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Improved Image Processing Technique Based Internet of Things and Convolutional Neural Network for Fault Classification of Solar Cells

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ABSTRACT

In the clean, renewable electricity generation, the solar photovoltaic (PV) classification structure became the most appealing. Furthermore, due to varied characteristics and ambient temperature, performance varies. To analyze its performance, a real-time and remote monitoring system is required. The use of the Internet of Things (IoT) in the solar cells classification and in the solar PV systems monitoring is dependent on image processing, and its effectiveness has been investigated. Data gathering, data gateway, and a Constitutional Neural (CNN) model for fault classification prediction in solar cells make up the enhanced proposed system. This research uses a 2,426 solar cells acquired datasets from high-resolution electroluminescence (EL) photographs for automated fault probability detection. The gathered images depict both faulty and functioning solar cells with varying degrees of degradation in polycrystalline and monocrystalline solar modules. Experts categorized the solar cells and labeled the photos basing on the fault possibility in each image. The tagged images could be used to develop machine-learning algorithms and computer vision for detecting and forecasting faults including cell quality, PID, fracture interconnects, and fractures, as well as anticipating power efficiency losses.

Keywords: CNN, IoT, solar cells, prediction, classification.

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INTRODUCTION

PV power is generated by converting sunlight into electricity utilizing solar cells (PV cells). At the industrial level, multi- and mono-crystalline silicon solar cells comprise over 97% of the commercial solar sector [1]. Faults in the Si wafer or undetectable micro fractures are common during the manufacture of solar cells. Because PV modules are made up of PV cells connected in series, cell faults have already been identified as module output deterioration's major cause [2].

Certain faults are not readily apparent, and even professionals will be unable to detect them. These flaws, particularly, reduce a PV module's efficiency, leading to high manufacturing costs for PV companies. However, a variety of imaging technologies (such as infrared) were developed for PV modules examination, electroluminescence (EL) imaging looks to become the most viable option when compared to other imaging methods due to its high resolution. Electroluminescence (EL) imaging is a well-established method for visual inspection of solar modules [3, 4].

EL imaging enables for the collection of high resolution photos of photovoltaic modules and the identification of flaws in an individual solar cells [4, 5]. And from the other side, manual inspection of EL images takes time and requires specific knowledge. As a result, an automated visual examination method is preferred. In most cases, data collection is the first stage in an automatic visual inspection technologies development. The data includes images of both broken and working solar panels. Furthermore, in order to identify faults at the solar cell level, EL images of solar modules should be separated firstly into individual solar cells [6]. The data in EL imaging, which detects different types of damage in solar modules, is not cheap. Solar modules don't fail on a regular basis; instead, they fail over time. But at the other side, artificial aging is not a commercially viable solution. As a result, data collection could consume the time, if not impossible, for the quantitative and development evaluation for algorithms of visual inspection. Because of that, the datasets used for evaluating the methods of visual inspection in the literature are tiny, cover just specific problem areas, and aren't made public for taking benefits of getting this data. Because different datasets worked by several authors, comparing methods of different inspection is practically being not possible.

We designed an annotated solar cell photos library that produced from high resolution EL photos of photovoltaic modules to encourage proper scientific practice and the visual evaluation tools development. With the help of a specialist, all of the shots were labelled, and the solar cell images were divided into numerous fault probability categories. Using the available data, we developed a classifier that could estimate fault probability in solar cells with an accuracy of 88.42 percent using only photographs. This allows us to quickly identify solar module breaking patterns and evaluate if whether testing is required to confirm the likely loss of power efficiency.

RELATED WORKS

In the section of related work, we will offer works that related CNN and solar cells. Binbin Ni [7] in his article describes the approach of deep learning based intelligent fault detection. The method begins with the creation of a network on the base of sample attributes. To obtain the initial network value, training is used. Then, changing the network parameters using neural technique to gain the mapping link between the templates of defect-free and the training samples. As a result, test sample defect identification is done by comparing the faulty image to the reconstructed image.

The results of the experiments reveal that the deep-learning approach could address the problem of fault identification in the EL picture of a solar module successfully. Additionally, the strategy allows for considerable flexibility. However, whenever it comes to the actual applications, this method still has several flaws. For instance, network training takes a long time for producing high pixel level image processing difficult. SCC fault pictures were collected utilizing photoluminescence (PL) and evaluated by utilizing preceding lightweight convolutional neural network (CNN), according to Huaiguang Liu [8].

The silicon wafer pictures were separated depending on the local difference extremum of edge projection for the high pixel SCC image identification problem (LDEEP). Second, the 3-scale feature prediction layer and the feature fusion layer are being improved, a model with the deep backbone feature extraction network that is CNN that is lightweight was recommended for identifying small sized flaws or weak edges in silicon wafers; the model revealed further details about the features. According to the final trial's findings, the updated model's mean average precision (MAP) was 87.55%, 6.78% higher than the original method. In addition, the detection velocity was 40 frames per second (fps), which met the accuracy requirements and realtime detection.

The method of detection may be more effective at detecting SCC defects, laying the foundation for automated SCC fault diagnosis. On the base of actual data from Mexico, Morelos, Temixco, Mario Tovar [9] proposed a 5-layer CNN-LSTM model for solar power forecasts in his work. In the proposed hybrid model, the CL (CL) works as a filter, capturing local data properties before the long short-term memory networks gathers temporary information. In the end, comparing the 5-layer hybrid model performance with the two famous benchmark, 2-layer hybrid model (CNN-LSTM), and a single model (a single LSTM).

