UNIVERSITI TEKNOLOGI MARA
Cawangan Perak

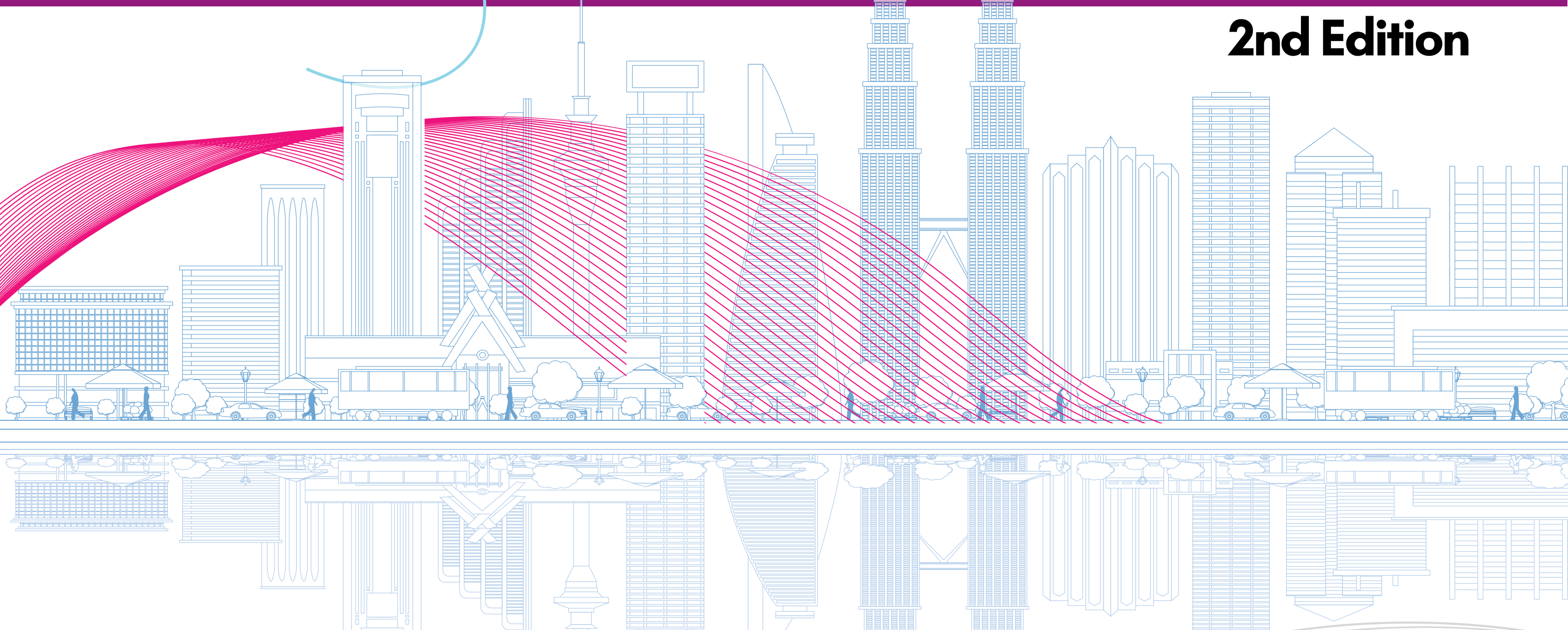
e - Proceedings

IUGeT

Proceeding for International Undergraduates Get Together 2024 (IUGeT 2024)

"Undergraduates' Digital Engagement Towards Global Ingenuity"

2nd Edition



Organiser :

Department of Built Environment Studies and Technology, College of Built Environment, UiTM Perak Branch

Co-organiser :

INSPIRED 2024. Office of Research, Industrial Linkages, Community & Alumni (PJIMA), UiTM Perak Branch

Bauchemic (Malaysia) Sdn Bhd

Universitas Sebelas Maret

Universitas Tridinanti (UNANTI)

Publication date :

November 2024

e - Proceedings

Proceeding for International Undergraduates Get Together 2024 (IUGeT 2024)

"Undergraduates' Digital Engagement Towards Global Ingenuity"

Organiser :

Department of Built Environment Studies and Technology, College of Built Environment, UiTM Perak Branch

Co-organiser :

INSPIRED 2024. Office of Research, Industrial Linkages, Community & Alumni (PJIMA), UiTM Perak Branch

Bauchemic (Malaysia) Sdn Bhd

Universitas Sebelas Maret

Universitas Tridinanti (UNANTI)

