NRC·CNRC

NRC Publications Archive
Archives des publications du CNRC

Application of deep-learning via transfer learning to evaluate silicone rubber material surface erosion

El Haj, Youssef; El-Hag, Ayman H.; Ghunem, Refat A.

This publication could be one of several versions: author’s original, accepted manuscript or the publisher’s version. / La version de cette publication peut être l’une des suivantes : la version prépublication de l’auteur, la version acceptée du manuscrit ou la version de l’éditeur.
For the publisher’s version, please access the DOI link below./ Pour consulter la version de l’éditeur, utilisez le lien DOI ci-dessous.

Publisher’s version / Version de l'éditeur:
https://doi.org/10.1109/TDEI.2021.009617
IEEE Transactions on Dielectrics and Electrical Insulation, 28, 4, pp. 1465-1467, 2021-08-17

NRC Publications Archive Record / Notice des Archives des publications du CNRC :
https://nrc-publications.canada.ca/eng/view/object/?id=8d69ff91-ff1a-4214-87cc-0d84ea990c2b
https://publications-cnrc.canada.ca/fra/voir/objet/?id=8d69ff91-ff1a-4214-87cc-0d84ea990c2b

Access and use of this website and the material on it are subject to the Terms and Conditions set forth at
https://nrc-publications.canada.ca/eng/copyright
READ THESE TERMS AND CONDITIONS CAREFULLY BEFORE USING THIS WEBSITE.

L’accès à ce site Web et l’utilisation de son contenu sont assujettis aux conditions présentées dans le site
https://publications-cnrc.canada.ca/fra/droits
LISEZ CES CONDITIONS ATTENTIVEMENT AVANT D’UTILISER CE SITE WEB.

Questions? Contact the NRC Publications Archive team at
PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca. If you wish to email the authors directly, please see the first page of the publication for their contact information.

Vous avez des questions? Nous pouvons vous aider. Pour communiquer directement avec un auteur, consultez la première page de la revue dans laquelle son article a été publié afin de trouver ses coordonnées. Si vous n’arrivez pas à les repérer, communiquez avec nous à PublicationsArchive-ArchivesPublications@nrc-cnrc.gc.ca.

National Research Council Canada | Conseil national de recherches Canada

Canada

Application of Deep-Learning via Transfer Learning to Evaluate Silicone Rubber Material Surface Erosion

Youssef El Haj
Ontario tech University
Oshawa, Canada

Ayman H. El-Hag
University of Waterloo
Waterloo, Canada

Refat A. Ghunem
National Research Council Canada (NRC-CNRC)
Ottawa, Canada

ABSTRACT

In this letter a deep learning-based model is proposed for online inspection of silicone rubber outdoor insulators. The inclined plane tracking and erosion test is used as per ASTM D2303 in order to simulate standard erosion on silicone rubber insulation composites. Photos taken for the tested composites are used as training and testing inputs for a convolutional neural network topology in the proposed deep learning model, thereby classifying the degree of erosion damage into light, moderate and severe. The remarkable classification accuracy obtained shows the potential of utilizing the proposed framework for online monitoring of outdoor silicone rubber insulators in the transmission and distribution grid.

Index Terms — Silicone Rubber, Outdoor Insulators, Transmission and Distribution, Condition Monitoring, Deep Learning

1 INTRODUCTION

OUTDOOR silicone rubber (SiR) insulators have been commonly used as backbone infrastructure of the overhead transmission and distribution lines in the power system. However, SiR insulators are prone to long-term aging, thus erosion leading to insulator failure. Hence, it is imperative to develop inspection techniques that can detect the degree of erosion on SiR insulators as precursors of insulator failure.

Among other methods such as radio frequency (RF) antenna, acoustic sensors, infrared (IR) and ultraviolet (UV) camera [1], visual inspection has been a common inspection method applied on currently installed SiR insulators on transmission and distribution lines. However, these existing methods can be time consuming, difficult to use in the detection of small defects and subjective. In addition, a correlation between what the sensors can measure and the physical damages such as erosion area and depth has yet to be found.

With the rise of computational power, image processing and machine learning (ML) have become popular for a wide number of outdoor insulator inspection applications. While the application of ML has led to high accuracy outcomes, extracting statistically significant features as input predictors in the ML model has been always a tedious process [2]. Deep learning algorithms like convolutional neural network (CNN) on the other hand have shown great potential to replace the existing conventional ML algorithms. One of the major benefits of using deep learning algorithms is their ability to learn directly from the input data without the need to extract any features. Few attempts have been recently applied using deep learning-based models in order to detect damages in SiR insulators with promising results [3]. In this paper the authors are extending the work of [3] by improving the generalization of the proposed deep learning model. It should be noted that this paper investigates the feasibility of a potential framework for the application of deep learning to evaluate surface damages on silicone rubber insulators, rather than introducing a robust monitoring system at this early stage.

Manuscript received on xx Month 20yy, in final form xx Month 20yy, accepted xx Month 20yy. Corresponding author: A. El-Hag.

