Araştırma Makalesi
Adıyaman Üniversitesi
Mühendislik Bilimleri Dergisi
23 (2024) 363-377

EFFICIENT BUSBAR SLIP DEFECTS DETECTION IN PHOTOVOLTAIC CELL ELECTROLUMINESCENCE IMAGES

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Geliş Tarihi/Received Date: 03.06.2024 Kabul Tarihi/Accepted Date: 20.08.2024 DOI: 10.54365/adyumbd.1494765

ABSTRACT

PV panel quality control is crucial for their efficient and long-lasting operation. Detecting defects in PV panels during production is essential. Electroluminescence imaging is a commonly used method for fault detection in PV panels. This study focuses on detecting busbar slippage, a specific PV panel malfunction. Automatic error detection was researched using machine learning methods on a dataset of 500 EL images taken from the production line. Feature extraction was performed using two pre-trained deep learning architectures: ResNet and SqueezeNet. Additionally, the study aimed to observe the impact of combining features from different deep learning architectures on success parameters. The highest accuracy rate of 0.9920 was achieved using deep features extracted by Relu34 and Relu25+Conv10 layers.

Anahtar Kelimeler: *Deep Learning, Busbar Slip, Defect Detection, Electroluminescence, Solar cell classification.*

FOTOVOLTAİK HÜCRE ELEKTROLÜMİNESANS GÖRÜNTÜLERİNDE VERİMLİ BARA KAYMA KUSURLARININ TESPİTİ

ÖZET

PV panellerin kalite kontrolü, verimli ve uzun ömürlü çalışmaları için çok önemlidir. PV panellerdeki kusurların üretim sırasında tespit edilmesi de ayrıca önem arz etmektedir. Elektrolüminesans görüntüleme, PV panellerde arıza tespiti için yaygın olarak kullanılan bir yöntem olarak karşımıza çıkmaktadır. Bu çalışma, spesifik bir PV panel arızası olan bara kaymasının tespitine odaklanmaktadır. Üretim hattından alınan 500 EL görüntüsünden oluşan bir veri seti üzerinde makine öğrenmesi yöntemleri kullanılarak otomatik hata tespiti araştırılmıştır. Özellik çıkarma, önceden eğitilmiş ResNet ve SqueezeNet derin öğrenme mimarileri kullanılarak gerçekleştirilmiştir. Ayrıca çalışmada, farklı derin öğrenme mimarilerindeki özellikleri birleştirmenin başarı parametreleri üzerindeki etkisini gözlemlenmiştir. En yüksek doğruluk oranı olan 0,9920, Relu34 ve Relu25+Conv10 katmanları tarafından çıkarılan derin özellikler kullanılarak elde edilmiştir.

Anahtar Kelimeler: *Derin Öğrenme, Bara Kayması, Elektrolüminesans, Güneş Hücreleri Sınıflandırma*

1. Introduction

One of the most important problems of the world is the need for energy, which is largely met by carbon-based energy sources. In addition, the negative effects of carbon-based energy systems on the environment are more evident today. Recently, there has been intense use of energy due to the increase in industrial production, the increase in consumption, the rapid increase in the population and the advancement of technology. In addition, with the growing environmental awareness and the more pronounced damage to the environment, all countries have started to make investments, projects and

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cooperation to find solutions and to strive to reduce the carbon impact in all fields. These developments have led to a serious increase in interest in renewable energy sources with the aim of reducing carbon emissions.

The demand for renewable energy has also led to an increase in the demand for PV solar panels [1]. Today, the PV panel production sector is among the fastest growing sectors in the world. Advancement in the technologies, decrease in the cost and increase in the productivity are among the most important reasons for this. The installed power in the world has increased 30 times even between 2009-2019 [2]. Thus, PV panel production gains more attractions. As seen in Figure 1, PV panel production stages are a complex process. In order for the production of the PV panels to be flawless, all of the process steps must be completed accurately. EL imaging is performed to find some cell defects especially during the production phase. These images are reviewed and labeled by experts. Thus, the PV panels produced can be partitioned into different quality classes.