Perpustakaan Negara Malaysia Cataloguing in Publication Data

No e- ISBN: 978-967-2776-42-0

Cover Design: Muhammad Anas Othman
Typesetting : Arial

e-ISBN: 978-967-2776-42-0

iVUTI 2024 Committee

Project Leader
Ts Muhammad Naim Mahyuddin

Assistant Project Leader 1
Dr Ezzat Fahmi Ahmad

Assistant Project Leader 2
En Mohd Fadzli Mustaffa

Secretariat 1
Syahmimi Ayuni Ramli

Secretariat 2
Nur Afiqah Anuar

Treasurer
Dr Izrahayu Che Hashim

Registration Team
Dr Asmaa' Che Kassim
Dr Fatin Syazwina Abdul Shukor
Dr Suwaibatul Islamiah Abdullah Sani

Certification Team
Ts Nurul Huda Abdul Hadi
Ir Raja Nurulhaiza Raja Nhari
Dr Siti Jamiah Tun Jamil

Graphic Team
Mohammad Fitry Md Wadzir
Jannatun Naemah Ismam,
Nor Azizah Talkis
Wan Nur Hanani Wan Abdullah

Promotion Team
Nurulanis Ahmad@Mohamed
Najma Azman
Ts Sr Dr Asmat Ismail

Evaluation Team
Dr Suzanah Abdullah
Haslina Hashim
Azlizan Adila Mohamad
Noorsazwan Ahmad Pugi
Gs Dr Munirah Radin Mohd Mohktar
Mohd Najib Husain

Publication Team
Nur'Ain Ismail (Head)
Siti Nurhayati Hussin (Chief)
Dr Nuramira Anuar (Sub-chief)
Dr Paul Gnanaselvam A/L Pakirnathan
Noorlinda Alang
Norasyikin Abdul Malik
Halimatussaadiah Iksan
Nurdiyana Mohamad Yusof
Syaza Kamarudin
Dr Wan Nordiana Wan Ali
Dr Ida Nianti Mohd Zin
Dr Nurul Sahida Fauzi
Dr Noor Rizallinda Mohd Ishak
Dr Lizawati Abdullah
Iza Faradiba Mohd Patel
Nurfatima Wahida Nasir
Nazirul Mubin Mohd Noor

Proceeding for International Undergraduates Get Together 2024 (IUGeT 2024)
Undergraduates' Digital Engagement Towards Global Ingenuity
e-ISBN: 978-967-2776-42-0

CONCRETE SURFACE INSPECTION BY USING UNMANNED AERIAL VEHICLE (UAVS) AND DEEP LEARNING ALGORITHMS YOLOV7

Saffa Nasuha Rusdinaidi[1*], Khairil Afendy Hashim [2], and Zaki Ahmad Dahlan[3]

[1,2,3] Universiti Teknologi Mara Perlis
College of Built Environment
A20600, Arau, Perlis

*2022855546@student.uitm.edu.my

Abstract
Concrete surface inspection is a critical aspect of infrastructure maintenance, traditionally performed through manual methods that are time-consuming, labor-intensive, and prone to human error. This research aims to evaluate the detection and analysis of cracks on concrete surfaces by utilizing Uavs and Yolo algorithms. Uavs offers a versatile and cost-effective solution for capturing high-resolution orthophotos of large and hard-to-reach concrete structures. These images are then processed using Yolov7, a state-of-the-art object detection algorithm, to accurately identify and classify surface cracks. The study involves the collection of a comprehensive dataset of concrete surfaces with varying crack patterns, pre-processed using Roboflow and OpenCV tools to enhance crack features. The annotated dataset is utilised to train and validate the Yolov7 model, ensuring high precision which is 96.8% and 90.1% recall in crack detection. The performance of the model is evaluated through metrics such as precision, recall, and F1-score, demonstrating its robustness and reliability in detecting both fine and prominent cracks. The results indicate that the combined use of Uavs and Yolov7 significantly improves the efficiency of concrete surface inspections, providing a scalable and automated solution for infrastructure monitoring. This research contributes to the field of automated infrastructure inspection by integrating Uav technology with advanced deep learning algorithms, presenting a novel approach that reduces manual effort and enhances the accuracy of concrete surface assessments. The findings suggest potential applications in various fields including geomatic fields emphasizing the importance of technological advancements in maintaining the safety and longevity of critical infrastructure.

