

Research Paper

A Deep Learning Approach for Road Damage Detection Using UAV-Based Imagery

Sadia Nikhat¹, Mudassir Mustafa², Mirza Saif-Ur-Rahman Baig³, Mohammed Shafi Pasha⁴,
Nasr Ahmed⁵

¹Department of CSE (Data Science),

Lords Institute of Engineering and Technology, Hyderabad, Telangana, India.

^{2,3,4,5}UG Students, Department of CSE (Data Science),

Lords Institute of Engineering and Technology, Hyderabad, Telangana, India.

Abstract— Road networks are essential to contemporary transportation, and early detection of faults is crucial for ensuring safety and reducing maintenance expenses. Traditional road inspection techniques predominantly depend on manual surveys, considered time-consuming, labor-intensive, and frequently susceptible to human mistake. This study presents an automated approach for identifying road damage from photos obtained from Unmanned Aerial Vehicles (UAVs) utilizing deep learning methodologies. The system analyzes aerial photographs captured by drones and employs object detection techniques to recognize various road issues, including cracks, potholes, as well as surface degradation. Previous methodologies frequently employed models such as YOLOv5 for detecting tasks; however, these techniques may encounter difficulties in sustaining constant accuracy across varying illumination and ambient conditions. This study applies and assesses various deep learning models to enhance performance, utilizing YOLOv5 as the the beginning, YOLOv7 as the enhanced model, & YOLOv8 as the advanced version. The comprehensive system comprises multiple stages: dataset upload, preprocessing of data, dataset partitioning, model deployment, and performance evaluation using graphical analysis. The primary aim of this methodology is to improve detection precision and processing efficiency for the application of advanced YOLO structures, specifically optimized for UAV-based datasets.

The experimental results demonstrate that the latest models attain superior accuracy and expedited detection relative to the basic model. The suggested system provides a dependable and adaptable solution for autonomous road condition monitoring, facilitating efficient maintenance of infrastructure and smart city redevelopment.

Keywords— UAV imagery, road damage detection, deep learning, YOLOv5, YOLOv7, YOLOv8, object detection, smart infrastructure.

I. INTRODUCTION

Preserving an efficient road network is crucial for a nation's comprehensive development and for guaranteeing safe and seamless transit. Roads are utilized daily by millions, thus even minor defects such as cracks or potholes might result in significant accidents and heightened automobile repair expenses if not promptly detected. Consequently, consistent monitoring and management of road infrastructure are essential to enhance road quality and prolong their durability. This process has traditionally been executed manually by governmental or private entities. Inspection trucks outfitted with cameras and sensors are typically employed to identify road issues. This method is labor-intensive, necessitates a substantial workforce, and is frequently costly. Furthermore, inspection by manual may overlook minor problems and could jeopardize worker safety, particularly on congested roadways.

Recent technological breakthroughs have introduced Unmanned Aerial Vehicles (UAVs), usually referred to as drones, in conjunction by Artificial Intelligence (AI) approaches for automated road inspection, to address these constraints. Unmanned Aerial Vehicles (UAVs) have gained significant popularity in urban surveillance operations due to their adaptability, rapidity, and capability to reach challenging locations [4], [5]. These drones are outfitted with high-resolution cameras and sensors capable of capturing intricate photos of roadway surfaces from various altitudes and perspectives. This enables a more effective analysis of road conditions compared to conventional ground-based assessment methods. A significant benefit of UAVs is their ability to traverse extensive areas rapidly, hence diminishing operational costs and human labor.

The integration of UAV technology with deep learning significantly enhances the system's capabilities. Deep learning models can analyze extensive image datasets and discern patterns indicative of various types of road damages. These models can autonomously identify flaws such as fissures, depressions, and surface degradation with great precision [8], [11]. This diminishes the necessity for manual review and enhances the efficiency of inspection. Consequently, numerous academics are concentrating on the creation of intelligent systems that utilize UAV imagery and deep learning for effective road damage identification.

In numerous regions globally, including nations such as Spain, road inspections continue to be conducted manually. This necessitates employees to traverse extensive distances to identify damaged regions, hence augmenting time, expense, and exertion. Simultaneously, nations like China possess extensive road networks, and climatic factors such as substantial rainfall can lead to swift road degradation via fissures and water infiltration. If undetected, such damages may result in severe repercussions, including heightened vehicle deterioration, traffic collisions, and escalated maintenance expenses. Consequently, there exists a significant demand for autonomous systems capable of swiftly detecting and reporting road damage at the present moment [19], [20].

