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Comparison of ML classifiers in automatic diagnostics of PV panels using deep image features

Porównanie klasyfikatorów ML w automatycznej diagnostyce paneli PV z wykorzystaniem głębokich cech obrazowych

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Abstract: This paper presents a hybrid approach for diagnosing photovoltaic panels using deep image features extracted from the ResNet18 network and classical machine learning classifiers such as SVM and Random Forest. A comparative analysis of various classifiers was conducted, showing that the CNN combined with SVM provided the highest classification accuracy (95.5%). The solution is computationally efficient and effective for detecting defects commonly encountered in PV installations.

Keywords: photovoltaics, image diagnostics, machine learning, neural networks, defect classification

Streszczenie: Artykuł przedstawia hybrydową metodę diagnostyki paneli fotowoltaicznych, wykorzystującą głębokie cechy obrazowe pozyskane z sieci ResNet18 oraz klasyfikatory uczenia maszynowego takie jak SVM czy Random Forest. Przeprowadzono analizę skuteczności różnych klasyfikatorów, wskazując, że połączenie CNN i SVM osiągnęło najwyższą dokładność klasyfikacji (95,5%). Rozwiązanie jest wydajne obliczeniowo oraz skuteczne w wykrywaniu defektów typowych dla instalacji PV.

Słowa kluczowe: fotowoltaika, diagnostyka obrazowa, uczenie maszynowe, sieci neuronowe, klasyfikacja defektów

Introduction

The dynamic development of renewable energy sources (RES), and in particular photovoltaics (PV), is due to the growing demand for energy and the need to reduce greenhouse gas emissions. To maintain the high efficiency and reliability of PV systems, regular monitoring is necessary. Even minor defects or contamination can lead to production losses and module damage. Traditional inspection methods, based on manual inspections, are time-consuming, expensive and difficult to scale, especially in large installations. Automation using computer vision (CV) significantly improves this process. Initially, classic CV techniques were used for PV defect detection [1], but convolutional neural networks (CNNs) have revolutionized defect detection thanks to the ability to automatically learn features [2], [3].

In recent years, there has been a dynamic development of machine learning (ML) and deep learning (DL) applications in image analysis for the needs of the power industry. Classic algorithms such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN) or Random Forest are commonly used in the tasks of detecting defects in thermal or RGB images, due to their simplicity and interpretability [4]. In particular, SVM has been used in the detection of damage to insulators and conductors on transmission lines [5]. In turn, more advanced deep learning approaches, such as CNNs, dominate in tasks requiring high accuracy and analysis of complex image structures, e.g. in automatic inspection of photovoltaic farms [6], detection of hot spots on transformers [7] or assessment of the condition of wind turbines [8]. Models such as ResNet, EfficientNet or MobileNet offer the possibility of extracting rich visual features, which significantly improves the detection efficiency [9].

The choice of the appropriate model depends on the available computational resources, data complexity and requirements for the interpretability of results – therefore, hybrid approaches are also often used, combining CNNs with classic ML classifiers [10].

The paper presents a hybrid architecture in which the features extracted from the ResNet18 [11] network are classified using algorithms such as SVM or Random Forest. This solution reduces the computational requirements, facilitates implementation on edge devices and provides modelling flexibility. A realistic data partitioning is used, covering typical defect categories such as contamination, electrical damage or bird droppings. Experiments confirm the effectiveness of the approach: the best results were obtained for the hybrid CNN + SVM model, reaching an accuracy of 95.5%, which outperforms both classical models and the standard CNN network.

Dataset

A specialized set of PV panel images was used in this study, containing both properly functioning modules and various types of damage. The data was manually classified into one of six classes:

1. Bird-drop (contamination with bird droppings),
2. Clean (panels clean, in perfect condition),
3. Dusty (contamination with dust),
4. Electrical-damage (including hot spots, delamination),
5. Physical-damage (mechanical damage such as glass cracks),
6. Snow-covered (panels partially or completely covered with snow).

Example images from each class are presented in figure 1.

Fig. 1. Sample images from each class

The original dataset consists of 1,574 RGB images of photovoltaic panels, distributed across six defect categories. The dataset was divided into training (929 images), validation (550 images), and test (95 images) sets. While the validation set is larger than usual, this decision was motivated by the need to closely monitor model generalization during hyperparameter tuning of multiple classifiers. The test set, although smaller, was kept independent and representative for unbiased evaluation, with an equal number of samples per class (n=13-18). A detailed summary of the data is presented in table 1.