Keywords: *Unmanned Aerial Vehicles (UAVs), Yolov7, Deep Learning, Crack Detection.*

1. INTRODUCTION

Traditional infrastructure inspection methods, such as visual assessments by human inspectors and non-destructive testing (NDT) methods like ultrasonic and radiographic testing, have been effective but often require significant time, labor, and resources, and may pose safety risks, especially in hard-to-reach areas (Ayele et al., 2020). These methods can be subjective, leading to potential errors and impacting inspection accuracy, and are particularly challenging for large structures due to time consuming and resource intensive processes that disrupt traffic flow. Additionally, safety hazards for inspectors and high costs further limit traditional inspections. The problem is exacerbated in construction sites with challenging terrain, where environmental factors like dust and strong winds complicate access and increase risks. These inspections also often require costly heavy machinery and aerial work platforms, further complicating the process (Ayele et al., 2020; Toriumi et al., 2023). To address these issues, the objectives of the study are to produce orthophotos using UAV data, establish automatic crack detection on concrete using YOLOv7 algorithms, and analyse this detection method's effectiveness.

However, the UAV-based approach must overcome limitations such as sensitivity to environmental noise and difficulty in removing image noise, while also exploring its applicability to other infrastructure types (Bin Lei et al., 2018).

1.1 Related to study

1.1.1 Inspection

Traditional methods for inspecting infrastructure, such as bridges, roads, and buildings, have historically relied on manual visual examination by human inspectors. This includes techniques like visual inspection, where inspectors physically assess structures for signs of deterioration, as well as non-destructive testing (NDT) methods like ultrasonic and radiographic testing. Additionally, structural load testing and material sampling, along with a review of documentation and records, have been part of the traditional inspection toolkit. While these methods have been effective, they often require significant time, labor, and resources, and may pose safety risks, particularly in accessing challenging areas (Ayele et al., 2020).

The reliance on human judgment in traditional methods introduces subjectivity and potential errors, impacting inspection accuracy. Moreover, conventional approaches often involve time consuming and resource- ntensive processes, especially for large structures, leading to labour-intensive procedures and causing disruptions to traffic flow. Visual inspections may also lack comprehensiveness, particularly in concealed areas, potentially resulting in oversight of structural issues. To ensure the safety and longevity of bridge infrastructure, these issues must be addressed. Emerging technologies like UAVs and deep learning-based analytics offer promising solutions, providing more efficient and accurate methods for inspection and damage detection (Ayele et al., 2020).

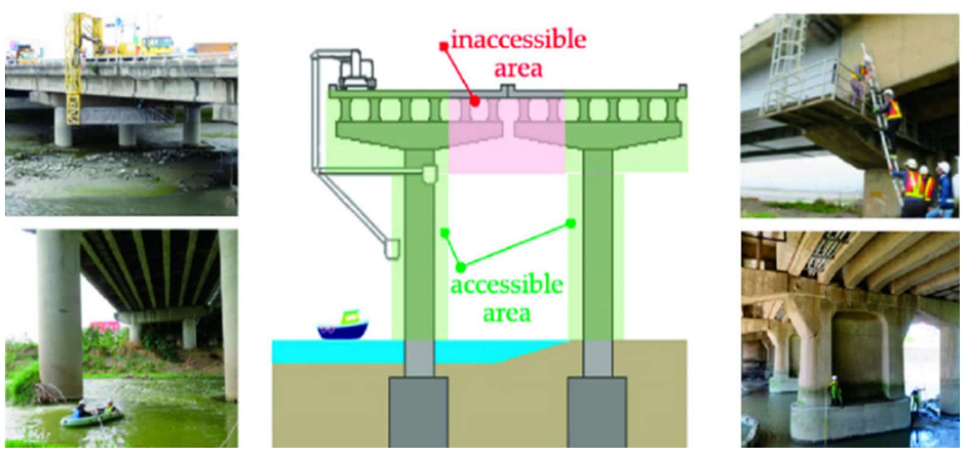


Figure 1. Traditional concrete inspection operation

1.1.2 Unmanned Aerial Vehicle

An unmanned aerial vehicle (UAV), commonly referred to as a drone, is an aircraft that can be operated remotely without a human pilot onboard. UAVs offer great versatility and find applications across various fields such as aerial photography, scientific research, military operations, mapping and surveying, search and rescue, and more. In recent years, UAVs have also been increasingly utilized for bridge maintenance and inspection, offering an economical and effective means to access and evaluate bridge components that are hazardous or challenging to reach using traditional inspection techniques (Aliyari et al., 2020). Equipped with cameras and sensors, UAVs are capable of capturing detailed pictures and data that can be utilized to plan maintenance and repair tasks as well as spot potential problems.

