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Transfer Learning-Based Fault Detection in Solar Panels Using Pretrained DenseNet121 DenseNet169 and DenseNet201Architectures

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Physical and electrical residue, dust, and other foreign contaminants accumulated on the surfaces of solar panels negatively impact the efficiency of solar modules and the amount of energy directly produced. At the same time, solar energy is a natural resource that is becoming increasingly important globally for sustainable energy production. Therefore, early and accurate detection of faults that may occur in solar panels is crucial for the continuity of energy production. Furthermore, timely monitoring and cleaning of solar panel surfaces with the right techniques is also ciritical for increasing the efficiency of these modules. Traditional observational or sensor-based methods for monitoring, cleaning, troubleshooting, and maintaining solar panels exhibit limited performance due to their high cost and vulnerability to human error. Thus, this study proposed an innovative transfer learning-based autonomous deep learning (DL) approach to detect faults from solar panel images. The proposed system utilized a publicly available solar system image dataset consisting of six classes. After completing the data cleaning and preprocessing steps, feature extraction was performed using three different pre-trained DenseNet121, DenseNet169, and DenseNet201 transfer learning architectures. Six different artificial intelligence (AI) based classification algorithms were executed to perform predictions on the resulting feature maps. The performance of the proposed innovative DL-based system was evaluated using quality metrics such as accuracy, precision, recall, AUC, and F_1-score. The experimental results demonstrate that the highest accuracy rate of 88.14% was achieved with the DenseNet201+Logistic Regression (LR) hybrid model. Other results obtained in this proposed study were explained in detail and compared using tables and graphs. The findings demonstrate that AI-assisted DL and transfer learning-based approaches offer effective, fast, and low-cost solutions for solar panel monitoring and maintenance processes.

Key words: *Transfer learning, Faulty detection, Solar panels, DenseNets,*

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1. Introduction

Considering the environmental and climatic disasters caused by the use of fossil fuels, renewable energy sources play a critical role in mitigating climate change, reducing carbon emissions and air/water pollution [1]. Among renewable energy sources, photovoltaic systems are rapidly gaining global popularity and achieving widespread capacity thanks to their ability to convert solar energy, the world's most abundant and inexhaustible energy source, into electricity. Installed photovoltaic capacity has increased by approximately 28% annually on average over the past decade and is projected to reach competitiveness among energy production sources in the future [2, 3]. This widespread adoption also contributes to increased awareness of ecological sustainability. The crucial role of photovoltaic systems in meeting global energy demand necessitates their long-term, error-free, cost-effective, and reliable operation.

Solar panel modules are designed to last 25 years or more under normal conditions [4-6]. However, due to the outdoor operation of solar power plants, external factors such as mechanical stress, moisture, dust, bird droppings, snow, ice, physical or electronic damage, high temperatures, and environmental factors cause the module's protective materials to deteriorate over time. This deterioration causes the module's performance to deteriorate even before the warranty period expires. Failures can occur at any stage of the solar panel module's lifespan (early, mid-stage, or wear-and-tear).

These faults can cause significant interruptions in energy production and, in some severe cases, even dramatic drops in power output of up to 50%. Common types of faults encountered in solar panel modules include microcracks, hot spots, diode faults, potential-induced degradation, soiling, shadowing, electrical connection faults, and cell cracking [7-9]. Therefore, fault detection and monitoring activities are vital to ensure continuous power production in solar panel plants, prevent operational declines, reduce operating and maintenance costs, and ensure system longevity.

Traditional fault detection and maintenance methods typically rely on manual visual inspection. However, manually examining high-resolution images requires extensive human labor, expertise, and time. In large-scale solar power plants with millions of modules or in hard-to-reach locations, manual inspections are costly, subjective, and inefficient. Furthermore, simple image processing techniques may not reliably distinguish complex fault characteristics, such as noisy data or small inter-class differences, that are often found in solar panel images [10-12].

To overcome these challenges and automate maintenance processes, image processing-based automated systems have become a critical solution. In recent years, rapid developments in the field of computer vision and AI have provided automatic, fast and accurate solutions in the field of fault detection in solar panels. Traditional ML techniques such as Support Vector Machines (SVM), Random Forest (RF), k-nearest neighbor (kNN), multilayer perceptron (MLP), XGBoost, and LR may be insufficient on complex left-hand panel image datasets. DL and Convolutional Neural Networks (CNN) methods, on the other hand, have become the most powerful tools for fault detection and classification thanks to their ability to automatically learn hierarchical feature representations from large and complex image datasets. CNN-based models have outperformed traditional ML methods in detecting and classifying solar panel faults. All of these studies constitute a major step in making solar energy a more reliable and cost-effective energy source.

