Checking the Status of High Voltage Disconnect Switches Using Siamese Convolutional Neural Networks

Celso Soares Godoy[1], Marcelo Denadai Marcon[1], Gustavo Maia de Almeida.[1], Daniel Cavalieri[1], Cassius Rezende[1]

[1]*Dept. Engenharia de Automação do Instituto Federal do Espírito Santo – IFES*
Rodovia ES-010 - Km 6,5 - Manguinhos, 29173-087 - Serra - ES, Brasil
celsosgodoy@gmail.com, marcelodenadaimarcon@gmail.com, gmaia@ifes.edu.br,cassius@ifes.edu.br, daniel.cavalieri@ifes.edu.b

Abstract.
A high-voltage power substation is a crucial infrastructure for energy transmission and distribution, managing voltages between 69kV and 230kV. Essential for maintaining the operation of homes and industries, these substations contain various power equipment, such as circuit breakers, transformers, and disconnect switches, which can be controlled both locally and remotely. Disconnect switches, which are electromechanical devices with moving parts, are critical for the reliable operation of substations. Due to mechanical stress, vibration, and temperature fluctuations, failures in these switches can lead to significant losses, including equipment downtime and total power outages. To mitigate such risks, this paper proposes utilizing artificial intelligence (AI) and machine learning techniques, specifically a Siamese Convolutional Neural Network (CNN), to monitor the open and closed statuses of disconnect switches in a steel industry substation.

Keywords: Power Substation; Disconnect Switches; Siamese Convolutional Neural Network.

1 Introduction

High-voltage power substations are integral to the transmission and distribution of electricity, operating at voltages above 69kV and below 230kV. These substations house various critical components, including circuit breakers, transformers, and disconnect switches, which ensure uninterrupted operation. Disconnect switches, often activated manually or via motorized mechanisms, are vital for isolating parts of the electrical system. However, their mechanical complexity makes them prone to failure, potentially leading to severe operational disruptions. The image in Fig. 1 is an example of a AIS - Air Insulated Substation.

Figure 1. Power Substation

The disconnect switch is a fundamental component for the proper operation of a substation. This equipment consists of mechanical parts, typically made of aluminum, which are movable and can be activated either by a motor-reduction mechanism or manually via a crank located in the control cabin. The maneuvering device transmits movement to the switch poles through an axis connected between the control cabin and the switches. The switches are mounted on insulator assemblies to ensure electrical isolation and prevent unintended current flow between the components and the ground.Figure 2 shows a typical 138kV vertical disconnect switch model. Alves et al. [1] demonstrated the development of a system for monitoring disconnect switch sensors using ultrasound technology transmitted via optical fiber. The data were collected in real-time through an application developed in LabVIEW. The results from the tests indicated that the system accurately measured the position of the disconnect switch arm and effectively established the quality of the electrical contact. Khan, Yang, and Wuttisittikulkij [2] proposed a new non-destructive approach for analyzing defects in high-voltage equipment using infrared thermography and a deep learning approach derived from machine learning techniques. In their approach, thermal images of the components were captured using a FLIR T630 infrared camera without interfering with substation operations. In the first stage, features such as convolutional layer maps from the pre-trained AlexNet model were extracted, followed by feature extraction, and then random forest (RF) and SVM were used for network learning, considering defective and non-defective high-voltage electrical equipment. In experimental analysis, the random forest classifier (RF) achieved over 96% accuracy in classifying defective versus non-defective equipment. Nassu et al. [3] proposed a non-intrusive computer vision system for monitoring the status of disconnect switches in power distribution substations. This system used standard surveillance cameras, which can serve multiple purposes, thereby reducing costs and simplifying installation and maintenance compared to using individual sensors for each switch.