Table 1. Summary of the PV dataset by class

Class	Training	Validation	Test	Sum
Bird-drop	177	104	17	298
Clean	169	102	18	289
Dusty	162	97	16	275
Electrical-damage	135	77	13	225
Physical-damage	132	78	15	225
Snow-covered	154	92	16	262
Sum	929	550	95	1574

For models trained on raw image data (CNN, CNN+SVM), preprocessing included resizing to 224×224 pixels, normalization to the [0,1] range, and data augmentation applied exclusively to the training set. The following transformations were used: random rotation (±15°), horizontal flipping, brightness and contrast adjustments (±20%), which were applied on-the-fly during training and did not increase the dataset size. These transformations enhanced the model's robustness to variations in illumination, orientation, and visual noise – conditions commonly encountered in real-world PV imagery. As emphasized by [12] and [13], the quality and diversity of image data are crucial for effective PV defect detection. Similarly, [2] analyses the impact of the type of damage on classification efficiency, and [11] indicates the need for models to be robust to noise and natural interference (e.g. dust, snow).

The dataset was carefully curated from publicly available sources [14] , ensuring visual diversity across damage types. Manual inspection and class balancing were performed to ensure each defect class is well represented. This structured preprocessing pipeline aimed to maximize the utility of a relatively small dataset for deep learning tasks while preserving the realism of PV panel conditions. The data was used in accordance with the licenses and for research purposes only.

Methodology

All analyzed models were based on a common pipeline, including feature extraction, classification and effectiveness verification. Both ResNet-18 and MobileNetV3, as deep CNNs, were used as feature extractors – the former for its simplicity and popularity, the latter for efficiency on edge devices. Images were mapped to feature vectors and subjected to further analysis. The following approaches were compared, selected with a balance between performance and computational efficiency in mind:

- SVM and Random Forest – trained on colour histograms (RGB); included for their simplicity, robustness and interpretability. Hyperparameter tuning was applied.

- XGBoost – trained on ResNet18-extracted features (with PCA); chosen as a strong tabular baseline.
- CNN – MobileNetV3 with transfer learning; selected for its efficiency and high performance on mobile and edge devices.
- A hybrid CNN + SVM model – using ResNet18 for feature extraction and SVM for classification; this setup decouples learning and classification, combining deep representation with lightweight inference.

In all cases, a consistent evaluation procedure was used: confusion matrix analysis, standard classification metrics (accuracy, precision, recall, F1-score) and learning curves. Augmentation (rotation, brightness and contrast changes) was applied only to the training set to increase its diversity. The validation set was used to monitor the learning process and assess the generalization ability of the models.

Finally, the best variant – a hybrid CNN + SVM model – was tested on a separate test set, which allowed for independent verification of its effectiveness in realistic conditions.

Results

A comparison of classical ML models (SVM, Random Forest, GridSearch RF, XGBoost) and deep learning models (Keras CNN, hybrid CNN + SVM) was conducted using consistent metrics: accuracy, precision, recall and F1-score (table 2). The best results were achieved by deep models – Keras CNN (95.27%) and CNN + SVM (95.45%), which significantly outperformed classical approaches, especially XGBoost, which turned out to be the least effective.

Table 2: Model comparison results

Model	Accuracy	Precision (macro)	Recall (macro)	F1-score (macro)
SVM	0,9200	0,9225	0,9200	0,9210
Random Forest	0,9418	0,9463	0,9423	0,9438
RF (GridSearch)	0,9491	0,9520	0,9490	0,9502
XGBoost	0,7327	0,7516	0,7271	0,7281
Keras CNN	0,9527	0,9555	0,9541	0,9546
CNN + SVM	0,9545	0,9578	0,9536	0,9553

Selecting the best model

The CNN + SVM model, combining feature extraction from ResNet18 with SVM classification, achieved the highest F1-score (0.9553) and a very good balance between classes. To assess the proposed hybrid architecture's generalisation capability, the trained CNN + SVM model was evaluated on an unseen test dataset containing 95 images equally distributed among the six defect classes. The obtained confusion matrix, presented in figure 2., confirms the high effectiveness: all classes were recognized with high accuracy, and the number of classification errors was minimal – no class was significantly confused. The classification results are summarized in figure 2 and table 3.

