Solar Cell Busbars Surface Defect Detection based on Deep Convolutional Neural Network

Yavuz Selim Balcıoğlu, Bülent Sezen, Ceren Cubukcu Cerasi

***Abstract*—Defect detection of the solar cell surface with texture and complicated background is a challenge for solar cell manufacturing. The classic manufacturing process relies on human eye detection, which requires many workers without a steady and good detection effect. In order to solve the problem, a visual defect detection method based on a new deep convolutional neural network (CNN) is designed in this paper. First, we develop a CNN model by adjusting the depth and width of the model. Then, the optimal CNN model structure is developed by comparing the performance of different depth and width combinations. This research focuses on finding a way to distinguish defects in solar cells from the background texture of busbars and fingers. The characteristics of solar cell color images are analyzed. We find that defects exhibited different distinguishable characteristics in various structures. The deep CNN model is constructed to enhance the discrimination capacity of the model to distinguish between complicated texture background features and defect features. Finally, some experimental results and K-fold cross-validation show that the new deep CNN model can detect solar cell surface defects more effectively than other models. The accuracy of defect recognition reaches 85.80%. In solar cell manufacturing, such an algorithm can increase the productivity of solar cell manufacturing and make the manufacturing process smarter.**

***Index Terms*—Convolutional neural networks, Deep Learning, Solar Cell, Surface Defect.**

I. Introduction

Solar power has become an exciting alternative to electrical energy due to possible environmental and global oil shortages. Solar cells that transform the photons from the sun to electricity are frequently based on crystalline silicon in the present market [1]. They can achieve good performance in practical lifespan and conversion productivity among the currently feasible techniques. However, the latest printing process of solar cells has some defects [2]. These defects may lead to poorer performance or even adverse effects such as reducing the power productivity of solar cells [3]. To prevent the reduction of product power, the defects need to be monitored during the production line.

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As a result, surface defect detection of solar cells is essential for checking the quality of solar cell products during the manufacturing process [4]. Today's manufacturing corporation is progressively subject to countries' competition because of boosting production costs and expanding customer needs. In today's world, products are more regulated with their technology—these circumstances pressure to cut down production costs and raise the quality of goods [5]. To meet the expanding quality standards of industrial manufacturing processes, computer vision systems are used for automated surface inspection to automatically test the surface of a finished product for defects such as scratches or holes, et cetera [6]. Computer vision systems are advantageous compared with manual inspection because they can achieve a higher level of automation and objectivity, which has allowed them to be applied in many industries [7].

For most cases, manual surface defects inspection is still performed in the production process [8]. This results in misjudgments and scale-down manufacturing efficiency due to human fatigue. However, computer vision technologies are being developed to track these defects and significantly improve efficiency and reliability [9]. Computer vision-based mainly includes image acquisition through an optical system and a defect detection process to capture images [10].

Computer vision's next step is optical quality control (OQC) [11]. Two processes are crucial in manufacturing and production to fulfill customer requirements during the quality control procedure. First, a good product will be made during the inspection by fulfilling the customer requirements through sales continuity [12]. Two processes that care for the product inadequacy or defects during visual quality control are crucial to this primary process. Industrial sectors such as manufacturing and agriculture have been employing humans to handle the visual investigation of products and goods [13]. Although this is one of the critical elements in the production process, it is a tiring and demanding job that may lead to mistakes resulting from fatigue, possibly compromising the entire production procedure. Because of that OQC system has helped increase the inspection of products produced quality [14].

Silicon solar cells are equipped with a grid or mesh of metalized lines [15]. They are printed on both the front and rear of the cell. These grid or mesh lines and the finger lines, often screen-printed, facilitate the transfer of the DC electricity produced by the cells when struck by photons [16]. In general, solar cells used for energy production include one or more busbars whose metallic coatings facilitate higher current generation. Additionally, these coatings guard against oxidation, further degrading the device's performance [17]. Furthermore, a grid of super-thin metallic fingers conducts the produced DC to one or more busbars in order to fully utilize each solar cell's production potential [18].

