INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 09 ISSUE: 04 | APRIL - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

Unmanned Aerial Vehicle-Based Road Damage Detection Using Convolutional Neural Networks

G.Prasanth Kumar[1] ,PamulaSona[2], Konjarla Bharat Kumar[3], B.Koushik Venkata Ramakrishna[4]

#1 Assistant Professor, Computer Science and Engineering, Sasi Institute of Technology & Engineering
#2,#3,#4 Student, Computer Science and Engineering, Sasi Institute of Technology & Engineering

Abstract: **Using images taken by unmanned aerial vehicles (UAVs) and deep learning algorithms, this study introduces a novel method for detecting road damage and cracks. Maintaining sturdy roadways depends on regularly inspecting and repairing street foundations, but manual data collection is often hazardous and time-consuming. To address this, we leverage UAV technology and artificial intelligence (AI) to improve roadway hazard identification. Our approach utilizes YOLOv4, YOLOv5, and YOLOv7, which are advanced object detection models for processing UAV imagery. Experimental results on Chinese and Spanish datasets demonstrate that YOLOv7 achieves the highest accuracy in identifying road damage. Furthermore, we introduce YOLOv8, an improved method that enhances prediction precision, surpassing prior models when trained on road damage and crack detection datasets. This study paves the way for future advancements by showcasing the potential of UAV-based deep learning in automating and improving road condition assessments.**

Keywords:Deep learning,Road damage,YOLO

I. INTRODUCTION

Improving the nation's roads is an important step in boosting the economy. Maintaining safe and long-lasting roads requires regular inspections. In the past, organizations from the government or commercial sector would use sensor-equipped trucks to manually identify road damage. This process is costly, time-consuming, and potentially harmful to humans. To get around these problems, engineers and researchers have developed automated road damage identification systems that use UAVs and AI. The development of efficient and cost-effective road damage detecting technologies has recently attracted attention, with a focus on merging UAVs with deep learning. Urban areas may be surveyed using multipurpose unmanned aerial vehicles. They are quickly replacing more conventional road inspection methods due to their many useful benefits. These vehicles can evaluate the road surface from a variety of heights and angles because to their high-resolution cameras and other sensors. The need of risky human inspectors is rendered unnecessary by the rapid coverage of large areas by unmanned aerial vehicles. Road inspections using UAVs are thus of interest to academics and engineers. Road degradation may be efficiently and cheaply detected using UAVs and deep learning. Pools[1], rooftops[2], vegetation[3], and cities[4,5] are common places to find it in use.

II. LITERATURE SURVEY

a) RDD2022: A multi-national image dataset for automatic Road Damage Detection:
[2209.08538] RDD2022: A multi-national image dataset for automatic Road Damage Detection (arxiv.org)
Abstract: With 47,420 images, the Road Damage Dataset (RDD2022) covers routes in China, Japan, India, the Czech Republic, Norway, and the United States. More than 55,000 road damage notes are displayed in the photographs. Alligator, longitudinal, and transverse road damage as well as pothole damage are all part of the dataset. The annotated dataset will be used to train deep learning algorithms that can identify and categorize road

damage automatically. The Crowd Sensing Road Damage Detection Challenge (2022) launched this dataset. The CRDDC2022. is an international call for researchers to provide solutions for automated road damage detection in a variety of nations. Automatic road condition monitoring made affordable with RDD2022 and its versions is a boon to road authorities and municipalities. Researchers in computer vision and machine learning can also utilize the dataset to compare methods for categorization and object recognition, two image-based applications that are similar.

b) Road damage detection using super-resolution and semi-supervised learning with generative adversarial network:

Road damage detection using super-resolution and semi-supervised learning with generative adversarial network - ScienceDirect

Abstract: Technologies for road maintenance are necessary to keep driving conditions safe and accident-free. Sensor technology is necessary for detecting road degradation. In this study, we developed a road damage sensor using an algorithm for image processing that is based on deep learning. If implemented, the suggested system would employ generative adversarial networks for both semi-supervised and super-resolution learning. The former makes the road look worse by enhancing the image of the damage. The second method uses 5327 road photographs and 1327 label photos to enhance detection. Four convolutional neural networks for lightweight segmentation were trained using these two methods. For 400 road pictures, the mean intersection over union recognition performance was 81.540% and the F1-score recognition performance was 79.228%. The suggested method of training improves the algorithm for identifying road deterioration and has applications in future road management.

c) Crowdsensing-based Road Damage Detection Challenge (CRDDC'2022):