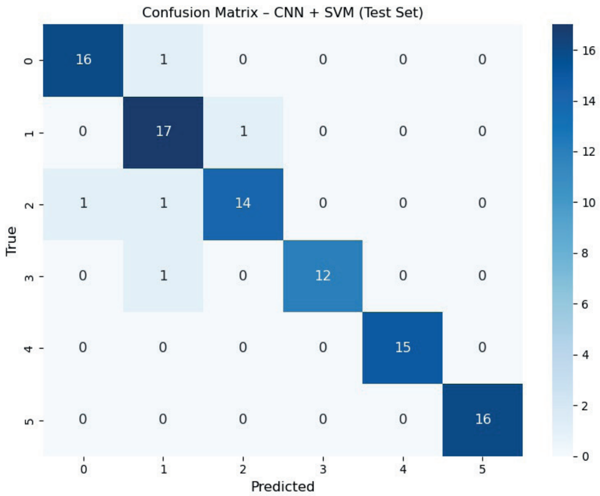

Fig. 2. Confusion matrix for the CNN + SVM hybrid model on the test set.

The model showed full effectiveness in detecting the Physical-damage and Snow-covered classes, achieving ideal precision, recall and F1-score values for them (table 3). It coped equally well with the Electrical-damage class (F1 = 0.96), despite a single classification error. Slightly lower effectiveness was noted for the Bird-drop, Clean and Dusty classes, where single errors occurred – according to the error matrix, they mainly concerned neighbouring classes.

Table 3: Model comparison results

Class	Precision	Recall	F1-score
Bird-drop	0,89	0,94	0,91
Clean	0,89	0,89	0,89
Dusty	0,88	0,88	0,88
Electrical-damage	1,00	0,92	0,96
Physical-damage	1,00	1,00	1,00
Snow-covered	1,00	1,00	1,00
Accuracy			0,94
Macro avg	0,94	0,94	0,94
Weighted avg	0,94	0,94	0,94

The CNN + SVM model demonstrated not only high accuracy but also stable performance under test conditions, making it a promising candidate for applications in real-world PV inspection systems, especially on resource-constrained devices.

Figure 3 illustrates six representative test samples classified by the CNN + SVM model. For each image, the true class (T) and the predicted class (P) are shown. Correct classifications are indicated in green, while misclassifications are marked in red.

The majority of examples were correctly classified, confirming the model's ability to generalize to previously unseen data. Particularly, Physical-damage, Dusty, and Electrical-damage panels were accurately identified, despite variations in illumination, camera angle, and background context. This suggests that the CNN-based feature extractor successfully captures relevant structural and textural cues.

A single misclassification is observed, where an image labelled as Bird-drop was predicted as Clean. Visual inspection reveals that the droppings are relatively small and sparse, potentially resembling typical surface dirt or shadows. This supports the earlier observation that visually subtle or low-contrast defects remain a challenge, especially when their appearance overlaps with benign surface features.

Fig. 3. Example predictions of the CNN + SVM model on the test set.

The qualitative results align well with the overall quantitative performance of the model and highlight both its robustness and limitations in the fine-grained visual classification of PV panel conditions.

Discussion

The results demonstrate that the hybrid CNN + SVM approach provides an effective trade-off between model complexity and classification performance. By decoupling feature extraction and classification, the architecture maintains high accuracy while significantly reducing computational overhead. This makes it particularly well-suited for deployment in resource-constrained environments, such as edge devices used in industrial or mobile photovoltaic (PV) inspection systems.

Furthermore, the modularity of the hybrid pipeline allows for flexible experimentation with different classifiers, potentially improving interpretability and facilitating model tuning without retraining the convolutional backbone.

In contrast, the XGBoost model, while powerful in tabular data scenarios, performed poorly on image-based features. This suggests a limited capacity to capture complex spatial patterns in visual data and highlights its unsuitability for tasks involving high-dimensional image representations.

Despite the overall high accuracy achieved by the proposed models, certain classes posed greater challenges for the classifiers. Specifically, Dusty and Clean panels were more frequently confused, which is consistent with their subtle visual differences. These classes exhibit low-contrast patterns and lack distinct structural features, making them harder to differentiate using both traditional and deep learning methods. Misclassifications in these categories suggest that the feature representations may benefit from more refined cues or additional domain-specific preprocessing (e.g., contrast enhancement or saliency mapping).