The results show that the model of hybrid neural network performs better than the model of single prediction, the Ridge regression, the Lasso regression, and the two-layer hybrid model in terms of prediction accuracy. In his study [10], V S Bharath presented a fault detection method based upon IR thermography to identify PV models and detect any potential faults. PV strings from a solar facility were photographed in the field infrared for the aim of identifying PV panels.

The techniques of image-processing depend on edge detection and the "Hough transform" were used to diagnose defects effectively. The addressed photo is liable to feature extraction before being submitted via the algorithm of classification for identification and localization of the defect type. The following are some of the advantages of the suggested classification method: effective monitoring, quick detection, and great efficiency in fault classification.

The created technique's testing and training accuracy are approximately 94 and 93.1 percent, correspondingly, according to experiment findings, which is superior to traditional techniques. The work [11] submitted by S. Naveen Venkatesh shows how to detect defects in PVM using deep learning and aerial photos from UAVs. The photos were classified using the softmax activation function, and high-level features were obtained using "CNN." Feature extraction and fault classification were performed using a pre-trained "VGG16" network. In contrast to “AlexNet”, “VGG16” uses a series of smaller filters' convolutional layers which layered together to extract and learn complicated characteristics from the pictures. When comparing it to different pre-trained networks with less convolution layers, the “VGG16” performs better.

CNN's main benefit is its capacity to deal with photos of low resolution and poor quality. The research took into account a total of six test settings. Several test circumstances were investigated, including glass breakage, snail trail, delamination, discolorations, burn marks, and excellent panel. The model showed a great accuracy in fault classification which is 95.40 percent in categorizing all of the “PVM” situations; according to the findings. An unruled technique basing on a novel image-processing method to detect PV slopes was developed [12] by Tito G. Amaral to achieve the necessary fault diagnostics.

A problem is detected by comparing the slopes of various modules. The method was based on principle component analysis (PCA), a recent image processing technique. It is recommended that instead of utilizing the "PCA" to lower data dimensions, it be used to calculate the slope of an object. The suggested method has various advantages, including eliminating the usage of a large data range and particular sensor, quick identification, and dependability also when pictures are partial owing to reflections and other issues. A deviation index was also suggested based on this method, which was used to distinguish the defective panel(s). To verify and validate the suggested technique, many test scenarios were employed. The findings show that the "PCA" could be modified and employed in image-processing approaches to identify the PV slope panels and therefore efficiently detect a failure, even when the picture contains partial sections of an item.

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Table 1. Comparison of Related Works

Research Title	Year	Aim	Research Approach	Reported accuracy
"Intelligent Defect Detection Method of Photovoltaic Modules Based on Deep Learning" [7]	2018	The aim is to provide a deep learning-based intelligent flaw detection method to tackle the fault identification problem in the solar module's EL picture	Creating a network based on the sample attributes. Training is used to acquire the initial network value. The network parameters are then adjusted using the neural technique to get the mapping link between defect-free templates and training samples. At last, defect identification of test samples is accomplished by comparing the reconstructed picture to the defect image.	N/A
"Research on Online Defect Detection Method of Solar Cell Component Based on Lightweight Convolutional Neural Network" [8]	2021	The aim is to provide an online method for detecting defects of solar cell component depending on Lightweight CNN	For LDEEP, the silicon wafer images were split depending on the local difference extreme of edge projection. For detecting small sized defects or weak edges in silicon wafers, a "CNN" model with a deep backbone feature extraction network architecture that is lightweight is suggested	87.55%
"PV Power Prediction, Using CNN-LSTM Hybrid Neural Network Model. Case of Study: Temixco-Morelos, México" [9]	2020	The aim is to predict PV power using a 5-layer "CNN-LSTM" model for solar power projections.	The convolutional layer works as a filter in the proposed hybrid model, extracting local data characteristics before the long short-term memory network extracts temporal information	N/A
"Fault Classification for Photovoltaic modules using Thermography and Image Processing" [10]	2019	The aim is to develop a fault classification system to identify PV panels and detect any possible problems	Image processing methods based on edge detection and "Hough transform" are used for fault detection. For localization and identification of the kind of defect, the addressed picture faces feature extraction and then is sent via a classification algorithm. The proposed classification method has the following benefits: great efficiency in fault classification, quick detection, and effective monitoring.	93.1%
"Fault Detection in aerial images of photovoltaic modules based on Deep learning" [11]	2020	The aim is to provide a deep learning approach based on VGG16 network to classify faults in pv panels.	The defect detection in "PVM" depending on deep learning using aerial photos received from UAVs is presented in the work. A pre-trained "VGG16" network was used to perform feature extraction and defect classification	97.9%
"Fault Detection in PV Tracking Systems Using an Image Processing Algorithm Based on PCA" [12]	2021	The aim is to develop an unruled technique depending on a novel image processing method to detect PV slopes for fault detection	This method is based on principle component analysis (PCA) to calculate the slope of an object	95.4%

