Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

DETECTING DUST ACCUMULATION ON SOLAR PANELS USING IMAGE PROCESSING AND DEEP LEARNING

Dr. DALIA MAHMOUD

Associate Professor, Department of Control Engineering, Faculty of Engineering, Al-Neelain University, Khartoum, Sudan. Email: d.daliamahmoud@yahoo.com

Dr. RAED A. SHALWALA

Associate Professor, Department of Electrical Engineering, Faculty of Engineering and Architecture, Umm Al-Qura University, Makkah 24381, Saudi Arabia. Email: rashalwala@uqu.edu.sa

MOHAMED O. KHOZIUM

Professor, College of Computing & Information Technology, Arab Academy for Science, Technology, and Maritime Transport. Email: prof.khozium@adj.aast.edu

Abstract

Recently, there has been an increasing need for solar energy production plants due to the expansion of economic activities worldwide and the growing demand for clean and environmentally friendly energy sources to meet these requirements. These fields are usually established in wide areas. Various environmental factors such as dust, snow, pollen, and bird droppings can affect the full penetration of sunlight onto the solar panels, reducing their electricity production efficiency. Therefore, regular inspection and cleaning of solar energy fields are required. However, even regular inspections are usually not sufficient, especially in countries with harsh and unpredictable climates, where energy losses from solar fields are common. In this paper, an automated inspection system based on image processing and deep learning has been designed to ensure continuous monitoring and assessment of the status of solar panels. An Elman neural network has been designed with a focus on improving the image pre-processing algorithm to ensure optimal performance.

Keywords: Solar Plants; Power Losses; Elman Neural Networks; Median Filter**.**

1. INTRODUCTION

The need for clean and environmentally friendly sources of energy has led to an expansion in the construction of solar energy fields worldwide. However, the energy efficiency of solar cells is frequently constrained by defects that arise, leading to a decrease in their overall performance and lifespan [1].

The regions characterized by the highest levels of annual sunlight are mainly desert regions [2]. Dust and environmental factors affect energy production from solar panels. Dust particles, pollens, rains, snow and birds' droppings accumulation on the surface of the solar panel reduce the arrival of light to it, and this reduce the generated energy [3]. Figure 1 illustrates the status of a solar plant after wind storms; While Figure 2 illustrates the energy losses of solar plants in different countries due to dust and other environmental factors.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

Figure 1: Dust Accumulation on The Surface of Solar Panels

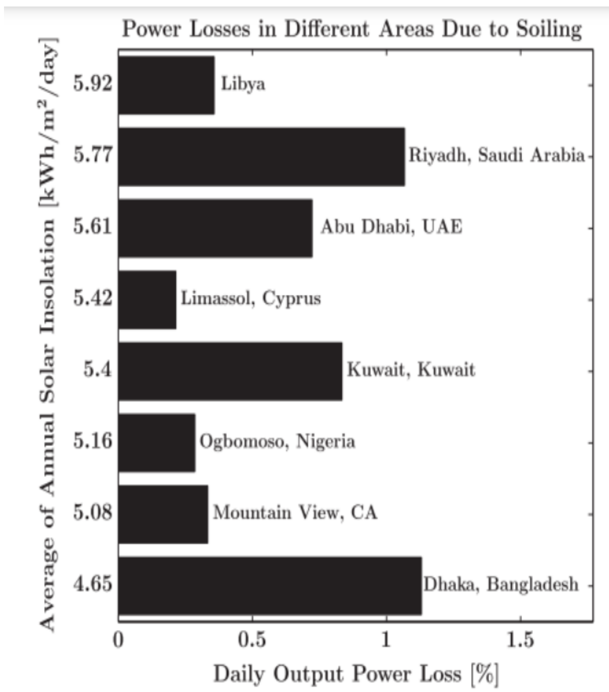

Figure 2: Power Losses per Day from Some Solar Plants [3]