Figure 2. Vertical Disconnect Switch

2 Materiasl and Methods

This chapter outlines the theoretical foundations used in the development of this work. Understanding these foundations is crucial for fully grasping the methods and procedures described. The study used vertical disconnect switches rated at 145kV-1200A. These switches are installed in a substation within a steel mill, which features a double busbar system and approximately 17 circuits, incorporating over 40 disconnect switches. Given the number of circuits, it is evident that the system is highly complex. The reliable operation of the plant's electrical distribution system is critical for its stability. A malfunctioning disconnect switch can lead to significant losses for the company, ranging from equipment failures to complete power outages. Currently, the operational states of disconnect switches are monitored via remote signaling from dry contacts located on limit switches mounted on the motor switch axes. This state information is transmitted to the substation's control and supervision system, which is managed from the electrical system operation center. However, this method does not always accurately reflect the true state of the disconnect switches, necessitating additional visual confirmation by the operator to ensure proper equipment functionality. This verification is performed either through on-site inspection or by using cameras installed within the substation. To enhance the reliability of switch state identification and reduce the potential for errors, this work proposes leveraging artificial intelligence (AI) techniques—specifically, computer vision and machine learning. These technologies will be used to accurately determine whether the disconnect switches are in the open or closed position. The flowchart in Fig. 3 illustrates the planned approach for developing this solution.

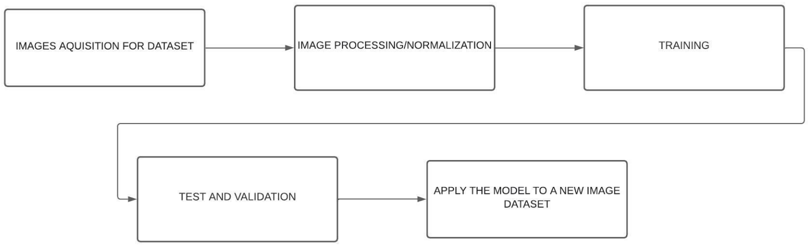

Figure 3. Project Development Pipeline

Several challenges were encountered, including cluttered backgrounds, occlusions, variations in lighting, and the fact that it is not always possible to maneuver the switches during installation. These challenges were addressed by combining data provided by a human operator during installation with multiple machine learning models. The approach utilized techniques such as Support Vector Machines (SVMs) for classifying Scale-Invariant Feature Transform (SIFT) or Histogram of Oriented Gradients (HOG) features, along with deep learning methods. By integrating multiple outputs, the system achieved a success rate of 99.7365% in experiments conducted over several days in a real substation

2.1 Concepts

The solution proposed in this paper for identifying the states of disconnect switches involves comparing the similarity of training data (images of disconnect switches) with images of previously unseen classes (disconnect switch images not used in the training phase). To accomplish this, it is necessary to find a function that maps input patterns to a target set in such a way that a simple distance in this target set approximates the "semantic" distance of the input set. One technique well-suited for this task is the Siamese neural network architecture. A key challenge in this approach will be assembling the dataset due to the low quality and limited number of images. Figure 4 illustrates an example of a real image extracted from the monitoring system used in the substation, showing low clarity, particularly at the disconnect switch connection point.

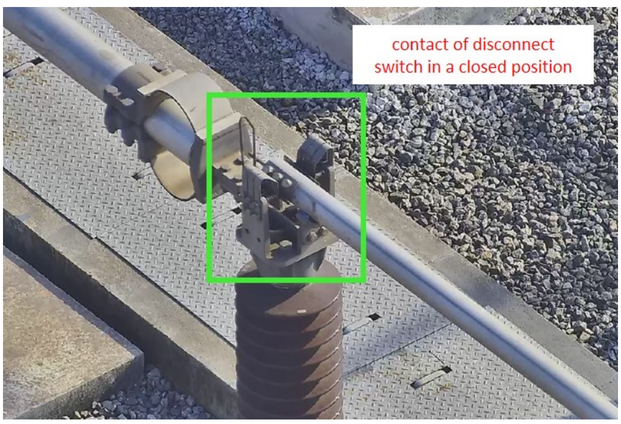

Figure 4. Disconnect switch contact details

2.2 Image processing in low-light environments

As previously explained, one of the main challenges of this project is the identification of disconnect switch images in low-light environments. Low light or insufficient exposure can result in images with poor brightness, low contrast, and increased noise. While one direct solution is to improve hardware—such as using infrared monitoring or increasing the camera's aperture—these options can significantly increase costs. Therefore, an alternative approach is to use image enhancement techniques as a pre-processing step before performing high-level image recognition tasks, as discussed by Lin et al. [4].

Object detection in low-light conditions presents significant challenges. The lack of sufficient reflected light results in images with many dark areas and high noise levels. Although many object detection algorithms are considered state-of-the-art, their performance often degrades under low-light conditions. Even with additional lighting, these algorithms may still struggle due to uneven brightness distribution, which obscures object details. Enhancing low-light images is crucial for improving image recognition accuracy for operators.