Quality control in the production process of panels, which is the most basic building component of a PV system, is very important. PV panels are exposed to thermal and mechanical stresses during production and later life stages. These stresses cause cracks and other defects in modules that can affect power output [3]. To understand the effect of a defective cell in PV panels, M. Köntges et al. analyzed the effects of microcracks experimentally after artificial aging. With an accelerated aging test, it is observed that the crack resistance between cracked cells increased, and the number of cracked cells was linearly time dependent and associated with the power drop after the accelerated aging test. They concluded that inspection is critical to prevent the inclusion of defective cells in the panel, thereby ensuring high efficiency and reliable performance of the panels produced [4]

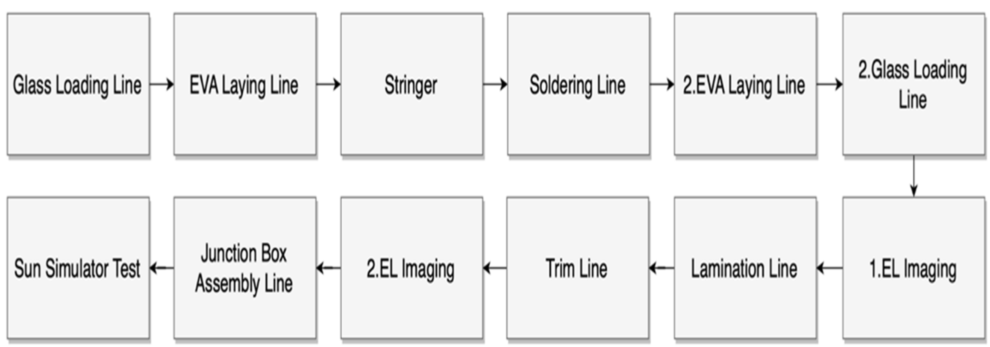

Fig.1 PV Panel Production Stages

When the panels, which come out of production as defective, are passed to the operation stage in the field, they do not work at the desired quality and efficiency. For this reason, in order to achieve maximum output, modules should be monitored in the production line and the subsequent stages, and defect detection should be performed by checking each cell one by one [5].

Defects seen on PV cells at the production stage may or may not be visible to the naked eye. Visible defects are dirt, active fractures, etc. And another group of defect types is invisible defects. Some methods have been developed for the detection of these invisible defect types. Today, one of the most used techniques to detect these defects is Electroluminescence imaging, which provides high resolution images in which the defects are highlighted. In this way, these defective cells can be removed from production line before reaching the final product. EL images are grayscale images acquired in the dark. Although EL imaging is an advanced method, its interpretation is a time-consuming process that requires expertise. In order to improve this challenging inspection process, work is being done on a model that automatically analyzes EL images and detects defects. In addition, very successful results have been obtained in many areas with artificial intelligence methods [6-8].

In this study, we focused on busbar slip defect on PV cell. Busbar slippage is the defect of the conductive paths (busbars) that carry the direct current produced on the PV cells from the solder pads on the cell. PV cells have solder pads for the busbars to be soldered, depending on the technology of the cell. These pads are ways that facilitate the adhesion of the conductive busbar and also determine its positioning on the cell by collecting better current.

The current that occurs in all active areas where electricity is generated on the cell is carried to the busbars first by the finger lines, which are carrier paths thinner than the busbars. The current is carried from the fingers to the busbars, which are the main collector. Fingers and busbars on the cell have a standardized design, taking into account the cell size and the number of busbars, in order to keep the losses at the lowest level while carrying the current. The reason why the position of the busbars on the cell is important is that there are power losses in non-standard busbar positions. Because the increase in the distance of the fingers to the busbars means the length of the path where the current is carried and therefore the decrease in its power. In this case, the first solution that can come to mind would be to shorten the busbar distance. However, shortening these distances in cells with standard dimensions means increasing the number of busbars on this fixed area. The increase in the number of busbars causes resistance losses and power losses as there will be more shadowing on the cell. In this context, there are some studies of leading companies in the PV production sector, and modules produced with multibusbar technology consisting of twelve busbars are one of these studies. Studies that include the idea of increasing the number of bars like this support the importance of finger-bar distance. It should be noted that as the number of busbars increases, the cross-sections should decrease. Otherwise, when the number of busbars increases with the same cross-sections, the resistance losses will increase and the power of the cell will decrease contrary to what is desired, since the areas on the cell that produce active current will be occupied. It can be said that two concepts such as the area covered by the busbar on the cell and the location of the busbar are very important. The need to detect the type of defect, which we call busbar slip, is also very important from these two issues.