Road detection of damages has emerged as a prominent research domain, employing several methods to enhance detection precision. Certain methodologies employ vibration sensors to identify anomalies in road surfaces, whereas others utilize LiDAR technology to acquire intricate 3D data regarding the road structure [6]. Nonetheless, image-

based approaches are increasingly prevalent because to their cost-effectiveness and ease of implementation. In the past few years, advanced deep learning image analysis has demonstrated exceptional efficacy in identifying road damage from various forms of image data. Researchers have utilized images obtained from cellphones, vehicle-mounted camera systems, UAVs, and satellites to train these types of models [9], [10].

Effective operation of these systems necessitates extensive datasets for training. These datasets often comprise photographs gathered from many sources along with environments to guarantee diversity. Publicly accessible datasets, such as RDD2022, have been extensively utilized in studies for road damage identification tasks [13]. The photos are meticulously annotated, indicating that various sorts of damage, including fractures, potholes, and surface deformations, are distinctly labeled. This annotation aids the model in acquiring significant features and enhances its capacity to effectively detect and categorize damages in real-world scenarios.

Furthermore, contemporary object identification techniques such as YOLO (You Only Look Once) along with its enhanced iterations have gained significant popularity in this domain owing to their rapidity and precision [14]–[18]. These models can identify various forms of road damages in real time, rendering them exceptionally appropriate for practical applications like smart city infrastructure surveillance.

The amalgamation of UAV technology in deep learning offers a rapid, dependable, and scalable solution towards the detection of road damage. This method markedly minimizes manual labor, decreases operational expenses, and enhances detection precision. It facilitates expedited decision-making for road repair, hence enhancing road safety and fostering the advancement of intelligent and sustainable urban environments.

II. LITERATURE SURVEY

Spain possesses one of the highest quantities of swimming pools around Europe, ranking second overall; yet, over 20% of these pools operate either unregistered or fail to comply with regulatory standards. Presently, authorities rely on manual inspection techniques, wherein people scrutinize satellite or drone imagery to detect unusual structures, rendering the procedure time-consuming, labor-intensive, and reliant on human judgment.

Héctor Sanchez San Blas et al. [2023] [1] proposed an automated method utilizing GIS (Gradient Information System) tools, orthophotography, and sophisticated machine learning approaches for object detection. The system employs a multi-agent design, facilitating efficient collaboration among many components while dividing the task. The suggested approach demonstrated efficacy in reliably identifying irregular swimming pools, achieving an F1-score of 97.1% during tests conducted in multiple places throughout Spain.

Mobile robots, particularly unmanned air vehicles (drones), are progressively employed for activities including surveillance, inspection, monitoring, and data acquisition across various structures, infrastructures, and surroundings. Precise and ongoing surveillance is essential for early detection of issues, so averting their escalation into significant difficulties. This necessitates the development of smart and autonomous droning systems capable of making efficient decisions and adapting to various circumstances. These systems must possess the capability to learn by integrating data from various sensors instead of being restricted to a certain purpose. Victoria Hodge et al. [2021] [2] suggested a comprehensive navigation strategy wherein the drone utilizes onboard sensor data to navigate towards areas of interest or possible issues. Their approach utilizes a deep reinforcement learning method called local policy optimization, as well as incremental curriculum learning as well as extended short-term memory networks, to enhance the system's adaptability and efficiency. The new model was evaluated against conventional heuristic methods and shown superior performance in accuracy and efficiency. The study further assessed safety by analyzing the drone's reliability in real-life situations and safety-critical scenarios.

In recent years, extensive infestation caused by the European spruce bark beetles have caused considerable damage on coniferous forests, rendering early diagnosis of afflicted trees crucial for controlling the spread. Early identification of diseased trees facilitates prompt preventive measures and mitigates overall harm. The improvement of technology has enabled high-resolution photos obtained from Unmanned Aerial Vehicles (UAVs), in conjunction with deep learning models, to demonstrate significant potential in addressing this issue. Anastasiia Safonova et al. [2022] [3] did a study evaluating and comparing three YOLO-based

deep learning models—YOLOv2, YOLOv3, and YOLOv4—for the detection of infested trees utilizing UAV pictures. The researchers developed a specialized dataset for model training and evaluation, employing a preprocessing technique known as balance enhancement of contrast technique (BCET) to boost model efficacy. Their findings indicated that YOLOv4 exhibited superior performance, with mean average precision with a maximum of 95%. The implementation of data augmentation significantly enhanced the models' performance, yielding substantial improvements across each of the three architectures.

