Insulator visual non-conformity detection in overhead power distribution lines using deep learning

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\begin{abstract}
Overhead Power Distribution Lines (OPDLs) correspond to a large percentage of the medium-voltage electrical systems. In these networks, visual inspection activities are usually performed without resorting to automated systems, requiring a significant investment of time and human resources. We present a methodology to identify the defect and type of insulators using Convolutional Neural Networks (CNNs). More than 2500 photographs were collected both from inside a studio and from a realistic OPDL. A classification model is proposed to automatically recognize the insulators conformity. This model is able to learn from indoors photographs by augmenting these images with realistic details such as top ties and real-world backgrounds. Furthermore, Multi-Task Learning (MTL) was used to improve performance of defect detection by also predicting the insulator class. The proposed methodology is able to achieve an accuracy of 92\% for material classification and 85\% for defect detection, with F1-score of 0.75, surpassing available solutions.

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\end{abstract}

\section{1. Introduction}

In Brazil, Overhead Power Distribution Lines (OPDLs) comprise more than 95\% of total medium voltage power circuits [1]. Other countries, including the United States and Japan, also adopt this network topology, sharing space with the underground distribution networks.

Conformity in the power supply is closely related to the quality of the preventive and corrective maintenance services practiced by the power companies in high and low voltage distribution grids. As a prerequisite for performing these activities, the first step is to search for non-conformities present in the power lines, such as defective elements (broken, cracked, deformed and polluted), badly placed, missing or non-registered components, current leaks, hot spots, among others.

Insulators are important components of power lines and their correct functioning increases the overall security and stability of the power system. Detection of failures on insulators may reduce power cuts and economic losses related to the instability of such systems [2]. Furthermore, given that these lines include urban settings, detecting imminent failures of the...
insulators is of paramount importance not only to avoid power failures, but also due to public hazard reasons in such highly dense areas. Fig. 2 shows examples of OPDL insulators.

Nowadays, field inspection activities in medium and high voltage networks are, in part, performed by professionals trained by the electric utility company, either on visual inspection by “walking patrol” or assisted by helicopter [3]. In most cases, they are performed in the live lines, which can bring safety risks to these professionals.

Visual inspection activities performed by humans are also susceptible to subjective interpretations, which can lead to inaccurate or incorrect identification/diagnosis of the inspection, resulting in component registration flaws and inadequate maintenance plans. Such inspection could be performed automatically by an intelligent system embedded in a drone, as exemplified by Fig. 1.

Intelligent systems and computer vision have been widely used for visual inspection tasks in different situations, such as manufacturing processes [4], healthcare systems [5], and agricultural industry [6]. Other recent technologies are being considered either for sensing devices, such as high performance photo-detection [7], or for offline characterizations of ceramic components [8,9], that could be used for failure analysis. The usage of computer vision and intelligent techniques for insulators inspection on distribution power systems is a current issue that has been under-explored. Furthermore, to the best authors’ knowledge, available published works on the subject neither provide any information on the used dataset nor deals with defect detection of such components [10,11].

Recently, deep learning algorithms, like Convolutional Neural Networks (CNNs), have been presenting significant improvements on image classification, semantic and instanced segmentation and real-time object detection in images and videos [12]. CNNs are also present in advanced visual recognition systems, such as self-driving cars [13] and image understanding algorithms [14]. These computer models have a wide generalization range among related tasks and can be easily adjusted through different training techniques. Such benefits provide opportunities for the use of deep learning in visual-based inspection tasks.

In this work, an innovative technique for recognition of insulators and detection of defective components is developed. The proposed framework is based on a new conception about the use of CNN algorithms and image generating processes. A dataset comprised of several insulators, defective and faultless, was collected. As a way to increase the number of analyzed components in the dataset and to simulate more realistic environments, an image generator procedure was developed. The procedure provided the means to construct the model from dataset acquisition in the laboratory, and successfully extrapolate inference to an external environment. A multi-task learning setup was also considered for analyzing both issues – insulators type recognition and defects detection. These approaches reduced the workload of the data acquisition process and improved the classification efficiency of the proposed computer models.