An empirical investigation was conducted by Ahmed et al. [4], to analyze the impact of dust accumulation on the surface of photovoltaic (PV) modules within a solar power facility. The findings of the investigation revealed that the presence of dust on PV modules leads to an average decline of 14.6 W/month in power output, a decrease of 0.3%/month in efficiency, and a reduction of 1.84% in performance ratio. Specifically, for PV modules with a power capacity of 780 W, the overall performance is impaired by 2.21% as a result of dust buildup. [4]. In study [5] Athar et al. found that dust accumulation reduces PV system efficiency significantly. Rice husk led to the minimum power value of 3.88 W. Also they found that smaller dust particles block more solar radiation on PV modules.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

In order to solve this problem a regular cleaning for solar modules must applied. However, due to the nature of these environmental conditions we may need for a monitoring technique to constant monitoring and evaluating for the panels in order to increase the efficiency of photovoltaic panels [3]. The use of image processing and deep learning methods can help in solving this issue.

This paper consists five sections; the main problem and the importance of the study are illustrated in the Introduction in section 1. Section 2 reviews the related works. Section 3 and 4 contain the methodology and the obtained results respectively. Section 5 represents the conclusion of the paper.

2. LITERATURE REVIEW

Several studies were made in order to automate the monitoring of the solar plants. Aline Kirsten et. al. [6] presented a review of automating PV plant inspection using aerial infrared thermography. The study focus on fault detection, classification, and automation algorithms for efficiency.

Onim, M.S.H. et. al. [7], a novel convolutional neural network (CNN) structure, termed SolNet, is suggested for the purpose of detecting dust accumulation on solar panels. An evaluation of the efficacy and outcomes of SolNet is conducted by comparing it to other advanced algorithms in the field.

Olorunfemi et al. [8], proposed solar panel dirt detection and removal system using color sensing technology.

Dust detection on PV modules using image processing for optimization was proposed by Qasem et al. [9]. Method involves aerial robotics, high-resolution cameras, and MATLAB tool. Algorithm detects dust concentration and assesses level of dust.

Muhammed Unluturk et al. [2], investigated impact of dust shading on PV module energy efficiency, and they used image processing to predict PV module pollution levels.

Y. Shao et al. [10], proposed a new dust detection method for solar panels with economic benefits. They improved algorithm outperforms Adam algorithm in dust detection task.

Tolga Ozer and Omer Türkmen [11], developed AI drone for solar panel detection using YOLOv5 was done by. The system achieved F1 score of 97% for panel detection. Proposed Histogram Equalization-based preprocessing technique. Used deep learning algorithms YOLOv5, YOLOv7, and YOLOv8.

The paper [12] which prepared by Tonatiuh et al., compared image segmentation techniques for detecting dust on PV panels. The paper analyzed unsupervised, supervised ML, and Deep Learning models' performance. They found supervised ML models balanced performance and speed; Deep Learning excelled with unstandardized inputs.

A novel method to detect hot spots in PV panels proposed by T. Sun, H. Xing, S. Cao et al. [13]. The linear hot spots of PVpanels are radioactive strips caused by a mixture of

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

bird droppings, dust, and rain. The authors utilized AP-YOLOv5 network with improved anchors and prediction heads.

S. Fan et al. [14] developed a novel image enhancement algorithm for dust level evaluation on PV panels. The algorithm achieved 83.78% accuracy in estimating dust level on PV panels.

R.M. Arias Velásquez and T.T. Pando Ezcurr [15], proposed dust analysis in PV solar plants system using satellite data for evaluation.

3. METHODOLOGY

In this paper, the power of deep learning was utilized along with image processing techniques to recognize dust accumulation and other impediments on the surfaces of solar cells. The methodology used can be divided into two parts: Pre- processing of solar panels images and designing a deep learning system for image classification.

3.1 Image Samples Pre-Processing:

The image pre-processing stage represents a crucial step in designing any image analysis and recognition system. In this stage, images are converted from a pixel data format to a digital vector format at the end of the processing operation. The algorithm used in the pre-processing stage is illustrated in Figure 3 below.

