iJETRM
International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

# AUTOMATED ROAD DAMAGE DETECTION USING UAV IMAGES AND DEEP LEARNING TECHNIQUES

**Mr. Dr. M. Bheemalinghaiah**
Professor, Department of Computer Science and Engineering,
J.B Institute of Engineering and Technology, Moinabad

**Chilam Varenya Reddy, Kunta Meghana Reddy, Racharla Rithika, Ravikanti Shravya**
UG Students, Department of Computer Science and Engineering,
J.B Institute of Engineering and Technology, Moinabad

## ABSTRACT
Keeping road infrastructure in good condition is essential for maintaining safety and supporting a reliable, sustainable transportation network. However, the manual collection of road damage data can be labor-intensive and unsafe for humans. Therefore, we propose using UAVs and Artificial Intelligence (AI) advanced technologies can greatly enhance the efficiency and precision of road damage detection. Our proposed method employs three algorithms—YOLOv4, YOLOv5, and YOLOv7—for object identification and analysis.
detection and localization in UAV images. We trained and tested these algorithms using a combination of the RDD2022 dataset from China and a Spanish road dataset. These results demonstrate the potential of using UAVs and deep learning for automated road damage detection and pave the way for future research in this field. The main objective of this project is to improve the autonomous monitoring a system designed to assess road conditions by utilizing drone-captured images combined with advanced computer vision techniques. and intelligence techniques. The proposed system will notify the maintenance company about detected road damage, including the ability to send messages with the geographical coordinates of the damages found.

**Keywords:**
UAVs and Artificial Intelligence (AI) technologies, YOLOv4, YOLOv5, and YOLOv7, deep learning for automated road damage detection

## INTRODUCTION
Managing the maintenance of all the roads in a country is essential to its economic progress requires regular evaluation of road conditions to ensure their proper maintenance and reliability.
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. Moreover, UAVs are capable of surveying extensive areas in a comparatively efficient manner quickly, reducing the need for manual inspections, which can be dangerous for human operators. Consequently, employing UAVs for road inspections has attracted considerable interest 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. 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. In the absence of prompt identification and quick access to information on road defects, excessive wear on vehicles and an increased likelihood of traffic accidents can occur, leading to further financial losses. To facilitate the learning process, these datasets are often annotated to identify the different types of road damage, including but not limited to potholes, cracks, and rutting. Annotating these images enables the algorithm to learn how to detect and classify various types of road damage accurately. By leveraging 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.

---

## PROBLEM STATEMENT

Road infrastructure plays a vital role in transportation and economic development, but maintaining road quality remains a major challenge. Traditional methods of road inspection are mostly manual, time-consuming, costly, and often unsafe, especially in large or high-traffic areas. These methods are also prone to human error and may fail to detect minor damages such as small cracks at an early stage.

With the increasing expansion of road networks, there is a growing need for an efficient, accurate, and automated system to monitor road conditions. Existing approaches lack scalability and real-time capabilities, making it difficult for authorities to perform timely maintenance and prevent further deterioration.

Therefore, the problem is to develop an automated and reliable system that can detect and classify road damages using UAV (drone) images and deep learning techniques. The system should be capable of analyzing large volumes of data quickly, identifying different types of damages accurately, and providing useful insights to support effective road maintenance and management.

## PROPOSED SYSTEM

**1. UAV-Based Image Collection:**

Drones like DJI Mavic Air 2S capture high-resolution road images from 50m altitude.
UAVs cover large areas quickly without risking human safety.

**2. Deep Learning–Based Damage Detection:**

The system uses object detection models:
YOLOv4 (baseline)
YOLOv5
YOLOv7 (highest accuracy)
These models are trained to detect:
D00 – Longitudinal cracks
D10 – Transverse cracks
D20 – Alligator cracks
D40 – Potholes
Repairs Block cracks

**4. Automated Damage Localization:**

The trained model detects cracks/potholes and places bounding boxes on UAV images.
The system identifies damage location and severity.

**5. Automation & Reporting**

The system will send alerts containing detected damage details and geographical coordinates to road maintenance authorities.

---

## SYSTEM ARCHITECTURE

The system architecture for automated road damage detection is designed as a pipeline that integrates UAV image acquisition with deep learning-based analysis and result visualization. The system consists of multiple interconnected modules that work together to capture, process, analyze, and present road damage information efficiently.