In practical terms, the proposed methodology has the potential to be experimentally employed in specific tasks of automatic OPDL visual-based inspection. To enable its use in real-world environments, it would be necessary to use drones, with a CCD camera attached, to collect images from the Overhead Power Lines under evaluation. The computational model adjustment and digital information processing for classification would be performed on a ground-located computer. The data exchange between the drone and the computer would take place via wireless communication.
The present paper is structured as follows. Section 2 explores existing methods for automatic inspection. Section 3 details the data acquisition process. Section 4 describes the pipeline proposed for classifying insulators and defects, as well as the Convolutional Neural Network architectures employed in this study. Section 5 presents the experimental analysis and results. Finally, we conclude the article and discuss future lines of work in Section 6.

2. Related work

Automated visual inspection in OPDLs is highly complex due to the following challenges: high variability of backgrounds present in real-world environments, differences in lighting conditions, and rapid view changes [15].

For the image acquisition stage, some authors suggested the application of mobile robots such as Unmanned Aerial Vehicles (UAVs) and climbing robots as viable solutions [3,16]. For intelligent conformity analysis of OPDLs, there are different approaches using Adaptive-fuzzy inference System (ANFIS), Support Vector Machine (SVM) and Hidden Markov Model (HMM) [16]. A recent review covers existing works that consider aspects such as pointing the UAV towards the desired object, the influence of camera accuracy and a wide range of classification methods [10].

Regarding the use of advanced optical devices in potential applications for autonomous visual-based inspection, in addition to CDD devices from digital cameras, there is the possibility of using new types of high sensitivity sensors, such as the perovskite and antimonene based devices [17–20]. This could provide better optical responses to specific problems and improve defect identification for insulating materials.

Taking into account the use of deep learning for visual-based OPDL inspection, an initial study was presented on the possibilities and challenges of using deep CNNs to the following stages: UAV navigation; object detection; mapping and inspection of power line components [11]. Despite the potential of deep learning for OPDL visual-based inspection, to the best of the authors’ knowledge, no techniques have yet been proposed to classify the types of distribution insulators and their respective conformity status from an artificially generated training dataset.

3. Data acquisition

For the data acquisition stage, an image collection was created containing information about the components, defects and possible sources of interference. The flexibility to update the dataset should be evaluated, considering technological innovations and changes in construction standards. In the case of distribution insulators, there are continuous changes in design and type of building material. This may hinder the development of a properly “universal dataset” that works for all types of overhead networks.

In practical terms, it is possible to propose two procedures for image acquisition of overhead lines:

1. Acquisition in locus, from real power lines, or through adapted structures (didactic networks), built with the sole purpose of data collection.
2. Acquisition in photographic studios with controlled lighting and backgrounds.

For the first alternative, more robust datasets can be achieved, since the collected images reflect the real features present in the power lines. However, there are some disadvantages on using this procedure:

(a) Risks of accidental contact of the image acquisition system with live conductors or support structures of the electric grid;
(b) difficulties related to build-up a balanced dataset;
(c) challenges in updating the datasets for new types of components installed in electrical networks;
(d) high costs for the implementation of didactic networks.

For the procedure performed in a photographic studio, there is the advantage of the collection being performed in a safe environment and with controlled external conditions. However, there is a lack of some information of the acquired images that are present in the real environment, namely:

(a) Sources of interference, such as vegetation, buildings or objects found in the backgrounds from urban and rural environments;
(b) the presence and/or overlap of conductors or minor components, such as the top tie (preformed tie wire);
(c) variations of component brightness, dimensions and angles.

In this work, the first step on the acquisition stage was the selection of four types of distribution insulators that operate in 15kV, namely: Ceramic Pin Insulator (CPI), Ceramic Bicolor Insulator (CBI), Polymeric Grey Insulator (PGI) and Glass Green Insulator (GGI). Representative images of these components can be seen in Figs. 3 and 4, taken inside and outside the studio.