As mentioned before, the metal lines arranged in strips on the front and back of the silicon solar cells provide the electric current between the cells [19]. Along with these, vertical lines are called fingers. Surface defects on the surfaces of solar cells reduce the performance of solar cells [20]. However, with this problem, the destruction of the busbars on the solar cell and the surfaces of the fingers likewise reduces the efficiency of the solar cells [21].

This article proposes a low-cost image processing system to solve the above problems [22]. Deep convolutional neural networks were used as a method. First, a low-cost image system is set up to acquire image data. In the second stage, images of the surfaces of the solar cells are obtained thanks to this system. In the third step, this received image data is divided into pixel areas in a 2D environment, and error segmentation and classification are made. Finally, the model performance of the deep convolutional neural network model formed in the last step was compared with the model performances of the classical convolutional neural networks [23]. In this fig. 1, the main contributions of the proposed method are summarized.

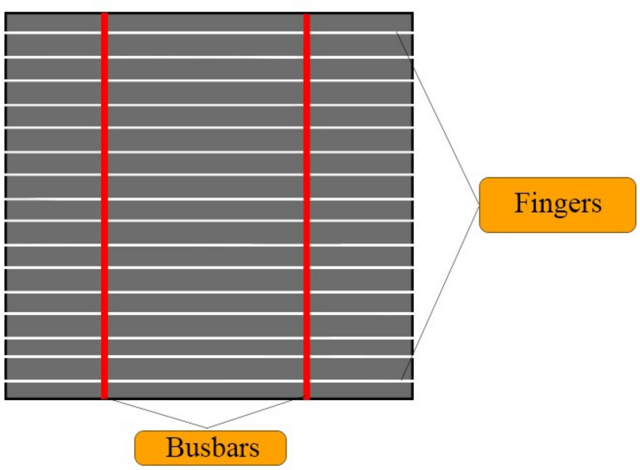

Fig. 1. Busbars and fingers.

A. Problem Statement

The manufacture of solar cells relies heavily on production flexibility, individualization, and quality control. Hence, the development of intelligent manufacturing often focuses on these aspects of manufacturing. In particular, the manufacturing processes involved in the solar panel production industry place a significant emphasis on flaw identification and categorization. The identification of flaws is one of the most important aspects of effective product quality control. The conventional technique of detection is dependent on human labor. However, when carried out for an extended period of time, manual detection may result in poor detection efficiency as well as a high rate of missed inspections. Also, most broken solar panels are either recycled or reprocessed, and the ones that can't be fixed are usually just thrown away.

Therefore, in order to process them more effectively, it is necessary to categorize damaged solar cells according to the kind of defect present. This offers a wealth of information that may be used for manufacturing defect checks. On the other hand, the vast majority of the detection techniques still rely on manual detection methods. Therefore, intelligent detection techniques of solar cell failures are still a challenge and have always been a particular concern of solar panel processing manufacturers in an automated industrial production line. This is due to the fact that solar cells have been around for a very long time.

Faults due to a small section missing from the margin are the main focus of this study.Due to its precision and speed, the CNN approach has become more popular for application in object detection. Despite this, the identification of tiny targets, particularly flaws on solar panels, continues to provide a number of hurdles and difficulties. As a result, the purpose of this work is to propose a small area defect detection technique called DCNN that is based on CNN for the purpose of improving the detection performance of small area defects.

II. RELATED WORKS

Over the past ten years, deep learning - or deep neural networks has become dramatically more effective and widely applied to various fields, including image detection and speech recognition [24]. In addition, many industrial practices have also served deep learning development, including machinery fault diagnostics, operational verdict making, et cetera [25]. In general, various hidden layers are stacked in the deep neural network architecture, which largely contributes to the learning capacity of the data-driven model [26]. Apart from a more conventional multilayer structure, more capable variants have also been suggested and achieved great success, including convolutional neural network (CNN), deep neural network, recurrent neural network, generative neural network [27]. Furthermore, high-level granularity to data using CNNs has made it easy to detect discoveries. With a limited number of parameters, a machine learning model's overall complexity and ability to process raw data can be measured in both high-frequency and low-frequency signals [28]. Hence, CNN has been widely adopted to explore different kinds of industrial data, including digital vision and imaging [29].

