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Solar photovoltaic panel cells defects classification using deep learning ensemble methods

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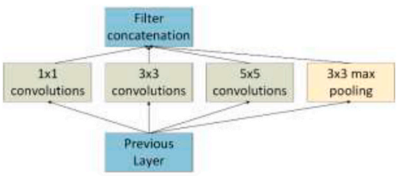
GRAPHICAL ABSTRACT



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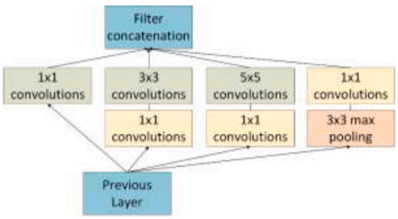

Bottleneck Version of Inception Module in GoogleNet Model

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A B S T R A C T

Solar photovoltaic (PV) systems are essential for sustainable energy production; however, their reliability may be undermined by unfavorable weather conditions, resulting in defects in the individual cells. Conventional manual inspection techniques are labor-intensive and susceptible to human error. This study utilizes drone-acquired electroluminescence (EL) images to identify and categorize solar cell defects through an ensemble-based deep learning framework. Eight advanced models—AlexNet, SENet, GoogleNet (Inception V1), Xception, Vision Transformer (ViT), Darknet53, ResNet18, and SqueezeNet—were fine-tuned on the 2624-sample ELPV benchmark dataset. Experimental findings indicate that the proposed voting and bagging ensembles attain accuracies of 68.36 % and 68.31 %, respectively, exceeding the previously documented accuracy of a hybrid model at 61.15 %. Significantly, the ResNet18 model achieves an accuracy of 73.02 % in a straightforward binary classification task, highlighting that individual models can surpass ensembles in particular circumstances. This study emphasizes the efficacy of integrating various deep learning architectures to augment defect detection precision in photovoltaic systems, enhancing operational reliability and enabling prompt maintenance under challenging environmental conditions.

1. Introduction

Solar photovoltaic (PV) systems are essential for sustainable energy production [1]; however, their efficiency and reliability are frequently undermined by environmental stressors that induce defects in solar cells [2,3]. The photovoltaic system consists of multiple solar panels organized in arrays on a structural framework. It additionally comprises other elements, including an inverter/charger controller, battery bank, transformer, and AC grid systems. This produces electricity that can be allocated to residential, commercial, or industrial locations. The solar panel consists of multiple modules configured in either parallel or series for optimal electricity generation. The modules can be installed on building rooftops or facades, independently supplying electricity to the structures [4]. Nonetheless, outdoor installations might expose the modules to severe weather conditions, potentially diminishing the performance of the solar panel modules and resulting in defects in the solar cells. The identification of these defective cells is generally conducted by experts [5], which can be unreliable due to inaccurate identification of defects caused by environmental conditions. Electroluminescence (EL) is utilized in the panel modules to rectify this inaccuracy, involving the application of current and the emission of infrared (IR) light. High-resolution infrared cameras capture these infrared rays, enhancing the visibility of defective cells. Variations in the cell's defects depend on the degree of exposure to weather conditions. Four distinct variations are identified in the Electroluminescence Photovoltaic (ELPV) benchmark datasets [6]: functional, moderate, mild, and severe. The classifications correspond to probabilities of 0.0, 0.33, 0.67, and 1.0, with 0.0 indicating functional solar panel cells, as illustrated in Fig. 1.