The swift expansion of urban regions necessitates that municipalities consistently oversee land utilization and environmental alterations to develop more intelligent and sustainable cities. A significant problem in this process is the absence of dependable technology that can provide high-quality data for efficient planning and decision-making. Substantial quantities of geographical data are produced; yet, the analysis and extraction of valuable insights necessitate considerable effort. Luis Augusto Silva et al. [2022] [5] presented a technique for mapping and classifying several zones in Itajaí, Brazil, to address this issue. Their methodology employs many object-based classification algorithms, including OneR as well as Naive Bayes, J48, IBk, & Hoeffding Tree, in conjunction with GeoDMA, while also investigating deep learning approaches such as R-CNN and YOLO for object detection. The system was engineered to categorize regions including vegetation, bare soil, asphalt, and structures in rural as well as urban environments. The findings indicated that the optimal model attained an accuracy of approximately 85% and the kappa coefficient about 76 percent, which is signifying dependable performance. This study emphasizes that the integration of various data processing techniques can enhance the comprehension of urban development and facilitate more rapid and informed decision-making. The suggested technique offers a systematic and pragmatic strategy for enhancing urban development and resource management via precise geospatial analysis.

This study introduces an efficient and economical approach for the automatic detection and quantification of various damage types across flexibly and stone pavement on roads. The methodology is engineered for real-time application and utilizes deep learning techniques, notably the

algorithm known as YOLOv3 for object detection. In this study, Marco Guerrieri et al. [2022] [8] created a dataset of around 9,150 photos with 15,585 annotated occurrences of pavement damage, utilized for training neural network models. The system's performance was assessed using standard measures, including loss, precision, recall, and RMSE, each of which demonstrated robust detection capacity. The findings indicated that the model effectively identified pavement faults, with detection rates between 91.0% and 97.3%, contingent upon the pavement type and extent of damage. Furthermore, validation was conducted by juxtaposing the identified damages with real ground truth data, so affirming the method's trustworthiness. This research illustrates that the integration of devices with low prices with AI methodologies offers an efficient option for comprehensive and extensive road assessment.

III. DATASET DESCRIPTION

In our proposed study, we utilized road damage image dataset comprising several sorts of road surface problems, including cracks, potholes, as well as other surface imperfections. This dataset is primarily utilized to train deep learning algorithms for the automatic detection of damaged regions on roadways. The photos are gathered in various environmental conditions such as daylight, shadows, and diverse backgrounds, facilitating the model's effective learning and performance in real-world scenarios. Every image in the collection is annotated with bounding boxes that distinctly delineate the damaged areas of the road. The bounding boxes correspond to distinct labels that denote the sort of damage depicted in the image. This form of annotation assists models such as YOLOv5, YOLOv7, & YOLOv8 in accurately comprehending and identifying various damage patterns. The dataset reveals that sample photos feature highlighted sections indicating detected damage areas, hence confirming the accuracy of the tagging.

Upon dataset collection, it undergoes a crucial preprocessing phase before to being input into the deep learning algorithms. During this phase, the photos are scaled, standardized, and randomized to ensure uniformity and eliminate any bias within the dataset. Data preparation enhances the model's overall performance. Upon completion of preprocessing, the dataset is partitioned into both training and testing subsets. The data used for training is utilized to develop the models, whereas the

test data is applied to assess the model's performance on unfamiliar images. This division guarantees that the model isn't merely memorizing the input but is genuinely acquiring patterns. Utilizing this curated dataset enables the models to properly identify road damage and enhance accuracy. The dataset is crucial for developing a dependable road damage detection system also facilitates the comparison of various algorithms' performance.

IV. IMPLEMENTATION DETAILS

The execution of the suggested system adheres to a sequential process, commencing with the initiation of the application and culminating with the identification of road damage in testing photographs. The system operates via a "run.bat" file, which launches the user interface & initializes all requisite components. Upon application initiation, the dataset comprising road damage photographs has been uploaded within the system. Upon loading, the system presents the total count of photos in the dataset, thereby verifying that the data was successfully linked and is prepared for subsequent processing.

The subsequent phase involves preprocessing the dataset to ready the images for training models. This stage entails scaling photos to a predetermined dimension, balancing pixel values, including structuring the data in a uniform format. An image processed sample is presented within a bounding box encircling the damaged region, facilitating visual confirmation of the accuracy of the annotations. Subsequent to preprocessing, the data set is randomized to eliminate bias and subsequently partitioned into test and training subsets. This separation is crucial to guarantee that the model is assessed on novel data and does not merely retain the training samples.