- In a switchgear with busbar slippage, the current will not be collected as well as it should, as the busbar will deviate from the solder pad. For this reason, there will be losses in the transmission of the generated power.
- With the busbar slip, there will be a decrease in the power production due to the busbar occupying the active area on the cell.

Since the cells in PV panels are connected in series with each other, the importance of detecting these defects is clearly seen when it is considered that the power loss in a single cell will reduce the entire current. In addition, it is not preferred in terms of visuality, since the busbar slides create an image that breaks the symmetry on the cell. In addition, since a single cell affects the entire panel power, a faulty installed panel will affect all the modules to which it is connected in series within the panel array, and the effect of a single defective cell can be quite serious. For these reasons, automatic detection of busbar slippage defects on the cell is very important during module manufacturing.

Since controlling each module individually in a PV panel production line would be a somewhat difficult and time-consuming process, the necessity of an automatic defect detection system emerges. In EL images of PV panels, the scarcity of defective cell samples and the very similarity of images of successive industrial products make deep learning algorithms more prone to application. Deep learning is one of the applications where image analysis shows its full potential, and it has proven to greatly improve the results of solutions using traditional vision techniques regarding precision, robustness and flexibility [9-11]. In this context, in this study, studies were carried out with deep learning algorithms, which have been shown to be effective among different methodologies developed when the literature is examined, in order to detect busbar slips.

In this study, it is aimed to classify busbar slippage, which is one of the PV panel manufacturing defects, from EL images by feature extraction with pre-trained deep learning networks. For this purpose, an image dataset consisting of EL images was created and features were obtained by sending these images to pre-trained deep learning networks. Obtained features were classified by k-NN and Bayes classification methods. The classification results showed that busbar slip defects can be found in the EL imaging step, which is a processing step in the production phase.

The remainder of this article is organized as follows: In Chapter 2, the literature review on the subject is given. In Chapter 3, the methods and materials used in the study are explained. In Chapter 4, the experimental results for the study are presented. In Chapter 5, the results obtained in the study are discussed. In the last section, the contributions obtained in the study are emphasized.

2. Literature Review

There have been many studies investigating the automatic detection of PV manufacturing defects. When the studies are considered in general, it is possible to say that they are divided into two main groups: methods that find the defect rate and methods that find the defect type.

When we consider the studies aiming to classify the defect rate, we come across two-class (defective, flawless) [12] or multi-class studies [13]. It was noticed that in most of the models examined, binary classification was used to determine whether cells were defective or flawless, and models examining multiclass classification were less common than binary classification. Multiscale detection of defects in electroluminescence images of PV cells is difficult. Many researchers have developed various hybrid models to solve this problem [14-16]. Demirci et al. in their study, they divided PV cell images from a general EL image dataset containing 2624 individual cell images into two classes (defective, flawless) using deep convolutional neural networks. They used the AlexNet, GoogleNet, MobileNetv2 and SqueezeNet architectures for transfer learning in their studies in which they chose the transfer learning method due to the limited data. The results showed that convolutional neural networks and transfer learning can be successfully used for PV cell defect detection [12].

In addition, M. Demirci et al. proposed a new classification model for multiclass defect detection. Here classification means the effect of defects as a percentage (4 classes: perfect (0 percent), possibly faultless (33 percent), possibly faulty (66 percent), faulty (100 percent) 2 classes: faultless (0 percent), faulty (100 percent). By determining the best features obtained from different layers of deep neural networks, results were obtained for both 4-class and 2-class datasets. Classification success rates were taken as 0.9057 and 0.9452 for the 4-class and 2-class dataset, respectively [13].

Studies aiming to find defect types vary greatly. In this context, many methods and methodologies have been developed in the literature for the detection of many different types of defects. Some studies focused on only one type of defect, while other studies identified more than one type of defect. It is seen that studies are mostly carried out for the detection of cell breaks in studies with uniform defect detection [17-19]. In studies with multiple defect detection, it is seen that mostly fractures, microcracks and finger cuts are tried to be detected [19-21]. However, there are studies in which different cell defects such as soldering problems are detected using EL images [23],[24].

