Identification of Electrical Faults in Underground Cables using Machine Learning Algorithm†

Paramasivam Alagumariappan [1,*], Mohamed Shuaib Y [2], Sonya A [3] and Irum Fathima [4]

[1,2,4] Department of Electrical and Electronics Engineering, B. S. Abdur Rahman Crescent Institute of Science and Technology, Chennai 600048, India; parama.ice@gmail.com

[2] Department of Information Technology, B. S. Abdur Rahman Crescent Institute of Science and Technology, Chennai 600048, India; sonya.yasmin152@gmail.com

[*] Correspondence: parama.ice@gmail.com; Tel.: +91-984-378-0801

[†] Presented at the 6th International Electronic Conference on Sensors and Applications, 15–30 November 2019; Available online: https://ecsa-6.sciforum.net/

Abstract: Transmission and distribution play a vital role in delivering electricity. Presence of any fault in these systems may stop the delivery of electricity, which may create a huge problem in today's world. Hence, fault detection has become essential for delivering uninterrupted power supply. In this work, a portable and intelligent system is designed, and the fault detection on underground transmission lines is done using developed hardware system. Also, the proposed system has a thermal camera which is an 8 × 8 array of infrared thermal sensors interfaced with a system-on-chip device, which collects the real-time thermal images when connected to the device. Further, the thermal camera returns an array of 64 individual infrared temperature readings, of the transmission line and locates the point of damage which might occur due to the aging of conductor insulation, physical force, etc. Also, 200 images with thermal information from the different instances and directions are utilized to train the adapted machine learning algorithm. The python software is utilized to code the machine learning algorithm inside the system-on-chip device. The convolutional neural network-based machine learning algorithm is adopted and it is validated using various performance metrics such as accuracy, sensitivity, specificity, precision, negative predicted value, and F1_score. Results demonstrate that the proposed hardware is highly capable of locating faults in underground transmission lines.

Keywords: convolutional neural network; electrical faults; system on-chip; transmission line

1. Introduction

Recent years, electricity has become one of the survival factors. Electricity being a form of energy which is converted from various other forms of energy and it has to be transmitted from one place to another so that it is distributed to everyone. Energy is existing in various forms. According to many researchers, the most commonly used form of energy is electrical energy, which is produced from various sources like coal, solar, nuclear etc. [1–5]. As it is possible to produce clean electrical energy using various renewable sources like wind mill, solar, hydro etc. and these are considered for generation point of view, the other two important aspects are transmission and power distribution. Transmission is better if produced energy is in the form of alternating current (AC) instead of direct current as it is very easier and cost effective to step-up or step-down the voltage level with minimal losses.

Transmission and distribution play a vital role in delivering electricity. Presence of any faults in these systems may stop the delivery of electricity which is a huge problem in today's life. Hence fault

detection has become essential for delivering uninterrupted power supply. Faults occur due to various reasons and can be classified either as a man-made or a natural disaster. Faults occurring under man-made are more likely to be more predictable when compared to the faults occurring due to natural disasters, as it can't be predicted when, where and how it'll happen. Bulent and Donmez [6] (2010) have proposed that the natural disasters not only faults the power system but also creates disturbances in the power system and can tend to cause blackouts. Musa et al. [7] (2018) have developed a technique for the detection of faults in power transmission system focusing on the fusion of the current signal co-variance with the cumulative approach during power swing. Further, the authors have tested for different fault conditions and the results showed a reasonable time response.

Ashrafi et al. [8] (2015) have proposed a method for identifying DC faults in transmission system with the help of VSC (voltage source converter) HVDC system using sheath voltage, transient voltage and wavelet transform to distinguish the different DC faults. Further, the authors have concluded that the proposed method is fast, reliable and novel strategy for detection of DC faults. Samantaray [9] (2009) has discussed about the identification of fault zone in flexible AC transmission line with the help of decision tree (DT). Further, the authors have experimented the fault inspection by considering one cycle of current and voltage samples post fault as input vector which is given against the target output '1' for faults succeeding the flexible AC equipment's in line and the target output is '0' for faults proceeding the flexible AC equipment's in line. Also, the authors have concluded that the outputs of this system were dependable for fault zone detection and categorization of fault in a flexible AC transmission line.