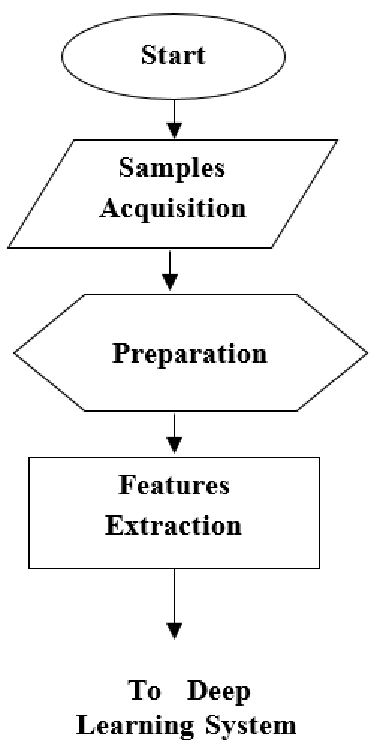

Figure 3: Pre-Processing Algorithm

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

Sample Acquisition:

In this study, the sample set in [16] was used. The sample set included various images of clean solar panels and other images that were dirty due to dust, bird droppings, and other environmental factors. Figure 4 shows some of the images used in this study.

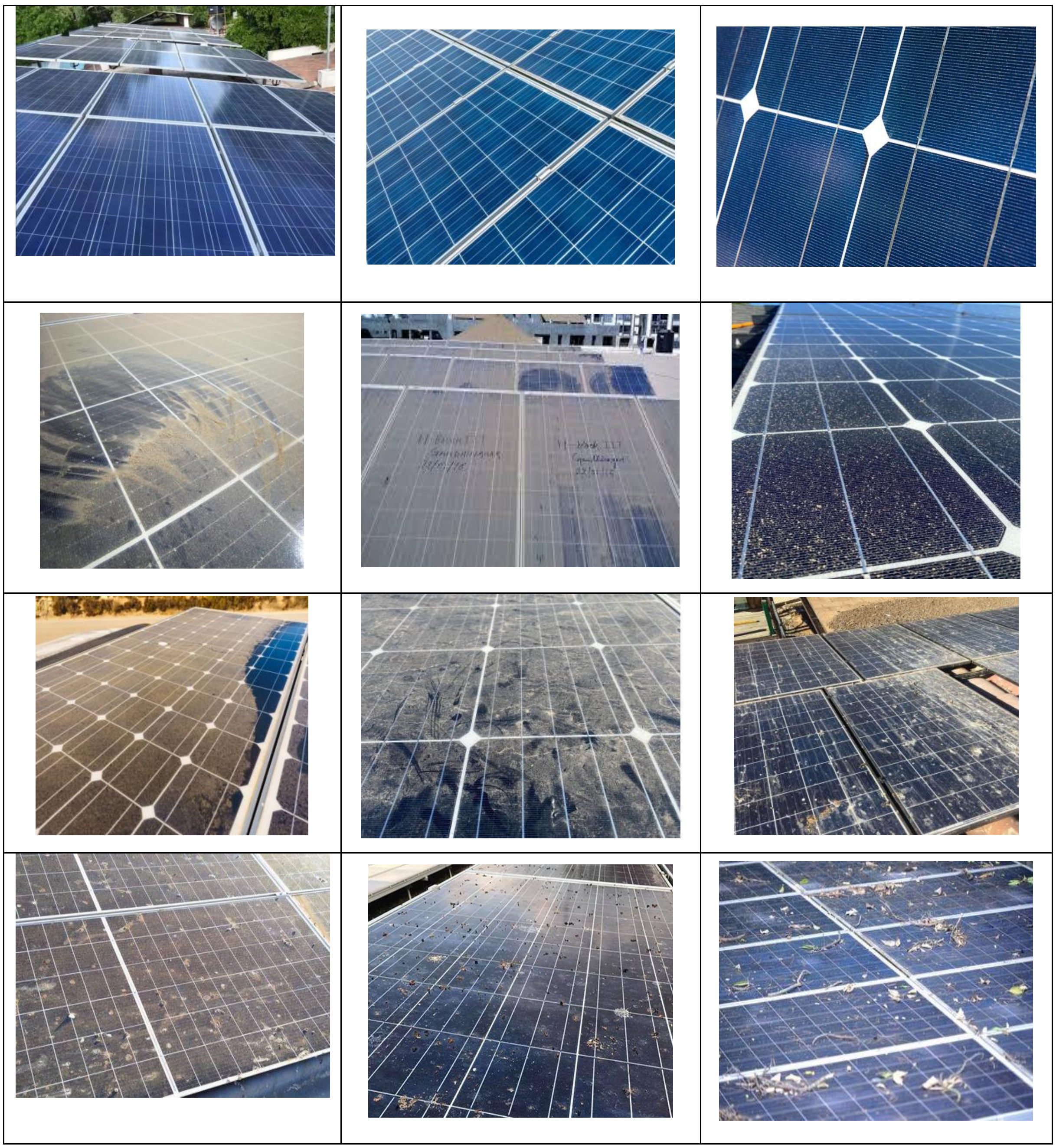

Figure 4: A Part of the Dataset

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

Sample Preparation:

This step is crucial as it first enhances the quality of the images using a filter; a Median Filter was used to perform this task. Secondly, the images are divided into frames to ensure that each part of the image is examined properly. The sample in Figure 5 was divided into 3 frames with an average of 90 pixels in each frame.

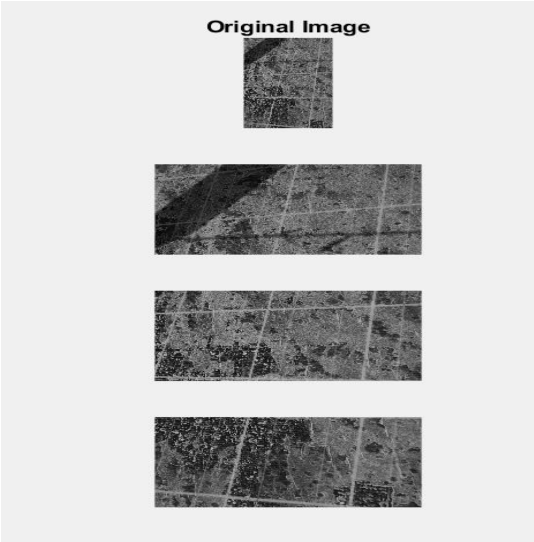

Figure 5: Segment the Sample to Frames

Feature Extraction:

Here, key features representing the images are extracted since an image contains a lot of data and very little information. The importance of this step lies in preparing main features that enable the recognizer to classify the sample. In this study, Haralick's method was used for feature extraction as shown in equations from 1 to 14 [17].