In this study, a publicly available dataset organized according to defects in solar panel images was used. Feature extraction was achieved by applying pretrained models from the CNN-based DenseNet family to the dataset. Transfer learning approaches, namely DenseNet121, DenseNet169, and DenseNet201, were used for feature extraction. Six different ML-based AI algorithms were run for defect detection using the resulting feature maps. Performance evaluation metrics such as accuracy precision, recall F_1-score, and Area Under Curve (AUC) were calculated to measure the performance of the proposed system for solar panel defect detection. Based on the findings obtained with this hybrid system, it was determined that it is an effective method for detecting defects in solar panels. The ultimate goal of this proposed automated system is to minimize the need for human intervention and maximize the long-term efficiency and reliability of solar panel plants by detecting faults early and accurately.

The remainder of this solar panel fault detection study is organized as follows: Section 2 presents a literature review of the study. Section 3 provides detailed information about the dataset and methods used. Section 4 presents the experimental results in tabular form, followed by a comparative analysis of the results. The conclusion summarizes the findings of the study in detail.

2. Literature Review

There are many studies in the literature developed using AI-supported ML, DL, and CNN approaches to monitor fault maintenance and repair processes in solar panels.

Yousif et al. present an end-to-end hybrid DL model combining Histogram of Oriented Gradient (HoG) and CNN to detect defects in solar panel images. VGG-16 was used as the base architecture, and HoG features were extracted via the HoG layer and concatenated with the outputs of VGG-16. Among the key performance metrics obtained, the model's Accuracy is 0.9055, and the macro-average F-measure is 0.8841. This hybrid approach combines both automatic (VGG-16) and HoG feature extraction, avoids overfitting in training, and demonstrates higher classification performance than six current methods, including those using the same base CNN model [12].

Han et al. propose a DL approach to detect faults in solar panels. The YOLOv3-tiny version was implemented in their study. Compared to the standard version, the improved YOLOv3-tiny model achieved high performance metrics such as 96.45% accuracy, 92.00% F_1-score, 97.00% recall, and 88.00% precision. This improved model aimed to address the challenges of real-time detection and processing speed [5].

Abdelsattar et al. comprehensively evaluated the effectiveness of 24 different CNN architectures (ResNet, DenseNet, VGG, Inception, MobileNet, Xception, etc.) for automatic defect detection in solar cell images. The study focused on a binary classification task on a balanced dataset of 3,102 images (1,570 defective, 1,532 perfect). MobileNetV2 showed the best performance with 99.95% accuracy and 99.85% F_1-score. MobileNetV2's excellent accuracy, minimal loss, and lightweight architecture make it the most efficient model for resource-constrained real-time applications [1].

Duranay's study investigates the potential of DL for detecting panel defects using solar module images. The publicly available Infrared Solar Modules dataset is used, consisting of 20,000 infrared images (obtained by UAV systems) and 12 different defect classes (Hotspot, Crack, Shadowing, Contamination, etc.). The implemented methodology involves a hybrid approach combining deep feature extraction using Efficientb0 as the base model, feature selection with NCA, and finally, an SVM classifier. The proposed method achieved an average accuracy of 93.93%, an average F_1-Score of 89.82%, a precision of 91.50%, and a sensitivity of 88.28% for the 12 classes. These results demonstrate that the proposed hybrid method is successful in accurately classifying solar panel defects based on infrared images [3].

Pierdicca et al. present a DL-based inspection system for detecting anomalies in large-scale solar panel power plants. The Mask R-CNN architecture, capable of simultaneous object detection and instance segmentation, was used as the baseline method. They also compared other semantic segmentation networks such as U-Net, FPN, and LinkNet. Jaccard and Dice indices were used as evaluation metrics. The Dice index for U-Net showed high values around 0.841. This Mask R-CNN-based approach is suitable for automatic inspection tasks by pinpointing the exact location of defective cells using thermal images [9].

These studies clearly demonstrate how DL and other AI-based methods have become important techniques for detecting and classifying faults in solar panels. These methods, across a wide range of applications, aim to improve the reliability and efficiency of solar panel systems. Additionally, the performance of models belonging to DenseNet architectures is analyzed for this problem.