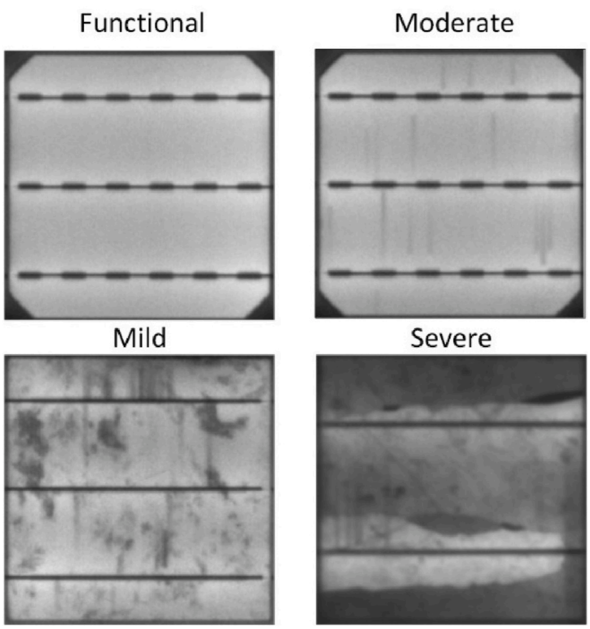

Fig. 1. Typical solar panel cell defect classification in the ELPV benchmark dataset.

Recent literature highlights the increasing significance of innovative strategies to enhance the performance and durability of photovoltaic (PV) systems in challenging environmental conditions. A primary emphasis is on employing cooling methods to alleviate the effects of temperature-related efficiency declines [7]. Hasan et al. in Ref. [8] investigated the function of micro-jet channels and booster mirror reflectors in sustaining electrical efficiency under diverse conditions, whereas Ogbulezie et al. in Ref. [9] measured the effect of temperature on photovoltaic efficiency, demonstrating a 0.05–0.16 % reduction for each 1 °C rise in cell temperature. Furthermore, research conducted by Bhakre et al. [10] has examined hydraulic cooling techniques, revealing substantial enhancements in cell performance through the regulation of optimal temperature conditions. Kassar et al. [11] demonstrated that particular phase change materials (PCMs), specifically PVT-RT35HC combined with graphene nanoparticle nanofluids, can efficiently manage temperatures and diminish thermal stresses in systems, thereby maintaining photovoltaic efficiency. These findings establish a robust basis for applying advanced defect detection methodologies, such as Electroluminescence (EL) imaging, to classify and evaluate photovoltaic cell performance with enhanced precision.

Recent studies have offered valuable insights into enhancing solar panel performance through innovative techniques, building on advancements in photovoltaic optimization. Sheikholeslami et al. [12] demonstrated that using intricate tube geometries, including three-lobed and five-lobed configurations, in conjunction with twisted tape inserts, significantly improved heat dissipation in CPV/T systems. This method diminished temperature gradients and enhanced electrical and thermal performance by 4.2 % and 5.1 %, respectively. Moreover, applying Al2O3-H2O nanofluids significantly enhanced heat transfer rates, emphasizing the ability of advanced cooling techniques to improve environmental factors that impair PV cell performance. Sheikholeslami and Khalili [13] integrated paraffin-based spectral filters with ZnO-water nanofluid mini-channels to enhance temperature uniformity and increase electrical efficiency by 38.63 %. Their research highlighted the necessity of tackling environmental issues like dust accumulation via self-cleaning SiO2 coatings, which enhanced transmissivity and preserved efficiency in practical conditions. These studies collectively emphasize the essential role of material and design innovations in alleviating the impacts of environmental factors on photovoltaic systems.

Despite significant progress in enhancing photovoltaic (PV) systems via innovative materials and design methodologies, the accurate identification and categorization of defects in photovoltaic cells remains insufficiently investigated. Contemporary techniques, including those employing the Electroluminescence (EL) method, are significantly dependent on human expertise, which is frequently variable and labor-intensive. The ELPV dataset serves as a benchmark for defect classification, while advanced machine learning techniques, specifically deep learning ensemble methods, present a promising solution to these challenges.

This research highlights the effectiveness of ensemble methods, such as voting and bagging, in enhancing defect classification accuracy relative to standalone deep learning models. This study systematically evaluates the performance of popular computer vision architectures—AlexNet, SENet, GoogleNet (Inception V1), Xception, Vision Transformer (ViT), Darknet53, ResNet18, and SqueezeNet—in classifying defects in photovoltaic panels. The ensemble models, which integrate the advantages of these individual models, are utilized on the ELPV dataset, exhibiting enhanced predictive accuracy. This study addresses a significant gap in photovoltaic system research by integrating sophisticated defect detection techniques with machine learning ensemble methods, thereby improving the reliability and efficiency of solar energy systems in adverse environmental conditions.