Many researchers have demonstrated the significance of *Raspberry PI* in various research works and projects irrespective of their fields, from agriculture to medicine. *Raspberry PI* has been an important part in various innovative researches like health care based IOT, iris movement-based wheelchair control, robotic arm control in space with colour recognition, automated blood bank, WSN based automatic irrigation and security system [10–14]. Recently, thermal cameras have been proving its strength through various innovations that is not only beneficial for business point of view but also for humanities greater good, from being used in medical field for detection of various types of disease like breast cancer, thyroid disease, Reynaud's phenomenon and so on. Thermal camera is also used in neonatal intensive care units to measure the body temperature as it is accurate and a non-contact type method and has also proven its worth in security fields as it is deployed for face recognition which is far more secure than normal facial recognition system [15–17].

Once the fault detection in transmission lines is non-contact type, then the mechanism will have diverse advantage over the contact type fault detection. The advantages incorporate lesser operating time, minimizing the deterioration of quality material, reduced use of labors, can be deployed from any location as it can be connected using cloud. The objective of this work is to simplify the method of fault detection by designing a compact mobile non-contact type fault detector capable of capturing thermal images of conductors and determining location of faults.

2. Materials and Methods

2.1. Thermal Image Acquisition system

Figure 1 shows the block diagram of a proposed system for the identification of electrical faults. Further, the proposed system consists of thermal camera and Raspberry PI based system-on-chip device. In this work, the thermal camera AMG8833 consisting an 8X8 array of IR thermal sensors is utilized for the acquisition of thermal images. Also, the AMG8833 type themal camera module is connected directly to the Raspberry PI based system-on-chip device using Inter-Intergrated Circuit (I2C) protocol. The AMG8833 type themal camera module captures thermal images of the conductors which is given as input to the Raspberry PI, where it converts the given thermal image into corresponding matrix and stores it. Further, these stored image matrices are utilized to train the adopted Convolutional Neural Network (CNN) for classification process.
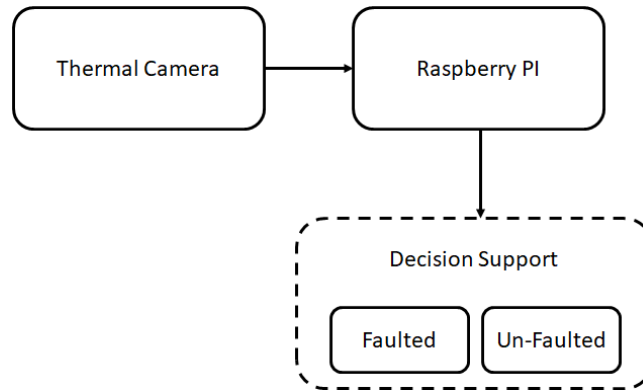
Figure 1. Block Diagram of a proposed system for the identification of electrical faults.

2.2. Convolutional Neural Network

In this work, the deep learning model is developed using Convolutional Neural Networks with LetNet architecture. The LeNet architecture consists of two sets of convolutional, activation, and pooling layers, followed by a fully-connected layer, activation, another fully-connected, and finally a softmax classifier [18,19]. The CNN classifier with LeNet network architecture has been implemented using Keras and Python. Also, a total of 200 images are utilized to train the CNN classifier and additional 100 images are utilized for testing the performance of the classifier. In short, the adopted CNN architecture can be represented as [INPUT - CONV - RELU - POOL - FC] which is explained as:

- INPUT [32 × 32 × 3] holds the raw pixel values of the image, whereas the image of width 32, height 32, and with three color channels R,G,B.
- CONV layer computes the output of neuron that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. This may result in volume such as [32 × 32 × 42] if the filter size is set to 42.
- RELU layer applies an elementwise activation function, such as the max(0,x) thresholding at zero. This leaves the size of the volume unchanged ([32 × 32 × 42]).
- POOL layer performs a down sampling operation along the spatial dimensions (width, height), resulting in volume such as [16 × 16 × 42].
- FC or Fully-Connected layer computes the class scores, resulting in volume of size [1x1x2], where each of the 2 numbers correspond to a class score, such as among the 2 categories (Faulted or Un-faulted).

2.3. Performance Metrics

Total of six metrics such as accuracy, sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and F1 score are computed to evaluate the performance of two different classification systems. The following equations are used to compute the performance metrics of the adopted CNN based classification system.

$$Accuracy = (TP + TN) / (TP + FP + TN + FN) \tag{1}$$

$$Sensitivity = TP / (TP + FN) \tag{2}$$

$$Specificity = TN / (TN + FP) \tag{3}$$

$$Positive\ predictive\ value = TP / (TP + FP) \tag{4}$$

$$Negative\ predictive\ value = TN / (TN + FN) \tag{5}$$

$$F - Measure = 2*\left(\frac{(\text{Pr}\,ecision*\text{Re}\,call)}{\text{Pr}\,ecision + \text{Re}\,call}\right) \tag{6}$$

where, TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

3. Results and Discussion

The proposed hardware was connected to the computer system for analysis purpose. Total of 200 thermal images taken at different instances and direction were utilized to train the adopted CNN classifier. Further, 100 thermal images were utilized as the test image to analyze the performance of the adopted CNN based decision support system.