There are many types of defects that can occur in a production line. Yang Zhao et al. They conducted a study using deep learning-based automatic detection of multi-type defects to meet the inspection requirements of a production line. First, they created a dataset of 5983 labeled EL images of defective PV modules, introducing 19 types of defects and dividing them into four groups according to their degree of influence. The performance of the best model in the test set was measured and a value of 0.702 was reached. They noted that scratches and finger cuts were the two most difficult flaws for CNN to learn. They also stated that they are one of the rare studies examining the busbar slip problem in the cell, and they have difficulty in detecting these defects due to the lack of data. For this reason, in our study, a higher success rate was obtained by creating a data set with a more balanced and sufficient number of samples for busbar slip [24].

In addition, if we evaluate the studies according to the methods they use, we come across studies using machine learning methods and deep learning methods. Natasha Mathias et al. detected microcracks in PV cells using EL images. The classification accuracy obtained using SVM and BPNN is 0.9267 and 0.9367, respectively. Here, it has been seen that Back Propagation Neural Network (BPNN) outperforms SVM for classification by making binary classification, and it is one of the sample studies showing that deep learning will give better results than classical machine learning methods [25].

In addition to this study, Sergiu Deitsch et al. used a Support Vector Machine (SVM) and an end-to-end deep Convolutional Neural Network (CNN). Both approaches were trained on 1968 cells extracted from EL images. The CNN-based methodology achieved a higher success rate, with an average accuracy of 0.8842. The SVM-based methodology, on the other hand, achieved a slightly lower average accuracy of 0.8244 [20]. Examining Convolutional Neural Network (CNN) for classifying EL images, Z. Luo et al. presented a method to augment the existing dataset of EL images and proposed a model named Generative Adversarial Network (GAN) that targets this. Three CNN models (AlexNet, SqueezeNet, ResNet) were used to examine the effectiveness of the proposed GAN model. The models were used to detect four different types of defects (finger defect, material defect, microcrack, active cracks). In the augmented data set created with the proposed model, it was observed that the classification accuracy improved and the maximum improvement was up to 0.14. In the CNN models used, SqueezeNet had the worst performance and ResNet had the best classification results in all categories with the highest accuracy [21].

It has been confirmed that training the developed models can be improved by applying data augmentation procedures for the recognition of PV cell defects [26][3],. With data augmentation, it is possible to create or modify completely new images by capturing the required features from the image and expanding the training set. In addition, applying different transformations can greatly expand the initial training set [27]. In the studies examined, it was seen that the most frequently used procedures for data augmentation were translation and rotation operations. Fawzi et al. confirms the importance of data augmentation in deep learning (DL) methods for two purposes; The first is lack of data: in training DL models, especially in multilevel classifications. Another is because the images are in different formats from the trained images (not visible to the model) because new images affect the model and lead to incorrect results.

In conclusion; it was observed that most of the studies examined focused on deep learning models. Although the application of deep learning methods in detecting PV cell defects is relatively new, it has been observed that deep learning methods are more successful [28]. In most of the deep learning approach models, classification results with an accuracy exceeding 0.90 are seen [3],[10],[28]. However, the performance of other models [9],[25] is lower due to the inappropriate nature of the models or their ability to separate input features. It should be noted that the results of the hybrid models outperform the standard models and this depends on the methods included [16],[22],[29]. In this study, machine learning methods will be run by using the features obtained with the deep learning model in order to find the busbar slip defect.

3. Materials and Methods

3.1. Dataset

The data set used in the study was created with PV panel electroluminescence images with and without busbar-slip defect. In the study, due to the fact that the busbar slip was tried to be determined from the Electroluminescence images, the Electroluminescence images were examined one by one by the expert and labeled as busbar slip present or absent. A total of 500 EL images were studied on the dataset. These images consist of 300 flawless EL images and 200 EL images with busbar slip defects. Figure 2 shows one EL image that is flawless and the other has a busbar slip defect.

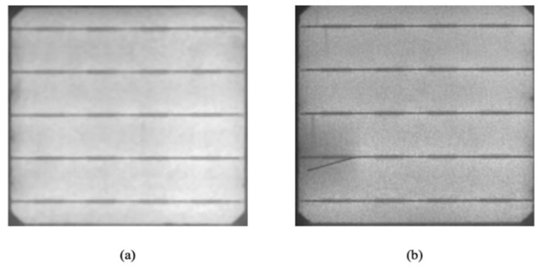

Fig 2. Two Sample Images from the Image Set (a) Normal PV Cell (b) PV Cell with Busbar Slip Defect

As can be seen in Figure 2, in cells with busbar slippage defect, the current will not be collected as well as it should, since the busbar will deviate from the solder pad. In addition, the transmission line with the slip defect will cause a decrease in power since it will occupy the active area on the cell. Considering that this powerful dream is in series connected cells, it can be said that all cells and all panel arrays in macro dimension can be relatively affected. Therefore, the busbar slip defect is important for PV panel production and it will be possible to automatically find it in the production phase with this data set.