2. Literature review

Machine learning (ML) techniques are essential for enhancing the efficiency and performance of solar energy systems, as evidenced in Refs. [14,15]. Specifically, ML-based methodologies provide a data-centric framework for modeling intricate parameters and outputs, minimizing computational demands, and expediting design and analysis procedures [14]. concentrates on enhancing heat transfer devices through the application of Random Forest (RF), LASSO Regression (LaR), and Support Vector Regression (SVR) to elucidate complex system dynamics, whereas [15] prioritizes predictive modeling for phase change materials (PCMs) within photovoltaic (PV) systems, demonstrating the superior forecasting capabilities of an Auto-Regressive Integrated Moving Average (ARIMA) model for melting fraction and temperature.

Our research advances the application of machine learning to the automated identification of flaws in photovoltaic cells, a crucial aspect of the dependability and durability of solar energy systems. Utilizing insights from Refs. [14,15], which emphasize machine learning's ability for effective prediction and optimization in diverse solar applications, we implement sophisticated deep learning ensemble techniques to enhance classification precision in the analysis of drone-acquired electroluminescence (EL) images. This methodology mirrors the optimization techniques utilized in heat transfer and thermal management, applying them to a vision-based fault detection context. The ensemble methods—voting and bagging—utilize many deep learning architectures, combining each model's advantages and achieving greater overall accuracy. This ensemble-based approach aligns with the multilayered optimization frameworks in Refs. [14,15], where the integration of various ML approaches or models repeatedly results in enhanced performance.

Various types of deep learning vision models like Alexnet [16], ResNet18 [17], and YOLOv3 [18] have been cited in the literature with better performances in classifying defective cells. Combining a few basic models has also shown more promising results in achieving higher accuracy performance than individual models.

According to Ref. [19], two deep-learning fused models, Inception-V3 and ResNet50, were used for defect detection in ELPV images. The results indicated that the hybrid model has a higher accuracy performance of 61.15 %, unlike the individual performances of 52.68 % for ResNet50 and 48.39 % for Inception-V3. Similarly, a YOLO-based model, YOLO-PV, was used on the ELPV benchmark [19]. This achieved 94.55 % AP (average precision), unlike in Ref. [20], where the YOLO model had only 78 % AP.

Therefore, combinations of basic models could be applied in a broader view by using ensemble techniques to the ELPV dataset. This approach can increase the inference accuracy performance, especially when considering the same number of models as the number of classes [21]. This is regarded as the ideal number of estimator models. Also, the diversity of the dataset could influence the number of models for the ensemble techniques. However, a lower number of models than the number of classes in the dataset will be insufficient to give a compelling performance measure. In our case, we have four classes in the dataset, and we choose eight different independent deep-learning vision models that provide better performance when compared with the individual model performance.

3. Methodology

In classifying the solar panel cell defects on the 2624 ELPV benchmark dataset [22], we first applied random hyperparameters search techniques before the models were used. This ensures common ground in training the models to give optimum accuracy performance results. The best hyperparameter values are batch size of 25, learning rate of 0.01, number of epochs of 40, Adam optimizer, and image resolution of 256. Then, the selected models are trained using the hyperparameter chosen values. Voting and bagging ensemble techniques were applied to get better performance results. They treated all the selected models as a base estimator and then combined them to form a single model. Each basic model in the ensemble is trained on small batches of the dataset.

3.1. Dataset

The dataset for this work was obtained from ELPV [22], an online resource for open-source datasets for computer vision. The ELPV datasets are in two variations: monocrystalline and polycrystalline. The dataset is extracted from 44 solar panel modules with 60 cells per module. The dataset is 300 x 300 8-bit greyscale images with four classifications in probability. The dataset is categorized into four classes: functional, moderate, mild, and severe, with corresponding counts of 1,502, 123, 298, and 701 solar panel cells in each class, respectively. We converted the 4-class datasets into binary by combining the functional and moderate classes as non-defective and mild and severe as defective classes. This gives 1625 non-defective and 999 defective classes. Fig. 2 presents the 2624 solar cell images in the dataset, with color overlays indicating the likelihood of defects in the corresponding solar cells.