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

No	Features	Formula
1	Angular Second Moment	$\Sigma i\, \Sigma j\, p(i,j)^2$
2	Contrast	$\Sigma_{n=0}^{Ng-1} n^2\{\Sigma_{i=1}^{Ng} \Sigma_{j=1}^{Ng} p(i,j)\}, \lvert i-j \rvert = n$
3	Correlation	$\frac{\Sigma i \Sigma j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
4	Sum of Squares: Variance	$\Sigma_i \Sigma_j (i-\mu)^2 p(i,j)$
5	Inverse Difference Moment	$\Sigma_i \Sigma_j \frac{1}{1+(i-j)^2} p(i,j)$
6	Sum Average	$\Sigma_{i=2}^{2N_g} i p_{x+y}(i)$
7	Sum Variance	$\Sigma_{i=2}^{2N_g} (i - f_{8)})^2 p_{x+y}(i)$
8	Sum Entropy	$-\Sigma_{i=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\} = f_8$
9	Entropy	$-\Sigma_i \Sigma_j p(i,j) \log(p(i,j))$
10	Difference Variance	$\Sigma_{n=0}^{Ng-1} i^2 p_{x-y}(i)$
11	Difference Entropy	$-\Sigma_{n=0}^{Ng-1} p_{x-y}(i) \log\{p_{x-y}(i)\}$
12	Info. Measure of Collection 1	$\frac{\mathrm{HXY} - \mathrm{HXY1}}{\max\{HX, HY\}}$
13	Info. Measure of Collection 2	$(1 - \exp[-2(HXY2 - HXY)])^{\frac{1}{2}}$
14	Max. Correlation Coefficient	*The square root of the second largest eigenvalue of Q, where* $Q(i,j) = \Sigma_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$