3.2. Deep Learning Models

Today, Artificial Neural Network (ANN)-based machine learning approaches have made remarkable contributions in many different research areas [30],[31]. With the increase in the developments in GPU technologies and the significant improvement of the processing capacities of the processors, the use of deep learning algorithms has intensified instead of ANN-based systems.

DL models are instantaneous object recognition from images, person recognition, etc. can be a solution to problems. The simplest deep learning model architecture can be built with convolution, pooling, dropout, fully connected layers. In this study, deep features will be obtained from EL images by using Res-Net, Squeeze.Net, which are pre-trained deep learning architectures.

3.2.1.ResNet Architecture

ResNet Deep learning architecture won the ILSVRC 2015 competition by providing the lowest error rate [32]. There are many different types of ResNet DL architecture. In this study, the most widely used ResNet50 architecture will be used. The ResNet50 architecture consists of 72 sub-layers. The general structure of the ResNet50 architecture is shown in Figure 3.

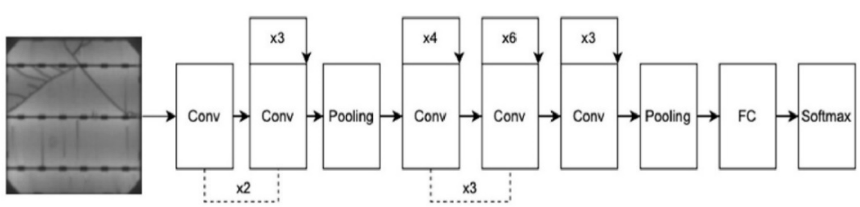

Fig 3. ResNet50 Deep Learning Architecture

3.1.2.SqueezeNet Architecture

Another popular architecture among deep learning architectures is SqueezeNet architecture. The SqueezeNet architecture was developed in 2016 by researchers at DeepScale, University of California, Berkeley, and Stanford University. The aim of this architecture is to create a neural network with fewer parameters and to provide accuracy at the level of other architectures with 50 times fewer parameters [33]. The advantage of the SqueezeNet architecture is that thanks to more effectively distributed layers, the processing load in the neural network is reduced and thus it works faster. It generally differs from other architectures by reducing filter sizes and subsampling in deeper layers.

3.3. Deep Feature Extraction with Deep Learning Models

Deep learning has been used frequently in many different fields recently and successful results have been obtained. Deep learning methods are used in decision-making in many areas, especially due to successful results. In addition, in order to obtain successful results from deep learning models, a very high amount of examples is needed for training. These dependencies limit the use of deep learning methods in areas where many examples cannot be produced. In order to overcome this limitation, pre-trained deep learning architectures have been used frequently recently. In this study, due to the scarcity of EL image samples containing busbar slip, features were extracted using pre-trained deep learning methods and classification was made. Thus, the feature extraction feature of deep learning architectures and the simplicity of machine learning methods are combined. In the study, different features were taken from the ResNet50 pre-trained deep learning model from 3 different layers. These three different layers were chosen from ReLU4, ReLU25 and ReLU34 layers as little deep, deep and very deep. The feature extraction process from different layers is used to observe how the success parameters will change with the features at different depth levels in the EL image classification problem.

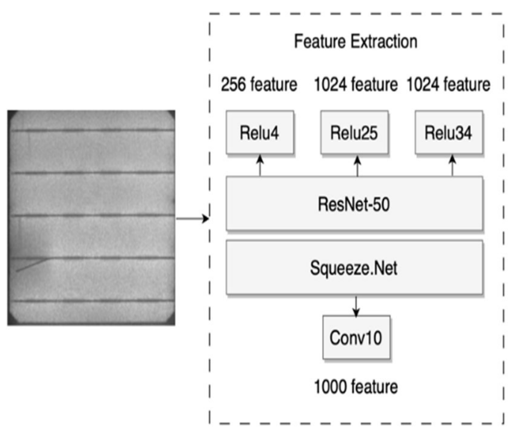

Fig 4. Deep Feature Extraction Steps

In Figure 4, the feature extraction procedure from pre-trained deep learning architectures is summarized. In addition, feature extraction was performed from the Squeeze.net pre-trained deep learning architecture. In order to observe how the success rates of EL image classification will be affected by combining the features obtained from these architectures, the classification was made by combining the features obtained from different layers.