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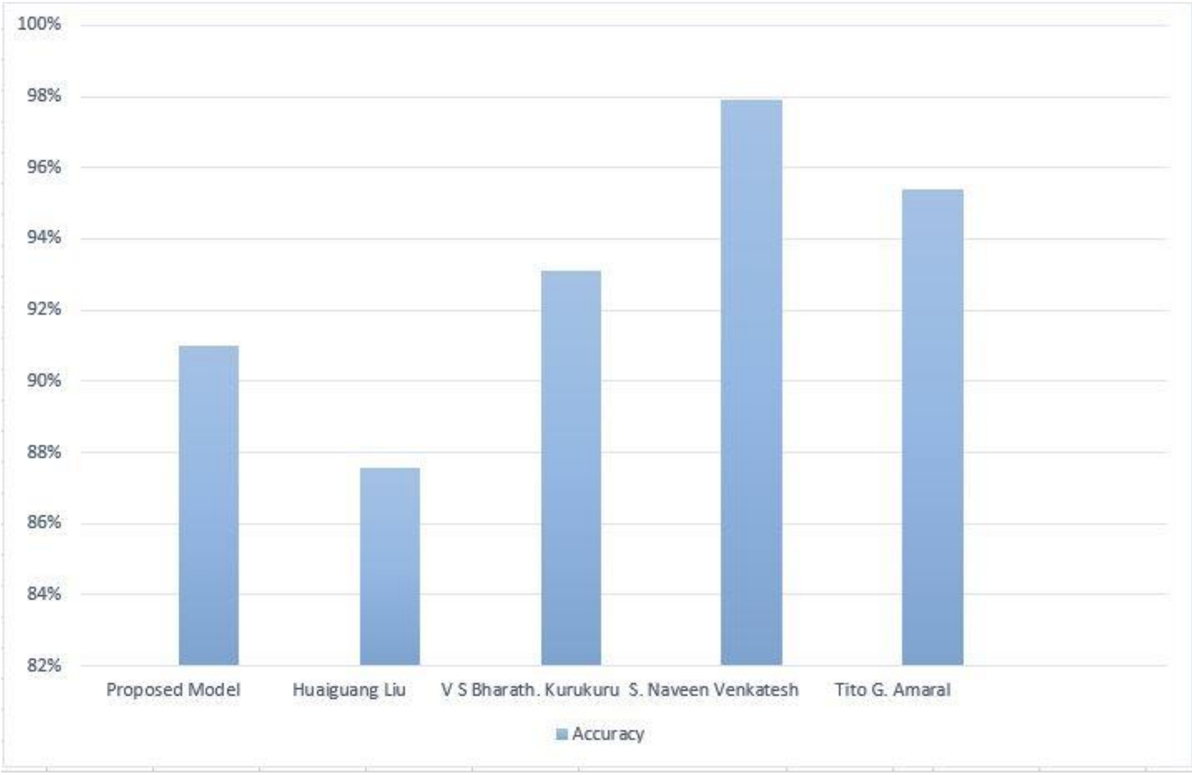

Figure1. Accuracy for similar systems

METHODOLOGY

The presented system in this work is able to measure the solar PV values temperature, current, and voltage, as well as the sunlight intensity it receives from the panel. A microcontroller Arduino ATMega2560 recorded all of the data, which was then sent to the internet using a wireless transmitter NodeMCU ESP8266. Thinkspeak, an open source IoT cloud platform, utilized to save overall data from the sensor and depict it in a graphical representation so that the user may watch the data remotely as long as there is an internet connection. The monitoring is done using the Thinkspeak website as well as a smartphone app created with MIT App Inventor. Figure 1 shows the system's block diagram. After constructing an IoT platform, we used a CNN model to predict solar cell fault categorization. In order to be taught to categorize photovoltaic cells, we will break the files images and it's values, the images was labeled depending on the values that precede every file image, like the image is the input of the network and the output is the address of it. The data is divided into a test section and a training segment, with the training part accounting for 70 percent of the total and the test section for 30 percent, because the numerical values that reflect the solar cell's state in the file were turned into evidence linguistically. This paper's methodology was based on the framework from [13] and [14].