3.2 Image Classification System:

The deep learning system used in this study is an Elman neural network which is a Recurrent network with a feedback loop giving it an additional advantage over other types of networks when used as an image recognizer [18]. Figure 6 illustrates an Elman neural network.

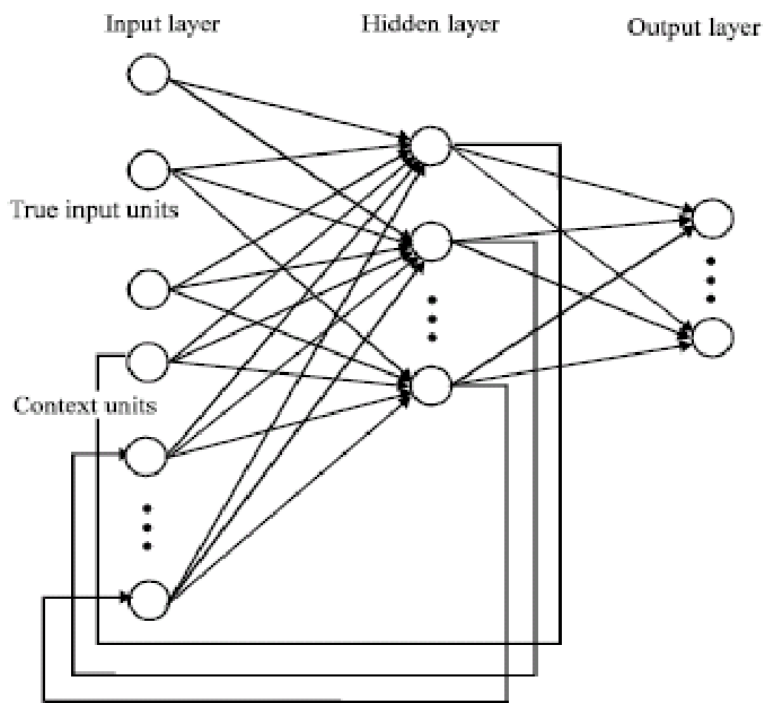

Figure 6: Elman Network Architecture

4. RESULTS AND DISCUSSION

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

When applying the image pre-processing algorithm, the image was first divided into 3 frames, meaning each frame was about 90 pixels long. This division process is crucial as it ensures that each part of the image is examined separately.

After preparing the samples, which represent training data for the neural network, an Elman-type network was used due to its good diagnostic ability for images, as mentioned earlier.

The neural network had 42 inputs and 1 output; it was three-layered and used Logsigmoid activation function between the input layer and hidden layer, and Purelinear function between the hidden layer and output layer. The number of neurons in the hidden layer was adjusted several times to achieve better performance, as shown in Figure 7.

