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Classification Of Superstructure Damage In School Buildings In Nusa Penida Bali Using YOLO V7

Anak Agung Gede Oka Kessawa Adnyana[1*], I Gede Indra Mahardika[2], Gde Bagus Andhika Wicaksana[3], I Nyoman Darma Kotama[4]

[1*,2]Program Studi Informatika, Institut Bisnis dan Teknologi Indonesia, Bali. [3]Program Studi Teknik Arsitektur, Universitas Warmadewa, Bali. [4]Program Studi Sistem Komputer, Institut Bisnis dan Teknologi Indonesia, Bali

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ABSTRACT

Structural damage in school buildings poses significant risks to safety and education quality, particularly in remote areas with limited maintenance resources. This study develops a YOLOv7-based model to detect building pillars and classify structural damages, focusing on school buildings in Nusa Penida, Bali. A dataset of 156 images, derived from an initial 521 images collected during field visits, was curated to include both damaged and intact pillars. Preprocessing and augmentation techniques, including resizing and rotation, were applied to optimize the dataset. Training was conducted over 55 epochs using Google Colab with a T4 GPU, incorporating parameter tuning to address dataset imbalance. Confidence thresholds were set at 0.7 for pillars and 0.2 for rebar detection to enhance sensitivity to underrepresented damage classes. Evaluation metrics, including the F1-score and confusion matrix, confirmed the model's accuracy and robustness in detecting and classifying structural damages. The results demonstrate the model's potential for real-world applications in damage assessment, particularly in resource-limited settings. Future research should focus on expanding datasets, incorporating multi-class classification, and integrating real-time detection and drone-based imagery to enhance scalability and efficiency. This work contributes to developing efficient, AI-driven solutions for structural health monitoring in critical infrastructure.

Corresponding Author:
Anak Agung Gede Oka Kessawa Adnyana
Program Studi Informatika, Institut Bisnis dan Teknologi Indonesia, Bali
kessawa@instiki.ac.id

INTRODUCTION

School buildings are vital infrastructure to support the learning process for students. According to the Regulation of the Minister of Public Works and Housing of the Republic of Indonesia number 22/PRT/M/2018, state-owned school buildings are funded through the national or regional budgets (APBN or APBD) and are managed by the Office of Education, Youth, and Sports (Disdikpora) in collaboration with the Public Works Department (Kementerian Pekerjaan Umum dan Perumahan Rakyat, 2018). Maintenance of school buildings is crucial to ensuring the quality of education. Well-maintained buildings not only provide a comfortable and safe environment for students and educators but also reflect the

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government's commitment to delivering quality education. Investment in school building maintenance is an investment in the nation's future.

Neglected school buildings are often caused by distance and budget constraints, especially in remote areas such as Karangasem, Jembrana, and Klungkung. Many schools in these regions face challenges in securing sufficient funds for maintenance and repairs, leading to deteriorating infrastructure (Radar Bali, 2024; radarbali.com, 2024; Tabelak, 2024).

The survey conducted faced significant challenges. For example, in Karangasem Regency in 2023, the Public Works Department (PU), in collaboration with a private institution, successfully documented 355 elementary school buildings (CV. YOGAWIDYA SARANA DESAIN, 2023a) and 45 junior high school buildings (CV. YOGAWIDYA SARANA DESAIN, 2023b) over the course of a year. This process took a considerable amount of time due to travel distances and manual recording methods. Similar challenges were encountered in Klungkung Regency, which managed to document 50% of damaged elementary school buildings in Nusa Penida. The area's separation by the Badung Strait increased transportation costs and extended observation times (BALIPOST.com, 2024). These budget limitations and the lengthy observation process hinder the optimal handling of building damage, highlighting the need for support in improving this process.

To address the aforementioned challenges, a system is needed to facilitate an accessible reporting process, supported by a classification process powered by artificial intelligence. Such a system would enable accurate assessments and improve efficiency in classification, allowing decisions to be made more quickly and accurately.

This study focuses on the development of an artificial intelligence model that targets the superstructure of buildings, specifically the pillars of school buildings and their types of damage, using a dataset of 156 images. The model being developed is expected to support the creation of a self-reporting analysis and classification system for building damage in an optimal manner.

METHODS

Literature Review

Several studies have been conducted on the classification process related to building superstructures. Research by Rizki A. and Marina M. in 2019 developed a Convolutional Neural Network (CNN) model using VGG-16 to classify damage to school buildings in Indonesia, achieving a best accuracy of 67.8% after training and testing on three-class classification (Abuzairi et al., 2021).