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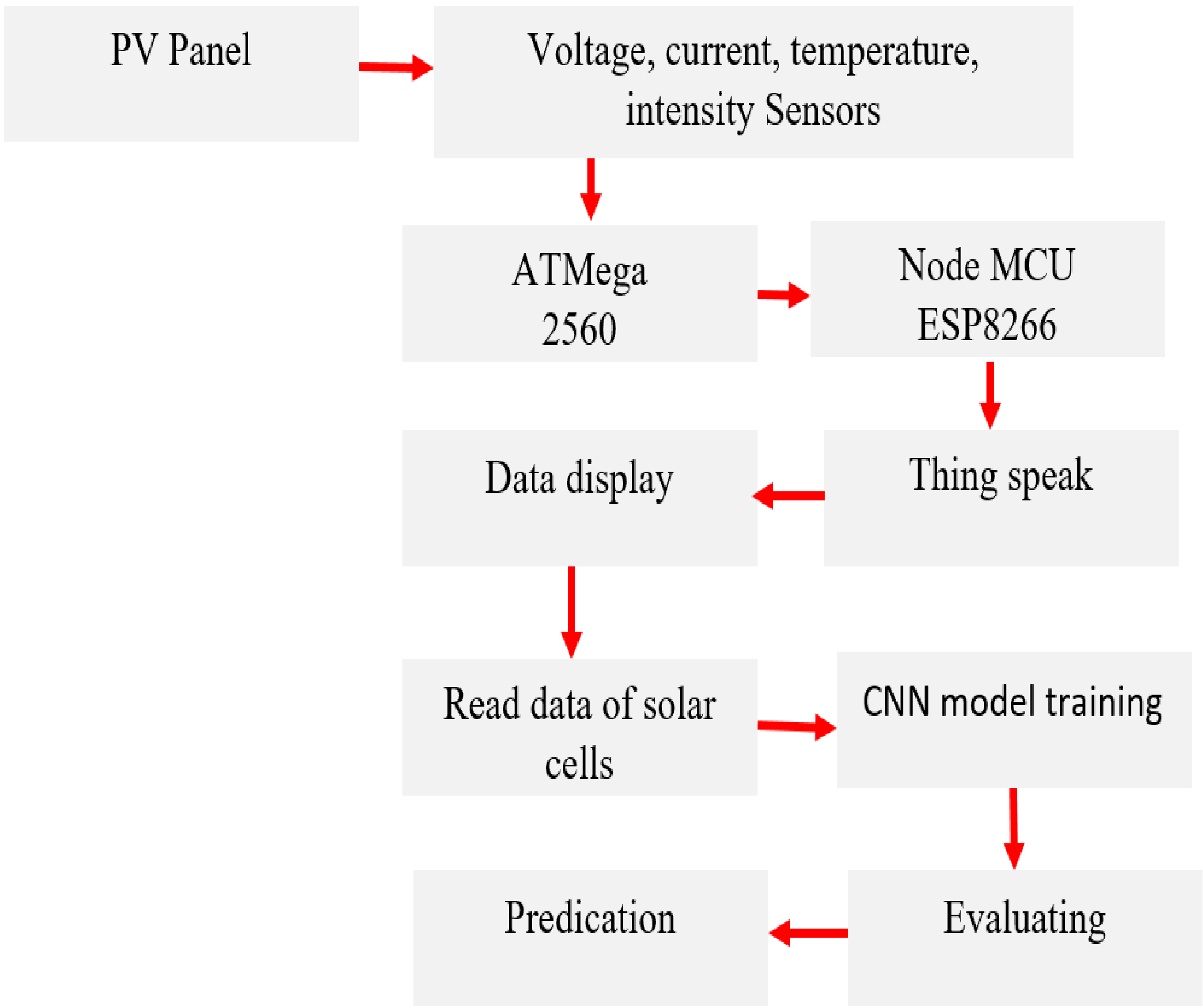

Figure 2. Proposed Framework

Data Category

This research makes use of Thinkspeak, an open source IoT cloud platform application. This application uses the hypertext transfer protocol (HTTP) to retrieve and store data from the sensor over the internet. The sensor's data was uploaded to the cloud using the board of Arduino that connected to wifi module. It keeps all of the sensor's data up to date and provides the status application for the users. For utilizing these features, the user must first generate an IP address or an account that contains multiple channels in order to monitor the system's various parameters.

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Figure 3 depicts the data gateway system's flowchart diagram. This platform allows users to see data as a graphical representation. The data must be accessible easily via online interface with internet-based monitoring (via smartphone or computer).
The main benefit of this system is that the output information from solar PV panels could be easily monitored from any place within the internet connection [14].