3.2. Models

The following models: AlexNet, SENet, GoogleNet (Inception V1), Xception, Vision Transformer (Vit), Darknet53, ResNet18, and SqueezeNet are selected for the solar panel cell defects classifications. These models have been applied to various image classification-related problems, including face recognition, object identification, and segmentation. They are considered as the basis estimators for the ensemble model. These models were applied to four-class and binary classifications of the ELPV benchmark dataset, which include.

1) Alexnet: an eight-layer sequential model comprising five convolutional layers, one max-pooling layer, and three fully connected layers as its final three layers. It has 650,000 neurons and 60 million parameters [16]. The architecture was developed to support training on Multiple GPUs, which reduces training time. This is due to the limited memory of 3 GB for early GPUs, which has increased recently to 80 GB [23].
2) SENet: uses the concept of Squeeze-and-Excitation (SE) block to model the interdependencies between channels of images so that it can be sensitive to features [24]. The squeeze operation or global information embedding involves converting feature maps into a single value for each channel using global average pooling. The excitation operation or adaptive recalibration is then used to convert the single value to a channel weight of the same size as the input. The SE blocks are stacked with other architectures like ResNet and Inception, which utilize residual and inception modules. In the case of the PV cell defect classification, the SE blocks were stacked with the residual module.

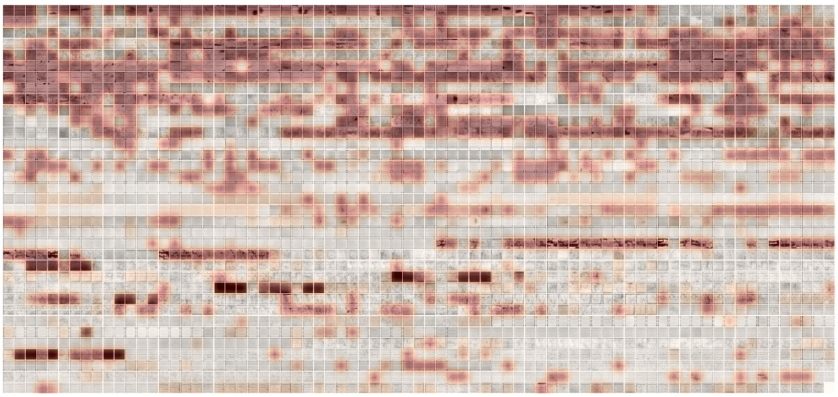

Fig. 2. Overview of the 2624 solar cell images in the dataset, with color overlays indicating the likelihood of defects in the corresponding solar cells [22].