2 PROPOSED DEEP LEARNING FRAMEWORK

A Deep learning model using convolutional neural networks (CNN) with a transfer learning is proposed. Transfer learning is a relatively faster learning approach that requires a smaller number of images with respect to training a network from scratch. In addition, transfer learning aims to perform a fine tuning over the weights of the selected deep learning network in order to classify new objects that are not included in the original training of the network. The proposed model is implemented in the MATLAB® environment. A summary of the model framework is summarized in the block diagram shown in Fig.1.

Figure 1. Block diagram description of implementing the transfer learning.

Three different deep learning networks have been used in this study, namely; AlexNet, GoogleNet and ResNet50. Alexnet is a deep Convolutional Neural Network (CNN) that was trained on 1.2 million high resolution images. The structure of the neural network is composed of 60 million parameters and 650 thousand neurons. Furthermore, the CNN has 8 layers distributed as following: 5 convolutional layers and 3 fully connected with softmax layers. The number of the softmax layers is selected based on the number of the classes that the system is needed to identify. Alexnet has the capability to mitigate the overfitting issues by utilizing a state of art regularization method in the fully connected layers and this technique is called "dropout" [4]. On the other hand, GoogleNet is a pretrained deep CNN network that is based on inception architecture. This architecture increases the computer memory efficiency in the training process because it increases the number of neurons at each stage without uncontrolled increase in the computational complexity. GoogleNet has 22 deep layers and it was trained using 1.2 million images, 50 thousand images for validation and 100 thousand images for testing. The GoogleNet was developed to classify 1000 objects and it can be used through transfer learning to identify other objects [5]. Finally, ResNet50 has been designed to classify 1000 objects and it can be used via transfer learning to classify other objects and it can be used for other applications such as face and voice recognitions. It has 50 deep layers and 25.6 million parameters with a capability to overcome the issue of the vanishing gradient [6].

To ensure fair comparison between the different classifiers the following parameters were fixed for all classifiers.

Table 1. Training options for the developed classifier via transfer learning.

Training Option	Assigned Value
Training Solver	Stochastic Gradient Descent with Momentum (SGDM)
Initial Learning Rate	1×10^{-4}
Maximum Number of Epochs	10
Batch Size	5
Using of the Validation Data	Enabled

3 CASE STUDY

Samples of SiR composites tested in the inclined plane tracking and erosion test (IPT) as per ASTM D2303 and showing different degrees of erosion on the surface were collected. Three sets of images were taken for use in the proposed model. In the first set, images for the eroded surfaces were taken indoors under the following controlled conditions with (1) direct lighting applied on the object, (2) the camera set perpendicular to the object's surface and placed 20 cm away from the object and (3) no filters or modifying lenses used to take the image. The images were classified into three categories based on the degree of erosion, i.e light, moderate and severe erosion as depicted in Fig. 2. It should be noted that this criterion was developed based on experience with testing SiR insulation in the IPT for erosion evaluation [7]. Since the main objective is to explore the feasibility of the proposed framework, the investigation was limited to classifying erosion area in this paper. However, it is important to note other parameters require investigation before achieving a robust monitoring system, such as erosion depth.

Photos were also taken at different angles in order to increase the size of the dataset used in the model. A total of 1810 images were obtained while maintaining a balanced distribution as follows: 669 images for light erosion, 546 images for the moderate erosion, and 595 images for the severe erosion. It is worth mentioning that all the punctured marks on the images resulted from electrodes holding the samples during the IPT (Fig. 2), not actual erosion, and therefore were cropped out of the model. The training, testing and validation sets had respectively 70%, 25% and 5% of the entire data set. The second and the third sets of images were taken outdoors and respectively in the day and nighttime.

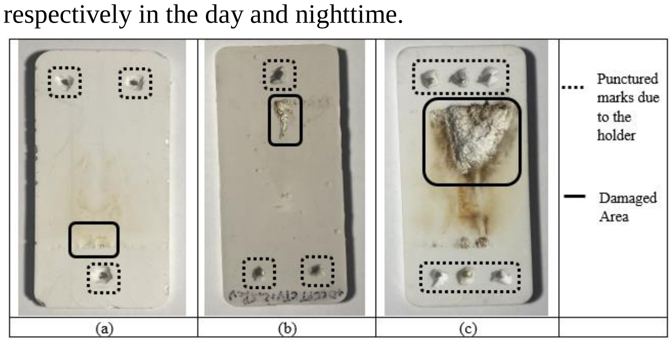

Figure 2. Samples from the data set representing the classified classes: (a) Light erosion (damaged area < 1 cm^2) (b) Moderate erosion (1 $cm^2 \leq$ damaged area $\leq$ 4 cm^2) and (c) Severe erosion (damaged area $\geq$ 4 cm^2).

Two CNN training techniques, thus models, were developed. In both models AlexNet was applied. In the first training approach only first set of images were used (Model G-I); whereas, in the second model 15% of the second and third set of images were added to the training set (Model G-II). As such each of the two models was tested three times to evaluate the ability of the model to classify images taken in the controlled environment, in the daytime and nighttime outdoor conditions.