Crowdsensing-based Road Damage Detection Challenge (CRDDC'2022) | IEEE Conference Publication | IEEE Xplore

Abstract: The Crowdsensing-based Road Damage Detection Challenge (CRDDC), a Big Data Cup held at the IEEE International Conference on Big Data'2022, is detailed in this paper. Problems in the Big Data Cup are well-defined, and there are clear metrics for success because the assignments leverage publicly available datasets. Participants can access their online scores in real-time on data competition platforms. The suggested case study provides algorithms for autonomous road damage detection based on 47,420 road photos sourced from China, Norway, Japan, the Czech Republic, India, and the United States. There were almost 70 teams from 19 different countries who participated. The solutions provided for the unseen test photographs from each of the six countries were evaluated using five leaderboards. What follows is a synopsis of the eleven solutions proposed by these groups. For test data from all 6 nations, the best F1 score of 76% was achieved via ensemble learning utilizing YOLO and Faster-RCNN series models. A comparison of past, present, and future challenges and directions is included at the end of the article.

d) Drones to manage the urban environment: Risks, rewards, alternatives

(PDF) Drones to manage the urban environment. Risks, rewards, alternatives.

Abstract: One of the many uses for aerial transport and surveillance is to record changes in the weather, vegetation, and visibility, as well as to gather samples of various substances for analysis in labs. Drones have its uses in studying urban environments, however there are concerns about privacy, security, and safety when using them. Without sacrificing security or personal information, ground-based surveillance through the Internet of Things can fulfill numerous of these possibilities. To protect people and the environment, drones flying at lower altitudes may be subject to stricter regulations, while those flying at higher altitudes may be able to operate freely within clearly delineated geographical zones. Although technology is improving, civilian usage of military drones has a dismal safety record. It is debatable if the public will place a high value on drone protection from shark attacks or traffic jams.

e) Active actions in the extraction of urban objects for information quality and knowledge recommendation with machine learning

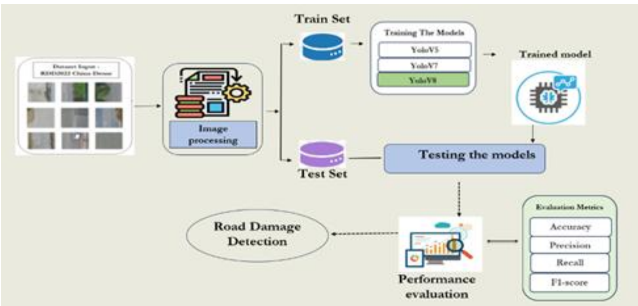
Active Actions in the Extraction of Urban Objects for Information Quality and Knowledge Recommendation with Machine Learning

Abstract: In order to create smart and sustainable cities, municipalities are compelled to have a permanent understanding of land use and ecological processes. They can also deploy technical solutions for land monitoring. A big problem is that there isn't enough technology to check the quality of information used to construct strategies. It takes a lot of work to understand the architecture of the massive amounts of data used and to get good results. In Itajaí (SC), Brazil, this initiative is intended to meet the need for zone mapping. To help with object detection, we use the following algorithms: OneR, NaiveBayes, J48, IBk, and Hoeffding Tree. We also use GeoDMA and an earlier method that used R-CNN and YOLO. This encompasses both urban and rural regions, including plants, asphalt, exposed soil, and structures. After finding the best classifier with an accuracy of 85% and a kappa agreement coefficient of 76%, the model for active identification of geographical objects with similarity levels enabled data crossover. The case study exemplifies how data is collected, organized, and made ready for rapid management responses in response to urban and rural expansion.

III. PROPOSED SYSTEM

Modern artificial vision and intelligence technologies are integrated into the proposed pavement monitoring and road damage detection system, which enhances autonomous road inspection using images taken by UAVs (drones or satellites). In order to accurately detect road damage, this system compares and evaluates YOLOv4, YOLOv5, and YOLOv7, three YOLO (You Only Look Once) object identification methods based on previous research. Of all the forecasts, YOLOv7 is the most precise. In order to comprehend various types of pavement damage, the system utilizes a dataset from previous work in conjunction with the Crowdsensing-based Road Damage Detection Challenge. Data augmentation is employed during training to enhance detection accuracy by adjusting to the sizes of visual objects. The technology takes human overrides and recommendations beyond damage detection from roads into account to increase accuracy. It is capable of autonomously planning inspection paths without the need for a pilot thanks to PIX4D. This add-on makes use of YOLOv8, a road damage recognition algorithm that, when trained on datasets of such damage, improves the accuracy of predictions.