3) GoogleNet: involves applying the concept of the inception module to the network. This helps to focus on efficiency by using 1x1 bottleneck convolutions and pooling instead of fully connected layers [25]. The bottleneck is for channel dimensionality reduction. Unlike AlexNet, which is a sequential model, GoogleNet has a parallel concatenation of networks with 22 layers and 5.98 million parameters. Compared to AlexNet, this has 12 times fewer parameters. Fig. 3 shows the naïve version of the Inception module without bottleneck and Fig. 4 with bottleneck.
4) Xception: is based on depthwise separable convolution [26]. Xception or Extreme Inception involves introducing an inception module between the regular convolution and a separable convolution (a depthwise convolution with a pointwise convolution). This concept leads to better performance.
5) Vision Transformer (ViT): Vit is based on the commonly used transformer architecture for Natural Language Processing (NLP). Unlike a transformer for NLP that uses an encoder and decoder, ViT uses a transformer encoder, followed by a multilayer perceptron (MLP) [27]. Before the transformer encoder, the input ELPV image is split into fixed-size linear patches, and a positional embedding is added to the sequence, which includes a classification token. The transformer encoder consists of alternating layers of multi-headed self-attention (MSA) and MLP blocks. This approach is then applied to classify defects in solar cells.
6) Darknet53/YOLOv3: one of the variants of Yolo-based models known for real-time object detection problems. Other variants include YOLOv2, YOLOv4, YOLOR (You Only Learn One Representation), YOLOX, PPYOLOE, YOLOv5, and YOLOv7. YOLOv3 uses the concept of residual connection with 3x3 and 1x1 convolutional layers. This is then stacked together to have 53 convolutional layers in the network. It is sometimes called DarkNet-53 [18] because of the 53 convolutional layers and darknet neural network framework [18].
7) ResNet: Residual Network (ResNet) uses the concept of residual blocks that help address the issue of vanishing gradients in feedforward networks. The gradient in conventional deep learning networks is backpropagated to the previous layers, and the deeper the network, the smaller the gradient. This can affect the performance of the networks. So, one way of solving this problem was the introduction of shortcut connections to fully connected layers, which perform identity mapping (known as residual mapping). Some common variants of ResNets include 18, 34, 50, 101, and 152 [17], which have stacks of residual or bottleneck blocks. The residual block comprises two convolutional layers, and it is used in ResNet18 and ResNet34. The bottleneck has three convolutional layers for other variants, as shown in Fig. 5. The bottleneck was introduced to allow fast training time in deeper ResNets variants like ResNet50, ResNet101, and ResNets152.
8) SqueezeNet: a small CNN architecture with accuracy comparable to AlexNet's despite having nearly 50 times fewer parameters [28]. The architecture uses the concept of a fire module consisting of a squeezed convolution layer with a 1x1 filter and two 1x1 and 3x3 expanded convolutional layers. The squeeze layer assists in reducing the number of input channels to 3x3 filters and replacing the 3x3 filters with 1x1 filters. Each replacement accounts for nine times fewer parameters, which facilitates a reduction in the network.

3.3. Ensemble methods

An ensemble method can be either a sequential technique like boosting ensemble or a parallel technique. The voting and bagging are parallel ensemble methods because they require the estimator models to act independently on the dataset, resulting in faster computations. In this paper, we used voting and bagging methods with the hyperparameters of batch size 25, 50 number of epochs, 0.0001 learning rate, and Adam optimizer. The weight decay and image resolutions are 0.0005 and 224, respectively. An adaptive learning rate scheduler of type Cosine Annealing [29] was applied to reduce the learning rate as the training progressed.

1) Voting: In the single model training, as shown in Fig. 6, the model is trained on all training data using batches and then sends each batch to the model sequentially. The trained model can now be utilized on the testing data to assess the model's performance. However, as shown in Fig. 7, we have eight trained models for the voting ensemble, each with unique performance values. The voting aggregation techniques are applied to improve overall performance. In this paper, we used the soft voting technique, which operates on a majority vote using the average performance values of each model.
2) Bagging: In bagging ensemble methods, as shown in Fig. 8, the training dataset is sampled and distributed to the various models, using soft voting aggregation for the performance metric.

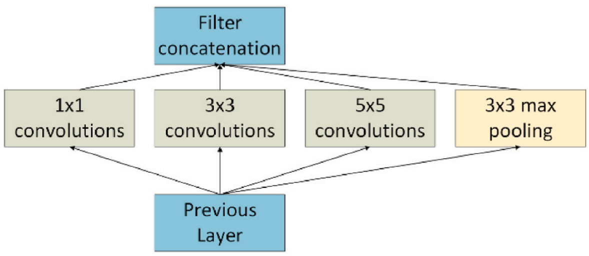

Fig. 3. Naïve version of inception module in GoogleNet model.

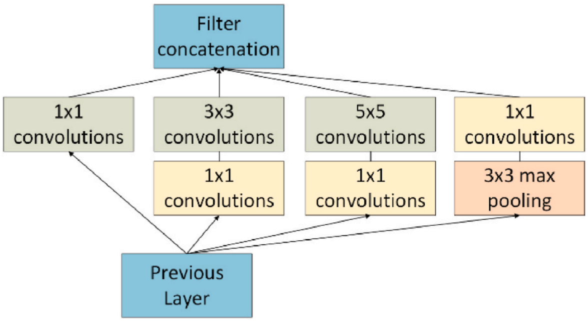

Fig. 4. Bottleneck version of inception module in GoogleNet model.