Subsequent research by Gaho R. et al. in 2024 developed a system titled "Classification of Road Surface Quality Using CNN Method Based on Xception Architecture," leveraging deep learning with the Xception transfer learning architecture to classify road quality efficiently, achieving maximum accuracy of 90.11% and 90% in testing (Gaho et al., 2024).

Research by Adityah D. in 2021 focused on digital image processing using YOLO-V3, introducing Darknet-53 as a detailed feature extractor. It was used to identify types of road damage, particularly cracks. The classification process included stages such as Bounding Box Prediction, Class Prediction, Prediction Across Scales, and Feature Extractor, with crack

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classification based on survey parameters from Balitbang. The study achieved a classification accuracy of 96.4% for potholes (Adityah, 2021).

In 2022, Wu P. successfully tackled accurate concrete crack detection using a YOLOv4 network enhanced with pruning techniques and the EvoNorm-S0 structure. The research demonstrated an increase in mAP50 from 91.69% to 92.54%, with a 15.9% reduction in inference time. Compared to other algorithms such as SSD300, YOLOv3, and YOLO X-L, the results were favorable (Wu, 2022).

In 2023, Amalia Y. utilized the YOLO algorithm to classify road damage. The study classified three types of damage: potholes, cracks, and patches. The results showed a precision value of 0.88, recall of 0.8, mAP50 of 0.87, and mAP50-95 of 0.53, with optimal classification accuracy of 92% at a confidence threshold of 0.50 (Amalia, 2023).

Research Method

The research framework for this study is designed to systematically address the challenges of damage classification in building superstructures, ensuring a robust and efficient model development process. The study comprises four key stages: data collection, data preprocessing, model training, and evaluation.

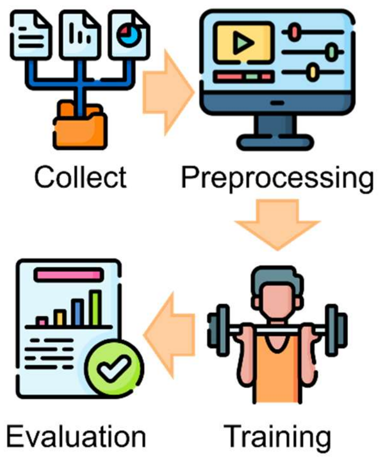

Figure 1. Method to Develop the Models

The research began with the process of collecting a dataset by visiting schools that had reported damage, as directed by the DISDIKPORA of Klungkung Regency. The schools visited included SD Negeri 2 Sekartaji, SD Negeri 3 Tanglad, SD Negeri 3 Kutampi, SD Negeri 3 Sakti, SD Negeri 4 Sakti, SD Negeri 7 Suana, and SD Negeri 6 Ped. From these schools, approximately 521 images were obtained, which were then filtered down to 156 images, specifically focusing on the pillars of the school buildings, whether damaged or intact.

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Figure 2. Samples of Pillars Photos and its defect

Data preprocessing and augmentation are critical steps in developing a robust and effective machine learning model, as they directly impact the quality of training and the model's ability to generalize well to unseen data (Nurqolbiah et al., 2023). Preprocessing prepares the raw data for analysis by ensuring it is clean, consistent, and standardized, while augmentation enhances the dataset by introducing variations that mimic real-world scenarios. These processes aim to address challenges such as data imbalance, noise, or limited diversity in the dataset, ultimately optimizing model performance.

In this study, preprocessing and augmentation were carried out using Roboflow, a comprehensive tool that streamlines the workflow by supporting annotation, preprocessing, and augmentation tasks. Roboflow enables researchers to create high-quality datasets efficiently by offering functionalities for precise annotation, automated transformations, and scalable data preparation. By leveraging this tool, the study ensured that the dataset used for training was both accurate and well-prepared for subsequent stages, laying a solid foundation for achieving high-performance results.

Figure 3. Notation on the Datasets

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The annotation process was performed manually to ensure accuracy, by drawing bounding boxes around the pillars and their respective damages. This manual approach ensures that the model receives precise and reliable information for training. During preprocessing, techniques such as auto-orient and stretch to 640x640 were applied. These methods aim to standardize the dataset and enhance the speed of both training and inference processes (Saputra et al., 2024). To make the model more robust, data augmentation was employed. This technique increases the diversity of training data, helping the model generalize better to unseen scenarios. Augmentation methods included rotation within a range of -10 to +10 degrees and brightness adjustments between -15% and +15%. These adjustments simulate real-world variations in image capture conditions, such as lighting and angles, thereby improving the model's ability to handle different situations effectively.