Recently, CNN and its variants have been studied for surface defects detection. The results in textiles, strip steel, healthcare and buildings have been preliminarily inspected [30]. Cortes and Sanchez, proposes using a deep learning approach for automatic diagnostic classification of chest X-ray imaging related to specific pathologies [31]. Lee et all, experiment use a deep convolutional neural network (CNN) to detect surface defect datasets such as textile and steel [32]. This paper examined the impact of different CNN models on the test results. In 2017, a new DCNN model structure was proposed to be used instead [33]. The model uses both samples without defects and pieces with defects as input, and the output is a twelve-class classifier. The examples are the two of each of the twelve classes. Wu et all, introduces a general surface defect detection method using deep learning and which achieves state of the art performance on both arbitrary textures and special structure images [34]. Another work, Tao et all; describes an approach to defective metal detection that takes into account real world conditions such as lighting, image capture quality, and defect patterns that are not uniform. This system, automatically localizes and classifies large defects on metallic surfaces using semantic segmentation [35]. Zhang et all; Proposes a one-class classification method based on deep convolution neural network, which effectively addresses the problem of feature extraction [36].

The dataset is small, which could lead to overfitting [37]. Furthermore, there are not enough labels to distinguish between the defects and non-defects. Another paper proposed an algorithm to detect defects based on an ensemble of existing defect detection models instead of building a new one. The proposed method can inherit weights from other models to reduce overfitting and improve model accuracy [38]. Apply a CNN to an LED surface, realize the identification and positioning of various defects in the multispectral characteristics of complicated surface defects in solar cells, and reach an accuracy of 94%. However, the datasets used in the literature are single-channel images, which are difficult to describe and contract with the multi-channel characteristics of complicated surface defects in solar cells [39]. The authors of "Solar Cell Testing with Convolutional Neural Networks" use CNN to detect defects in solar cells. The authors build and train a deep neural network to detect potential defects in solar cell images in their paper [40]. Some possible defects which can be seen using the CNN include missing connection and excess connection. The author's approach is relatively novel, as the CNN is trained using less than 70 images and thus obtains relatively low detection rates. Su et all; proposed CAN, a complementary attention network that selects features discriminative for both the background and defects, allowing for better defect detection. With this feature, addresses defects in solar cell EL images by integrating two networks that use spatial and channel attention, respectively [41]. Chen et all; derives a deep convolutional neural network model to classify solar cell surface defects based on multi-spectral light spectrum information [42]. Bartler et all; proposes DeepTransportNet, an end-to-end deep learning architecture for automatic differentiation from feature extraction to defect classification [43]. The research on solar cells that has been done so far utilizing the CNN approach has only reached the stage of locating faults [42], [44], [45], [46] on the panel surfaces of solar cell structures, according to an analysis of the relevant published literature. Nevertheless, the identification of faults on the busbar and finger surfaces of the solar cell is one of the most significant advances that can be attributed to this work.On the other hand, as part of this research, a novel method of image processing was developed, which we did not document in this work due to our plans to cover it in another study.

A. Contributions of this Study

The design that has been suggested for DCNN takes its cue from the model of the CNN network, but with several changes, especially for the identification of minor defects.

The first step is to capture picture data by putting up a simple and inexpensive imaging device. Additionally, there is an adaptive module for deep learning that is based on convolutional neural networks (CNNs). Deep Convolutional Neural Networks have the ability to learn hierarchical features in various layers, which gather information from objects of varying sizes. Specifically, spatially rich features in shallow layers have better resolutions, making them more useful for the identification of flaws in smaller areas. The DCNN method that was shown is better for figuring out where problems are in smaller areas.

Second, the k-fold cross validation approach is utilized to demonstrate that the newly developed deep CNN model is superior to previous models in terms of its ability to identify flaws on the surfaces of solar cells. It is required to first establish predefined boxes that are tailored to the sample size in order to increase the efficacy of fault identification in tiny areas. The previous anchor boxes are then used in the process of detecting, which could make the prediction scale more flexible.