e-ISBN: 978-967-2776-42-0

Furthermore, UAVs have revolutionized various tasks across industries and have become an essential tool due to their ability to provide efficient and accurate data collection capabilities (Droguett et al., 2020). The utilization of UAV technology revolutionizes inspection flow analysis, providing unprecedented access to high-quality, real-time data and fostering advanced analytical capabilities that hold significant promise for enhancing infrastructure planning and overall inspection system efficiency (Muhammad Adnan et al., 2020). Moreover, UAV-based inspections offer several notable advantages over traditional methods, including enhanced safety, cost-effectiveness, efficiency, early issue detection, remote monitoring, and advanced data analysis (Aliyari et al., 2021). Additionally, the versatility of UAVs is underscored by their ability to carry task-specific sensors, including laser scanners, infrared cameras, and DSLR cameras, facilitating comprehensive data collection for thorough inspection and analysis (Ali Mirzazade et al., 2021).

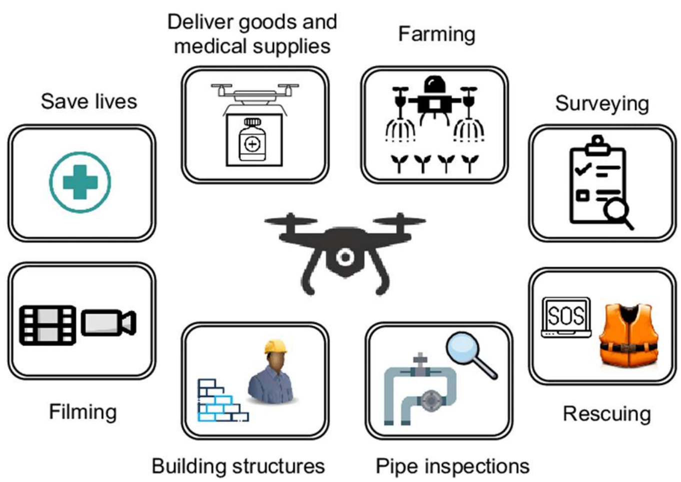


Figure 2. Advantages of UAV/drone

1.1.3 YOLO (You Only Look Once)

Real-time object detection plays a crucial role in diverse applications such as autonomous vehicles, robotics, video surveillance, and augmented reality. This review provides an overview of the development and advancements of the YOLO (You Only Look Once) framework, from its inception with YOLOv1 to the latest iteration, YOLOv8. YOLOv1 revolutionized object detection by treating it as a single regression problem, enabling the prediction of bounding boxes and class probabilities from full images in one pass. YOLOv2 (YOLO9000) enhanced accuracy and speed through batch normalization, high-resolution classifiers, and anchor boxes. YOLOv3 introduced multi-scale predictions, residual blocks, and a more robust backbone network, Darknet-53.

YOLOv4 further optimized the balance between speed and accuracy with innovations like Cross Stage Partial connections (CSP), a modified Mish activation function, and improved data augmentation strategies. Despite not being officially released by the original authors, YOLOv5 became popular for its ease of use and performance improvements, particularly its integration with PyTorch. YOLOv6 and YOLOv7 continued to refine model architecture for better speed and accuracy, with YOLOv7 being noted for its enhanced backbone and neck networks. YOLOv8, the most recent version, features additional refinements in architecture, loss functions, and training strategies, pushing the limits of real-time object detection (Diwan et al., 2022).

e-ISBN: 978-967-2776-42-0

Figure 3. A timeline of Yolo versions.

2. RESULTS AND DISCUSSION

2.1 Orthophoto

The orthophoto generated using the Agi soft Meta shape software serves as a critical component in this research. The high-resolution, geometrically corrected image provides an accurate representation of the concrete surfaces, which is essential for subsequent detailed analysis and crack detection. The orthophoto acts as a foundational layer, ensuring that the data collected is both precise and reliable. In this context, the orthophoto facilitates a structured approach to image processing and analysis. By offering a clear and accurate depiction of the study area, it ensures that any detected cracks are based on high-quality imagery, reducing the likelihood of errors in detection and measurement. This accuracy is vital for the integrity of the research, as it supports the identification of even the smallest cracks, which are crucial for assessing the condition of concrete structures. The orthophoto's role extends beyond mere visualization; it provides a baseline for comparing pre- and post-crack detection images, allowing for a comprehensive evaluation of the model's performance. The RGB legend included in the image aids in understanding the different bands used, highlighting the orthophoto's detailed and multifaceted nature. The generation of the orthophoto is a pivotal step in this research, underpinning the entire process of crack detection and analysis. By ensuring high-quality data input, it supports the production of accurate and reliable results, thereby enhancing the validity and applicability of the findings.

