ipynb	28-11-2023 23:46	IPYNB File	799 KB	
run	27-07-2023 23:41	Windows Batch File	1 KB	
signup	12-07-2023 11:12	Data Base File	1,012 KB	

Figure 8: Folder of a Road damage detection

Name	Date	Type	Size	Length
.ipynb_checkpoints	19-01-2024 15:58	File folder		
model	19-01-2024 15:58	File folder		
RDD2022_China_Dr...	19-01-2024 15:58	File folder		
static	19-01-2024 15:59	File folder		
templates	19-01-2024 15:59	File folder		
testImages	19-01-2024 15:59	File folder		
app	28-11-2023 23:29	Python File	5 KB	
best.pt	28-11-2023 23:42	PT File	13,982 KB	
rcnn	01-08-2023 13:36	Python File	6 KB	
RoadDamage	01-08-2023 15:54	Chrome HTML Do...	1,383 KB	
RoadDamage.ipynb	28-11-2023 23:46	IPYNB File	799 KB	
run	27-07-2023 23:41	Windows Batch File	1 KB	
signup	12-07-2023 11:12	Data Base File	1,012 KB	

Figure 9: File Sett

```

Anaconda Prompt (Anaconda)
(base) C:\Users\pavan>cd C:\Users\pavan\Videos\codes\13122023\Flask\Automated Road Damage Detection Using UAV Images and Deep Learning Techniques
(base) C:\Users\pavan\Videos\codes\13122023\Flask\Automated Road Damage Detection Using UAV Images and Deep Learning Techniques>python app.py
  
```

Figure 10: Anaconda Prompt

```

Anaconda Prompt (Anaconda)
(base) C:\Users\pavan>cd C:\Users\pavan\Videos\codes\13122023\Flask\Automated Road Damage Detection Using UAV Images and Deep Learning Techniques
(base) C:\Users\pavan\Videos\codes\13122023\Flask\Automated Road Damage Detection Using UAV Images and Deep Learning Techniques>python app.py
Downloading: "https://github.com/ultralytics/yolov5/zipball/master" to C:\Users\pavan\.cache\torch\hub\master.zip
Installing layers...
Model summary: 197 layers, 7912822 parameters, 0 gradients
Adding AutoShape...
Copying Flask app "app" (lazy loading)
Environment: production
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
Debug mode: off
Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
  
```

Figure 11: Anaconda prompt File



Figure 12: Localhost

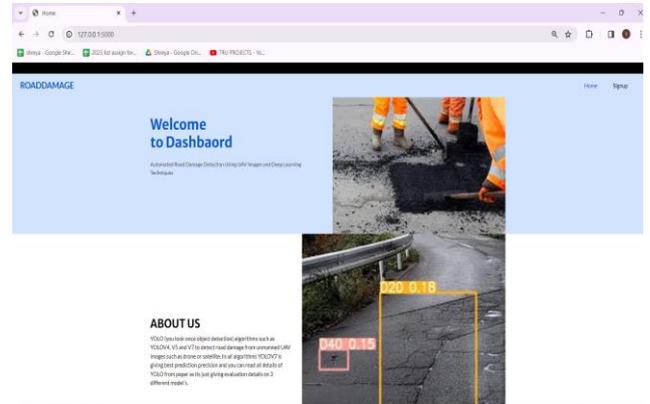


Figure 13: Main Web Page

SIGN UP

User

Name

Email

Mobile

Password

LOG IN

[Have an Account! Login](#)

Figure 14: Sign up Credentials

SIGN IN

admin

.....

LOG IN

[Forgot Password?](#)

[Register Here! Register](#)

Figure 15: Signin Login Credentials

Upload any image

Choose File No file chosen

Upload

Figure 16: Image Uploading from saved Files

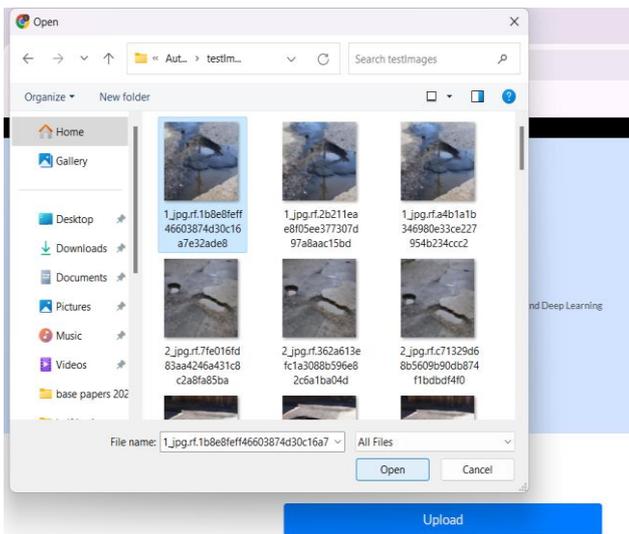


Figure 17: Selection Road Damage Detection

Upload any image

Choose File 1_jpg.rf.1b8e8feff46603874d30c16a7e32ade8.jpg

Upload

Figure 18 :Uploading File page



Real-time YOLO-based detection Result.

CONCLUSION

This paper presented an Hybrid deep learning and UAV vision system for road surface defect detection. The proposed approach addresses the limitations of traditional manual and vehicle-based inspection methods by providing a safer, faster, and more suitable solution for road condition monitoring. By integrating UAV-based image acquisition with YOLOv5, YOLOv7, and YOLOv8 models, the system effectively detects and classifies road damages such as potholes and cracks with

high accuracy. Experimental results states that YOLOv7 and YOLOv8 achieve superior performance in terms of detection accuracy and stableness under varying road and lighting conditions, while maintaining real time processing capability. The use of UAVs enables efficient coverage of large and hard-to-reach areas without disrupting traffic flow, significantly reducing inspection time and human involvement. Overall, the proposed method provides a reliable and cost-effective solution for modern road infrastructure maintenance. Future enhancements may include GPS-based damage mapping, severity analysis, and integration with smart city maintenance platforms to further improve decision-making and automation.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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