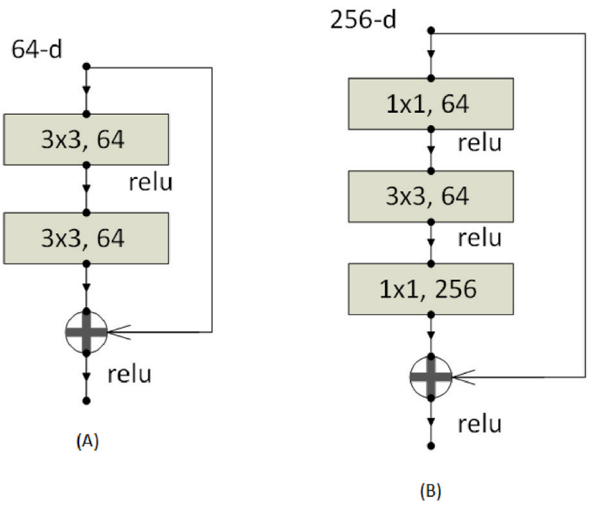

Fig. 5. (A) Residual block on 56x56 feature maps for ResNet34 and (B) Bottleneck block for ResNet-50/101/152.

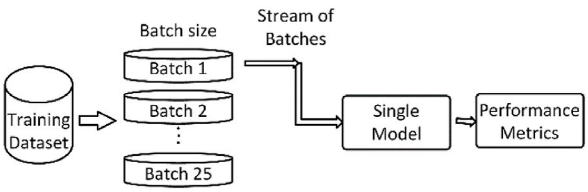

Fig. 6. A sequence training process using batches in a single model.

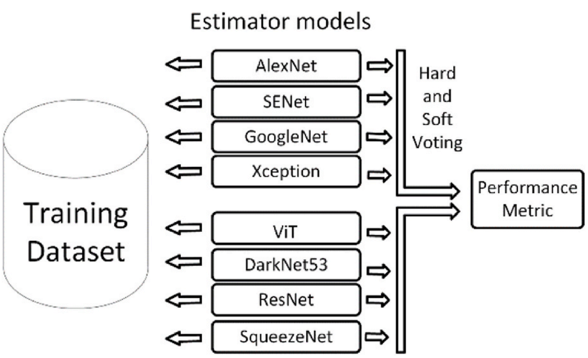

Fig. 7. Voting ensemble methods using the same batch for the models from the training dataset.

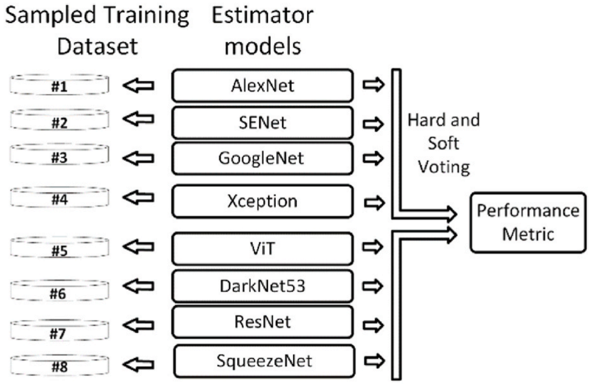

Fig. 8. Bagging ensemble methods using the different sampled datasets for the models from the training dataset.

4. Results

Fig. 9 illustrates the classification accuracies of eight distinct models—alongside the two ensemble methods—for both ELPV 4-class and binary classifications. The YOLOv3/ResNet50 fusion technique described in Ref. [16] is also presented for comparative reference.

4.1. ELPV with four classes

Ensemble methods demonstrate notably higher accuracies in the four-class setting, achieving 68.36 % (voting) and 68.31 % (bagging). In contrast, the lowest-performing single model is YOLOv3, with an accuracy of 51.27 %, whereas AlexNet attains 67.62 %, likely due to its relatively shallow eight-layer architecture, which can be advantageous when dealing with small datasets.