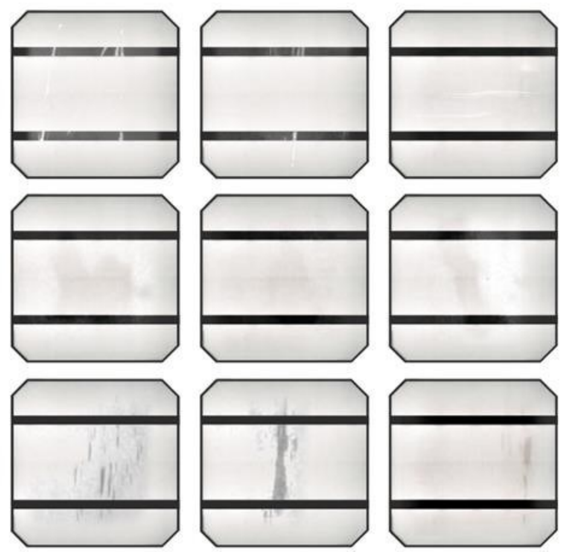

Fig. 2. Various surface defects of busbars and fingers on solar cell.

III.PROPOSED APPROACH

This study selected solar cell busbars and fingers as the inspection model. The Convolutional Neural Network, often known as ConvNet, is a variant of neural networks that is mostly used for applications in the fields of voice and picture recognition. The high dimensionality of pictures may be reduced by their built-in convolutional layer without any information being lost in the process. That is why CNNs are well suited for this use case.We focused surface defections on the surface of busbars and fingers. The color masking method selects only busbars and finger surfaces on solar cells. For this purpose, the regions with a blue cover on the solar cell were masked and excluded from the analysis [47]. We built a low-cost system to capture the dataset used in this paper, shown in (fig. 3). The testing solution can be incorporated on the production line in the constructive variation that has been provided. This removes the need for a machine and the manpower that is associated with it in order to test the solar cells. With the suggested method, the cost of a machine with comparable capabilities will be reduced to just 1000 euros, down from the current level of 5000 euros. This will be a huge savings for companies. The system established in this study consists of a camera working with a rail movement, lights, production line and solar panels. As the solar panels pass over the production line, their images are recorded according to their production ID numbers. For this purpose, we captured 600 labeled images. The images are in red-green-blue (RGB) color space; every image has 4128x3096 pixels. Before the analysis, we converted all images to grayscale image color format. Our study in the field of application was planned to carry out in-depth learning training on 200 different solar cell pieces with surface defects. Six hundred separate solar cell busbars and fingers images were to be analyzed through this learning. Fig. 1 shows the flow of the proposed approach.

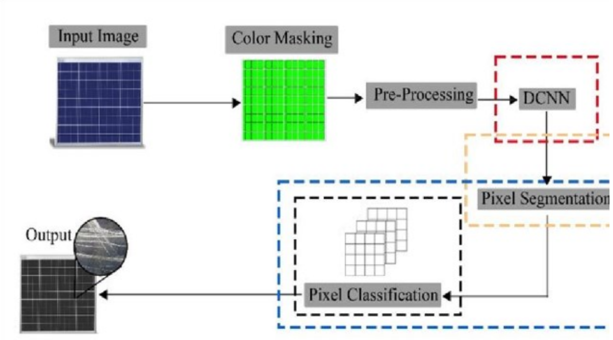

Fig. 3. Flow of the proposed approach.

The blue regions, which are the cell areas of the solar cells, were removed from the image by color masking, and only the busbars and fingers regions were left for analysis. Sharpen and despeckle filters are used to remove error elements from the image. Fig. 4 shows an example process.

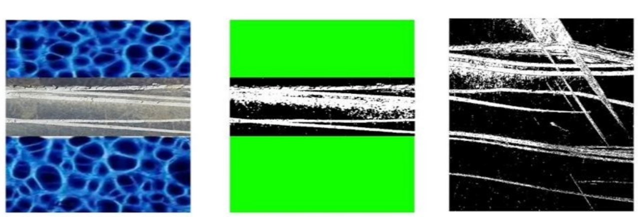

Fig. 4. Illıstration of segmentation.

The inspection system for surface defects of printed silicon solar cells is implemented to detect the above-mentioned flaws, as shown in (fig. 5).