Upon dataset preparation, various deep learning algorithms are developed for comparative analysis. The YOLOv5 model was initially employed as an initial model. This has been trained on data set and achieves an accuracy of approximately 65%, in addition to other evaluative criteria. A confusion matrix is produced to illustrate the correlation between predicted and real labels, with the diagonal values indicating accurate predictions. The YOLOv7 technique is further trained, enhancing performance and attaining an accuracy of roughly 82%. The

revised model has superior efficacy in identifying road damage relative to its predecessor.

The YOLOv8 model of the Ultralytics framework is utilized as an enhanced iteration. This model delivers superior performance, with approximately 85% accuracy. The enhancement in precision signifies the YOLOv8 is more effective in detecting road defects under various situations. A comparative graph is produced to elucidate performance for all models, wherein various algorithms are assessed based upon accuracy and additional evaluation metrics through visual bar charts.

The system enables user to upload new test photos for the assessment of real-time detection efficacy. Upon selection of a test image, the trained model analyzes it and presents the identified road damage in bounding boxes encircling the impacted areas. A variety of test images might be employed to assess the model's consistency and dependability. The implementation integrates loading of data, preprocessing, model training, assessment, and real-time prediction in a cohesive system, rendering it a viable and successful solution to automated road damage identification.

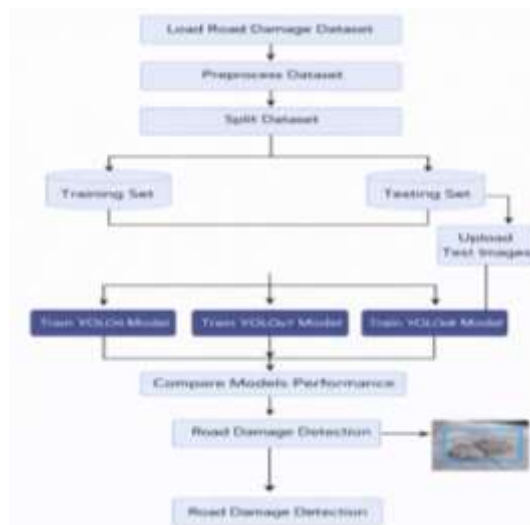


Figure 1: System Architecture for UAV-Based Road Damage Detection

V. RESULT AND DISCUSSION

The initial phase of our system commences with users interface, where each option are accessible as buttons on the left side. These encompass dataset

upload, preprocessing, data partitioning, executing YOLO models, and image testing. Upon selecting "Upload Dataset," the process retrieves all photos. Figure [2] illustrates the interface enables users to efficiently manage and execute each phase of the procedure.



Figure 2: User Interface for Road Damage Detection System

Subsequent to preprocessing and partitioning the dataset, this YOLOv5 algorithm is trained in order to identify road damage. Figure [3] illustrates the system's performance measures, including precision, recall, accuracy, and F1-score. The confusion matrix is generated in order to illustrate the model's predictions alongside these values. In matrix form, the horizontal axis denotes expected classes, whereas the y-axis signifies actual classes. A diagonal numbers represent accurate predictions, whilst the other values suggest misclassifications. This aids in assessing the model's efficacy in identifying various forms of road degradation.



Figure 3: YOLOv5 Model Performance and Confusion Matrix

Subsequent training of the YOLOv5 and the YOLOv7 algorithm is employed to enhance detection efficacy. Figure [4] illustrates that the system exhibits enhanced assessment metrics, including precision, recall, accuracy, and F1-score, in comparison to the preceding model. The confusion matrix provided to

model, and the y-axis displays the relevant metric values. The graph indicates that YOLOv8 outperforms the other models, with YOLOv7 and YOLOv5 following in performance. This comparison aids in determining the most efficient framework for road damage identification.

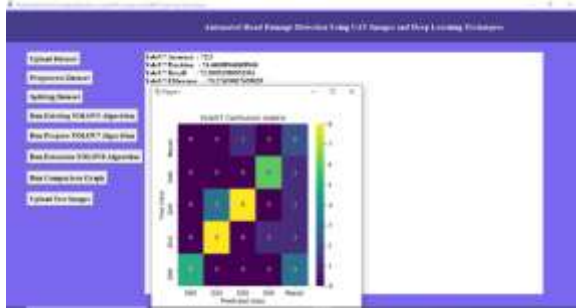


Figure 4: YOLOv7 Model Performance and Confusion Matrix

Subsequent to the training of the YOLOv7, the YOLOv8 model is deployed to get superior detection outcomes. Figure [5] illustrates that the system exhibits enhanced performance metrics, including precision, recall, accuracy, and F1-score, surpassing those of prior models. The confusion matrix is included to illustrate the model's predictive accuracy for each class. The diagonal numbers signify accurate predictions, but the other values suggest misclassifications. This chart indicates that YOLOv8 exhibits superior performance compared to all other models in the detection of road damage.

