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EFFECTIVENESS OF ROOFTOP PHOTOVOLTAIC INSPECTION BASED ON RGB AERIAL IMAGERY AND YOLOv11 COMPARED WITH CONVENTIONAL INSPECTION

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Abstract

Conventional rooftop photovoltaic (PV) inspection is still commonly performed through direct visual assessment by technicians. However, this approach is time-consuming, exposes workers to higher safety risks, and often produces less consistent documentation. This study develops an automatic inspection approach based on RGB aerial imagery and deep learning and compares its effectiveness with conventional inspection. A case study was conducted on a 60 kWp rooftop PV system at the Smart and Green Learning Center (SGLC), Faculty of Engineering, Universitas Gadjah Mada. A total of 150 RGB images were acquired using a drone, annotated, and used to train a YOLOv11 model through a Roboflow workflow. Technical evaluation was complemented by a 24-item Likert survey involving five technicians and by investment and operational cost analysis. The model achieved an mAP@50 of 98.3%, precision of 100%, and recall of 97.0%. Automatic inspection reduced inspection time from approximately 95 minutes to 18 minutes per session, corresponding to a time saving of about 81%. Technician perception also favored the automatic method, with an average score of 4.82 compared with 3.34 for the conventional approach, and the difference was statistically significant ($p = 0.000036$). Although the automatic method requires higher initial investment, it yields lower annual operational costs. These findings indicate that drone-based RGB imaging and YOLOv11 provide a feasible approach for modern rooftop PV maintenance, particularly for periodic inspection and multi-installation deployment.
Keywords: Rooftop PV; Automatic Inspection; Drone; RGB Imagery; YOLOv11; Deep Learning

Abstrak

Inspeksi panel surya atap konvensional (PV) masih sering dilakukan melalui penilaian visual langsung oleh teknisi. Namun, pendekatan ini memakan waktu, meningkatkan risiko keselamatan pekerja, dan sering menghasilkan dokumentasi yang kurang konsisten. Studi ini mengembangkan pendekatan inspeksi otomatis berbasis citra udara RGB dan deep learning, serta membandingkan efektivitasnya dengan inspeksi konvensional. Studi kasus dilakukan pada sistem PV atap berkapasitas 60 kWp di Smart and Green Learning Center (SGLC), Fakultas Teknik, Universitas Gadjah Mada. Sebanyak 150 gambar RGB diperoleh menggunakan drone, diberi anotasi, dan digunakan untuk melatih model YOLOv11 melalui alur kerja Roboflow. Evaluasi teknis dilengkapi dengan survei Likert 24 item yang melibatkan lima teknisi dan analisis biaya investasi dan operasional. Model mencapai mAP@50 sebesar 98,3%, presisi 100%, dan recall 97,0%. Inspeksi otomatis mengurangi waktu inspeksi dari sekitar 95 menit menjadi 18 menit per sesi, yang setara dengan penghematan waktu sekitar 81%. Persepsi teknisi juga lebih menguntungkan metode otomatis, dengan skor rata-rata 4,82 dibandingkan 3,34 untuk pendekatan konvensional, dan perbedaan ini secara statistik signifikan ($p = 0{,}000036$). Meskipun metode otomatis memerlukan investasi awal yang lebih tinggi, metode ini menghasilkan biaya operasional tahunan yang lebih rendah. Temuan ini menunjukkan bahwa

pemetaan RGB berbasis drone dan YOLOv11 menawarkan pendekatan yang layak untuk pemeliharaan panel surya atap modern, terutama untuk inspeksi berkala dan penerapan pada beberapa instalasi.
Kata kunci: Panel surya atap; Inspeksi otomatis; Drone; Pemetaan RGB; YOLOv11; Pembelajaran mendalam

1. Introduction

The rapid deployment of rooftop photovoltaic (PV) systems across residential, commercial, and institutional sectors has increased the need for inspection methods that are accurate, efficient, safe, and repeatable. In field practice, conventional inspection still relies heavily on direct visual examination by technicians. Although simple to implement, this approach is time-intensive, increases worker exposure to rooftop hazards, and limits the standardization of maintenance documentation.

Advances in unmanned aerial vehicles and computer vision have opened new opportunities to replace part of the manual inspection workflow with remote observation based on RGB aerial imagery. Previous studies have shown that high-resolution RGB images can be used to identify PV modules from aerial views, while deep learning models can automate object detection with high accuracy. The integration of drones, data annotation, and YOLO-based models is therefore attractive for building a relatively fast and operational inspection system.

Despite this progress, many previous studies have focused primarily on module detection or specific fault identification, while relatively few have directly compared automatic inspection with conventional inspection under realistic operational conditions. Accordingly, this study aims to develop an automatic rooftop PV inspection model based on RGB aerial imagery and YOLOv11 and to compare it with conventional inspection in terms of model performance, time efficiency, technician perception, cost, and scalability potential.

2. Research Method

This study employed an experimental-comparative quantitative approach. The case study was conducted at the 60 kWp rooftop PV installation of the Smart and Green Learning Center (SGLC), Faculty of Engineering, Universitas Gadjah Mada. A single site was selected to maintain consistency in visual conditions, panel geometry, roof background, and drone flight permission requirements.