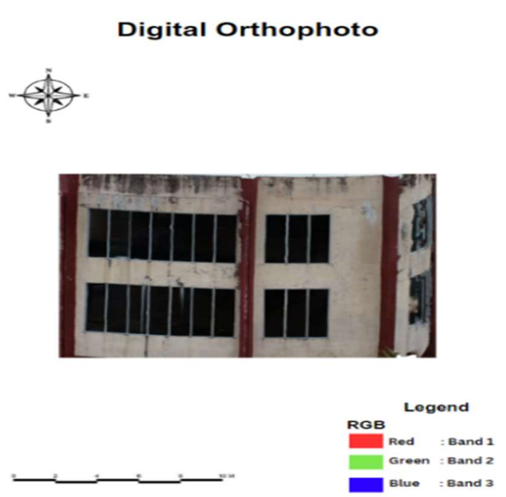


Figure 4. Orthophoto result

e-ISBN: 978-967-2776-42-0

2.2 Crack detection by using deep learning algorithm

The analysis of crack detection using yolov7, as shown in the provided images, reveals several important observations and insights. Initially, the images on the left depict concrete surfaces with visible cracks, representing the state before any processing with the yolov7 model. These images show the cracks as they would be seen manually without any automated assistance. In contrast, the images on the right, which have been processed by the yolov7 model, clearly highlight the detected cracks with bounding boxes and display confidence scores for each detection.

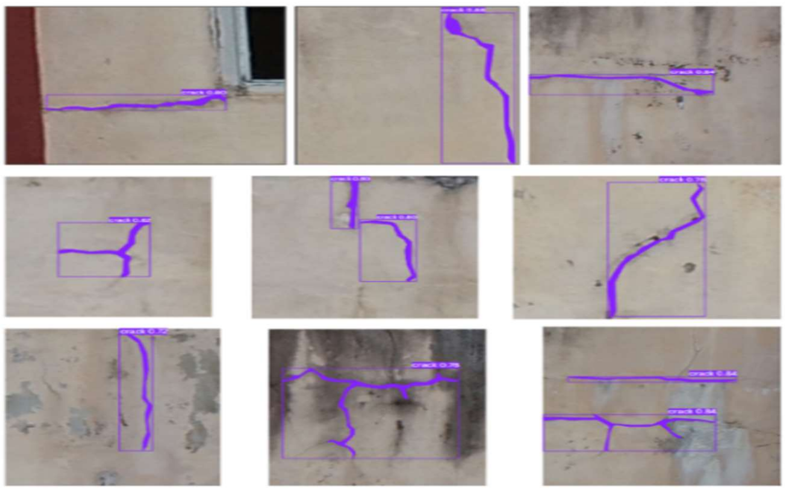


Figure 5. Result deep learning detection

The yolov7 model demonstrates a high level of effectiveness in identifying and highlighting cracks on concrete surfaces. The bounding boxes accurately follow the contours of the cracks, indicating precise detection of both the location and shape of the cracks. The confidence scores, such as 0.88 and 0.90, suggest a high level of certainty in these detections. This indicates that yolov7 can effectively identify cracks that might be challenging to discern manually, particularly small or intricately located cracks. The use of yolov7 in this context brings several advantages. Firstly, it enhances precision and accuracy, as evidenced by the clear and accurate bounding boxes around the cracks. This reduces the likelihood of false positives and negatives, leading to more reliable inspections. In addition, the automation of crack detection significantly improves time efficiency. Instead of manually inspecting each image, the model quickly processes and identifies cracks, saving considerable time and resources. Furthermore, the use of a trained model ensures consistent detection results, reducing variability and potential errors that can occur with manual inspections.

The automated crack detection using yolov7 has numerous potential applications, particularly in infrastructure maintenance. It can be used for regular monitoring of bridges, buildings, and roads, facilitating early identification of structural issues and allowing for timely maintenance and repairs. The integration of yolov7 with uav technology enhances its utility by enabling large-scale inspections of hard-to-reach areas without the need for scaffolding or other costly infrastructure. However, there are challenges and limitations to consider. The accuracy of crack detection can be affected by environmental factors such as lighting, shadows, and weather conditions, which can introduce noise into the images and impact the model's performance. Moreover, the effectiveness of the yolov7 model depends heavily on the quality and diversity of the training data. a model trained on a limited dataset may not generalize well to different types of cracks or surfaces.