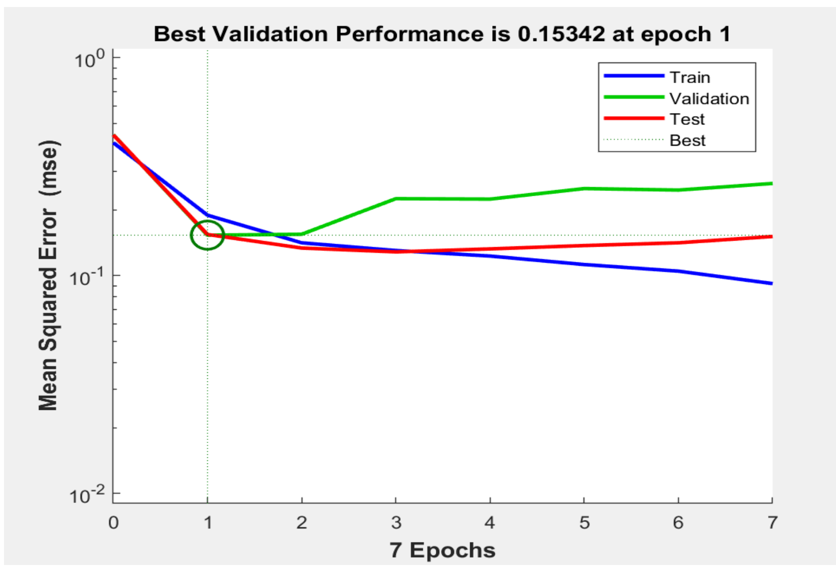

Figure 7: Performance Error in Training Samples

As it clear from Figure 7, the training data error decreased to 0.15 when the number of neurons in the hidden layer was 47, which was the best value achieved. Also the regression of the network showed good performance for training data, as indicated in Figure 8.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

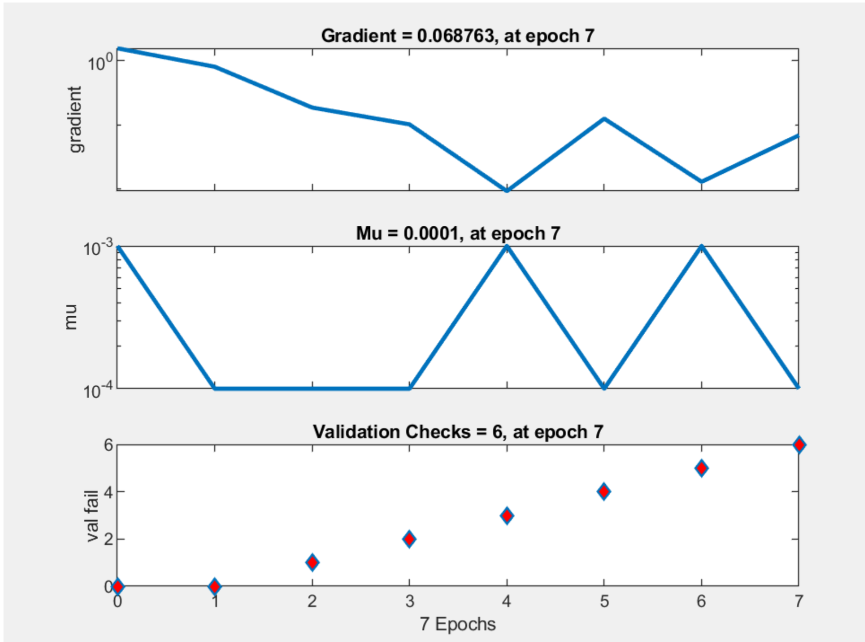

Figure 8: The Regression of the Network during the Training Stage

After completing the training phase, the neural network was tested on a new sample set different from the training set; however, the output for all samples was one, indicating that the neural network could not correctly classify the new samples.

To improve performance, the frame length in the initial processing stage was adjusted to 30 pixels in average, and Haralick features were extracted from each frame. A new Elman-type neural network was designed with 140 inputs (outputs of feature extraction stage) and one output. The structure of the neural network that gave the best performance is shown in Figure 9; while Figure 10 illustrates the decrease in training data error during training phase and ending training using early stopping algorithm at the best point for training, validation and testing data, to ensure network generalization; it also shows the regression value for the trained network at that point.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