There are several techniques that can be used to improve an image, Among the most used in low lighting images, one of them is the Feature Pyramid Network (FPN). This feature was first implemented as an extension of the Network Regional Convolutional Neural or R-CNN to better represent objects in multiple scales. FPN improves the standard extraction feature by adding a second pyramid which takes high-level resources from the first pyramid and passes them down to the lower layers. It is a general strategy that combines top-down fusion with layering and jumping. multiscale pyramid predictions. The use of FPN is very suitable for adapting to detection of objects in low lighting, as it presents pyramids with strong information semantics without relevant computation cost at all scales. Xiao et al [5] Another strategy that can be applied to improve images is the use of a joint structure, as well as the one proposed by Tao et al [6] which made use of a Convolutional neural network (CNN) based architecture to denoise images in low light. Then, based on the atmospheric dispersion model, we introduced a low-light model to improve image contrast. combined with a filter designed to adaptively estimate ambient light in different areas of the image.

2.3 Convolutional Neural Networks Siamese Architecture

The experiment utilized images captured in environments with insufficient lighting. To achieve satisfactory results under these conditions, it was proposed to use two identical convolutional networks with a Siamese architecture, which share a common parameter vector to apply a learned similarity metric (see Fig. 5). Convolutional neural networks (CNNs) use various filters, each consisting of trainable parameters that adapt to spatial features in the image, such as edges and shapes. These filters capture spatial features based on weights learned through the back-propagation process and are organized in stacked layers to detect spatial shapes at each subsequent level. Consequently, CNNs can synthesize an image into a highly abstract, easy-to-predict representation.

CNNs are multilayer, non-linear systems capable of learning both low- and high-level features in an integrated manner, operating at the pixel level of an image. They map images to outputs by detecting local features, ensuring shift invariance or spatial invariance, and achieving robust representations that are resilient to geometric distortions of the input images (Alencar and Bezerra [7]).

With the advent of deep learning, object detection using convolutional neural networks (CNNs) has become critical in areas such as autonomous driving. In contrast to normal lighting conditions, dark environments pose challenges for object detection due to poor lighting and increased noise. To enhance object detection in low-light conditions, Lin et al. [4] introduced a new Dark Transformation-Equivariant (DTE) algorithm designed to explore feature consistency between normal and low-light conditions. Their methodology involved developing dark transformation techniques to simulate poor lighting conditions by darkening regular images and incorporating sensor noise.

2.4 Data Acquisition

Due to the inability to perform constant maneuvers on disconnect switches in a real operational environment, a disconnect switch pole was used in a controlled setting to create the image dataset through simulations. Figure 6 illustrates the disconnect switch pole used in the experiment.

In the data processing stage, the obtained images were resized using dimensional variation techniques. After processing, 30% of the images were allocated to the model training phase, while the remaining data were used to validate the model. Once training and validation were complete, the model was deployed for production. The

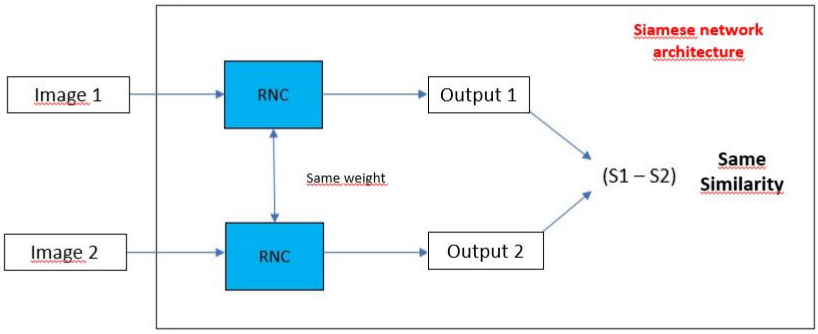

Figure 5. Siamese network architecture

Figure 6. Disconnect switch experimental

computational code for developing the algorithm was implemented in Python, using either the Anaconda or Google Colab development platforms on a personal computer. To ensure that the system effectively learns to detect, recognize, and identify the state of the disconnect switches, it is crucial to provide data that accurately represents various operational scenarios, making the model as reliable as possible under real-world conditions. For this project, the algorithm was trained with approximately 1,200 images of disconnect switches in both open and closed positions, captured under different lighting conditions and from various angles. Figure 7 illustrates an example of a disconnect switch in the closed position (A) and in the open position (B).