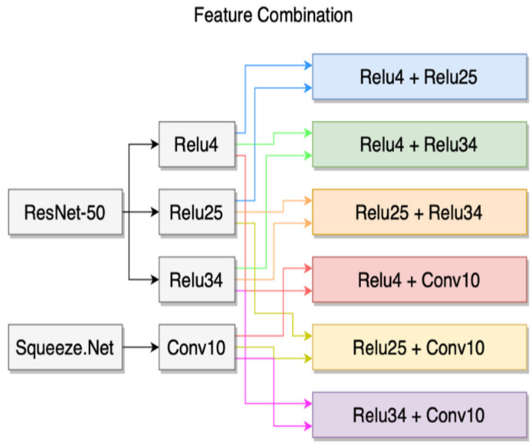

Fig 5. Combined Features Workflow

In Figure 5, new feature sets obtained by combining features extracted from different layers of pre-trained deep learning architectures are shown. With this merging process, the effect of different pre-trained deep learning architectures on the EL image bus slip classification problem can be measured.

3.4. Machine Learning Methods

Machine learning is a sub-application of artificial intelligence. It focuses on predictions made from learned data based on known features. They are models obtained by the development of algorithms that can learn structurally and make predictions on data. Such algorithms work by constructing statistical models to make inferences and decisions with sample input data instead of explicit instructions, and they can predict the results. Machine learning algorithms are basically designed to classify events, find examples, and predict results.

3.4.1. k-NN Classification Method

The k-NN classification algorithm is one of the most frequently used classification methods in many fields, thanks to its simplicity and ease of use [34]. In the k-NN classification algorithm, the distances between the test sample and the training samples are calculated. According to the calculated distances, the classes of the k training samples closest to the test sample are considered and it is estimated that whichever class is the closest neighbor, the test sample belongs to that class. In this study, the Euclidean distance criterion was chosen as the distance criterion. Euclidean distance criterion is formulated in a D-dimensional space in formula 1.

$$d(A,B) = \left(\sum_{i=1}^{D} |a_i(x) - a_i(y)|^2\right)^{1/2} \tag{1}$$

In Equation 1, $a_i(x)$ represents the numerical value in the ith dimension of the x point determined for each attribute. $a_i(y)$ represents the numerical value in the ith dimension of the y point determined for each attribute. In addition, the k value was taken as 1 in the study.

3.4.2. Naive Bayes Classification Method

Classification with the Naive Bayes method is one of the probability-based classification methods. This method is used to determine the probability that a particular set of attributes belongs to a particular class. The classification references Bayes' theorem [35]. The probability of finding the tested sample based on all classes and training samples is calculated and it is estimated that the test sample belongs to the class with the highest probability value. While calculating probability, probabilities are calculated according to formula 2.

$$P(C_i|X) = \frac{P(X|C_i)\,P(C_i)}{P(X)} \quad (2)$$

In formula 1, the probability that the sample $P(C_i|X)$ X belongs to class i is given. $P(C_i)$ represents the probability that class i is found among all classes, P(X) represents the probability of finding X in all samples, and $P(X|C_i)$ represents the probability that a sample belonging to class i is X. Thus, according to the probability of being found in the training data set, it is estimated to which class the test sample, which has not been seen before, belongs.

4. Experimental Results

In this study, it is aimed to find the busbar drift defects in PV panels with deep features extracted from EL images. Studies carried out for this purpose are shown in Figure 6. In the study, firstly, El image set was created with EL images taken from PV panel production facilities. The EL image set was composed of a total of 500 EL images, consisting of 300 flawless and 200 busbar shift EL images. Deep features were extracted from 500 EL images using Resnet-50 and Squeeze.Net pre-trained deep learning networks. The obtained deep features were combined to observe the effects of features in different depth layers and different pre-trained deep learning models on classification success parameters, and success parameters were calculated with different combinations.

Probability and distance-based methods were chosen for classification, so that the effect of different classification methods could be observed. Naïve Bayes was chosen as the probability-based classification method, and k-NN methods were chosen as the distance-based classification method. While using these methods, 125 images (75 flawless - 50 busbar shift flawed) were used for testing. The remaining images were used for training. In addition, accuracy, precision, sensitivity and f-score values were calculated for the evaluation of classification methods.