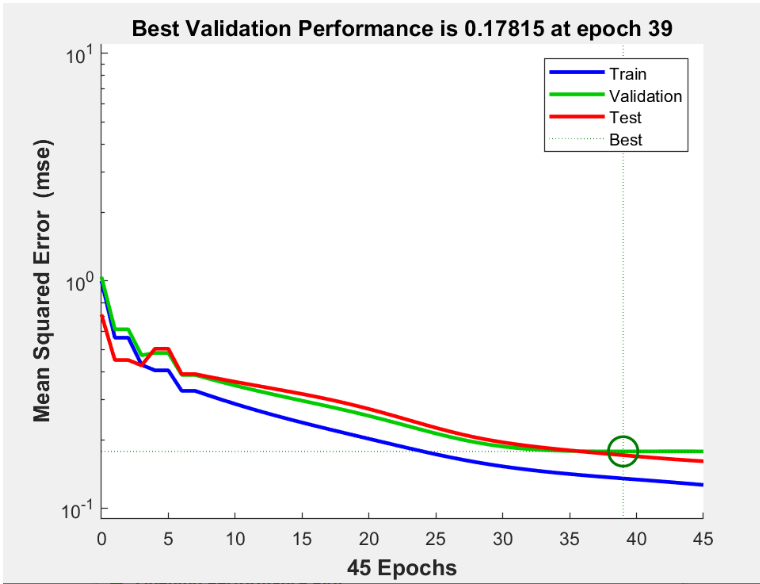

Figure 9: The Elman Network Training Performance

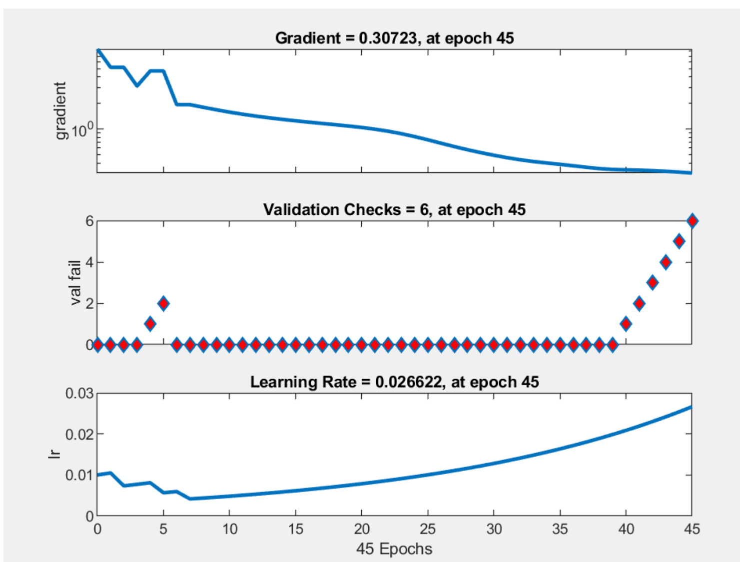

Figure 10: The Regression of the Network

Using a test sample set, the accuracy of the neural network in recognizing new samples that were not trained on during the training phase was examined, and the network's performance was measured. The network showed a performance of 99% in recognizing new input samples, which is a very excellent percentage compared to previous studies reviewed in this study.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 05:2024
DOI: 10.5281/zenodo.11144260

5. CONCLUSION

Expanding the construction of solar energy plants must be accompanied by attention to the quality of those plants. Environmental conditions expose solar panels to various types of pollutants, which affect their power production and increase power loss rates. This paper presented an automatic technique for identifying and recognizing panels that have accumulated dust and other pollutants on their surface. The study demonstrated the ability of Elman neural networks, with the assistance of image preprocessing algorithms, to accurately determine the condition of the panels. These algorithms can be added to survey drones or cameras mounted in solar energy production plants to continuously monitor the condition of the panels.

References

1) Ula Hijjawi, Subhash Lakshminarayana, Tianhua Xu, Gian Piero Malfense Fierrob, Mostafizur Rahman, " **A review of automated solar photovoltaic defect detection systems: Approaches, challenges, and future orientations** ", Solar Energy 266, 2023.

2) Muhammed Unluturk, Ahmet Afsin Kulaksiz, Ali Unluturk, " **Image Processing-based Assessment of Dust Accumulation on Photovoltaic Modules** ", 2019 1st Global Power, Energy and Communication Conference (IEEE GPECOM2019), Cappadocia, Turkey, 2019.