- **UAV Module:** Captures road images
- **Transmission Module:** Sends data to system/cloud
- **Preprocessing:** Image resizing, cleaning, augmentation
- **Dataset Split:** Training, validation, testing
- **Deep Learning Model:** Detects & classifies damages
- **Post-processing:** Refines results, removes errors
- **Visualization:** Shows damages with bounding boxes

- **Reporting:** Generates damage reports
- **User Interface:** Displays results to users

**Workflow of the Proposed System**

The workflow of the automated road damage detection system begins with capturing high-resolution images of roads using UAVs (drones). These images are then transmitted to a processing system or cloud platform for further analysis. In the next step, the images undergo preprocessing, where they are resized, cleaned, and enhanced to improve quality. Data augmentation techniques may also be applied to increase dataset diversity. The processed images are then used to train and test a deep learning model, such as CNN or YOLO, which learns to identify patterns of road damages.

Once the model is trained, it is applied to new UAV images to detect and classify different types of road damages like potholes and cracks. The system generates outputs by marking damaged areas with bounding boxes and labels. These results are further refined through post-processing to reduce errors and improve accuracy. Finally, the detected damages are visualized and presented through a user interface, and reports are generated to assist authorities in road maintenance and decision-making.

---

## OBJECTIVES

The primary objective of this research is to develop an automated system that detects and classifies road damages using UAV (drone) images with the help of deep learning techniques. The specific objectives are as follows :

**1. Data Acquisition**

- To collect high-resolution road images using UAVs under different environmental and lighting conditions.

**2. Data Preprocessing**

- To clean, enhance, and annotate UAV images for accurate model training.
- To apply techniques like resizing, normalization, and augmentation.

**3. Model Development**

- To design and implement deep learning models such as CNNs for detecting road damages.
- To use advanced architectures like YOLO or Faster R-CNN for real-time detection.

**4. Damage Classification**

- To classify different types of road damages such as potholes, cracks, and surface wear.

**5. Model Training and Evaluation**

- To train the model using labeled datasets.
- To evaluate performance using metrics like accuracy, precision, recall, and F1-score.

---

## METHODOLOGY

The methodology of the proposed system begins with data collection using Unmanned Aerial Vehicles (UAVs). High-resolution images of roads are captured using drones at different altitudes and angles to ensure comprehensive coverage. The data is collected under various environmental conditions such as different lighting and weather situations to improve the robustness of the system. Next, the collected images undergo data preprocessing to enhance their quality and make them suitable for model training. This includes resizing images to a standard dimension, reducing noise, and adjusting brightness and contrast. Data augmentation techniques such as rotation, flipping, and scaling are also applied to increase dataset diversity. The images are then annotated with labels indicating different types of road damages like potholes and cracks. After preprocessing, the dataset is divided into training, validation, and testing sets. This ensures proper evaluation of the model and prevents overfitting. The training set is used to train the model, while the validation set helps in tuning hyperparameters, and the testing set is used to evaluate the final performance.

In the next phase, an appropriate deep learning model is selected and designed. Models such as Convolutional Neural Networks (CNN), YOLO (You Only Look Once), or Faster R-CNN are commonly used for object detection tasks. These models are capable of identifying and localizing road damages within images. The model is then trained using the labeled dataset. During training, the model learns to detect patterns associated with different types of road damage. Optimization techniques such as Adam or Stochastic Gradient Descent (SGD) are used to minimize the loss function and improve accuracy. Hyperparameters like learning rate and batch size are tuned for better performance. Once training is completed, the model undergoes evaluation using performance metrics such as accuracy, precision, recall, F1-score, and mean Average Precision (mAP). These metrics help in assessing how well the model detects and classifies road damages.

After evaluation, the trained model is used for road damage detection and classification. The system processes UAV images and identifies damaged areas by drawing bounding boxes around them. It also classifies the type of damage, such as potholes, cracks, or surface wear.
The system is then extended for real-time or near real-time implementation, where the UAV can capture images and the model processes them instantly or with minimal delay. This allows quick identification of road damages in practical scenarios.
Finally, the results are visualized and presented in a user-friendly format. Detected damages are highlighted in images, and reports are generated indicating the type, location, and severity of the damage. Further optimization techniques are applied to improve the speed, accuracy, and scalability of the system for real-world applications.

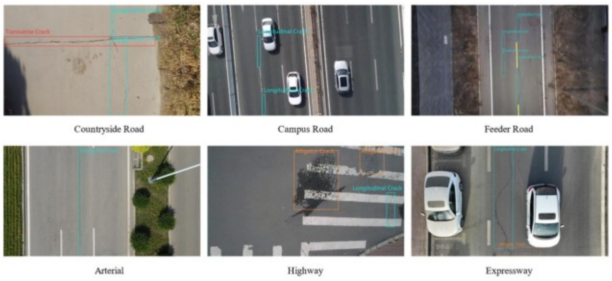


***Figure 8 Facial Recognition Process***

---

## ALGORITHM

Algorithm: Automated Road Damage Detection System

**Input :** Road images (both damaged and undamaged)
Geo-location tag with image
Timestamp / upload time
**Output :** Detection of only damaged road images
Damaged images displayed on dashboard
Location and estimated repair time shown