The 100 test images with un-faulted and faulted conductors are given to the CNN classifier. Figure 3a,b show the output of CNN based decision support system namely un-faulted and faulted respectively. It is seen that the CNN classifier gives the confidence level of 99.90% for un-faulted condition. Further, it is seen that the CNN classifier gives the confidence level of 99.53% for faulted condition. Also, it is observed that there is a significant change while comparing thermal images acquired from both faulty and un-faulty conductors. This is due to the heat generated by the flow of current through the conductor. The amount of current flowing through the conductor changes with respect to its geometry. However, the variation in thermal signatures cannot be visualized or identified normally, the adopted CNN based decision support system classifies faulty and un-faulty conductors accurately.
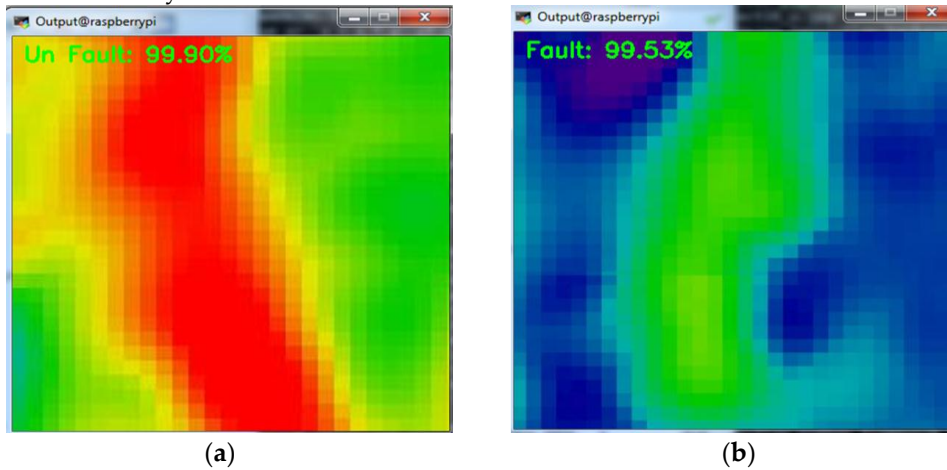

(**a**)　　　　　　　　　　　　　(**b**)

Figure 3. The output of CNN based decision support system on input thermal test image (**a**) Un-faulty condition; (**b**) Faulty condition.

The performance measures such as accuracy, sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and F1 score of CNN classifier are presented in the Table 1. It is seen that the accuracy and sensitivity of the adopted CNN classifier is 93% and 91% respectively. Further, the specificity of the adopted CNN classifier is 95%. Also, it is observed that the performance of a CNN classifier can be improved by increasing train images.

Table 1. Performance Measures of Convolutional Neural Network Classifier.

Performance Measures	Convolutional Neural Network
Accuracy (%)	93
Sensitivty (%)	91
Specificity (%)	95
PPV (%)	95
NPV (%)	90
F1_Score	0.93

4. Conclusions

In this work, a hardware system with AMG8833 thermal camera module and *Raspberry PI* was developed for the acquisition and identification of faults in underground cables. Further, the Convolutional Neural Network (CNN) based classifier was utilized for automated decision support system. Also, the python programming language was used to code CNN based machine learning algorithm. Results demonstrate that the accuracy, sensitivity and specificity of the adopted CNN classifier is 93%, 91% and 95% respectively. Further, the PPV, NPV and F1_Score of the adopted CNN classifier is 95%, 90% and 0.93 respectively. Also, the output of the CNN classifier acts as a decision support to classify faulty and un-faulty conductor. This work appears to be highly capable of locating faults in underground transmission lines.