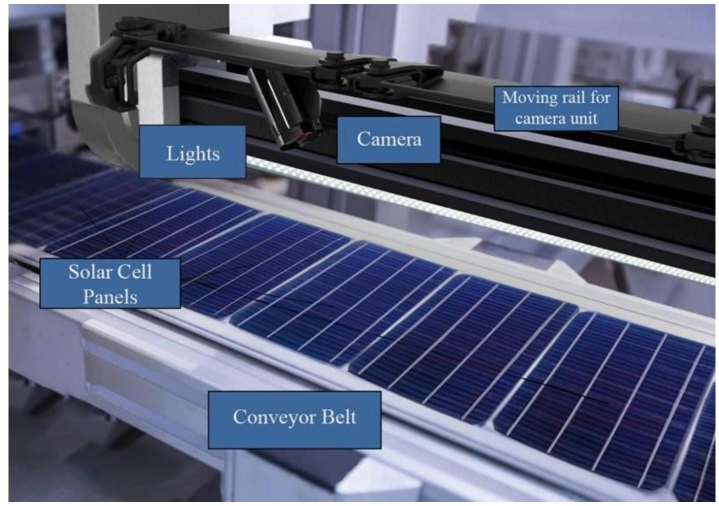

Fig. 5. Inspection system for surface defects of printed silicon solar cells.

Our application will apply the learning-based model and examine preliminary data processing and detailing operations independently from the model. The paper has the following research improvements.

1. Proposes an image-processing-based, low-cost defect detection for a hardware-software solutiın for the end of line production not only the quality of the product but also the stability and yield of the production process.
2. This paper analyzes the effect of model size and image quality of a DCNN model on defect detection. Our test results indicate that the DCNN model improves accuracy when the depth of the convolution kernel is significant and the image quality is high.
3. Experimental results show that surface defection on small pieces occurs more with clean captured images. Furtherly, camera quality is essential in this system.

The setup installed for this application is visually stated below in (Fig. 5). The line scan camera was used in the image capture process —a camera connected to the computer system. When the solar cells move on the production line, the system can analyze the parts in real-time. After that, it shows the results instantly to the screen which part is defective or not.

The images used in this study were created with data collected from the production line. Dataset images have the same resolutions and different crack sizes and types. For the dataset, 1200 visual data were used in the training phase. In the testing phase, 300 visual data were used. Visual data with a total of 80 different defects were analyzed. First, test the accuracy of the results; 20 error-free solar cells are randomly placed in the analysis. A total of 100 visual images were analyzed. This study's primary purpose is to calculate the quality ratios of solar cell busbars and fingers based on previously trained data. Against the traditional neural network method, deep learning neural networks are used here. The estimation rates obtained through the results and the deep learning are shown in table 1. Fig. 6 shows the DCNN structure that we have established.

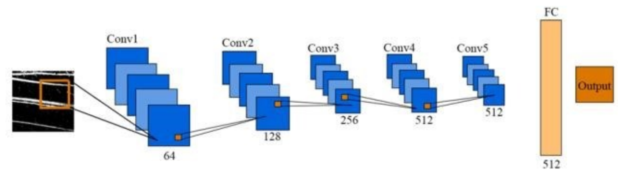

Fig. 6. Solar cell DCNN Structure.

TABLE I
THE ARCHITECTURE OF DCNN

Layer type (Height x Width x Channel)	Numb. of Filters	Size of feature map	Size of filters	Stride	Paddin
Conv1	**64**	**224x224x64**	**3x3x3**	**1x1**	**1x1**
Relu Layer					
Max pooling	**1**	**112x112x64**	**2x2**	**2x2**	**0**
Conv2	**128**	**112x112x128**	**3x3x64**	**1x1**	**1x1**
Relu Layer					
Max pooling	**1**	**56x56x128**	**2x2**	**2x2**	**0**
Conv3	**256**	**56x56x256**	**3x3x128**	**1x1**	**1x1**
Relu Layer					
Max pooling	**1**	**28x28x256**	**2x2**	**2x2**	**0**
Conv4	**512**	**28x28x512**	**3x3x256**	**1x1**	**1x1**
Relu Layer					
Max pooling	**1**	**14x14x512**	**2x2**	**2x2**	**0**
Conv5	**512**	**14x14x512**	**3x3x512**	**1x1**	**1x1**
Relu Layer					
Fully	**512**				

The 5-layer convolutional layer achieved the best results in our established CNN model trials. Pool6 has been removed from the model to avoid overfitting problems. In total, five layers and four pools are fully connected. The max-pooling layers are 2x2 stride 1x1. We use the LeNet architecture. The first convolutional layer is conv1; the second convolutional layer is conv2; the third convolutional layer is conv3; and so on. The resolution of the last convolutional layer is 14x14. The input layer's resolution is 224x224 [48], each input image is normalized to this size. Table 1 shows an illustration of the architecture of CNN.