3.1IMPLEMENTATION



a) Data Collection: Collect sufficient data and legitimate software samples.

b) Data Preporcessing: Data With enhanced technology, better results will be obtained.

c) Train and Test Modelling: Make two sets of data: test and train. Train and Test data will be utilised for model training and performance testing.

d) Modelling: Ensure that YoloV5, 7, 4, and 8 models are constructed. Find out how accurate the algorithm is.

e) User signup & login: Users are able to sign up and log in with this module.

f) User input: With this module, users can input data for prediction purposes

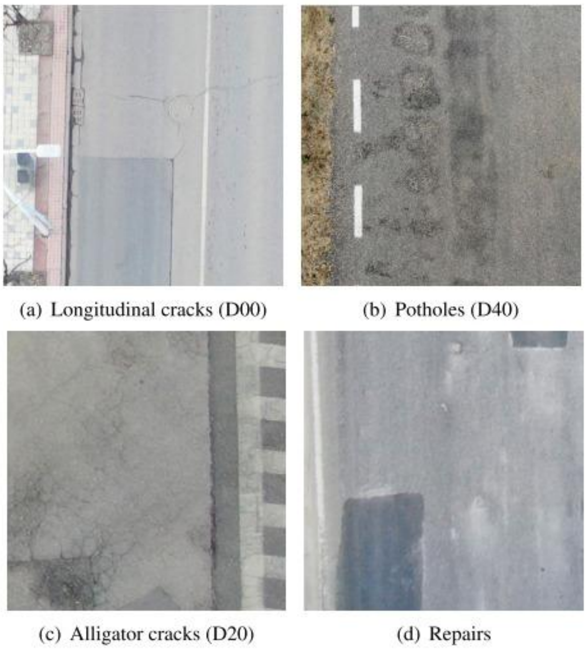
g) Predict: Beginning with a single image, we will learn how to process images and use CNN models to make predictions.

Note: Extension

Deep learning models such as YoloV4, Yolov5, and YoloV7—which achieved 73 mAP—were advocated for in the article.

By utilizing alternate methods such as YoloV8, which attained 82% mAP, we can enhance performance.

We can also build the front end for authentication and user testing using flask.



Class labels

3.2 ALGORITHM

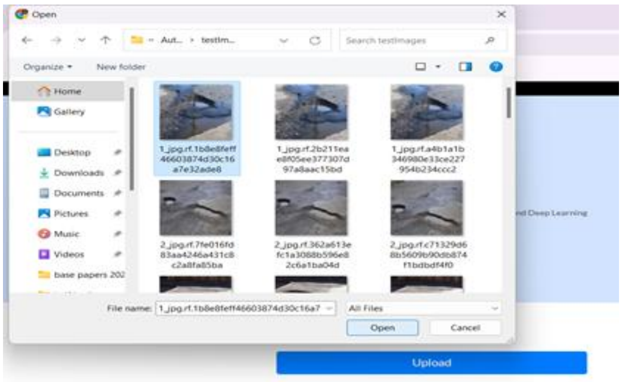
i) YOLOv5: You Only Look Once version 5, or YOLOv5, is an efficient and precise object recognition system that uses real-time bounding box and class probability predictions for objects in each grid cell to partition pictures into a grid.

ii) YOLOv7: Objects in photographs can be identified with just one forward pass using the advanced YOLOv7 (You Only Look Once version 7) approach. In order to improve the accuracy and speed of real-time object identification, deep neural networks predict class probabilities and bounding boxes.

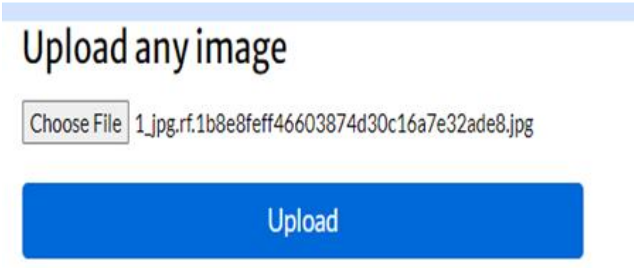
iii) YOLOv4: YOLOv4, a state-of-the-art method for object detection, anticipates visual objects' bounding boxes and class probabilities using a deep neural network. In YOLOv4, you'll find enhanced accuracy and performance thanks to technologies like PANet and the CSPDarknet53 backbone.

iv) YOLOv8: The eighth installment of the YOLO series, YOLOv8, focuses on road damage identification. YOLOv8 outperforms its predecessors that were trained on road damage data in terms of prediction accuracy. There has been a lot of progress in using deep learning for accurate infrastructure maintenance.