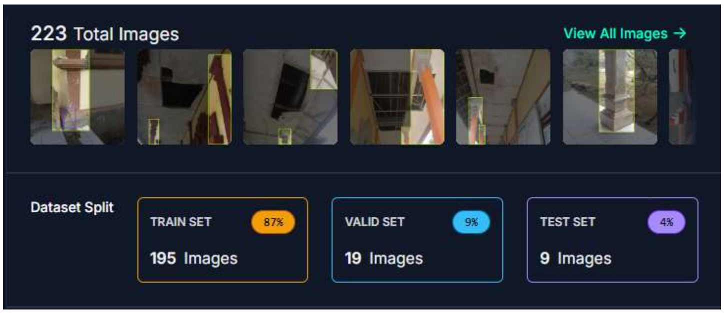

Figure 3. Dataset that has been augmented and notated

The training process in this research began with selecting the appropriate model to be utilized. The authors chose the YOLOv7 model, developed by Wang C. et al. in 2022, which is renowned for its capability to perform classification tasks effectively on both static images and dynamic videos. The model is highly versatile, capable of achieving frame rates between 5 and 160 FPS, depending on the computational resources and application context (Wang et al., 2022). YOLOv7 stands out for its balance between speed and accuracy, making it an ideal choice for tasks requiring real-time performance without compromising precision. By leveraging this model, the study aims to achieve optimal classification results while maintaining efficient processing times, which is particularly crucial for applications involving large datasets or time-sensitive operations. The selection of YOLOv7 aligns with the research objective to classify structural damage efficiently and accurately, ensuring that the system can handle diverse input conditions, such as varying image resolutions, lighting, and object complexities.

The YOLOv7 model and its necessary plugins were downloaded and configured to facilitate the training process, conducted in the Google Colab IDE with a T4 GPU High-RAM configuration. This setup significantly enhanced the speed and efficiency of training and inference testing. The model was trained over 55 epochs, enabling iterative refinement of pre-trained weights to improve accuracy and robustness in damage classification. The computational power of Google Colab allowed for efficient handling of the dataset and optimization of classification outcomes. Pre-trained weights generated during each epoch

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were evaluated to assess their effectiveness in classifying damage under various scenarios, ensuring the model's reliability for real-world applications.

The dataset was collected through field visits to structurally damaged schools, as directed by DISDIKPORA Klungkung Regency. Schools surveyed included SD Negeri 2 Sekartaji, SD Negeri 3 Tanglad, SD Negeri 3 Kutampi, SD Negeri 3 Sakti, SD Negeri 4 Sakti, SD Negeri 7 Suana, and SD Negeri 6 Ped. A total of 521 images were captured, which were filtered to 156 images, focusing on building pillars in both damaged and undamaged conditions.

This targeted data collection and rigorous filtering process provided a relevant and representative dataset, forming a solid foundation for training the YOLOv7 model. The systematic evaluation of pre-trained weights ensured a robust model capable of accurately identifying and classifying structural damage in school buildings.

RESULTS AND DISCUSSION

Results

The evaluation metrics used to assess the performance of the YOLOv7 model for detecting building pillars and their damage are the F1-score and the confusion matrix (Guntara, 2023). The F1-score, as shown in Equation (3), represents the harmonic mean of precision (Equation 1) and recall (Equation 2). It provides a comprehensive evaluation of the model's overall accuracy by balancing the trade-off between precision and recall. The formula for the F1-score is:

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}} \tag{1}$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \tag{2}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

To calculate the F1-score, the output of the YOLOv7 model is compared with the ground truth annotations. This involves determining the number of true positives (TP), false positives (FP), and false negatives (FN) for each image in the test set. The F1-score provides a single metric that encapsulates the precision of the model (its ability to avoid false positives) and its recall (its ability to detect all relevant instances). By balancing these two aspects, the F1-score offers a robust indicator of model performance, particularly in datasets with an uneven distribution of classes or a high cost of misclassification.