Author Contributions: Paramasivam Alagumariappan and Mohamed Shuaib Y conceived the idea of this manuscript. Irum Fathima designed the experiments and acquired the thermal images. Paramasivam and Sonya A have performed the analysis. All the authors have contributed towards preparing the manuscript. All the authors have read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Orosco, Eduardo Velasco. Simulation results of an efficient and innovative sun engine for solar to electrical energy conversion. In Collection of Technical Papers. 35th Intersociety Energy Conversion Engineering Conference and Exhibit (IECEC)(Cat. No. 00CH37022), Volume 2, pp. 908–914, 2000.
2. Gurkaynak, Yusuf, Zhihao Li, and Alireza Khaligh. A novel grid-tied, solar powered residential home with plug-in hybrid electric vehicle (PHEV) loads. In 2009 IEEE Vehicle Power and Propulsion Conference, pp. 813-816, 2009.
3. Lyons, James P., Michael C. Robinson, Paul Veers, and Robert W. Thresher. Wind Turbine Technology–The Path to 20% US Electrical Energy. In 2008 IEEE Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, pp. 1-4, 2008.
4. Kumar, Avinash, P.B. Karandikar, and Datta S. Chavan. Generating and saving energy by installing wind turbines along the railway tracks. In 2015 International Conference on Energy Systems and Applications, pp. 25-27, 2015.
5. ElKhodary, S.M., Mahmoud, H.M., Qotb, S.A., and Sharouda, E.E.D.F. The role of nuclear energy in the future of energy systems in Egypt. In 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), pp. 638-643, 2017.
6. Oral, Bülent, and Ferdun Dönmez. The Impacts of natural disasters on power systems: anatomy of the Marmara earthquake blackout. Acta Polytechnica Hungarica 7, no. 2 (2010): 107-118.
7. Musa, Mohammed HH, et al. A covariance indices based method for fault detection and classification in a power transmission system during power swing. *International Journal of Electrical Power & Energy Systems* **2019**, *105*, 581–591.
8. Niaki, SH Ashrafi, H. Kazemi Karegar, and M. Ghalei Monfared. A novel fault detection method for VSC-HVDC transmission system of offshore wind farm. *International Journal of Electrical Power & Energy Systems* **2015**, *73*, 475–483.
9. Samantaray, S.R. "Decision tree-based fault zone identification and fault classification inflexible AC transmissions-based transmission line.". IET generation, transmission &amp.distribution 3.5 (2009): 425-436.
10. Gupta, M. Surya Deekshith, Vamsikrishna Patchava, and Virginia Menezes. Healthcare based on iot using raspberry pi. In 2015 International Conference on Green Computing and Internet of Things (ICGCIoT), pp. 796–799, 2015.
11. Sharma, Jatin, M. Anbarasu, Chandan Chakraborty, and M. Shanmugasundaram. Iris movement based wheel chair control using raspberry Pi—A state of art. In 2017 Innovations in Power and Advanced Computing Technologies (i-PACT), pp. 1–5, 2017.
12. Szabó, Roland, Aurel Gontean, and Alexandru Sfiraṭ. Robotic arm control in space with color recognition using a Raspberry PI. In 2016 39th International Conference on Telecommunications and Signal Processing (TSP), pp. 689–692, 2016.

13. Adsul, Ashlesha C., V.K. Bhosale, and R. M. Autee. Automated blood bank system using Raspberry PI." In 2018 2nd International Conference on Inventive Systems and Control (ICISC), pp. 252–255, 2018.

14. Kumar, K. Kishore, S. Durai, M. Thanjai Vadivel, and K. Antony Kumar. Smart traffic system using raspberry pi by applying dynamic color changer algorithm. In 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), pp. 146–150, 2017.

15. Guzman, Ana M., Mohammed Goryawala, Jin Wang, Armando Barreto, Jean Andrian, Naphtali Rishe, and Malek Adjouadi. Thermal imaging as a biometrics approach to facial signature authentication. *IEEE journal of biomedical and health informatics* **2012**, *17*, 214-222.

16. Sruthi, S., and M. Sasikala. A low cost thermal imaging system for medical diagnostic applications. In 2015 International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM), pp. 621–623, 2015.

17. Savaşci, Duygu, and Murat Ceylan. Thermal image analysis for neonatal intensive care units (First evaluation results). In 2018 26th Signal Processing and Communications Applications Conference (SIU), pp. 1–4, 2018.

18. Golovko, Vladimir, Myroslav Komar, and Anatoly Sachenko. Principles of neural network artificial immune system design to detect attacks on computers. In 2010 International Conference on Modern Problems of Radio Engineering, Telecommunications and Computer Science (TCSET), pp. 237–237, 2010.

19. Mazare, Alin, Laurentiu-Mihai Ionescu, Adrian-Ioan Lita, Gheorghe Serban, and Marin Ionut. Mobile system with real time route learning using Hardware Artificial Neural Network. In 2015 7th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), pp. P–45, 2015.