Recall= TP/(TP+FN) (3)
Accuracy= (TP+TN)/(TP+TN+FP+FN) (4)
Precision=TP/(TP+FP) (5)
f-score=2*((Precision *Recall)/(Precision +Recall)) (6)

Given in equations 3,4,5 and 6, (TP) is the number of EL images with busbar slip imperfection estimated as busbar slip imperfection ; (FP) is the number of flawless EL images classified as busbar slip defective; (FN) number of EL images with flawless estimated as busbar slip imperfectly; (TN) is the number of EL images with flawless estimated as flawlessly. Calculations were made on a computer with a 2.8 GHz Intel Core i7 processor and 8 GB of RAM.

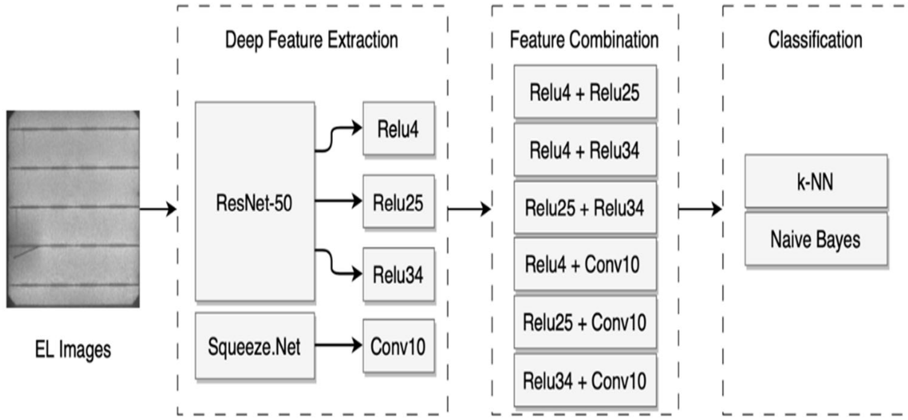

Fig 6. Applied Method Diagram

Table 1. Pre-trained deep learning networks k-nn classification results

Obtained feature vectors	Dimension	Accuracy	Precision	Recall	F-Score
Relu4	256	0.9760	0.9796	0.9600	0.9697
Relu25	1024	0.9840	0.9800	0.9800	0.9800
Relu34	1024	0.9920	0.9804	1.0000	0.9901
Conv10	1000	0.8720	1.0000	0.6800	0.8095

The results obtained with pre-trained deep learning networks using the k-NN classification method are given in Table 1.

Table 2. Combined pre-trained deep learning networks k-nn classification results

Obtained feature vectors	Dimension	Accuracy	Precision	Recall	F-Score
Relu4 + Relu25	1280	0.9840	0.9800	0.9800	0.9800
Relu4 + Relu34	1280	0.9840	0.9800	0.9800	0.9800
Relu25 + Relu34	2048	0.9760	0.9796	0.9600	0.9697
Relu4 + Conv10	1256	0.9360	1.0000	0.8400	0.9130
Relu25 + Conv10	2024	0.9920	0.9804	1.0000	0.9901
Relu34 + Conv10	2024	0.9840	1.0000	0.9600	0.9796

The results obtained by combining the attributes obtained from pre-trained deep learning networks using the k-NN classification method are given in Table-2.

Table 3. Pre-trained deep learning networks bayes classification results

Obtained feature vectors	Dimension	Accuracy	Precision	Recall	F-Score
Relu4	256	0.8480	0.9429	0.6600	0.7765
Relu25	1024	0.9600	0.9787	0.9200	0.9485
Relu34	1024	0.9600	0.9592	0.9400	0.9495
Conv10	1000	0.9360	0.8750	0.9800	0.9245

The results obtained with deep learning networks pre-trained with the Naïve Bayes classification method are given in Table 3.