IV. RESULT

To measure the capability of the proposed model, the defect detection capability of 4 different models was calculated based on the fault types, scratches, connection bridge breaks, and holes on the surface. The results obtained are shown in (Fig. 7). When Fig. 7 is examined, it is seen that the best result is obtained with DCNN. The second-best result was obtained with F-RCNN.

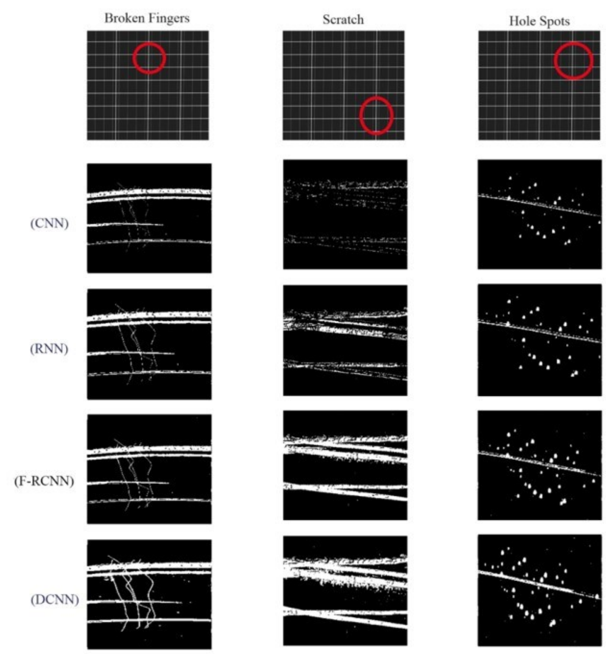

Fig. 7. Comparison of models.

When Table 1 is examined, one can see all the details of the created DCNN model. It consists of 5 layers, with a total of 4 max-pooling layers. Image reduction was made by decreasing the image resolution twice as much as each layer. In this way, it is aimed to increase the prediction success before the decision. At this stage, the primary aim is to determine the faulty parts on the surface. In the second stage, the cover error rates were determined by analyzing the authentic images compared to the wrong test images in the decision phase.

This paper designs four models of neural networks with various depths and sizes and analyzes their effectiveness for solar cell busbars and fingers. We use precision, recall rate, and F-measure to ensure better results to classify the uncertain scratches detection results. Precision measures the correctness of detection and separation and is calculated in equation 1. The recall equals the precision of detection and separation defined in equation 2. Therefore, F-measures consider both precision and recall and are measured in equation 3. Table 3 shows the precision, recall, and F-measure scores for the solar cell busbars and fingers.

$$Precision = \frac{\sum TP}{\sum TP+FP} \tag{1}$$

$$Recall = \frac{\sum TP}{\sum TP+FN} \tag{2}$$

$$F - measures = 2x\ \frac{PrecisionxRecall}{Precision+Recall} \tag{3}$$

TABLE II
RESULTS OF DIFFERENT ARCHITECTURES OF SOLAR CELL BUSBARS AND FINGERS NN

	CNN	RNN	F-RCNN	DCNN
Precision	%91	%90	%85	%90
Recall	%63	%56	%72	%82
F-measures	0.744	0.69	0.779	0.858

The empirical results for the four different architectures of solar cell busbars and fingers NN are given in Table 2. The results indicated that the 5-layer convolutional layer DCNN with a busbar solar cell finger model has a 5% higher precision than the 4-layer convolutional layer F-RCNN model. Furthermore, precision and recall are improved when kernel size is grown on the four-layer, convolutional, F-RCNN model. Table 2 shows that the DCNN architecture model has improved the detection value of surface defection compared to that of the previous FRCNN architecture model. Furthermore, as shown in Table 2, the recall of the DCNN model is relatively higher.