To further investigate each estimator's performance within the ensemble, a subset of 25 solar panel cells was extracted, as shown in Fig. 10, comprising 12 functional cells, three moderate defects, nine mild defects, and one severe defect. Under the voting ensemble, ViT, Xception, and GoogleNet each correctly classified 19 of the 25 samples, as presented in Fig. 11. Under bagging, ViT attained a higher accuracy of 23 correct classifications out of 25 samples. A general trend emerges in which individual base models perform better in bagging than voting; however, voting shows slightly superior overall performance on the entire test dataset. This observation underscores a key insight: while particular base learners may individually excel in an ensemble, their combined predictions do not always translate into the highest ensemble-level accuracy.

Comparisons with prior work reinforce the effectiveness of ensemble strategies. The hybrid technique reported in Ref. [5] reached 61.15 % accuracy on the ELPV dataset, whereas the proposed approach—combining multiple models—exceeds that figure. Likewise, other single models tested under similar conditions, such as GoogleNet (Inception V1) at 65.77 % and ResNet18 at 54.18 %, exhibit variation partly attributable to architectural differences and hyperparameter settings.

In ELPV with four classes, voting aggregates predictions from diverse architectures, offering a robust consensus that helps reduce individual model biases. Bagging trains multiple instances (or subsets) of base learners to reduce variance and improve generalization, often enabling individual base models to perform better when aggregated.

4.2. ELPV with binary classifications

Fig. 9 reveals that ResNet18 achieves the highest accuracy of 73.02 % for the binary classification setting, surpassing both voting (72.17 %) and bagging (72.06 %). This slight shift in ranking can be attributed to the simpler nature of the task—reducing four classes to two diminishes the classification complexity, thus benefiting models that excel at binary discrimination.

According to Ref. [21], aligning the number of classes to the number of models is advisable while simultaneously ensuring the number of classes does not exceed the number of base learners. Reducing the ELPV dataset from four classes to two could, in principle, bolster the performance of ensembles; however, in this particular case, ResNet18 alone surpasses both ensemble approaches, indicating that under specific data or task configurations, a well-tuned single model can outperform ensembles.

A separate evaluation of 16 solar cells (comprising nine non-defective and seven defective cells; see Fig. 12) corroborates the variability in base model performance within ensembles. AlexNet attains the highest correct predictions (14/16) under bagging, while Xception under bagging and SqueezeNet under voting achieve 13/16 and 12/16, respectively. Interestingly, ResNet18, which emerged as the top single model, scores the lowest (9/16) among ensemble members, underscoring that individual model behavior can differ significantly depending on how it is integrated into an ensemble.

Voting maintains strong performance through consensus among multiple architectures despite the simpler binary task. In contrast, bagging provides a robust mechanism for mitigating overfitting by training multiple variants of base learners. However, in specific cases, a single high-capacity or well-tuned network (e.g., ResNet18) may match or exceed ensemble-level accuracy.

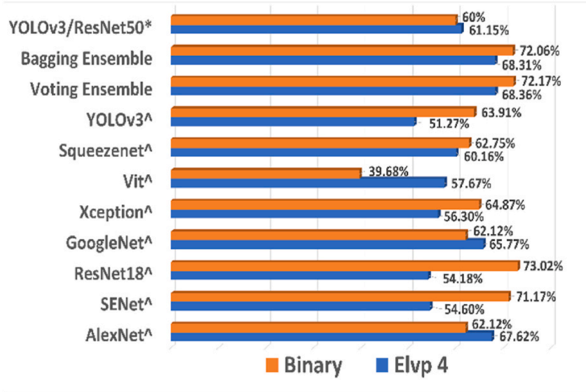

Fig. 9. The test accuracy results using the eight models and the two ensemble methods for binary and ELPV four classifications.