2.3 Roboflow training Metrics Result

Advanced image processing and crack detection were tested with various types of cracks. The steps began with the use of Roboflow to prepare and manage the custom dataset, which was then trained using the yolov7 model. The training process enabled the model to learn and recognize cracks of various types and classes. This approach ensured that the model could accurately detect and classify different crack formations on concrete surfaces, leveraging the capabilities of yolov7's deep learning algorithms to enhance the precision and reliability of the crack detection process.

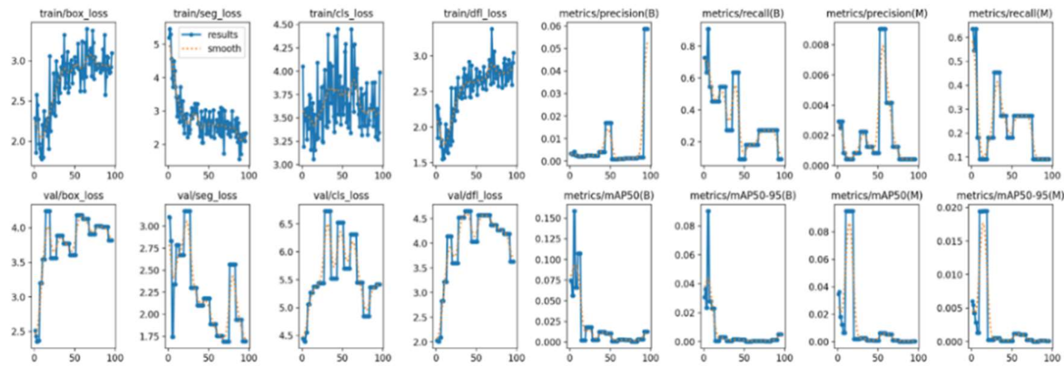


Figure 6 Training Metrics Result

The training metrics provided for the yolov7 model on Roboflow offer valuable insights into the model's performance and learning progress for concrete crack detection. The loss metrics, which include train/box loss, train/seg_loss, train/cls_loss, and train/dfl_loss, provide a detailed look at how the model is learning during training. The train/box loss metric, for instance, indicates how well the predicted bounding boxes match the ground truth boxes. The train/seg_loss represents the segmentation loss, measuring the accuracy of the model's segmentation predictions. The train/cls_loss shows the classification loss, reflecting how well the model classifies objects within the bounding boxes, while the train/dfl_loss refers to the distribution focal loss, which is part of the bounding box regression process. Similarly, the validation losses, such as val/box loss, val/seg_loss, val/cls_loss, and val/dfl_loss, provide insight into the model's performance on unseen data. Observing these validation losses is crucial for understanding how well the model generalizes beyond the training dataset. (Xu et al., 2021)

In terms of precision and recall, metrics/precision and metrics/recall track the precision and recall for bounding box predictions, while metrics/precision and metrics/recall do the same for mask (segmentation) predictions. These metrics are essential for evaluating the model's accuracy in detecting and classifying cracks. Initially, these metrics start low but show significant improvement towards the end of the training period. High precision and recall indicate the model's ability to detect cracks accurately, with fewer false positives and negatives. The mean average precision (map) metrics, including metrics/map 50, metrics/map 50-95, metrics/map 50, and metrics/map 50- 95, provide a comprehensive measure of the model's performance. Metrics/map 50 and metrics/map 50 at 50% IoU demonstrate the model's capability in detecting and segmenting cracks. The graphs exhibit an increasing trend, indicating enhanced performance. Metrics/map 50-95 and metrics/map 50-95, which average map across multiple IoU thresholds, also show improvement, suggesting the model's growing accuracy in predicting crack locations and shapes. (Xu et al., 2021)