The experiment is completed on the Raspbian o.s., kernel version: 5.10, the framework was used by the computer. Training took place on a high-end i9 computer with 64 GB of memory and GTX 2080 graphics cards. The learning rate of the DCNN model was 20000 epochs of training. The Dropout neuron ratio is 40%. Figure 8 shows the serial numbers of the solar cells barcodes used for analysis.

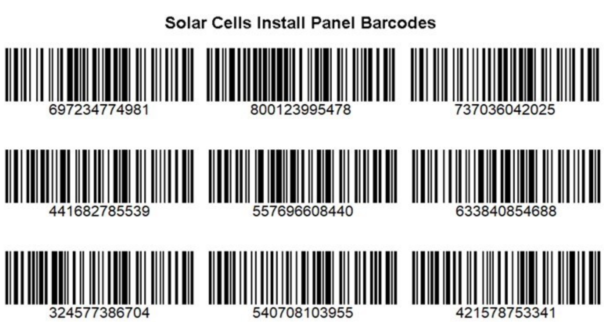

Fig. 8. Example of 1 to 9, solar cells serial number sheet.

TABLE III RESULT SCORES OF SURFACE QUALITY (TEN SAMPLES)

PART NO	SURFACE QUALITY RATE	SURFACE QUALITY DEFECTION RATE
697234774981	0.6450	0.355
800123995478	0.5254	0.4746
787041756437	0.7890	0.2110
441450162431	0.9235	0.4461
489873758501	0.6323	0.3677
447508661024	0.9604	0.0396
818251589587	0.4911	0.5089
327138997096	0.8619	0.1381
843255766445	0.9707	0.0293
688723573212	0.7743	0.2257

When we analyze Table 3, we can see the percentages of surface defect controls of 100 serially numbered solar cells. Two pieces (375962513219, 513698768324) included in the analysis process were detected as 100% error-free. Apart from these, there are defects on the surface of 98 parts with surface defects.

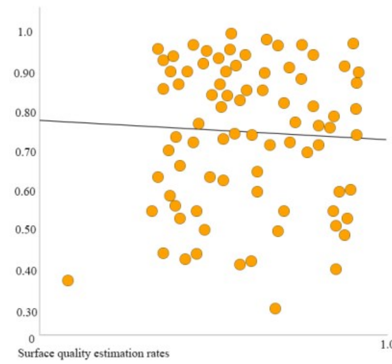

Fig. 9. Surface quality estimation rate.

When we examine the data visual above, it is seen that the error rates of the parts passing through the production line are generally low, and the pieces have common defects. However, even if the lowest error rate is below one percent, it will cause problems in its operation. Fig. 9 shows that the surface quality estimation rate resulted as a % and computed the total number of iterations during the analysis.

A. Defect Regıons Localızatıon

As a result of the analysis of 20 visual data selected as a sample in fig. 10, a high accuracy rate was achieved in detecting scratches and cracks on the surface. However, high performance was not achieved in detecting round, dot-shaped holes, preferably small ones. The reason for this is that the analysis is processed in one dimension. Therefore, more image layers should be increased for a much higher surface detection, and more detailed data augmentation should be done. However, these transactions will require massive systems and budgets.

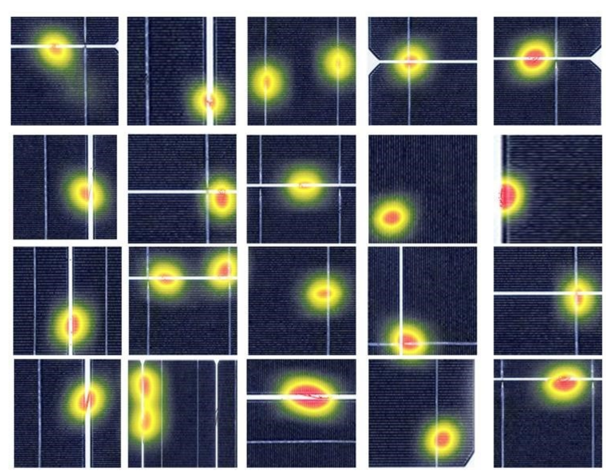

Fig. 10. Heat vision of surface defects detected on 20 visual data selected as samples.