**Step-by-Step Algorithm**
Step 1: Start
Begin the road damage detection system.
Step 2: Upload Images
User uploads road images through the website
Accept formats:
JPG
PNG
Folder / multiple files
Images may contain:
Damaged roads
Undamaged roads
Capture geo-location metadata along with each image
Step 3: Preprocess Images
Resize images to YOLO input size (for example 640 × 640)
Normalize pixel values
Convert image into model-compatible format
Step 4: Perform YOLO Detection
Step 5: Check Detection Result
Step 6: Filter Only Damaged Images
Create a separate collection that contains only the damaged road images.
Step 7: Send to Dashboard
Transfer only damaged images to the dashboard webpage.
Each dashboard entry should include:
damaged image
damage type
location coordinates

upload date and time
Step 8: Estimate Repair Time
Calculate estimated repair time based on damage severity.
Step 9: Display on Dashboard
Step 10: End
Stop the process after all images are analysed.

## EXPERIMENTAL SETUP

The experimental setup for the proposed system involves collecting high-resolution road images using UAVs under different environmental conditions such as varying lighting, weather, and road types. The dataset is then preprocessed through resizing, normalization, and data augmentation techniques to improve model performance and generalization.
The prepared dataset is divided into training, validation, and testing sets, typically in the ratio of 70:15:15. A deep learning model such as Convolutional Neural Network (CNN), YOLO, or Faster R-CNN is selected and implemented using frameworks like TensorFlow or PyTorch. The model is trained on the training dataset, while the validation set is used for hyperparameter tuning and avoiding overfitting.
Training is performed using suitable optimizers like Adam or SGD, with parameters such as learning rate, batch size, and number of epochs carefully adjusted. The trained model is then tested on unseen data (test set) to evaluate its real-world performance. The system is implemented on a machine with GPU support to ensure faster training and inference.

## PERFORMANCE METRICS

The performance of the model is evaluated using standard metrics as follows:

- **Accuracy**
  - Measures overall correctness of the model
- **Precision**
  - Percentage of correctly detected damages out of total detected
  - Reduces false positives
- **Recall (Sensitivity)**
  - Percentage of actual damages correctly detected
  - Reduces false negatives
- **F1-Score**
  - Balance between precision and recall
- **Mean Average Precision (mAP)**
  - Measures detection and localization accuracy
  - Important for object detection models
- **Inference Time**
  - Time taken to detect damages in an image
  - Important for real-time performance

## RESULTS AND DISCUSSION

The proposed system for automated road damage detection using UAV images and deep learning techniques produced effective and reliable results. The trained model was able to successfully detect and classify various types of road damages such as potholes, cracks, and surface wear from aerial images captured by UAVs. The use of high-resolution images significantly improved the detection capability, especially for small and fine cracks. During evaluation, the model achieved high performance based on standard metrics such as accuracy, precision, recall, and F1-score. The results indicated that object detection models like YOLO performed well in terms of speed and real-time detection capability, while models like Faster R-CNN provided slightly higher accuracy in identifying complex damage patterns. The mean Average Precision (mAP) score demonstrated that the model was able to accurately localize and classify damage regions within the images. The analysis also showed that preprocessing techniques such as image enhancement and data augmentation played a crucial role in improving model performance. Augmented data helped the model generalize better across different lighting conditions, shadows, and road textures. However, some challenges were observed in cases where the road surface had similar textures to damages, leading to minor false positives or misclassification. In real-time implementation, the system demonstrated the ability to process UAV images with minimal delay, making it suitable for practical applications like road inspection and maintenance planning. The detection outputs, including bounding boxes and labels, were clearly visualized, enabling easy interpretation by users and authorities. Overall, the system proved to be efficient, scalable, and cost-effective compared to traditional manual inspection methods. The analysis confirms that integrating UAV technology with deep learning provides a powerful solution for automated road condition monitoring. Future improvements can focus on increasing dataset size, enhancing model robustness, and integrating GPS-based mapping for precise localization of road damages.

## FUTURE ENHANCEMENT

The proposed system can be further improved by incorporating several advanced features and technologies. One major enhancement is the integration of GPS and Geographic Information Systems (GIS) to accurately map the detected road damages. This would enable authorities to pinpoint exact locations and plan maintenance activities more efficiently.

Another important improvement is the use of larger and more diverse datasets to train the model. Including images from different regions, road types, and environmental conditions can significantly enhance the model's accuracy and robustness. Additionally, advanced deep learning architectures such as transformer-based models or hybrid approaches can be explored to improve detection performance, especially for complex and subtle damages.