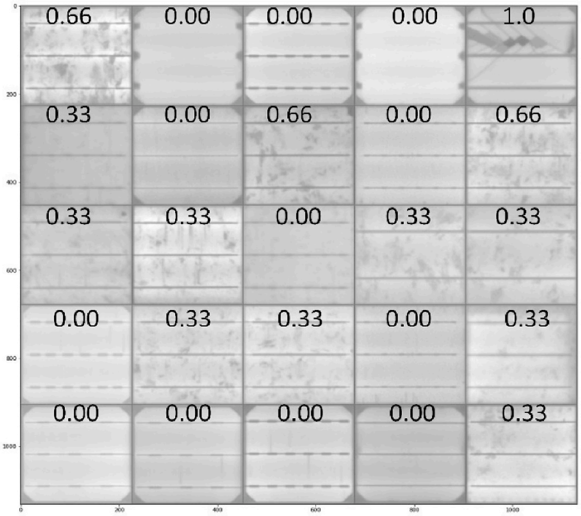

Fig. 10. 25 test solar panel cells with four classifications of functional – 0.00, moderate – 0.33, mild – 0.66, and severe – 1.00.

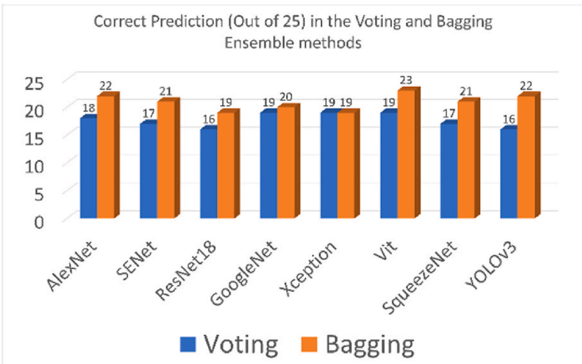

Fig. 11. Results of the 25 test data from Fig. 10 on voting and bagging ensemble methods for four ELPV classifications.

5. Conclusion

This study thoroughly examined solar PV cell defect classification by incorporating eight leading deep learning architectures and two ensemble techniques—voting and bagging—utilizing drone-acquired EL images. The experimental analysis demonstrated that

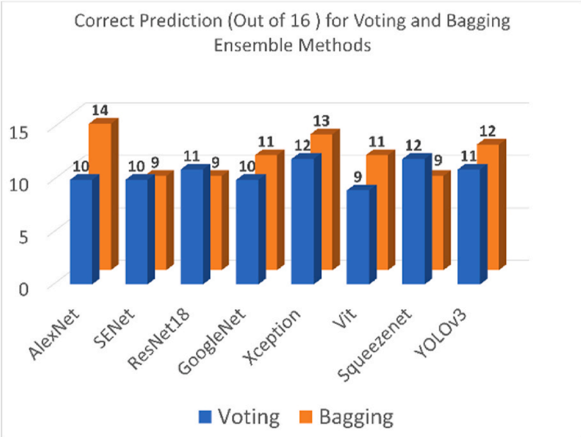

Fig. 12. Results of 16 test data from Fig. 10 on voting and bagging ensemble methods for binary classification (Defective and Non-Defective).

both ensemble methods provide strong performance for four-class classification, achieving overall accuracies of 68.36 % (voting) and 68.31 % (bagging). However, a finely tuned single model such as ResNet18 can surpass these results in simpler binary classification tasks, reaching an accuracy of 73.02 %.

These findings highlight the adaptive nature of machine learning solutions, wherein optimal configurations are contingent upon task complexity and dataset characteristics. This study validates ensemble strategies' efficacy in defect detection and highlights critical opportunities for future enhancement. Initially, data augmentation techniques may be employed to enhance and diversify the training dataset, thereby improving model generalization. Secondly, utilizing a comprehensive, more detailed ELPV dataset, such as the 12-class variant with over 18,000 images, may produce more robust training examples and enhance classification precision. The study enhances PV defect detection and paves the way for the broader implementation of intelligent, data-driven maintenance strategies in solar farms.

CRediT authorship contribution statement

H. Tella: Software, Methodology, Data curation. **A. Hussein:** Visualization, Validation. **S. Rehman:** Writing – review & editing, Supervision, Resources, Methodology, Investigation. **B. Liu:** Formal analysis, Data curation, Conceptualization. **A. Balghonaim:** Resources, Data curation. **M. Mohandes:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mohamed Mohandes reports financial support was provided by King Fahd University of Petroleum & Minerals (KFUPM) and SDAIA under grant number JRC-AI-UCG-03. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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