The analysis of loss trends reveals that the training losses (train/box loss, train/seg_loss, and train/cls_loss) generally decrease over time, indicating that the model is learning and improving during training. The validation losses (val/box loss, val/seg_loss, and val/cls_loss) also decrease, albeit with some fluctuations. These fluctuations are normal, but significant ones could suggest overfitting or instability in the training process. Precision and recall metrics for bounding boxes and masks improve significantly during training, highlighting the model's growing accuracy in detecting and classifying cracks. High precision and recall values indicate the model's effectiveness in minimizing false positives and negatives. The map metrics show a positive trend, with map 50 reaching higher values faster than map 50- 95. This pattern is typical as map 50 is an easier metric to achieve. The improvement in map metrics suggests that the model is effectively learning to predict crack locations and shapes accurately. In conclusion, the training metrics for the Yolov7 model on Roboflow demonstrate promising results for concrete crack detection. The consistent decrease in losses, significant improvement in precision and recall, and positive trend in map scores all indicate that the model is learning effectively and improving its performance over time. These insights are crucial for further fine-tuning and optimizing the model to ensure its robustness and reliability in practical applications (Bochkovskiy et al., 2020).

2.4 Accuracy of Crack detection

The categorization of cracks based on confidence scores into three severity levels which is low, moderate, and high provides a structured approach to prioritize maintenance efforts effectively. When cracks are detected using the yolov7 model with confidence scores ranging from 0.3 to 0.95, it signifies varying levels of certainty in their detection. Cracks categorized as low severity scores from 0.3 to 0.5 typically represent minor surface imperfections that may not immediately compromise structural integrity but should be monitored to prevent future deterioration. Moderate severity, cracks scores from 0.5 to 0.7 indicate more pronounced defects that warrant timely attention to prevent further deterioration and potential safety risks. High severity cracks scores from 0.7 to 0.95 denote critical structural issues requiring immediate intervention to ensure the safety and longevity of the concrete structure. By prioritizing maintenance efforts based on these severity levels, resources can be allocated efficiently. Addressing high-severity cracks first helps mitigate risks associated with structural damage, while simultaneously maintaining overall structural integrity. This approach supports proactive maintenance strategies, enhancing the long-term durability and safety of concrete infrastructure.

Table 1. Performance matrix of Yolo models

Model	Precision	Recall	map
Crack Detection	0.986	0.901	0.932

Based on the precision, recall, and F1-score calculations for the crack detection using Yolov7. The precision score of approximately 0.968 indicates that the model is highly effective at correctly identifying true cracks with very few false positives. This means that when the model predicts a crack, it is correct 96.8% of the time. The recall score of approximately 0.901 suggests that the model is able to detect 90.1% of the actual cracks present in the images. This indicates that the model has a strong ability to identify true cracks but may still miss some. The F1-score, which is the harmonic mean of precision and recall, is approximately 0.932, which is 93.2%.

This reflects a good balance between precision and recall, indicating that the model is both accurate and comprehensive in its detections Malche et al., (2023). Analysis that can be made from this result of the high precision, recall, and F1-score demonstrate that Yolov7 is highly effective for the task of concrete crack detection. The model can reliably detect cracks while minimizing false alarms and missed detections. The performance metrics also suggest that the dataset used for training the model is of good quality, with well-annotated images that allow the model to learn the features of cracks effectively. Despite the high scores, there is still room for improvement, particularly in recall. Strategies to enhance recall could include additional data augmentation techniques, collecting more diverse training data, or fine-tuning the model further. (Malche et al., 2023).

3. CONCLUSION

This study has successfully met its objectives, with the exception of the orthophoto training model in Yolov7. The first objective was to produce orthophotos using data from UAV images, which was accomplished using Agi soft Meta shape software. This software is essential for generating high-resolution, geometrically corrected images that accurately represent concrete surfaces. These orthophotos are crucial for detailed analysis and crack detection in subsequent phases of the research. Unfortunately, during the pre-training phase in Roboflow, the orthophotos encountered issues that prevented exporting the dataset for use in Yolov7. Despite this setback, the single-image analysis proved successful. Out of all single images, all provided outputs, including confidence scores and accuracy metrics for crack detection on concrete surfaces. The results showed a precision of 0.968 (96.8%), recall of 0.901 (90.1%), and an F1-Score of 0.932 (93.2%). These values indicate high accuracy, with precision and recall both close to 1, meaning the model performs well in detecting cracks with minimal false positives and false negatives. However, achieving a perfect accuracy of 100% is rare and usually indicates overfitting or an ideal scenario. Overall, the study demonstrates the effectiveness of using UAVs and Yolov7 for concrete surface inspection, highlighting the potential for high-precision crack detection. Further work is needed to address the challenges with orthophoto training to fully leverage the capabilities of Yolov7 in this context.