3. Materials and Methods

In this section 3, information about the solar panel dataset and methods applied in the study is presented.

3.1. Materials

The study utilized an open-source solar panel dataset obtained from the Kaggle platform. This dataset is specifically designed for the visual classification and analysis of solar panel. It consists of six classes: bird-drop (label->'0'), clean (label->'1'), dusty (label->'2'), electrical-damage (label->'3'), physical-damage (label->'4'), and snow-covered (label->'5'). The data distribution in each class is shown in Figure 3.1. In general, it was evaluated that the data set did not have a balanced distribution. These solar panel images were collected, labeled and created from different sources on the internet.

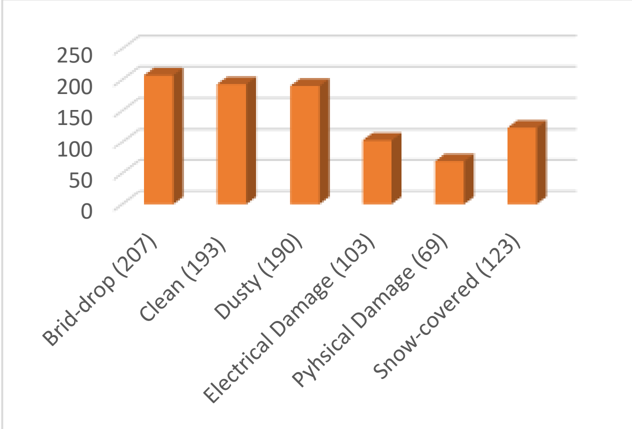


Figure 3.1. Class Distribution in Solar Panel Dataset

3.2. Methods

In this study, three different feature extraction architectures (DenseNet121, DenseNet169, and DenseNet201) and six different classification algorithms (MLP, XGBoost, LR, RF, kNN, and SVM) were employed for the fault detection in solar panel. The operational architecture of the proposed hybrid system for the fault detection in solar panel is presented in Figure 3.2.

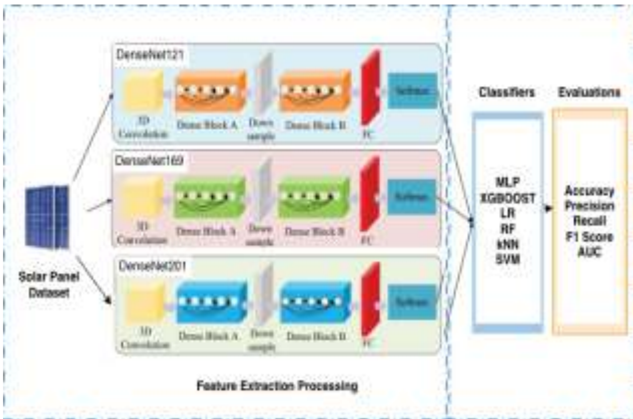


Figure 3.2. Pipeline of the Proposed Hybrid System

As summarized in Figure 3.2, the proposed hybrid system began by processing a dataset consisting of various images representing the causes of potential failures in solar panels. This image set was then used for feature extraction using advanced CNN-based DL models such as DenseNet121, DenseNet169, and DenseNet201 to derive meaningful features from the images. Another goal of this study was to observe the performance of the DenseNet family for this problem. Therefore, the selected models consisted solely of DenseNet models. The DenseNet architecture is also shown in Figure 3.2. In the next step, the extracted features were fed as input parameters to six different AL-based machine learning algorithms, including XGBoost, SVM, LR, RF, MLP, and kNN, for classification. Finally, the performance of the models comprising the proposed DenseNet family was evaluated using metrics such as accuracy, precision, recall, and F_1-score derived from the results of the confusion matrix and ROC curves. The results were comprehensively analyzed for classification accuracy. The results demonstrate the successful classification of solar panel degradation types, highlighting the potential of this approach to optimize maintenance, repair, and fault detection processes and promote environmental sustainability.

3.3. Performance Evaluation Metrics

The confusion matrix is a technique used to further analyze the performance of AI-based classification algorithms. Metrics such as accuracy, precision, recall, and F_1-score, calculated from the confusion matrix, are a statistical table used in the evaluation of classification models. Using these metrics together in research and applications provides a more comprehensive analysis of model performance. Each of these metrics allows for the analysis of different aspects of a model, its performance measurement, and improvement.