One important limitation of this study is the relatively small size of the dataset, especially for fine-grained defect classes. Although data augmentation helps, limited intra-class variability may reduce generalization. Moreover, some images include background elements (e.g., vegetation, sky), which could introduce spurious correlations. While the focus remained on panel defects, we cannot fully exclude their influence. Future work will address this by expanding the dataset and using cropped or segmented panel images.

In comparing model architectures, several trade-offs become evident:

- SVM is computationally efficient and performs well when used in conjunction with CNN-based features, but its expressiveness is limited when trained directly on raw image data or shallow representations.
- XGBoost, known for its strong performance in tabular learning problems, did not adapt well to image-based tasks and suffered from both low accuracy and longer training times.
- The CNN + SVM hybrid model combines the advantages of deep representation learning with the simplicity and interpretability of classical classifiers, offering a strong balance between performance and deployability.

Future directions for this research include:

- Model enhancement: Fine-tuning deeper architectures such as ResNet or EfficientNet on the specific PV domain to boost feature quality and robustness.
- Real-time deployment: Developing and testing a lightweight version of the CNN + SVM framework on edge hardware (e.g., NVIDIA Jetson, Raspberry Pi) to evaluate latency, energy efficiency, and scalability in field conditions.

These improvements aim to push the proposed system from an accurate research prototype toward a practical, real-world solution for automated PV inspection.

The CNN + SVM hybrid architecture not only matches the performance of deep end-to-end models but slightly outperforms them, offering a scalable and computationally efficient solution for real-world PV inspection systems.

Explainability and Model Interpretation

As deep learning models become more widely used in critical tasks–such as diagnostic imaging, security systems, and intelligent infrastructure analysis–the need for them to be understandable and interpretable also grows. High-performing models, such as CNNs, often function as “black boxes,” preventing users from seeing into the decision-making process. This lack of transparency can lead to a loss of trust, difficulty in diagnosing errors, and limited ability to deploy AI systems in regulated environments.

Explainability allows us to understand which input features had the greatest impact on the model’s decision. In the case of image classification, methods such as Local Interpretable Model-agnostic Explanations (LIME) provide a visual representation of the regions of the image that were key to assigning a particular class.

Figure 4 shows the LIME result for an image containing a photovoltaic panel classified by the model as Bird-drop. In the presented approach, feature extraction was performed by a CNN network, and the final classification was performed by an SVM classifier. Since methods such as Grad-CAM are not directly accessible to non-neural classifiers, LIME was used as a model-agnostic approach.

Image interpretation shows that yellow contours mark segments with the highest positive impact on the classification of the Bird-drop class. Importantly, the marked regions correspond to visible spots and streaks located mainly in the lower and middle parts of the panel, which corresponds to typical organic dirt patterns. The model ignored the background (clear sky) and the panel frames, focusing on real surface defects.

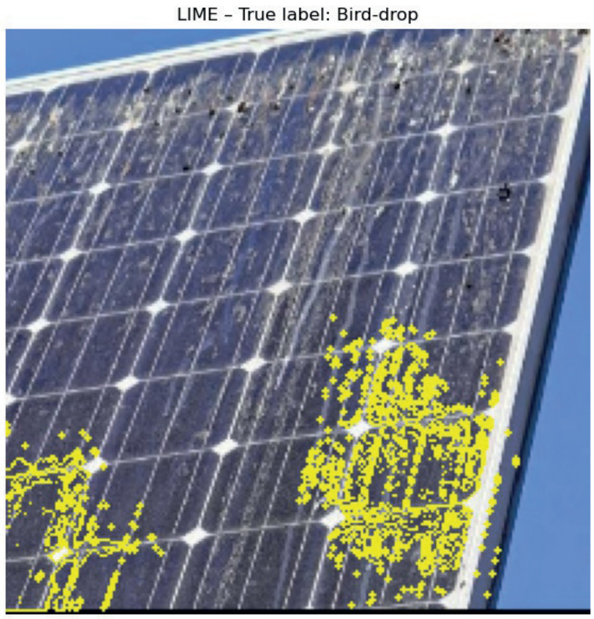

Fig. 4. The LIME result for an image containing a photovoltaic panel

This result confirms that the model not only learns differences between classes at a statistical level but also localizes important areas of the image in a way that is consistent with human diagnostic intuition. Thus, LIME interpretation is an important tool in the process of validation of hybrid models (CNN + ML classifier), allowing for a better understanding of the classification process and its justification.

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