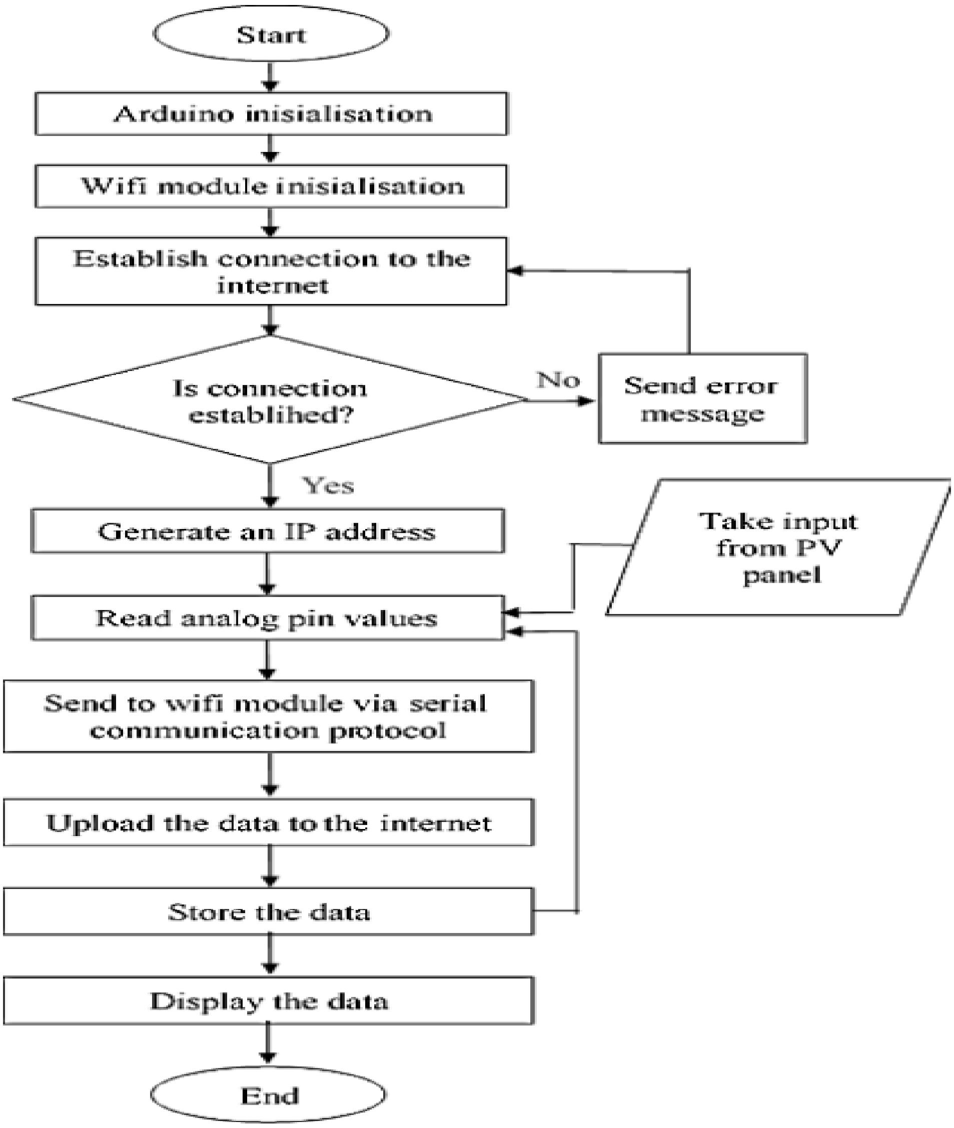

Figure 3. Data Gateway

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Data Description

The dataset includes 2, 624 images of photovoltaic cells, which are used in solar panels to transform light into electricity. The images include healthy, broken, and less efficiency cells. All of the photos are consistent in terms of size and perspective and are gathered from 44 various units. Furthermore, all distortions created by the camera's lens were removed. For the purposes of categorization, it doesn't matter if a fracture is orientated at negative or positive angles. It doesn't matter if the fracture is on the bottom or top edge. As a result, data augmentation could be used for better use.

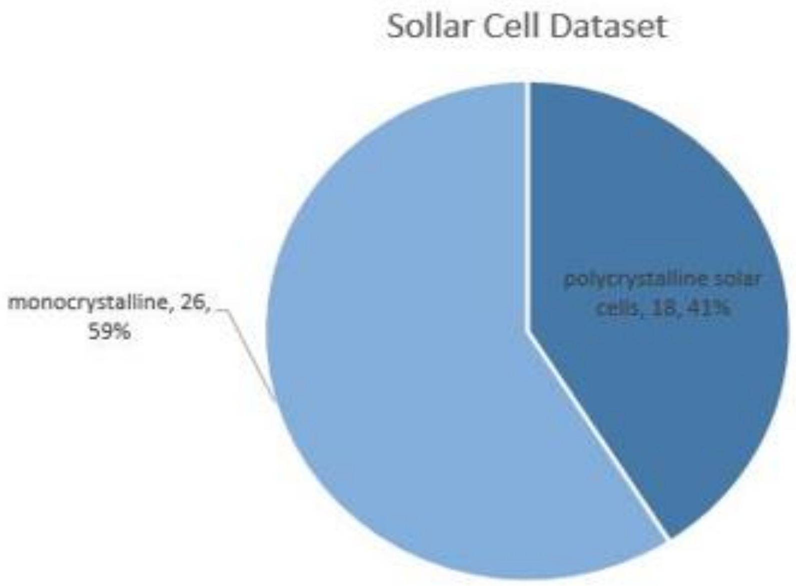

Figure 4. Data set description

CNN Model

We employed the CNN architecture that includes an input layer and output layer as well as three intermediary layers in our project. Every layer consists of a convolutional layer, a maxpooling layer, batch normalization layer which speeds the training, and an activation method layer. The model in our study is purely based on the EL photos collection of our subject. It has been thoroughly trained from the beginning. A number of CNN topologies are investigated, with the goal of proposing an excellent light network. This section offers their details. The model assessment criteria and the model optimization technique are covered in this section. The strategy flowchart that was used is shown in Figure 4. To start, data augmentation methods are applied to EL images in order to get additional information.

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These procedures aid in the model's performance optimization. After that, the pictures are put into a six-layers CNN architecture that was selected (4 CLs and 2 fully connected layers). The model is tuned and trained to learn how to categorize EL images. Lower CLs gain low-level EL image features, while higher CLs acquire high-level EL image specific information. The 12 model is then evaluated using the testing data against numerous performance indicators. The constructed model can determine whether an EL image is normal or not. CNN networks are useful for image recognition because their architecture is common in real-world photos. The computing neuron output equation in a CL is as follows [15]. A typical CNN architecture starts with a few CLs, then a pooling layer, then additional CLs, and so on. At the network's top, there are a few fully connected layers and the ultimate judgment layer. Unlike CLs, neurons in totally 11 connected layers have no limited receptive field. Also the layers stated above, CNN networks frequently contain batch normalization and a dropout layer [16].

ReLU: The input contains the greyscale EL images' pixel values. The image has size of 100 by 100 pixels. The photographs are in black-and-white. Neurons with programmable parameters make up CLs (biases and weights). In additional to the activation function, the calculations of these layers rely on learnable parameters. Based on tests, the size of the input picture, and the size of the dataset, we discovered that 4 CLs are enough to achieve great performance. Each CL's ReLU serves as its activation function. L2 weight regularization is applied to every layer as well. As shown in [17], convolution is a basic action for neurons.