Accuracy, defined in Equation (1), reflects the model's overall success rate, while precision, defined in Equation (2), is important for minimizing the impact of false positive predictions. Recall, defined in Equation (3), assesses the model's ability to identify all positive examples. Finally, the F_1-score, defined in Equation (4), provides a balanced measure of model performance, especially in situations where both precision and recall are critical. Figure 3.3 summarizes the confusion matrix.

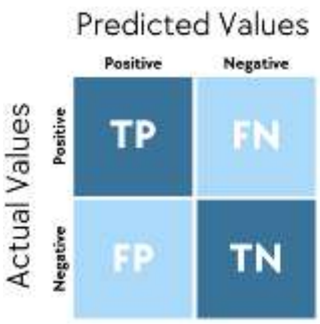


Figure 3.3 Confusion Matrix for Model Evaluation

$$Accuracy = \left(\frac{(TP + TN)}{(TP + FP + FN + TN)}\right) \quad (1)$$

$$Precision = \left(\frac{TP}{(TP + FP)}\right) \quad (2)$$

$$Recall = \left(\frac{TP}{(TP + FN)}\right) \quad (3)$$

$$F1 - score = 2\,x\left(\frac{Precision\ x\ Recall}{Precision + \ Recall}\right) \quad (4)$$

4. Experimental Results and Discussion

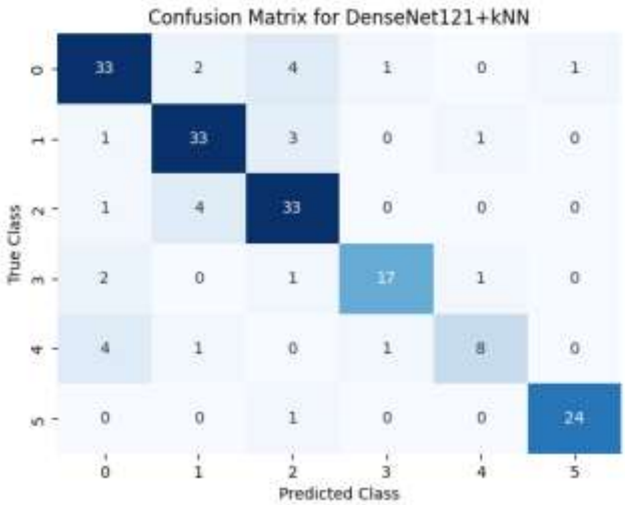
In this experimental study, feature maps of solar panel images were generated using CNN-based DenseNet121, DenseNet169, and DenseNet201 architectures. The resulting feature maps were classified using kNN, SVM, RF, MLP, XGBoost, and LR algorithms to propose a hybrid system for automatically detecting solar panel fault types. 80% of our dataset was used for training, while the remaining portion was reserved for testing. Model performance was evaluated using metrics such as accuracy, precision, recall, and F_1-score. Additionally, all experiments were conducted under equal conditions. All performance results for this experimental study are presented in Table 4.1.

Table 4.1. Experimental Findings *(Acc:Accuracy, Pre:Precision, Rec:Recal, F_1:F_1-Score, Alg: Algorithms)*