3) Gabriel Moura Dantas, Odilon Linhares Carvalho Mendes, Saulo Macêdo Maia, Auzuir Ripardo de Alexandria, "**Dust detection in solar panel using image processing techniques: A review**", Research, Society and Development, v. 9, n.8, e3219885107, 2020.

4) Ahsan Ahmed, " **Experimental Investigation of Dust Accumulation on the Performance of the Photovoltaic Modules: A Case Study of Karachi, Pakistan** ", Applied Solar Energy, 2021, Vol. 57, No. 5, pp. 370–376.

5) Athar Hussain, Ankit Batra and Rupendra Pachauri, "**An experimental study on effect of dust on power loss in solar photovoltaic module**", Renewables, 2017.

6) De Oliveira, A.K.V.; Aghaei, M.; Rüther, R., " **Automatic Inspection of Photovoltaic Power Plants Using Aerial Infrared Thermography: A Review**", Energies, 2022.

7) Onim, M.S.H.; Sakif, Z.M.M.; Ahnaf, A.; Kabir, A.; Azad, A.K.; Oo, A.M.T.; Afreen, R.; Hridy, S.T.; Hossain, M.; Jabid, and Md Sawkat Ali, "**SolNet: A Convolutional Neural Network for Detecting Dust on Solar Panel**", Energies, 2023,16, 155.

8) B.O. Olorunfemi, N.I. Nwulu and O.A. Ogboluman, "**Solar panel surface dirt detection and removal based on arduino color recognition** ", MethodsX 10, 2023.

9) H. Qasem, A. Mnatsakanyan and P. Banda, "**Assessing dust on PV modules using image processing techniques**," 2016 IEEE 43rd Photovoltaic Specialists Conference (PVSC), Portland, OR, USA, 2016, pp. 2066-2070.

10) Yichuan Shao, Can Zhang, Lei Xing, Haijing Sun, Qian Zhao, Le Zhang," **A new dust detection method for photovoltaic panel surface based on Pytorch and its economic benefit analysis** ", Energy and AI 16, 2024.

11) Tolga Ozer, Omer Türkmen, "**An-approach-based-on-deep-learning-methods-to-detect_2024_Computers-and-Elec**", Computers and Electrical Engineering 116, 2024.

12) Tonatiuh Cruz-Rojas, Jesus Alejandro Franco, Quetzalcoatl Hernandez-Escobedo, Dante Ruiz-Robles, Jose Manuel Juarez-Lopez, " **A novel comparison of image semantic segmentation**

techniques for detecting dust in photovoltaic panels using machine learning and deep learning ", Renewable Energy 217, 2023.

13) Tianyi Sun, Huishuang Xing, Shengxian Cao, Yanhui Zhang, Siyuan Fan, Peng Liu, "**A novel detection method for hot spots of photovoltaic (PV) panels using improved anchors and prediction heads of YOLOv5 network**", Energy Reports 8, 2022.

14) Siyuan Fan, Xiao Wang, Zun Wang, Bo Sun, Zhenhai Zhang, Shengxian Cao, Bo Zhao, Yu Wang, " A **novel image enhancement algorithm to determine the dust level on photovoltaic (PV) panels** ", Renewable Energy 201, 2022.

15) R.M. Arias Velásquez and T.T. Pando Ezcurr, "**Dust analysis in photo-voltaic solar plants with satellite data** ", Ain Shams Engineering Journal 15, 2024.

16) Dataset Source: https://www.kaggle.com/datasets/pythonafroz/solar-panel-images/data

17) Radityo Adi Nugroho, Arie Sapta Nugraha, Aylwin Al Rasyid, Fenny Winda Rahay, “Improvement **on KNN using genetic algorithm and combinedfeature extraction to identify COVID-19 sufferers based onCT scan image** “, Vol. 19, No. 5, 2021.

18) Eltaher M. Hussein, Dalia Mahmoud, “Brain **Tumor Detection UsingArtificial Neural Networks** “, Journal of Science and Technology Vol. 13, No. 2, 2012.