Fig. 3 summarizes the classification accuracy obtained for each testing condition. Insignificant influence was obtained for adding the day and nighttime images to the training testing set on classifying erosion on the images taken at controlled environment. On the contrary, a remarkable influence was obtained for adding the daytime and nighttime training set in the classification of erosion of photos taken in both the daytime and nighttime outdoor conditions. Such a finding shows that is very crucial to increase the conditions of the training samples to construct a more generalized classifier valid for a more practical application in the outdoors. Only fraction (15%) of the daytime and nighttime images were needed to be added in the training for improving the performance of the classifier, potentially showing a robust model.

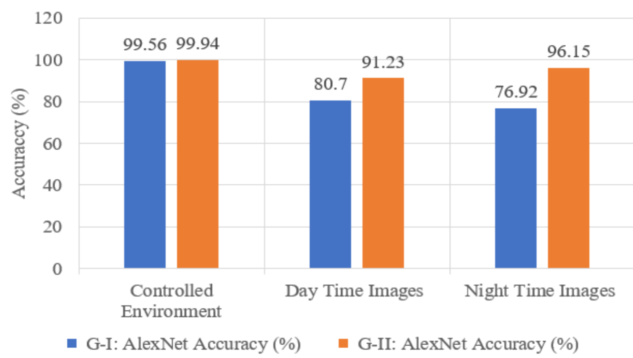

Figure 3. Comparison chart of the classifier accuracy using G-I and G-II for training and validating.

The effect of changing the deep learning classifier on the classification accuracy was also investigated. In particular, the classification accuracy of GoogleNet with 22 deep layers and ResNet50 with 50 deep layers as compared to AlexNet with 8 deep layers was determined as summarized in Table 2. least classification accuracy was obtained with ResNet50 especially for erosion in nighttime, despite the largest number of hidden layers. Such a finding could be explained as a result of the overfitting imposed with excessive number of the used deep layers.

Table 2. Confusion matrix for testing samples collected under daytime and sunset lighting conditions.

Type of Test	Training Done by Group-I			Training Done by Group-II		
	Alex Net	**Google Net**	**Res Net50**	**Alex Net**	**Google Net**	**Res Net50**
Controlled Environment	99.6	99.8	99.8	99.4	99.8 %	99.2
Daytime	80.7	73.8	78.9	91.2	92.9	87.7
Sunset Time	76.9	92.3	61.5	96.2	99.9	96.2

It is worth mentioning that the maximum achieved accuracy in reference [3] was 89.5% using AlexNet which is less than the reported accuracy in this study using the same classifier, Table 2. This could be attributed to the fact that the training dataset in our study is 1810 (extracted from 110 silicone rubber samples) but it was in reference [3] only 1240 images (extracted from 31 silicone rubber samples).

4 CONCLUSIONS

In conclusion, this letter presents a classification method of estimating the erosion level of SiR insulation non-invasively. With the aid of deep learning, the system can estimate the severity of erosion using transfer learning via three different networks. Furthermore, the robustness of the system against changing the lighting conditions was demonstrated, illustrating the potential of the proposed model for practical application. Also, the importance of the selection of the number of deep learning layers has been highlighted in order to avoid over fitting.

To further develop more robust and practical model that can be used for online inspection, other parameters need to be investigated like the influence of insulator surface color, using full insulators and conducting the measurements at different distances.

REFERENCES

[1] S. M. Gubanski, A. Dernfalk, J. Andersson, and H. Hillborg, “Diagnostic methods for outdoor polymeric insulators,” IEEE Trans. Dielectr. Electr. Insul., , vol. 14, no. 5, pp. 1065–1080, 2007.

[2] I. Jarrar, K. Assaleh, and A. H. El-hag, “Using a pattern recognition-based technique to assess the hydrophobicity class of silicone rubber materials", IEEE Trans. Dielectr. Electr. Insul., vol. 21, no. 6, pp. 2611–2618, 2014.

[3] Amr Ibrahim, Ahmad Dalbah, Ayaat Abualsaud, Usman Tariq and Ayman El-Hag, “Application of Machine Learning to Evaluate Insulator Surface Erosion”, IEEE Trans. Instrum. Meas., vol. 69, no.2, pp. 314 - 316, 2020.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”, in Advances in Neural Information Processing Systems 25, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2012.

[5] C. Szegedy et al., “Going deeper with convolutions”, 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, 2015, pp. 1-9.

[6] A. N. K. I. T. SACHAN, “Detailed Guide to Understand and Implement ResNets”, Learn Machine Learning, AI & Computer vision, 17-Sep-2019. [Online]. Available: https://cv-tricks.com/keras/understand-implement-resnets/. [Accessed: 04-Jan-2021].

[7] R. A. Ghunem, "Using the inclined-plane test to evaluate the resistance of outdoor polymer insulating materials to electrical tracking and erosion," IEEE Trans. Electr. Insul., vol. 31, no. 5, pp. 16-22, 2015.