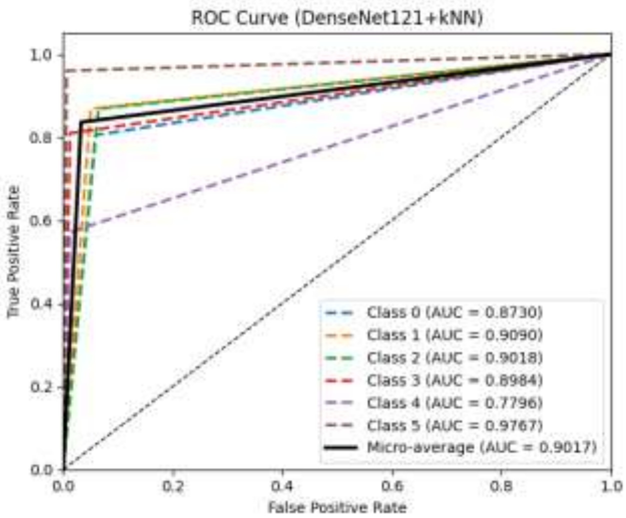
	Alg.	Performance Evaluation Metrics				
		Acc.	Pre.	Rec.	F_1	AUC
DenseNet121	**XGBoost**	0.8023	0.8046	0.7799	0.7862	0.8814
	SVM	0.8249	0.8626	0.7961	0.8090	0.8949
	LR	0.8136	0.8171	0.7929	0.7995	0.8881
	RF	0.8249	0.8519	0.8040	0.8131	0.8949
	MLP	0.8023	0.8088	0.7943	0.7995	0.8814
	kNN	0.8362	0.8451	0.8138	0.8254	0.9017
DenseNet169	**XGBoost**	0.8475	0.8530	0.8091	0.8217	0.9085
	SVM	0.8136	0.8518	0.7808	0.7904	0.8881
	LR	0.8701	0.8967	0.8541	0.8674	0.9220
	RF	0.8192	0.8640	0.7793	0.7950	0.8915
	MLP	0.8192	0.8638	0.8218	0.8311	0.8915
	kNN	0.7910	0.8253	0.7718	0.7924	0.8746
DenseNet201	**XGBoost**	0.8249	0.8521	0.7840	0.7898	0.8949
	SVM	0.8362	0.8760	0.8003	0.8108	0.9017
	LR	**0.8814**	**0.9072**	**0.8720**	**0.8843**	**0.9288**
	RF	0.7910	0.8358	0.7678	0.7813	0.8746
	MLP	0.8757	0.8906	0.8604	0.8711	0.9254
	kNN	0.8023	0.8484	0.7845	0.8018	0.8814

As can be seen in Table 4.1, the performance of each DenseNet model varies depending on the classifier used. In this study, the performance of DL-based CNN models such as DenseNet121, DenseNet169, and DenseNet201 was compared using different classifiers such as MLP, RF, LR, kNN, XGBoost, and SVM. Statistical analysis of the comparison was performed using metrics such as accuracy, precision, recall, and F_1-score. The results demonstrate that the choice of model and classifier plays a critical role in classification performance. A total of 18 different experimental results were obtained with 3 different CNN-based feature extraction models and 6 different classifiers. Performance evaluation metrics were calculated separately for 18 different experiments.

Figure 4.1 shows the confusion matrix and ROC curve for the kNN algorithm, which obtained the highest result for the first applied DenseNet121 model.



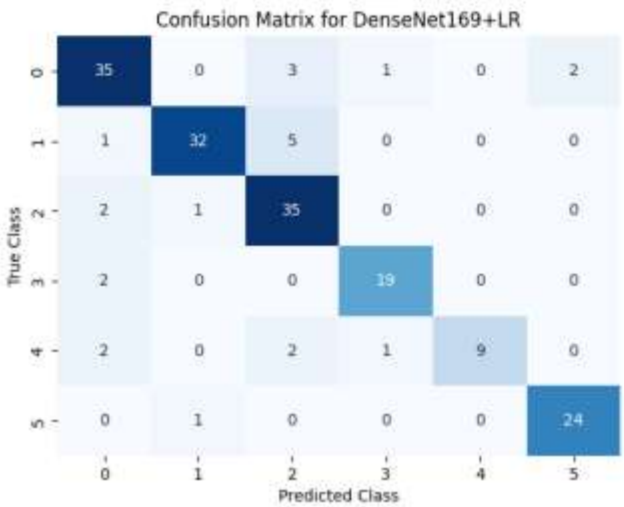
a) Confusion Matrix for DenseNet121+kNN Hybrid Model



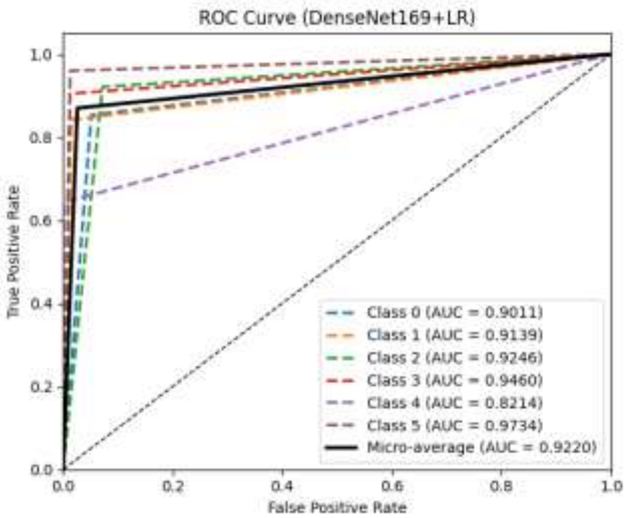
b) ROC Curve for DenseNet121+kNN Hybrid Model