Equation (2) defines the convolution process for one-dimensional discrete signals. The input is represented by f, the kernel function is represented by k, and the kernel/filter width is represented by w. ReLU utilized max (0, X) = X as activation function if X is the CL neuron input. By using ReLU activation function, the problem of vanishing gradient is eliminated. It has no effect on the size of the volume. Nonlinearity in the neuron's output coupled to the input is caused by the activation function. Batch normalization [18] permits the system to determine the best mean and scale for every input layer. It occurs prior to the function's activation. It standardizes every feature in a small batch at first. The dataset mean Subtracted from every datapoint, and then divide the difference by the standard deviation of the data generates the standardization technique. During the batch normalization operation, the standardized output is scaled and shifted by utilizing two new parameters for each layer after standardization. The scaling process is controlled by one parameter, while the shifting process is controlled by the other. Batch normalization is used when a weight in a neural network becomes extremely large during model training, producing instability (exploding/vanishing gradient issue). The entire technique is shown in equations 3 to 6 [19]. σ B is the standard deviation, μ B is the mean, m B is the occurrences number in a small batch, X ̂^((i)) is the input after 0 centering and normalization, the scaling parameter is γ, the shifting parameter is β , is the smoothing term is ϵ, and Z^((i)) is the output, which really is a scaled and shifted version of the input, after the batch normalization procedure. Fully connected (FC) layer: Each neuron in the completely connected layer is connected to all of the neurons in the layer before it, as the name implies. Convolution layer, on the other side, have a separate connection configuration and are referred to in the literature as hidden layers. The fully linked layer's dropout rate is set to 0.5. Dropout [20] is an occurrence in which units in neural networks drop out at random. Each neuron has a p probability of being temporarily dropped out during a training phase (here, p is 50 percent).

A neuron could be ignored in one phase yet active in the next step or steps. The neurons are just lost through the training procedure. Neurons that have been trained utilizing the dropout technique do not co-adapt with surrounding neurons and are as functional as possible on their own. Small adjustments in input have little effect on them. These characteristics contribute to the model's robustness.

$$(k * f)[n] = \sum_{m=0}^{w} k[m] f[m+n] \qquad (1)$$

$$\mu_B = \frac{1}{m_B} \sum_{i=1}^{m_B} X^{(i)} \qquad (2)$$

$$\mu_B = \frac{1}{m_B} \sum_{i=1}^{m_B} (X^{(i)} - \mu^B)^2 \qquad (3)$$

$$\hat{X}^{(i)} = \frac{X^{(i)} - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \qquad (4)$$

$$Z^{(i)} = \gamma . \hat{X}^{(i)} + \beta \qquad (5)$$

RESULTS

During developing and training the model multiple parameters should be chosen. Those factors are referred to as hyper parameters, and they affect the performance of neural network. In addition, nodes in the network and network layer number are two of the important characteristics. In this training procedure we chosen mini batch size = 128, Adam optimizer, as well as learning rate, small batch size, and optimizer. In figures below describes the losses and accuracy of every picture from dataset. The PV panel monitoring system could be reached via the Thinkspeak website as well as the PV Monitor app presented in this research. The data displayed by both ways is the same. There are just one difference which are the data was displayed on the website simultaneously. The PV Monitor application, on the other hand, allows the user to pick which data should be displayed and which should be hidden. The performance of the application, PV monitoring, evaluated from the time it took to transfer data from the hardware (data collection), via the data gateway, and in the end into the application displaying. The average transmission time was 60 seconds, with 30 and 150 seconds as the minimum and maximum transmission times, respectively.