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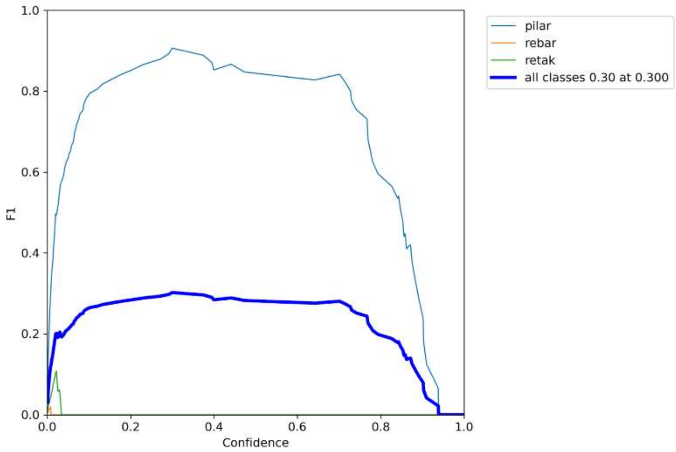

Figure 4. Dataset that has been augmented and notated

CA high F1-score indicates a good balance between precision and recall, reflecting the model's ability to minimize both false positives and false negatives. For instance, if we have a test set consisting of 100 aerial images and aim to evaluate the YOLOv7 model's performance in detecting building superstructures and their damages, we compare the model's output with the ground truth annotations. This process involves calculating the number of true positives (TP), false positives (FP), and false negatives (FN) for each image in the test set.

By analyzing these values, we can derive precision (the ratio of correctly identified positives to all predicted positives) and recall (the ratio of correctly identified positives to all actual positives). The F1-score then combines these metrics into a single value that provides a balanced measure of the model's detection capabilities. This approach ensures a comprehensive evaluation of the model's performance across diverse test scenarios and highlights its effectiveness in handling real-world datasets.

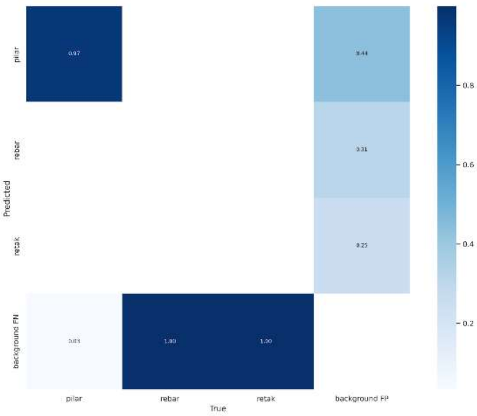

Figure 5. Confusion matrix pre-trained weight

In this case, the dataset for building pillars was significantly larger, resulting in an underrepresentation of the dataset for structural damage. This imbalance necessitated parameter tuning to adjust the resulting confusion matrix and improve model performance.

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Specifically, the confidence level for pillar detection was set to 0.7, while for rebar detection (exposed reinforcement), it was set to 0.2. This adjustment aims to account for the disparity in dataset representation, ensuring that the model can maintain sensitivity for underrepresented classes without compromising accuracy for well-represented ones. Following these adjustments, test trials were conducted using various images to evaluate and validate the performance of the trained model. These trials aimed to confirm that the model could accurately detect both building pillars and their associated damages under the adjusted confidence thresholds, providing a reliable assessment of the model's real-world applicability.

Figure 6. Detection Result for Pillar and Rebar Defects

Discussions

The YOLOv7 model demonstrated effective performance in detecting building pillars and associated damages, but an imbalance in the dataset led to underrepresentation of damage-related instances. To address this, parameter tuning was implemented, setting a confidence level of 0.7 for pillar detection and 0.2 for rebar detection. This adjustment aimed to enhance the model's sensitivity to underrepresented classes while maintaining overall accuracy.

Preliminary tests on various images confirmed the model's ability to detect and classify pillars and damages accurately, validating the effectiveness of the tuning process. Despite the dataset imbalance, these results highlight the model's adaptability and robustness, demonstrating its potential for real-world applications in structural damage assessment.

CONCLUSION

This study successfully developed a YOLOv7-based model for detecting building pillars and classifying structural damages in school buildings, demonstrating robust performance despite dataset imbalances. Parameter tuning and confidence level adjustments effectively enhanced the model's sensitivity to underrepresented damage classes, validating its potential for real-world applications in structural assessment, particularly in remote or resource-limited areas. Future research should focus on expanding the dataset to include more diverse damage types and structures, ensuring balanced class representation. Additionally, integrating advanced features such as multi-class damage classification, real-time detection, and drone-based imagery, coupled with edge computing, could enhance the system's scalability and efficiency. Employing semi-supervised learning techniques may also address dataset limitations, further improving the model's performance without extensive manual labeling efforts.

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