Figure 4.1 a) Confusion Matrix and **b)** ROC Curve for the DenseNet121+kNN Hybrid Model

An analysis of the results obtained for DenseNet121 in Table 4.1 reveals that the kNN algorithm achieved the highest classification performance in the solar panel fault detection problem. The kNN model, with 83.62% accuracy and 82.54% F_1-score, surpassed other methods in both overall classification accuracy and Precision (0.8451) and AUC (0.9017) values. This demonstrates that the kNN algorithm can effectively distinguish similarities between classes in the feature space obtained through transfer learning. The SVM and RF algorithms also demonstrated similarly high performance, yielding fairly balanced results with approximately 82.5% accuracy and 89.5% AUC. While the SVM model was particularly superior in terms of Precision, the RF model was notable for its higher Recall value. In contrast, LR achieved average success, and linear decision boundaries were found to be limited in representing complex visual features. The XGBoost and MLP models, however, lag behind the other methods with relatively low accuracies (≈80%). Overall, the results reveal that the kNN model is the most balanced and stable classifier on this dataset, while the SVM and RF algorithms offer strong alternatives with high generalization capabilities.



a) Confusion Matrix for DenseNet169+LR Hybrid Model



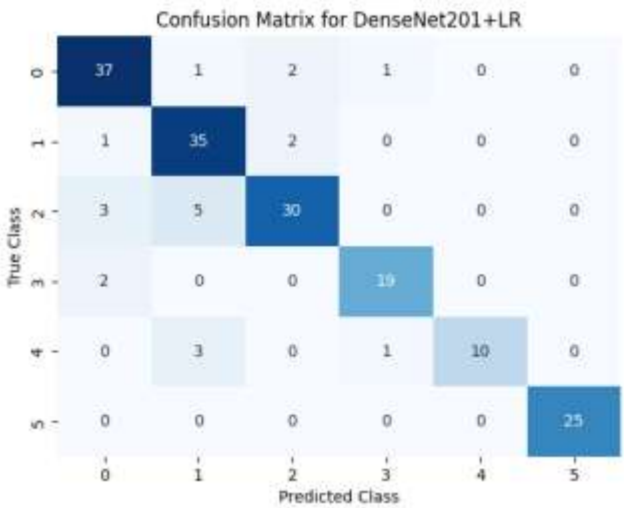
b) ROC Curve for DenseNet169+LR Hybrid Model

Figure 4.2 a) Confusion Matrix and **b)** ROC Curve for the DenseNet169+LR Hybrid Model

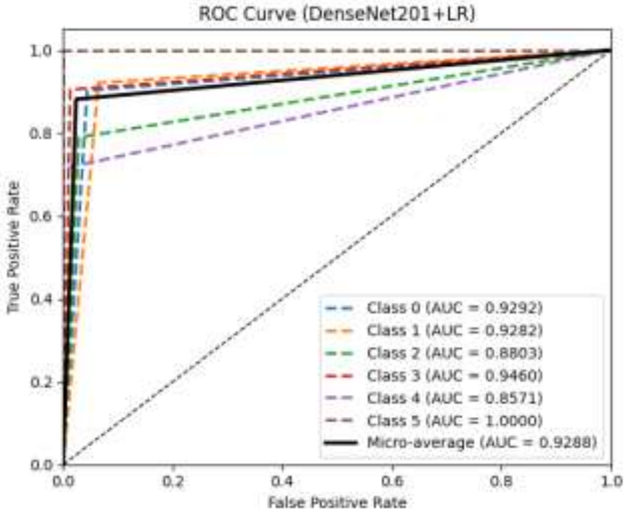
Figure 4.2 shows the confusion matrix and ROC curve for the LR algorithm, which obtained the highest result for the second applied DenseNet169 model.