IV. RESULTS AND DISCUSSION

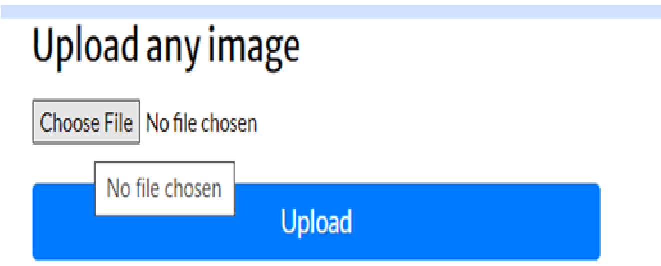


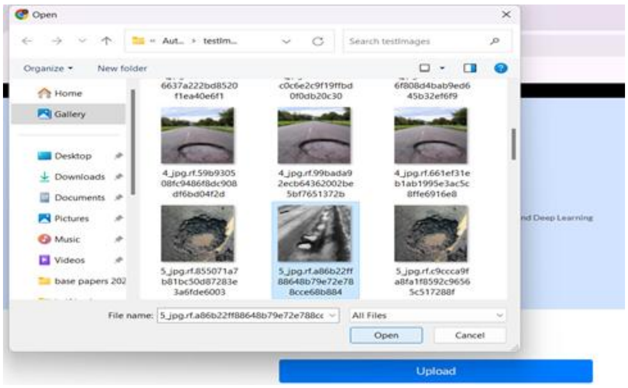
Step 1:



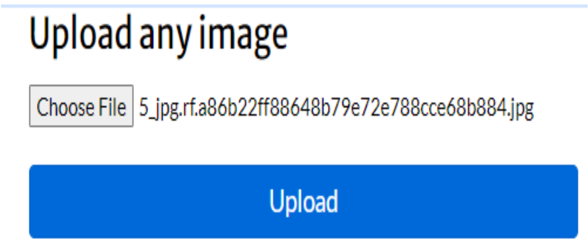
Step 2:

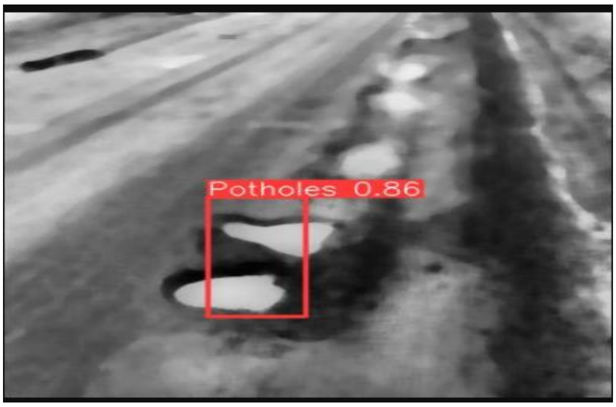
Results for Step 2:



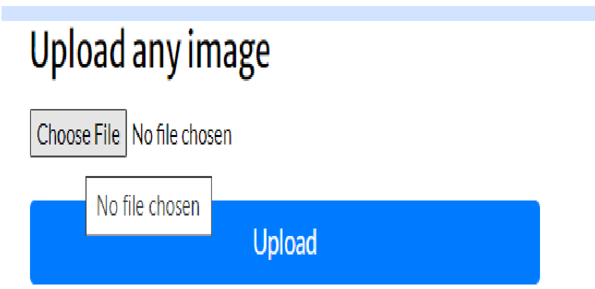


Step 5:

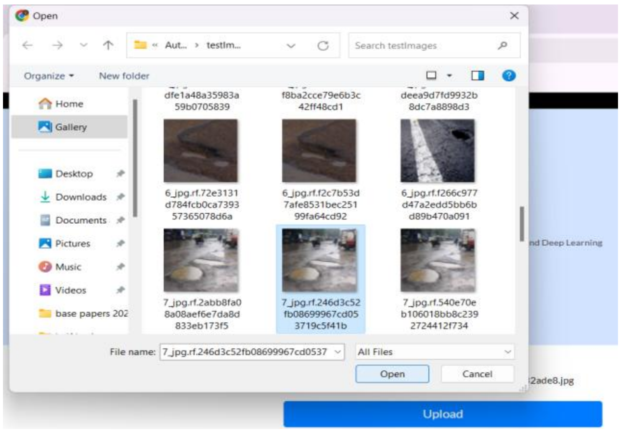




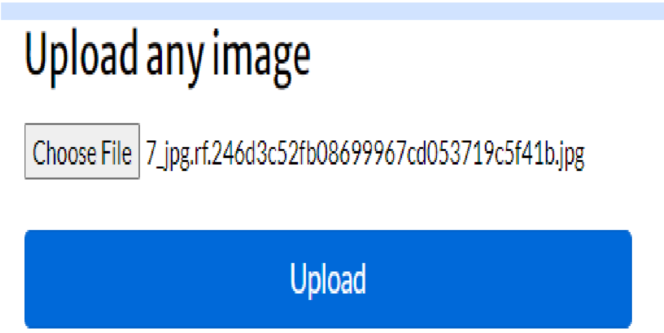
Results for Step 5



Step 6

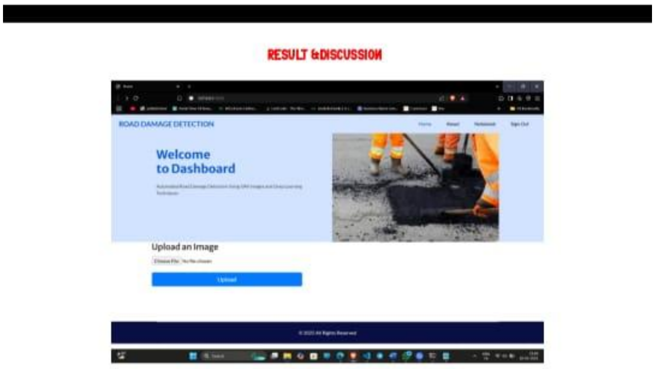


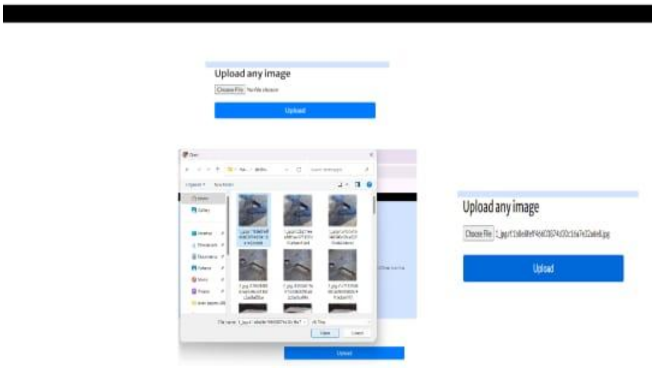
Step 7

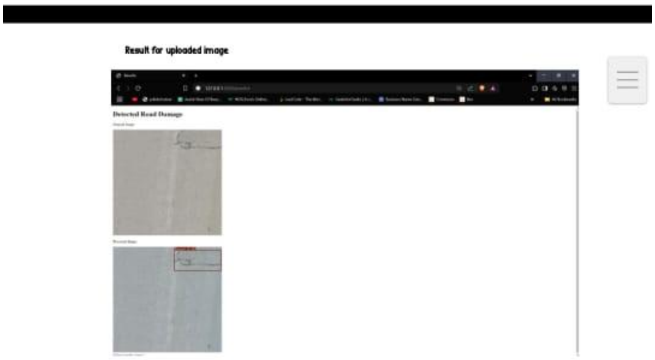


Step 8

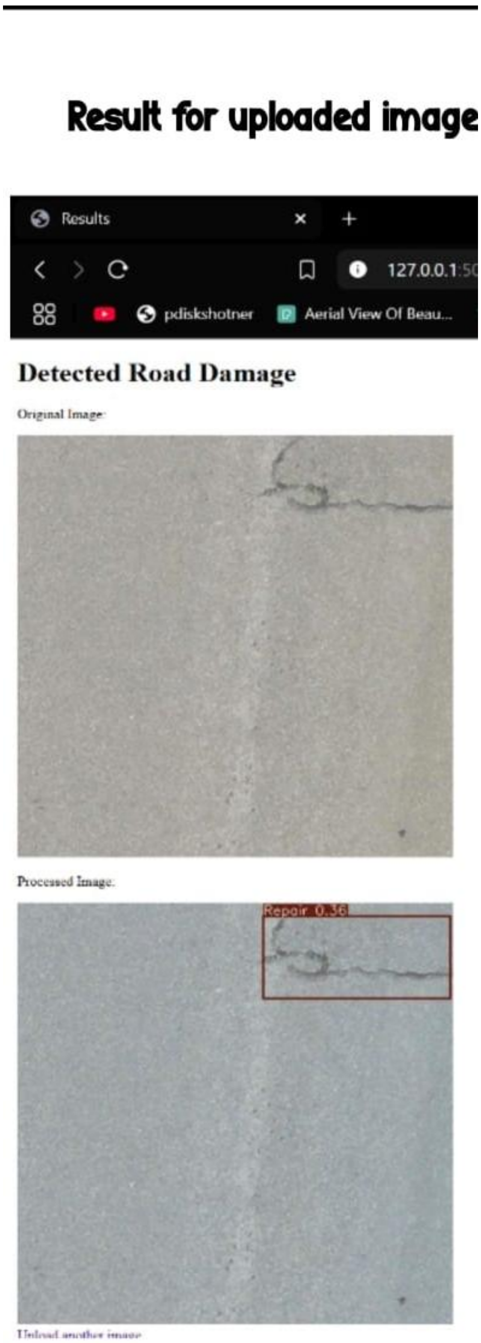
Resullts forstep 8



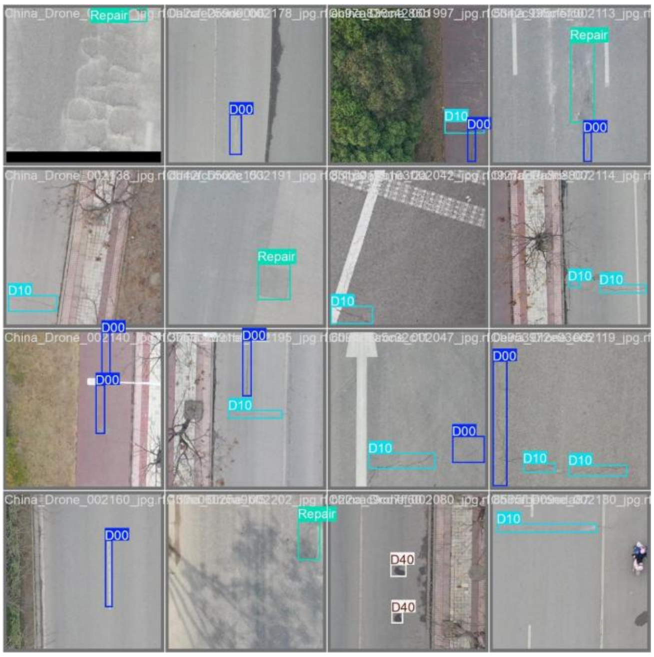




Crack detected 9



Crack detected 10



V. CONCLUSION

This study evaluated Transformer-based models alongside advanced YOLO architectures (YOLOv5, YOLOv7, and YOLOv8) to enhance the detection of road damage and cracks using UAV imagery. The results demonstrated a significant improvement in accuracy, with YOLOv8 achieving 85%, making it the most effective model for detecting both road damage and cracks.

To further refine model performance, we expanded the training dataset by integrating RDD2022 with UAV-captured images, effectively addressing class imbalance—particularly in Chinese and Spanish datasets. This enhancement improved road damage and crack detection, ensuring a more reliable assessment of pavement conditions.