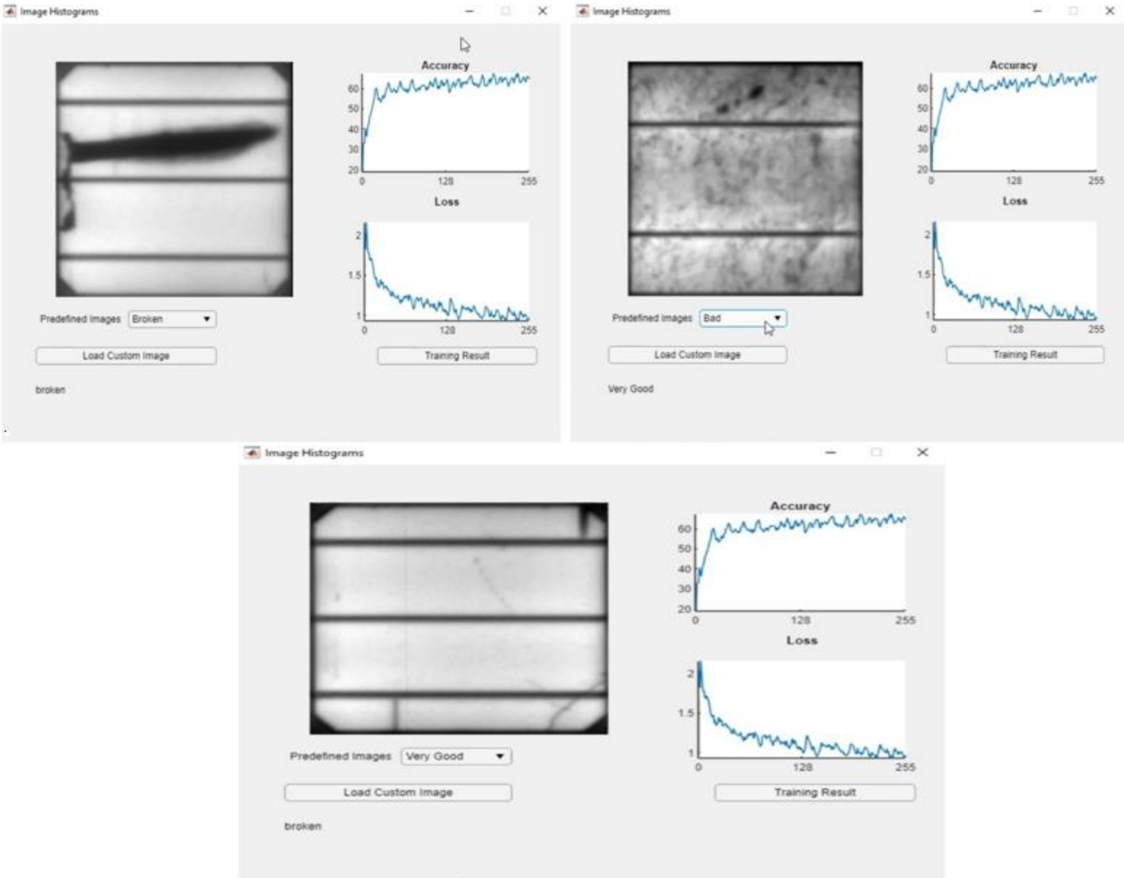

Figure 5. Accuracy and loss of images

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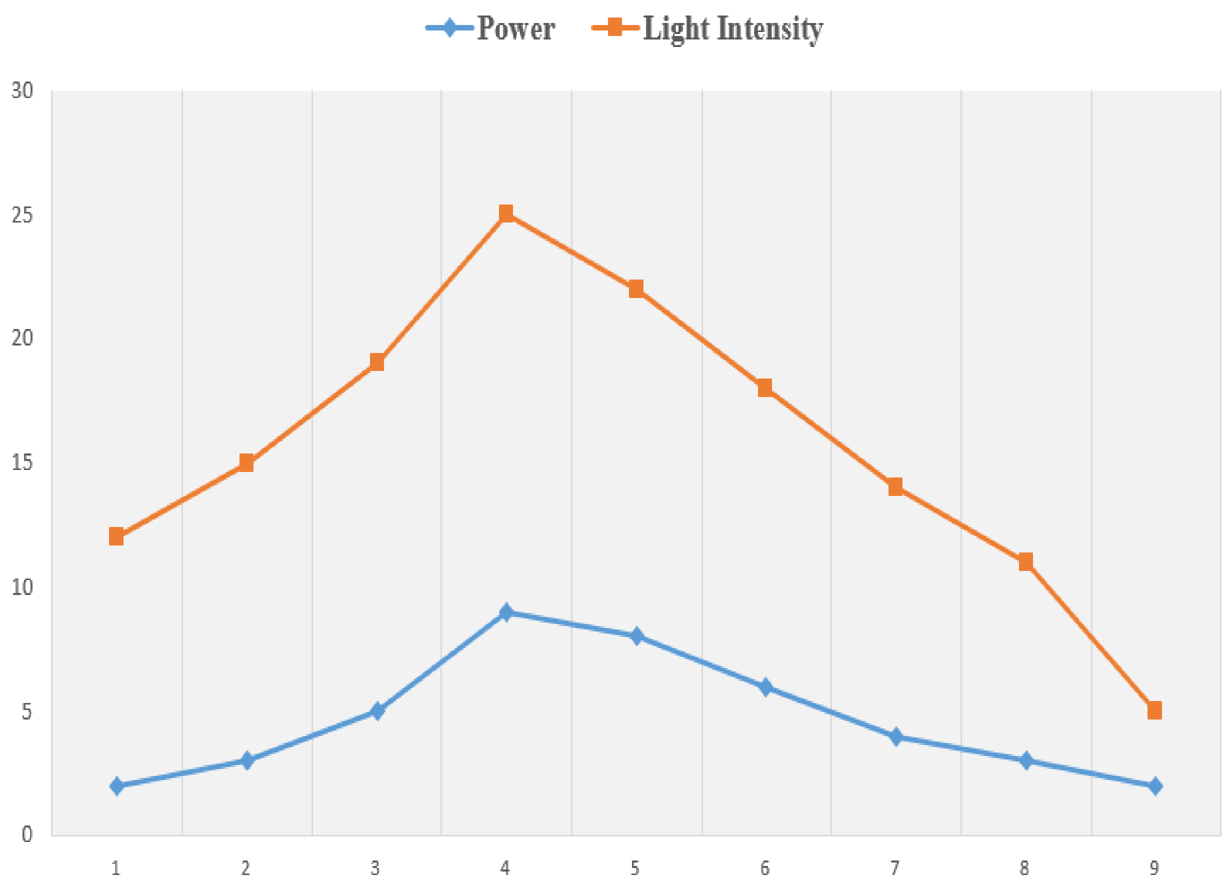

Figure 5. Power vs. light intensity

CONCLUSION

Data acquisition, data gateway, and a light CNN model were proposed as part of an Internet of Things (IoT) implementation in the monitoring of solar PV systems. The acquisition of the data was completed successfully with great accuracy. With a mean transmission time of 60 seconds, the data gateway was capable of sending the graphical data representation to the CNN model. The final research outcomes show that the suggested monitoring system could be a promising option for intelligent remote and realtime solar PV system monitoring. Also included CNN architecture for detecting solar cell faults in electroluminescence photos automatically. On the available first publicly solar cell datasets of EL images, the suggested method produced state-of-the-art results.