The proper operation of a disconnect switch is indicated when all three poles are in the same state, either fully closed or fully open. Throughout this study, the status of each pole of the switch will be analyzed individually. Challenges such as imbalance and limited sample sizes are anticipated during the database creation process. These issues arise due to the specificity of the study area: disconnect switches at 138kV. Rezende et al. [8] encountered similar challenges when identifying the states of 69kV disconnect switches.

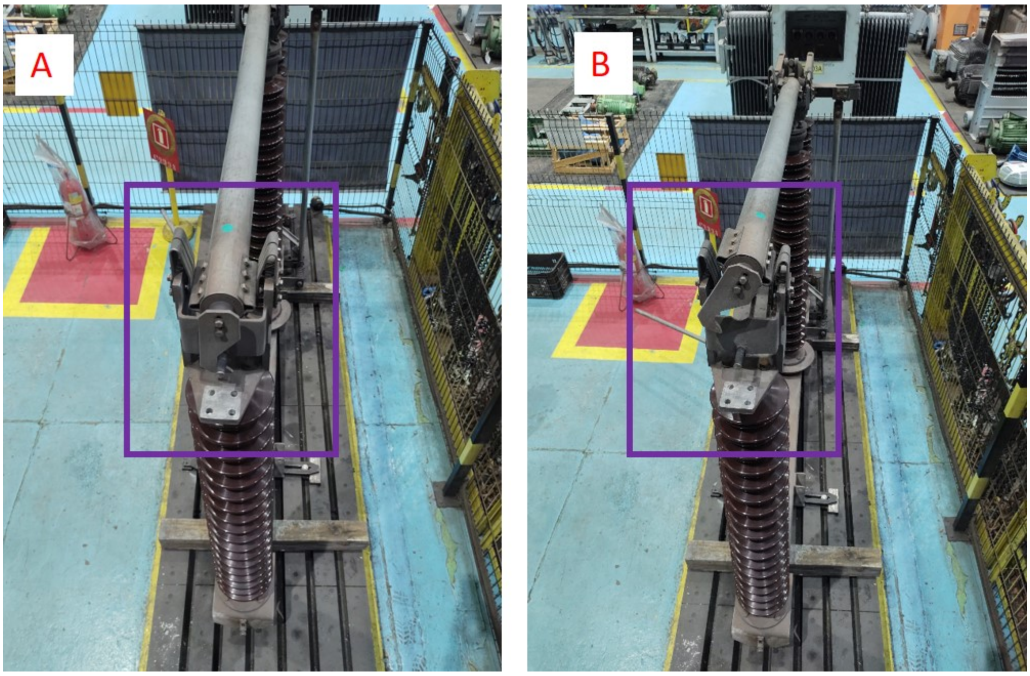

Figure 7. Disconnect switch closed (A) and opened (B)

2.5 Algorithm

parameters. Chaves and Nascimento [9]

Among the various image recognition techniques currently available in the literature, this work was developed using Siamese neural networks. The choice to use Siamese neural networks was driven by the limited dataset and the generally dark or low-clarity environment in which the images were captured—issues that presented significant challenges in the project.

The Siamese network architecture consists of two identical convolutional neural networks and a similarity or energy module. The system's input is a pair of images, one of which is labeled. These images are processed through the sub-networks, producing two outputs for the similarity module, which calculates the degree of similarity between the outputs of the sub-networks. This architecture was presented by Valadão, Santos, and Cavalieri [10].

The Siamese neural network was first introduced by Bromley et al. [11] for signature verification. This type of supervised neural network is designed to measure the similarity between two samples, determining whether a pair of vectors belongs to the same class. As shown in Fig. 6, a Siamese neural network architecture comprises two identical subnetworks that are joined at their outputs. These subnetworks share the same structure and are adjusted with the same weights and parameters, as described by Chaves and Nascimento [9].

3 Results

This section presents the results of the tests conducted using the Siamese Convolutional Neural Network to determine the status of the disconnect switch.

Siamese networks map the input samples into a new feature space. In this space, samples from the same class are positioned closer together, while samples from different classes are located further apart. The distance between the two samples in this feature space is then calculated. This distance is processed by another neural network (or a single neuron), which outputs a value between 0 and 1. If the samples belong to the same class, the similarity value will be closer to 1. Conversely, if the samples are from different classes, the value will be closer to 0 [9].