While the findings are promising, there is still room for advancement. Future research could explore multispectral and LIDAR data to enhance crack identification and classification further. Additionally, fixed-wing UAVs could provide broader coverage for large-scale road monitoring. This study underscores the potential of deep learning and UAV technology in automating road damage and crack detection, ultimately contributing to more effective road maintenance and safety strategies.

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,'' Int. J. Interact. Multimedia Artif. Intell., vol. 2023, pp. 1–13, Jan. 2023.
[2] V. J. Hodge, R. Hawkins, and R. Alexander, ''Deep reinforcement learning for drone navigation using sensor data,'' Neural Comput. Appl., vol. 33, no. 6, pp. 2015–2033, Jun. 2020, doi: 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 Access, vol. 10, pp. 10384–10392, 2022.
[4] D. Gallacher, ''Drones to manage the urban environment: Risks, rewards, alternatives,'' J. Unmanned Vehicle Syst., vol. 4, no. 2, pp. 115–124, Jun. 2016.
[5] L. A. Silva, A. S. Mendes, H. S. S. Blas, L. C. Bastos, A. L. Gonçalves, and A. F. de Moraes, ''Active actions in the extraction of urban objects for information quality and knowledge recommendation with machine learning,'' Sensors, vol. 23, no. 1, p. 138, Dec. 2022, doi: 10.3390/ s23010138.