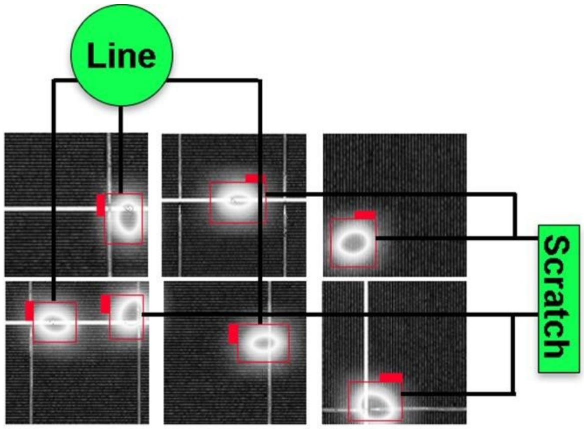

Fig. 11. Examples of localization on Solar cell busbars and fingers. The map highlight the detection region. Predicted bounding boxes from the dataset are in red.

Our CNN model performs remarkably well on defect regions localization. For two different surface problems, line and scratch marks from our dataset are generated, as shown in (Fig. 11). Afterimage processing on Solar cell busbars and fingers, defects are localized with a bounding box in red.

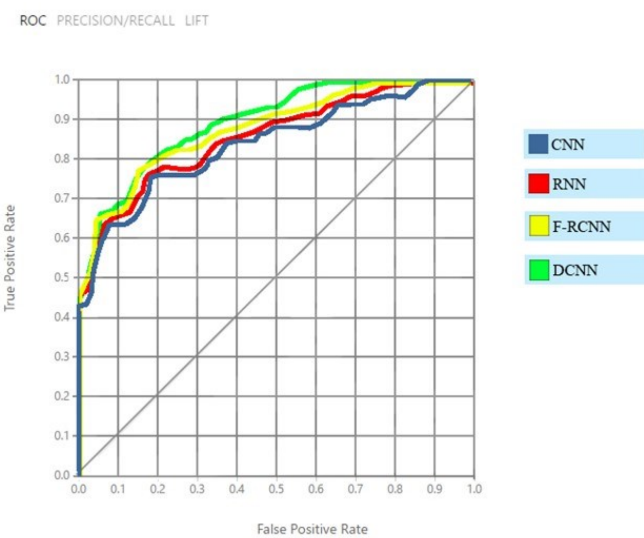

Fig. 12. The Comparing Receiver Operating Characteristic (ROC) Curves with the best quality metrics.

The receiver operating characteristic (ROC) curve is used to rate the prediction capacity of the model. When correlating different classing models, the ROC curves of each model be drawn, and the area under the curve can be used as a sign of the quality of the model. For example, it can be found in Fig. 12 that the DCNN model shows a more vital ability to defect defections, which helps to identify the complex surface defects problems. The experimental results also show that the DCNN model has higher accuracy and adaptability to defect detection problems than conventional models.

V. CONCLUSION

This study includes the quality control of solar cell busbars and fingers passing through the production line using the CNN method and comparing them with a standard test comparator, calculating the loss of surface quality, and classifying these losses by detecting them on the surface. The study is divided into two stages. The first stage detects the parts with defective surfaces and their ordering; the second stage examines the randomly selected samples' surfaces and categorization.

When we analyzed the model performance results, 98 pieces were defective, and two were non-defective. Therefore, when we look at the analysis results from table 1, 98 errors were detected; however, in two samples randomly placed to test the DCNN reliability, it was 100% successful. Therefore, the Equation was tested correctly.

Out of the obtained numerical values, thirty-five parts below 70 in the study; show the parts with the most errors produced in that production line. These were obtained as (0,30) between (0,69) respectively. Apart from these, the highest number of clusters was obtained between 90% and 99%.

We did not use a higher resolution image because to obtain a higher resolution it is necessary to use much higher quality image systems. Our aim in this study was to keep the cost at low levels.For future study could be carried out using image details by increasing the higher image layers and using higher resolution images.

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CONFLICTS OF INTEREST

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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