Abstract

The protection and reliability of photovoltaic (PV) systems are critically important, yet they present significant challenges. One of the main issues in this area is the difficulty of traditional methods in accurately detecting faults caused by bird droppings on PV modules. To address this problem, AI-based techniques—particularly deep learning architectures that utilize visual data—have become increasingly popular. However, these methods also have limitations, especially the requirement for large datasets to train deep learning models effectively. We employed the stable diffusion technique to generate and augment image data to overcome this challenge. This method enables us to generate varied, high-quality datasets, which improves model performance. Furthermore, we utilized data augmentation techniques to boost the size of our dataset and enhance the model's resilience to variations. Another significant challenge is the inadequate accuracy of deep learning models in detecting faults caused by bird droppings. To tackle this, we trained and evaluated modern object detection and classification architectures, including YOLO, DenseNet, VGG, and ResNet, ultimately selecting the best-performing model. Finally, to optimize performance, we used Keras Tuner to fine-tune the hyperparameters of the top-performing model, achieving a precision of 96.3% during the testing process.

Research Contributions

• We present the application of the stable diffusion model to create a high-resolution synthetic dataset depicting bird droppings on solar panels. This method assists in tackling the lack of annotated data while enabling both controlled and diverse fault simulations.

• By integrating these synthetically produced images into the training framework, we enhance the model's robustness and accuracy, especially in recognizing minor and infrequent faults like bird droppings.

• We perform a comprehensive comparative evaluation of several cutting-edge models, including YOLOv8s, YOLOv9s, YOLOv10s, DenseNet201, VGG16, and ResNet101. This yields important insights into their relative effectiveness in bird droppings detection.

• Among the models assessed, DenseNet201 exhibited the best performance. We further improved its efficiency through hyperparameter tuning with Keras Tuner, optimizing the learning rate and the choice of optimizer to enhance classification accuracy.

Proposed Method

The dataset was initially generated using the stable diffusion model through both image-to-image and text-to-image synthesis, as shown in Fig. 1. This approach enabled the creation of high-quality, customized images suitable for training deep learning models to detect bird droppings on photovoltaic panels. Data augmentation techniques were applied to the synthetic images to enhance model performance further and reduce the risk of overfitting. After augmentation, the data went through labeling and preprocessing steps, which included resizing and normalization, to ensure compatibility with the selected neural network architectures. Various deep learning models were then trained using the prepared dataset. Architectures such as VGG16, ResNet101, and DenseNet201 were employed for image classification, while object detection utilized YOLOv8s, YOLOv9s, and YOLOv10s. After training, the model with the highest accuracy was determined to be the best-performing architecture. To improve the model's performance even further, hyperparameter tuning was conducted using Keras Tuner, focusing on optimizing the learning rate and the type of optimizer. In the final phase, the optimized model was evaluated using a separate test set to validate its reliability and generalization capability.

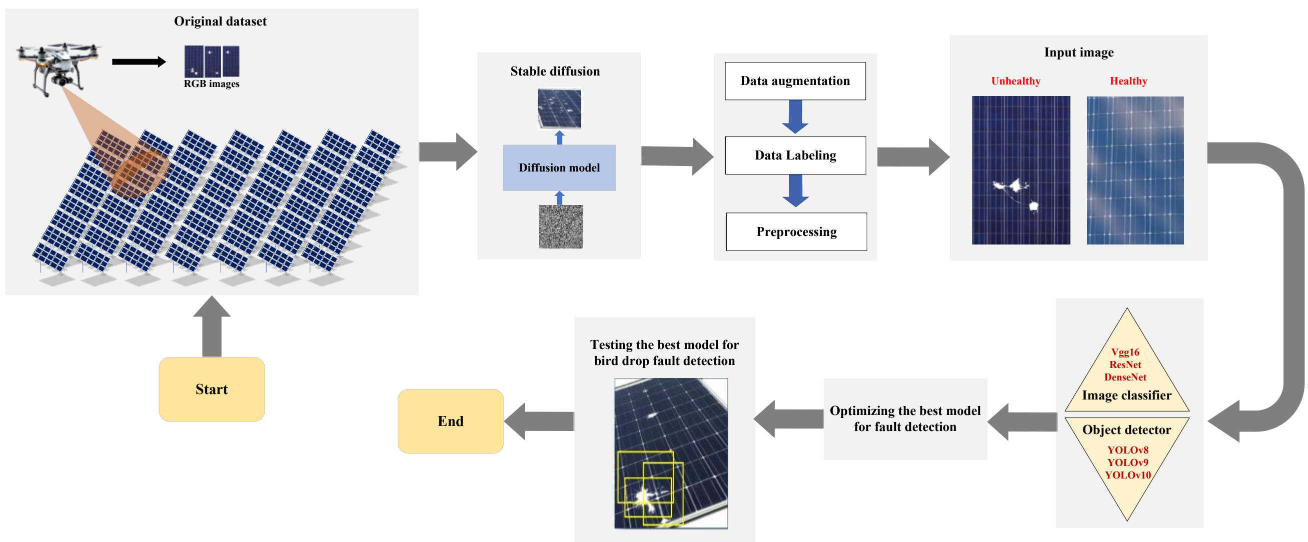

Fig. 1. Block diagram of the proposed intelligent framework for diagnosing bird drop faults in PV arrays.

Result

Finally, the optimized DenseNet201 model selected as the best model and must be exposed to some unseen or testing data for final validation and evaluation. The optimized DenseNet201 model has shown acceptable results in the testing process and has become a reliable model in the classification process with an accuracy of 95.23%.