An analysis of the results in Table 4.1 reveals that the LR classifier achieved the highest performance with features extracted from the DenseNet169 architecture. The LR model achieved the highest results across all metrics, with 87.0% accuracy, 89.6% precision, 85.4% sensitivity, 86.7% F_1-score,, and an AUC of %92.20. This demonstrates that the deep features extracted by DenseNet169 can be effectively discriminated using linear decision boundaries, and that the LR model's overall balancing ability is quite high. The LR model was followed by the XGBoost algorithm, which delivered a strong second-place performance with an accuracy of 0.8475 and an AUC of 0.9085. XGBoost's ability to model complex patterns was effective in detecting faulty panels. The SVM, RF, and MLP models demonstrated similar performance at approximately 81–82% accuracy. Among these models, MLP provided a more stable classification, yielding slightly higher results than the others, particularly in the Recall (0.8218) and F_1-score (0.8311) values. On the other hand, the kNN algorithm exhibited the lowest performance compared to the other models, with an accuracy of 0.7910 and an AUC of 0.8746, providing weaker discrimination between classes. Overall, the LR model performed best on features obtained from the DenseNet169 architecture, followed by XGBoost with a similar performance. These results demonstrate that the DenseNet169+LR hybrid model offers high accuracy and generalization capability in solar panel fault detection.

Figure 4.3 shows the confusion matrix and ROC curve for the LR algorithm, which obtained the highest result for the third applied DenseNet201 model.



a) Confusion Matrix for DenseNet201+LR Hybrid Model



b) ROC Curve DenseNet201+LR Hybrid Model

Figure 4.3 a) Confusion Matrix and **b)** ROC Curve for the DenseNet201+LR Hybrid Model

An analysis of the results in Table 4.1 reveals that the LR model achieved the highest performance when using features obtained from the DenseNet201 architecture. The LR model outperformed the other models in all metrics, with 88.1% accuracy, 90.7% precision, 87.2% sensitivity, 88.4% F_1-score, and 0.9288 AUC. These results demonstrate that the deep features extracted by the DenseNet201 architecture are highly discriminatory and that the LR model can effectively classify these features in a linear structure. The MLP model closely followed the LR model, demonstrating a very high overall performance with 87.6% accuracy and 0.9254 AUC. The MLP model's high F_1-score (0.8711) demonstrates its ability to balance the distinction between faulty and clean panel samples. The SVM algorithm stands out as a strong third alternative with 0.8362 accuracy and 0.9017 AUC. This demonstrates that SVM is particularly effective on deep features in terms of accuracy and discrimination. In contrast, the XGBoost and kNN algorithms achieved average results, with more limited performance, with accuracies of 0.8249 and 0.8023, respectively. RF achieved the lowest performance (0.7910 accuracy, 0.8746 AUC) and was weaker in class discrimination than the other models.

Overall, the DenseNet201+LR hybrid model achieved the highest accuracy, sensitivity, and AUC values among all tested models, providing the most stable and reliable results. This finding demonstrates that the transfer learning-extracted features of the DenseNet201 architecture are highly effective in solar panel fault detection when used in conjunction with linear classification approaches. In summary, the results show that transfer learning-based features generalize well in complex fault detection problems when combined with LR.

Results

This study once again demonstrates the increasing importance of renewable energy sources, driven by the ever-increasing demand for energy and the need for environmental sustainability. Among these sources, solar energy plays a critical role as a clean and inexhaustible source of energy derived directly from nature. However, for solar panels to operate efficiently over the long term, regular monitoring and maintenance are necessary. Faults that develop over time, such as contamination, surface cracks, hot spots, or cell damage, significantly reduce the panels' energy conversion efficiency and lead to economic losses. Traditional maintenance and monitoring methods typically rely on manual inspections or thermal camera analysis. These methods are costly, time-consuming, and prone to human error.

This study aims to automatically classify solar panel images using a transfer learning-based DL method. In this context, three different pre-trained architectures, namely DenseNet121, DenseNet169, and DenseNet201, were used for feature extraction. The discrimination power of these features was then tested with six different classification algorithms: SVM, RF, MLP, kNN, XGBoost, and LR. Experimental results showed that the model performance is directly related to the depth of the DenseNet architecture used. Among the three architectures, the DenseNet201+LR hybrid model achieved the highest overall performance. This hybrid model outperformed all other classifiers with 88.14% accuracy, 90.72% precision, 87.2% recall, 88.43% F_1-score, and 92.88% AUC. This result demonstrates that the DenseNet201 architecture can effectively capture complex visual features, and the LR model can classify these features in a linear structure with high generalization ability. In conclusion, the proposed method offers an effective, fast, and low-cost alternative solution for solar panel maintenance and monitoring processes.

Future work plans to enhance the visualization and interpretability of model decision-making processes by utilizing explainable AI techniques such as Grad-CAM and Vision Transformers (ViT). Furthermore, testing on a broader and more diverse solar panel dataset aims to further strengthen the method's generalization and industrial applicability.

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