The system can also be enhanced by enabling real-time processing with edge computing, where the model runs directly on UAVs or embedded devices. This would reduce dependency on cloud processing and allow faster decision-making during live inspections. Furthermore, optimizing the model for lightweight performance can make it more efficient for deployment on low-power devices.

Another future direction is the development of a user-friendly web or mobile application dashboard. This platform can display detected damages, generate reports, and provide analytics such as damage severity and frequency. It can also allow authorities to track maintenance status and prioritize repairs.

## ACKNOWLEDGEMENT

The authors thank the institution and project supervisor for their guidance and support. Gratitude is also extended to the contributors of medical imaging datasets used in this work, and to all who assisted in the completion of this project.

## CONCLUSION

In conclusion, this study compares the YOLOv4 from past work, the YOLOv5 and YOLOv7 architectures, and includes an implementation of the YOLOv5 with Transformer for road damage identification using UAV images. The research successfully achieved its goal of creating an architecture capable of detecting road damage and demonstrated that new architecture versions, such as YOLOv5 and YOLOv7, can improve upon previous work. A significant contribution of this study was the development of a UAV image database tailored explicitly for training the YOLO versions, which was further enhanced by merging with the RDD2022 dataset. This improved detection of road damage samples, particularly for Spanish and Chinese roads, and helped reduce class imbalance for specific forms of road damage, such as potholes and alligator cracks. The findings of this study provide a valuable contribution to the field and pave the way for future research in this area.

## REFERENCES

[1] H. S. S. Blas, A. C. Balea, A. S. Mendes, L. A. Silva, and G. V. González, "A platform for swimming pool detection and legal verification using a multi-agent system and remote image sensing," International Journal of Interactive Multimedia and Artificial Intelligence, vol. In the press, no. In Press, pp. 1–13, 2023.

[2] V. J. Hodge, R. Hawkins, and R. Alexander, "Deep reinforcement learning for drone navigation using sensor data," Neural Computing and Applications, vol. 33, no. 6, pp. 2015–2033, Jun. 2020. [Online]. Available: https://doi.org/10.1007/s00521-020-05097-x

[3] A. Safonova, Y. Hamad, A. Alekhina, and D. Kaplun, "Detection of Norway spruce trees (Picea abies) infested by bark beetle in UAV images using YOLOs architectures," #IEEE_O_ACC#, vol. 10, pp. 10 384–10 392, 2022. [Online]. Available: https://doi.org/10.1109/access.2022.3144433

[4] D. Gallacher, "Drones to manage the urban environment: Risks, rewards, alternatives," Journal of Unmanned Vehicle Systems, vol. 4, no. 2, pp. 115–124, Jun. 2016. [Online]. Available: https://doi.org/10.1139/juvs2015-0040

[5] L. A. Silva, A. Sales Mendes, H. Sánchez San Blas, L. Caetano Bastos, A. Leopoldo Gonçalves, and A. Fabiano de Moraes, "Active actions in the extraction of urban objects for information quality and knowledge recommendation with machine learning," Sensors-basel., vol. 23, no. 1, p. 138, Dec. 2022. [Online]. Available: https://doi.org/10.3390/s23010138

[6] L. Melendy, S. Hagen, F. Sullivan, T. Pearson, S. Walker, P. Ellis, Kustiyo, A. K. Sambodo, O. Roswintiarti, M. Hanson, A. Klassen, M. Palace, B. Braswell, and G. Delgado, "Automated method for measuring the extent of selective logging damage with airborne LiDAR data," ISPRS J. Photogramm. Remote Sens., vol. 139, pp. 228–240, May 2018. [Online]. Available: https://doi.org/10.1016/j.isprsjprs.2018.02.022

[7] L. A. Silva, H. Sanchez San Blas, D. Peral García, A. Sales Mendes, and G. Villarubia González, "An architectural multi-agent system for a pavement monitoring system with pothole recognition in UAV images," Sensors-basel., vol. 20, no. 21, p. 6205, Oct. 2020. [Online]. Available: https://doi.org/10.3390/s20216205

[8] M. Guerrieri and G. Parla, "Flexible and stone pavements distress detection and measurement by deep learning and low-cost detection devices," Eng. Fail. Anal., vol. 141, p. 106714, Nov. 2022. [Online]. Available: https://doi.org/10.1016/j.engfailanal.2022.106714

[9] D. Jeong, "Road damage detection using YOLO with smartphone images," in 2020 IEEE International Conference on Big Data (Big Data). IEEE, Dec. 2020, pp. 5559–5562. [Online]. Available: https://doi.org/10.1109/bigdata50022.2020.9377847