Euclidean distance was used to measure the separation between the outputs of each network. The "sigmoid" activation function was applied in the output layer of each neural network.

The dataset created during the laboratory experiment was used to train and test the proposed methodology. Performance metrics used for evaluation included recall, precision, specificity, F-score, and accuracy. Table 1 shows the performance results of the proposed methodology.

Table 1. Evaluation metrics results

Precision	Recall	Specificty	Fscore	Accuracy
0.92	0.92	0.89	0.92	0.92

Based on the results obtained, it is anticipated that the Siamese network architecture will perform better. The superior performance of the Siamese neural network can be attributed to its unique approach to exploiting image similarity. Unlike Inception-V3, which focuses primarily on classifying individual images, the Siamese neural network excels at identifying subtle differences and similarities between images [10].

4 Conclusions

This study demonstrated promising results using performance metrics with the Siamese convolutional neural network architecture for verifying the states of 138kV disconnect switches through image analysis.

The Siamese network methodology does not require a large volume database, but is capable to distinguishing subtle differences between samples.

A key consideration when using this architecture is the high computational cost involved. Generating genuine and imposed pairs for each class consumes a significant amount of RAM and requires substantial GPU resources during network training

As future work, the model will be implemented in the substation to monitor the status of different models of disconnect switches. Additionally, it will involve comparing the presented technique with other methods, such as YOLOv8, for example.

References

[1] T. Alves, S. Araújo, W. Lopes, C. Floridia, J. Rosolem, R. Strobel Penze, and F. Bassan. Monitoramento de chaves seccionadoras de alta tensão por sensores ultrassom alimentados por fibra Óptica. *Congresso Brasileiro de Automática*, vol. XXI, pp. http://www.cba2016.org.br/, 2016.

[2] Ullah, Khan, F. Yang, and Wuttisittikulkij. Deep learning image-based defect detection in high voltage electrical equipment. *Energies*, vol. 13, pp. 392, 2020.

[3] B. T. Nassu, B. Marchesi, R. Wagner, V. B. Gomes, V. Zarnicinski, and L. Lippmann. A computer vision system for monitoring disconnect switches in distribution substations. *IEEE Transactions on Power Delivery*, vol. 37, n. 2, pp. 833–841, 2022.

[4] T. Lin, J. Lin, J. Wang, Z. Deng, and G. Huang. A dark transformation-equivariant algorithm for dark object detection. New York, NY, USA. Association for Computing Machinery, 2023.

[5] Y. Xiao, A. Jiang, J. Ye, and M.-W. Wang. Making of night vision: Object detection under low-illumination. *IEEE Access*, vol. 8, pp. 123075–123086, 2020.

[6] L. Tao, C. Zhu, J. Song, T. Lu, H. Jia, and X. Xie. Low-light image enhancement using cnn and bright channel prior. pp. 3215–3219, 2017.

[7] R. Alencar and B. Bezerra. Sistema de comparação de imagens de faces, em múltiplas resoluções, baseado em redes neurais siamesas. *Revista de Engenharia e Pesquisa Aplicada*, vol. 5, pp. 50–57, 2020.

[8] B. A. S. O. G. M. V. d. P. G. P. d. S. D. C. E. L. D. A. O. d. S. Tamires M. Rezende. Visão computacional aplicada ao monitoramento de chaves seccionadoras de subestações de energia elétrica. *SBA-Sociedade Brasileira de Automática*, vol. 24, 2022.

[9] e. S. F. F. D. B. B. A.G.S.. Chaves and S. Nascimento. Extração de entidades de produtos utilizando técnicas de few-shot learning. *Anais do XV Simpósio Brasileiro de Automação Inteligente (SBAI)*, vol. 15, pp. 392, 2021.

[10] C. Z. R. C. T. Valadao. M. S. Santos and D. C. Cavalieri. Predicting diabetic retinopathy stage using siamese convolutional neural network. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, vol. 12, n. 1, pp. 2297017, 2024.

[11] J. Bromley, I. Guyon, Y. Lecun, E. Säckinger, and R. Shah. Signature verification using a siamese time delay neural network. volume 7, pp. 737–744, 1993.