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REFERENCES

[1] Hosenuzzaman, M., Rahim, N. A., Selvaraj, J., Hasanuzzaman, M., Malek, A. A., & Nahar, A. (2015). Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation. *Renewable and Sustainable Energy Reviews*, *41*, 284-297.
[2] Gangopadhyay, U., Jana, S., & Das, S. (2013). State of art of solar photovoltaic technology. In *Conference papers in science* (Vol. 2013). Hindawi.
[3] Abdelkader, M. R., Al-Salaymeh, A., Al-Hamamre, Z., & Sharaf, F. (2010). A comparative Analysis of the Performance of Monocrystalline and Multiycrystalline PV Cells in Semi Arid Climate Conditions: the Case of Jordan. *Jordan Journal of Mechanical & Industrial Engineering*, *4*(5).
[4] Makrides, G., Zinsser, B., Norton, M., Georghiou, G. E., Schubert, M., & Werner, J. H. (2010). Potential of photovoltaic systems in countries with high solar irradiation. *Renewable and Sustainable energy reviews*, *14*(2), 754-762.
[5] Kaplani, E. (2012). Detection of degradation effects in field-aged c-Si solar cells through IR thermography and digital image processing. *International Journal of Photoenergy*, *2012*.
[6] Sovetkin, E., & Steland, A. (2019). Automatic processing and solar cell detection in photovoltaic electroluminescence images. *Integrated Computer-Aided Engineering*, *26*(2), 123-137.
[7] Ni, B., Zou, P., Li, Q., & Chen, Y. (2018). Intelligent defect detection method of photovoltaic modules based on deep learning. *vol*, *161*, 167-173.
[8] Liu, H., Ding, W., Huang, Q., & Fang, L. (2021). Research on Online Defect Detection Method of Solar Cell Component Based on Lightweight Convolutional Neural Network. *International Journal of Photoenergy*, *2021*.
[9] Tovar, M., Robles, M., & Rashid, F. (2020). PV power prediction, using CNN-LSTM hybrid neural network model. case of study: Temixco-morelos, méxico. *Energies*, *13*(24), 6512.
[10] Kurukuru, V. B., Haque, A., Khan, M. A., & Tripathy, A. K. (2019, April). Fault classification for photovoltaic modules using thermography and machine learning techniques. In *2019 International Conference on Computer and Information Sciences (ICCIS)* (pp. 1-6). IEEE.
[11]Venkatesh, S. N., & Sugumaran, V. (2021). Fault Detection in aerial images of photovoltaic modules based on Deep learning. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1012, No. 1, p. 012030). IOP Publishing.
[12]Amaral, T. G., Pires, V. F., & Pires, A. J. (2021). Fault Detection in PV Tracking Systems Using an Image Processing Algorithm Based on PCA. *Energies*, *14*(21), 7278.
[13]Akram, M. W., Li, G., Jin, Y., Chen, X., Zhu, C., Zhao, X., ... & Ahmad, A. (2019). CNN based automatic detection of photovoltaic cell defects in electroluminescence images. *Energy*, *189*, 116319.
[14] Priharti, W., Rosmawati, A. F. K., & Wibawa, I. P. D. (2019, November). IoT based photovoltaic monitoring system application. In *Journal of Physics: Conference Series* (Vol. 1367, No. 1, p. 012069). IOP Publishing.
[15] Kim, J. J., Choi, H., Paek, S., Kim, C., Lim, K., Ju, M. J., ... & Ko, J. (2011). A new class of cyclometalated ruthenium sensitizers of the type CNN for efficient dye-sensitized solar cells. *Inorganic Chemistry*, *50*(22), 11340-11347.

[16] Balzategui, J., Eciolaza, L., & Arana-Arexolaleiba, N. (2020, January). Defect detection on polycrystalline solar cells using electroluminescence and fully convolutional neural networks. In *2020 IEEE/SICE International Symposium on System Integration (SII)* (pp. 949-953). IEEE.
[17] Luo, Z., Cheng, S. Y., & Zheng, Q. Y. (2019, October). Gan-based augmentation for improving cnn performance of classification of defective photovoltaic module cells in electroluminescence images. In *IOP Conference Series: Earth and Environmental Science* (Vol. 354, No. 1, p. 012106). IOP Publishing.
[18] Zhang, X., Hao, Y., Shangguan, H., Zhang, P., & Wang, A. (2020). Detection of surface defects on solar cells by fusing Multi-channel convolution neural networks. *Infrared Physics & Technology*, *108*, 103334.
[19] Bhattacharya, S., Arya, D., Bhowmick, D., Thomas, R. M., & Gupta, D. K. (2021). Improving Solar Cell Metallization Designs using Convolutional Neural Networks. *arXiv preprint arXiv:2104.04017*.
[20] Rahman, M. R., Tabassum, S., Haque, E., Nishat, M. M., Faisal, F., & Hossain, E. (2021, December). CNN-based Deep Learning Approach for Micro-crack Detection of Solar Panels. In *2021 3rd International Conference on Sustainable Technologies for Industry 4.0 (STI)* (pp. 1-6). IEEE.

BIOGRAPHY

Israa Hussain completed her master's study in 2017 from Yildiz Technical University / Turkey, in computer engineering, specializing in networks, and a bachelor's degree in computer technology engineering in 2010, as well as a bachelor's degree from the University of Baghdad, College of Education, Department of Home Economics, and she is a computer teacher in the Ministry of Education since 2001.

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