[6] L. Melendy, S. C. Hagen, F. B. Sullivan, T. R. H. Pearson, S. M. Walker, P. Ellis, A. K. Sambodo, O. Roswintiarti, M. A. Hanson, A. W. Klassen, M. W. Palace, B. H. Braswell, and G. M. 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, doi: 10.1016/j.isprsjprs.2018.02.022.
[7] L. A. Silva, H. S. S. Blas, D. P. García, A. S. Mendes, and G. V. González, ''An architectural multi-agent system for a pavement monitoring system with pothole recognition in UAV images,'' Sensors, vol. 20, no. 21, p. 6205, Oct. 2020, doi: 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. Failure Anal., vol. 141, Nov. 2022, Art. no. 106714, doi: 10.1016/j.engfailanal.2022.106714.
[9] D. Jeong, ''Road damage detection using YOLO with smartphone images,'' in Proc. IEEE Int. Conf. Big Data (Big Data), Dec. 2020, pp. 5559–5562, doi: 10.1109/BIGDATA50022.2020.9377847.
[10] M. Izadi, A. Mohammadzadeh, and A. Haghighattalab, ''A new neuro-fuzzy approach for post-earthquake road damage assessment using GA and SVM classification from QuickBird satellite images,'' J. Indian Soc. Remote Sens., vol. 45, no. 6, pp. 965–977, Mar. 2017.
[11] Y. Bhatia, R. Rai, V. Gupta, N. Aggarwal, and A. Akula, ''Convolutional neural networks based potholes detection using thermal imaging,'' J. King Saud Univ.-Comput. Inf. Sci., vol. 34, no. 3, pp. 578–588, Mar. 2022, doi: 10.1016/j.jksuci.2019.02.004.
[12] J. Guan, X. Yang, L. Ding, X. Cheng, V. C. Lee, and C. Jin, ''Automated pixel-level pavement distress detection based on stereo vision and deep learning,'' Automat. Constr., vol. 129, p. 103788, Sep. 2021, doi: 10.1016/j.autcon.2021.103788.
[13] D. Arya, H. Maeda, S. K. Ghosh, D. Toshniwal, and Y. Sekimoto, ''RDD2022: A multi-national image dataset for automatic road damage detection,'' 2022, arXiv:2209.08538.
[14] J. Redmon and A. Farhadi, ''YOLO9000: Better, faster, stronger,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Honolulu, HI, USA, 2017, pp. 6517–6525, doi: 10.1109/CVPR.2017.690.
[15] J. Redmon and A. Farhadi. YOLOv3: An Incremental Improvement. [Online]. Available: https://pjreddie.com/yolo/
[16] A. Bochkovskiy, C.-Y. Wang, and H.-Y. Mark Liao, ''YOLOv4: Optimal speed and accuracy of object detection,'' 2020, arXiv:2004.10934.
[17] G. Jocher, A. Chaurasia, A. Stoken, J. Borovec, Y. Kwon, K. Michael, J. Fang, C. Wong, D. Montes, Z. Wang, C. Fati, J. Nadar, V. Sonck, P. Skalski, A. Hogan, D. Nair, M. Strobel, and M. Jain, ''Ultralytics/YOLOv5: V7.0—YOLOv5 SOTA realtime instance segmentation,'' Zenodo, Tech. Rep., Nov. 2022. [Online]. Available: https://zenodo.org/record/7347926

[18] C.-Y. Wang, A. Bochkovskiy, and H.-Y. Mark Liao, ''YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors,'' 2022, arXiv:2207.02696.
[19] R. Ali, D. Kang, G. Suh, and Y.-J. Cha, ''Real-time multiple damage mapping using autonomous UAV and deep faster region-based neural networks for GPS-denied structures,'' Autom. Construct., vol. 130, Oct. 2021, Art. no. 103831. [Online]. Available: https://www.sciencedirect.com/ science/article/pii/S092658052100282X
[20] D. Kang and Y.-J. Cha, ''Autonomous UAVs for structural health monitoring using deep learning and an ultrasonic beacon system with geo-tagging: Autonomous UAVs for SHM,'' Comput.-Aided Civil Infrastruct. Eng., vol. 33, no. 10, pp. 885–902, Oct. 2018.
[21] Z. Xu, H. Shi, N. Li, C. Xiang, and H. Zhou, ''Vehicle detection under UAV based on optimal dense YOLO method,'' in Proc. 5th Int. Conf. Syst. Informat. (ICSAI), Nov. 2018, pp. 407–411, doi: 10.1109/ICSAI.2018. 8599403.
[22] P. Kannadaguli, ''YOLO v4 based human detection system using aerial thermal imaging for UAV based surveillance applications,'' in Proc. Int. Conf. Decis. Aid Sci. Appl. (DASA), Nov. 2020, pp. 1213–1219, doi: 10.1109/DASA51403.2020.9317198.