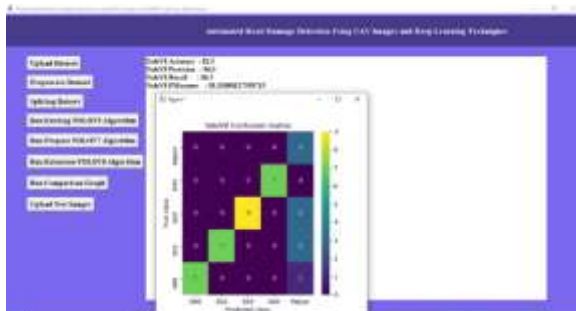


Figure 5: YOLOv8 Model Performance and Confusion Matrix

The comparison graphs is constructed to assess the performance of all trained models. Figure [6] illustrates various measures, including accuracy, precision, recall and F1-score, for YOLOv5, YOLOv7, and YOLOv8. The x-axis represents each

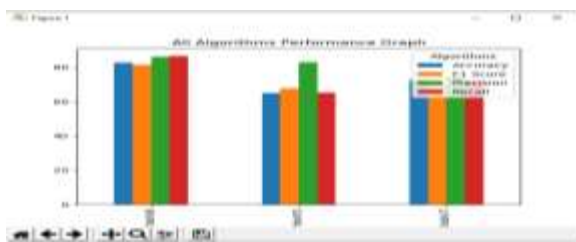


Figure 6: Comparison graph of all YOLO Models Performance

Upon training and identifying the optimal model, the platform is employed to evaluate novel input photos. Figure [7] illustrates an uploaded road image, wherein the model identifies damaged regions by encasing them in bounding boxes. The identified spots are designated as road damage, facilitating the recognition of problematic zones. This stage demonstrates the system's real-time functionality and validates its capacity to reliably identify road damage in previously unexamined photos.



Figure 7: Road Damage Detection on Test Image

Comparative Performance Summary

The efficacy of the proposed system is assessed utilizing different deep learning algorithms: YOLOv5, YOLOv7, and YOLOv8. The models are evaluated on the identical dataset to assess their efficacy in identifying road damage. Table 1 delineates the evaluation measures, encompassing accuracy, precision, recall, and F1-score, illustrating the performance of each model in detecting damaged road areas.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
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Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
YOLO v5	65.00	82.77	65.26	67.74
YOLO v7	72.50	74.46	72.30	70.27
YOLO v8	82.50	86.00	86.50	81.51

Table 1: Performance Comparison of YOLO Models

DISCUSSION

In recent years, automatic road damage monitoring has garnered considerable interest owing to the escalating demand for effective road maintenance & safety. Conventional inspection techniques are inefficient, expensive, and reliant on physical labour, rendering them inadequate for extensive use. The primary aim of this study was to create a precise and dependable system for identifying road damage utilizing deep learning methodologies and UAV-derived data. This work deployed and tested different models, including YOLOv5, YOLOv7, and YOLOv8, on the same dataset to assess their performance. The findings unequivocally demonstrate that upgraded models offer superior accuracy and detection capabilities relative to their predecessors. YOLOv8 demonstrated superior performance, signifying its capacity to discern complex patterns in damaged road imagery. Deep learning methods facilitate the automatic detection of faults such as cracks or potholes with very little assistance from humans. Evaluating several models underscores the significance of choosing an optimum algorithm for enhanced outcomes. This method enhances the system's overall reliability and diminishes detection errors. The system can accommodate various climatic conditions, rendering it appropriate for practical applications. The suggested technology offers an efficient and scalable alternative for road monitoring, facilitating smart infrastructure development through expedited and precise maintenance decisions.

VI. CONCLUSION

This project aims to enhance road damage detection through the integration of deep learning techniques and UAV-based photography. The study illustrates that the implementation and comparison of several models, including YOLOv5, YOLOv7, and YOLOv8, can markedly improve identification accuracy and efficiency through improved object identification algorithms. The suggested method automates the identification of road faults such as cracks and potholes, thereby diminishing the necessity for manual examination and minimizing human mistake. Among the evaluated models, YOLOv8 demonstrated superior performance, underscoring the need of employing optimized and contemporary architectures for practical applications. The amalgamation of preliminary processing, model training, along with performance analysis into a unified framework renders the system pragmatic and user-friendly. This method enhances detection accuracy and facilitates expedited decision-making regarding road maintenance. The proposed work advances smart infrastructure frameworks by offering a scalable and economical solution to track road conditions and enhancing traffic safety.

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