4. ACKNOWLEDGMENT

The authors would like to thank Centre of Studies Surveying Science and Geomatics, College of Built Environment, Universiti Teknologi MARA, Perlis and the authors would like to express appreciation for the all the anonymous reviewers.

5. REFERENCES

Aliyari, M., Ashrafi, B., & Ayele, Y. Z. (2021). *Hazards identification and risk assessment for UAV–assisted bridge inspections. Structure and Infrastructure Engineering,* 18(3), 412–428. https://doi.org/10.1080/15732479.2020.1858878

Aliyari, M., Droguett, E. L., & Ayele, Y. Z. (2021). *UAV-Based bridge inspection via transfer learning. Sustainability,* 13(20), 11359. https://doi.org/10.3390/su132011359

Ayele, Y. Z., Aliyari, M., Griffiths, D., & Droguett, E. L. (2020b). *Automatic crack segmentation for UAV-Assisted bridge inspection. Energies,* 13(23), 6250. https://doi.org/10.3390/en13236250

Bochkovskiy, A., Wang, C., & Liao, H. M. (2020b, April 23). *YOLOV4: Optimal speed and accuracy of object detection.* arXiv.org. https://arxiv.org/abs/2004.10934

Chen, S., Laefer, D. F., Mangina, E., Zolanvari, S. M. I., & Byrne, J. (2019b). *UAV Bridge Inspection through Evaluated 3D Reconstructions. Journal of Bridge Engineering*, 24(4). https://doi.org/10.1061/(asce)be.1943-5592.0001343

Chen, X., Liu, C., Chen, L., Zhu, X., Zhang, Y., & Wang, C. (2024). *A pavement crack*

Detection and Evaluation framework for a UAV inspection system based on deep learning. Applied Sciences, 14(3), 1157. https://doi.org/10.3390/app14031157

Diwan, T., Anirudh, G., & Tembhurne, J. V. (2022). *Object detection using YOLO: challenges, architectural successors, datasets and applications. Multimedia Tools and Applications,* 82(6), 9243–9275. https://doi.org/10.1007/s11042-022-13644-y

Feroz, S., & Dabous, S. A. (2021b). *UAV-Based Remote sensing Applications for bridge condition assessment. Remote Sensing,* 13(9), 1809. https://doi.org/10.3390/rs13091809

Han, Z., Chen, H., Liu, Y., Li, Y., Du, Y., & Zhang, H. (2021). *Vision-Based crack detection of asphalt pavement using deep convolutional neural network. Iranian Journal of Science and Technology. Transactions of Civil Engineering/Civil Engineering,* 45(3), 2047–2055. https://doi.org/10.1007/s40996-021-00668-x

Hishsan, N. a. B., Salleh, A. M., & Zin, N. a. a. M. (2024). *Application of unmanned aerial vehicle (UAV) for a safer roof inspection at high rise buildings. IOP Conference Series. Earth and Environmental Science, 1347*(1), 012023. https://doi.org/10.1088/1755-1315/1347/1/012023

Malche, T., Tharewal, S., & Dhanaraj, R. K. (2023). *Automated Damage Detection on Concrete Structures Using Computer Vision and Drone Imagery. Automated Damage Detection on Concrete Structures Using Computer Vision and Drone Imagery.* https://doi.org/10.3390/ecsa-10-16059

Saberironaghi, A., & Ren, J. (2024). *DepthCrackNet: a deep learning model for automatic pavement crack detection. Journal of Imaging*, 10(5), 100. https://doi.org/10.3390/jimaging10050100

Song, F., Liu, B., & Yuan, G. (2024). *Pixel-Level crack identification for bridge concrete structures using unmanned aerial vehicle photography and deep learning. Structural Control & Health Monitoring/Structural Control and Health Monitoring,* 2024, 1–14. https://doi.org/10.1155/2024/129909

Ya'acob, N. N., Zuraimi, N. M. D. I., Rahman, N. a. a. A., Yusof, N. a. L., & Ali, N. D. M. (2024). *Real-Time pavement crack detection based on artificial intelligence. Journal of Advanced Research in Applied Sciences and Engineering Technology,* 38(2), 71–82. https://doi.org/10.37934/araset.38.2.7182

Cawangan Perak

e - Proceedings

IUGeT

Proceeding for International Undergraduates Get Together 2024 (IUGeT 2024)

"Undergraduates' Digital Engagement Towards Global Ingenuity"

e-Proceeding IUGeT 2024 2nd Edition

e ISBN 978-967-2776-42-0

Unit Penerbitan UiTM Perak

(online)