[23] T. Petso, R. S. Jamisola, D. Mpoeleng, and W. Mmereki, ‘‘Individual animal and herd identification using custom YOLO v3 and v4 with images taken from a UAV camera at different altitudes,’’ in Proc. IEEE 6th Int. Conf. Signal Image Process. (ICSIP), Oct. 2021, pp. 33–39, doi: 10.1109/ICSIP52628.2021.9688827.
[24] L. Wang and Z. Zhang, ‘‘Automatic detection of wind turbine blade surface cracks based on UAV-taken images,’’ IEEE Trans. Ind. Electron., vol. 64, no. 9, pp. 7293–7303, Sep. 2017, doi: 10.1109/TIE.2017.2682037.
[25] D. Sadykova, D. Pernebayeva, M. Bagheri, and A. James, ‘‘IN-YOLO: Real-time detection of outdoor high voltage insulators using UAV imaging,’’ IEEE Trans. Power Del., vol. 35, no. 3, pp. 1599–1601, Jun. 2020, doi: 10.1109/TPWRD.2019.2944741.
[26] M. A. A. Khan, M. Alsawwaf, B. Arab, M. AlHashim, F. Almashharawi, O. Hakami, S. O. Olatunji, and M. Farooqui, ‘‘Road damages detection and classification using deep learning and UAVs,’’ in Proc. 2nd Asian Conf. Innov. Technol. (ASIANCON), Aug. 2022, pp. 1–6, doi: 10.1109/ASIANCON55314.2022.9909043.
[27] Y.-J. Cha, W. Choi, and O. Büyüköztürk, ‘‘Deep learning-based crack damage detection using convolutional neural networks,’’ Comput.-Aided Civil Infrastruct. Eng., vol. 32, no. 5, pp. 361–378, May 2017.
[28] M. Böyük, R. Duvar, and O. Urhan, ‘‘Deep learning based vehicle detection with images taken from unmanned air vehicle,’’ in Proc. Innov. Intell. Syst. Appl. Conf. (ASYU), Oct. 2020, pp. 1–4, doi: 10.1109/ASYU50717.2020.9259868.
[29] R. Li, J. Yu, F. Li, R. Yang, Y. Wang, and Z. Peng, ‘‘Automatic bridge crack detection using unmanned aerial vehicle and faster R-CNN,’’ Construct. Building Mater., vol. 362, Jan. 2023, Art. no. 129659, doi: 10.1016/j.conbuildmat.2022.129659.
[30] Y.-J. Cha, W. Choi, G. Suh, S. Mahmoudkhani, and O. Büyüköztürk, ‘‘Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types,’’ Comput.-Aided Civil Infrastruct. Eng., vol. 33, no. 9, pp. 731–747, Sep. 2018. 31] D. Kang, S. S. Benipal, D. L. Gopal, and Y.-J. Cha, ‘‘Hybrid pixel-level concrete crack
segmentation and quantification across complex backgrounds using deep learning,’’ Autom. Construct., vol. 118, Oct. 2020, Art. no. 103291.
[32] S. Shim, J. Kim, S.-W. Lee, and G.-C. Cho, ‘‘Road damage detection using super-resolution and semi-supervised learning with generative adversarial network,’’ Autom. Construct., vol. 135, Mar. 2022, Art. no. 104139, doi: 10.1016/j.autcon.2022.104139.
[33] D. H. Kang and Y.-J. Cha, ‘‘Efficient attention-based deep encoder and decoder for automatic crack segmentation,’’ Struct. Health Monitor., vol. 21, no. 5, pp. 2190–2205, Sep. 2022.
[34] R. Ali and Y.-J. Cha, ‘‘Attention-based generative adversarial network with internal damage segmentation using thermography,’’