The main dataset consisted of 150 aerial RGB images captured using a DJI Mavic 3 drone at an altitude of approximately 15-30 m under clear weather conditions. The images were manually annotated into two classes, namely normal_panel and shading, and then processed through the Roboflow platform. Data augmentation, including slight rotation, horizontal or vertical flipping, and brightness adjustment, was applied to increase data variability. The dataset was divided into training, validation, and testing subsets with an approximate proportion of 70%, 20%, and 10%, respectively.

Model training was performed using YOLOv11 with an image size of 640 x 640 pixels, 100 epochs, a batch size of 16, and a learning rate of 0.001. Performance was evaluated using mAP@50, precision, and recall. In addition, five technicians participated in a perception survey comparing the two inspection methods using 24 Likert-scale statements scored from 1 to 5. Differences in scores were analyzed using a paired t-test, while the economic evaluation covered both capital expenditure (CAPEX) and annual operational expenditure (OPEX).

Table 1. Summary of the main findings

Indicator	Conventional Method	Automatic Method
Inspection duration per session	±95 minutes	±18 minutes
Technician perception score	3.34	4.82

Initial investment (CAPEX)	IDR 24,000,000	IDR 39,000,000
Annual operating cost (OPEX)	IDR 102,400,000	IDR 71,800,000
Model performance	-	mAP@50 98.3%; P 100%; R 97.0%

3. Results and Discussion

3.1 Detection model performance

The developed YOLOv11 model showed very strong detection performance for identifying rooftop PV modules in RGB aerial images. The evaluation results yielded an mAP@50 of 98.3%, precision of 100%, and recall of 97.0%. The precision value indicates that the model produced virtually no false detections on the test data, while the recall value suggests that most panels present in the images were successfully identified. These results confirm that the combination of drone imagery, consistent annotation, and YOLOv11-based training is sufficiently reliable to support PV module inspection in the research setting.

Nevertheless, quantitative evaluation for the shading class cannot yet be generalized fully because of the limited number of anomaly samples during data acquisition. Most modules were in normal operating condition, so the main contribution of the model in this study lies in module detection and preliminary shading indication. This limitation is important to acknowledge so that the claims of the study remain proportional to the quality and composition of the available dataset.

3.2 Technical comparison between the two inspection methods

From the standpoint of operational efficiency, the automatic inspection method delivered a substantial time benefit. Inspection duration decreased from about 95 minutes under the conventional method to around 18 minutes per session under the automatic method, equivalent to a time saving of approximately 81%. This reduction is especially relevant for periodic inspection programs because inspection capacity per unit of time increases without requiring a proportional increase in personnel.

The survey of five technicians also showed a consistent preference for the automatic approach. The mean score for the conventional method was 3.34, whereas the automatic method obtained 4.82. A paired t-test resulted in $p = 0.000036$, indicating that the difference between the two methods was statistically significant. The strongest advantages perceived by technicians included time efficiency, work safety, documentation quality, ease of result analysis, and flexibility for inspecting larger areas. In this sense, the drone- and deep learning-based system should be viewed not as a replacement for technicians but as a supporting tool that enhances inspection quality and productivity.

Another practical strength of the automatic approach is the consistency of digital documentation. Aerial images can be stored, reviewed, and compared across inspection cycles, thereby supporting technical auditing and longitudinal monitoring of panel conditions. Such consistency is more difficult to achieve in conventional inspection, which depends more strongly on direct observation and field notes.

3.3 Cost analysis and scalability potential

The economic analysis revealed a clear trade-off between initial investment and operational efficiency. Conventional inspection required an estimated CAPEX of approximately IDR 24,000,000, whereas automatic inspection required about IDR 39,000,000. This difference was mainly driven by the procurement of a drone as the key inspection device. However, the annual OPEX of the automatic method was lower, at approximately IDR 71,800,000 per year, compared with IDR 102,400,000 per year for the conventional method.

From a medium-term utilization perspective, this cost structure suggests that the automatic method becomes more rational when the system is used repeatedly or deployed across more than one PV installation.

Reduced inspection duration, lower labor requirements, and reduced exposure to work hazards make the marginal cost per inspection increasingly competitive as the frequency of use rises. Therefore, the automatic method shows stronger scalability potential for institutional, multi-site, or high-frequency periodic inspection scenarios.

3.4 Research implications and limitations

Practically, the findings indicate that RGB aerial imagery combined with YOLOv11 can serve as an initial foundation for a more digitalized rooftop PV maintenance system. For institutions managing multiple PV installations, this approach can reduce the burden of manual inspection while improving the traceability of technical documentation.

The main limitation of the study lies in the dataset composition, which was dominated by normal panels. As a result, the model has not yet been widely tested for diverse fault types such as hotspots, cracks, delamination, or severe soiling. In addition, the study focused on a single site with relatively uniform roof characteristics. Broader generalization will therefore require dataset expansion, more diverse anomaly classes, and validation across multiple locations with more complex visual environments.

4. Conclusion

This study demonstrates that a rooftop PV inspection system based on RGB aerial imagery and YOLOv11 can detect PV modules with high performance and provide operational advantages over conventional inspection. The automatic method was shown to accelerate inspection, improve documentation quality, receive more favorable technician assessments, and reduce annual operating costs, although it requires a higher initial investment. In practical field applications, this approach is therefore promising as a modern maintenance solution for rooftop PV systems, particularly for periodic inspection and the simultaneous management of multiple installations.

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