Table 4. Combined pre-trained deep learning networks bayes classification results

Obtained feature vectors	Dimension	Accuracy	Precision	Recall	F-Score
Relu4 + Relu25	1280	0.8560	0.9706	0.6600	0.7857
Relu4 + Relu34	1280	0.8400	1.0000	0.6000	0.7500
Relu25 + Relu34	2048	0.9360	0.9773	0.8600	0.9149
Relu4 + Conv10	1256	0.8480	0.9429	0.6600	0.7765
Relu25 + Conv10	2024	0.9600	0.9787	0.9200	0.9485
Relu34 + Conv10	2024	0.9600	0.9592	0.9400	0.9495

The results obtained by combining the attributes obtained from pre-trained deep learning networks using the Naïve Bayes classification method are given in Table-4.

5. Discussions

In this study, the problem of detecting the busbar shift defect from PV Panel EL images using deep features is addressed. In this study, in order to solve the problem of detecting bus slip defect from PV Panel El images at the production stage, deep features were extracted from EL images with two different pre-trained deep learning architectures and EL images were classified in terms of bus slip defect using three different classification methods with the obtained features. In addition,in order to examine the effects of features at different depths of pre-trained deep learning architectures on classification performance, tests were conducted with features at different depths and results were obtained. Distance-based and probability-based classification methods were tested in order to examine the performance of classification methods in terms of bus-shift defect in EL images. When the results obtained in terms of deep learning architectures were examined, the results in Table 5 were obtained.

As can be seen in Table 5, the most successful classification results were obtained with the ResNet architecture. In addition, when the features at different depths are considered, acceptable classification results have been obtained with the features at the medium and high depth levels. In Table 6, the results of distance-based and probability-based classification methods are compared.

Table 5. The most successful results from deep learning architectures

Obtained feature vectors	Dimension	Accuracy	Precision	Recall	F-Score
Relu4	256	0.9760	0.9796	0.9600	0.9697
Relu25	1024	0.9840	0.9800	0.9800	0.9800
Relu34	1024	**0.9920**	0.9804	**1.0000**	**0.9901**
Conv10	1000	0.9360	**1.0000**	0.9800	0.9245
Relu4 + Relu25	1280	0.9840	0.9800	0.9800	0.9800
Relu4 + Relu34	1280	0.9840	**1.0000**	0.9800	0.9800
Relu25 + Relu34	2048	0.9760	0.9796	0.9600	0.9697
Relu4 + Conv10	1256	0.9360	**1.0000**	0.8400	0.9130
Relu25 + Conv10	2024	0.9920	0.9804	**1.0000**	**0.9901**
Relu34 + Conv10	2024	0.9840	**1.0000**	0.9600	0.9796

Table 6. The most successful results of distance-based and probability-based classification methods

Classification Method	Accuracy	Precision	Recall	F-Score
k-NN	**0.9920**	**1.0000**	**1.0000**	**0.9901**
Bayes	0.9600	**1.0000**	0.9800	0.9495

As can be seen in Table 6, distance-based classification methods have been more successful in terms of bus-shift defect of EL images in the PV panel production stage. In the results obtained in this study, F-score gives more significant results.

6. Conclusion

In this study, automatic determination of busbar slip defect from EL images taken in PV panel production facilities with pre-trained deep learning methods is discussed. In the study, two different pre-trained deep learning methods and two different machine learning methods were tested for the classification of busbar slip defect of EL images. Considering the results obtained, it was concluded that the results obtained with single and deep features in determining the busbar slip error, which is one of the PV panel production defects, by machine learning methods, are more successful than the results obtained by combining features at different depths and different architectures. Although the Relu 34 and Relu25 + Conv10 classification results provided equal success rates, it was observed that more successful results could be obtained with the deep features obtained in the Relu34 layer when other success parameters were taken into account. In addition, the classification results made with the features obtained from the Relu4, Relu25 and Relu34 layers, which are different layers of the same architecture, it is understood that the deeper the features are taken, the more successfully it can detect the busbar slip from the PV panel EL images.

In terms of classification methods, when the busbar slip detection in PV panel EL images is considered, it has been concluded that the distance-based classification method, k-NN, is more successful. In particular, the k-NN classification method adapted to the combination of features in different architectures and different layers much more successfully than the Bayesian classification method and significantly increased the classification success parameters. Thus, it has been concluded that it is possible to predict the busbar slip defect from EL images in PV panel production facilities with machine learning methods. In addition to the study, investigating the success parameters of feature selection methods will be a guide for researchers who plan to work on this subject in the future.

Acknowledgment

We would like to thank to Harran University Scientific Research Projects Commission for supporting our study (Project No:22256).

Conflict Of Interest

The authors declare that they have no conflict of interest.

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