In a second step, two procedures were designed for image acquisition:

1. Development of an Image Collection Station (ICS), with controlled illumination and background color. This apparatus consists of a swivel table for adjusting the angle $\phi$ in 360 degrees and a mobile shaft for camera coupling, with a slope of $\theta \in [0, 90]$, as seen in Figs. 5a and c.
Fig. 3. Images of insulators collected from the ICS.

(a) Intact insulators  (b) Defective insulators

Fig. 4. Images of insulators collected from the Didact Overhead Power Line (DOPL).

(a) Intact insulators  (b) Defective insulators

Fig. 5. Representation of the designed image acquisition apparatus.

(a) Image Collection Station (ICS)  (b) Didact Overhead Power Line (DOPL)

(c) Sketch representing rotation and inclination of the ICS  (d) Design of the DOPL arrangement  (e) Design of the DOPL central pole
2. Construction of a **Didactic Overhead Power Line (DOPL)** composed of three poles with 2.2 m high and 30 m long, shown in Figs. 5b, d and e.

Data acquisition at the Image Collection Station was performed with a series of photos taken from different insulators – 480 in total (120 of each component). From each subset of 120 images corresponding to each insulator, 60 were related to intact components (six for each angle of θ, with intervals of 10 degrees) and 60 were composed of defective components, with different angles and types of deformities. Figs. 3 and 4 contrast intact and defective components.

In the case of DOPL, the purpose was to reproduce similar conditions of actual Distribution Networks. Therefore, images with random positions, illuminations and backgrounds were collected. For each insulator, 520 photographs were obtained, totaling 2080 images. From the 520 images of each component, 400 were of intact components and 120 were of defective components, resulting in an approximate ratio of four images of intact components for each defective one. The above-mentioned dataset, containing 2560 images, is available at [http://www.dee.eng.ufba.br/dslab/index.php/opdl_dataset/](http://www.dee.eng.ufba.br/dslab/index.php/opdl_dataset/).

4. **Proposal**

A flowchart is presented in Fig. 6 which resumes the proposed methodology. In general terms, three CNN configurations were employed with the aim to classify the insulator material/design (called Type 1), the insulators defects (Type 2) and a combination of both in a multi-task environment (Type 3). The 480 ICS images were used as input to an image generator step prior to the CNN classification procedure to increase the number of image samples.

Since the network was trained with 100 epochs, a total of 48,000 images were used for training purposes. The classifier was then validated and tested with 2080 real DOPL images, that were also processed to simulate more severe scenarios. Details of these data processing steps are provided in the following subsections.

4.1. **Image Generator (IG)**

An Image Generator (IG) pipeline was developed using different image processing techniques to synthetically create new images from ICS acquired ones that looked as realistic as possible. This step did not only involve common transformations, such as rotation or translation, but also included further steps to the standard pipeline, since the purpose was to create the classification model using only images acquired from a controlled laboratory (ICS) and then evaluate it using real images. A diagram of the IG pipeline is shown in Fig. 7.

**Image segmentation.** In a first stage, the images were acquired by photographing against a white background as can be seen in Fig. 5a. This procedure showed to be problematic considering that real images has urban and rural landscapes as background (Fig. 5b), which made it harder to extrapolate performance to the testing set and evaluate more realistic environments.

To overcome that, images were segmented to provide a backdrop from which background augmentation and other techniques could be introduced. Images of insulators, top ties, and general wires were segmented, resulting in three types of component masks. The segmentation of the components was performed using the interactive Graph Cut algorithm [21].
Data augmentation and realistic detailing. Following the segmentation procedure, a process of data augmentation and realistic detailing was implemented, consisting of the following substeps:

1. In the upper half part of the segmented insulator masks, a segmented top tie mask was introduced by randomly placing the component sample between the horizontal center and one-third of the vertical bounding box.
2. Common data augmentation transformations were then applied on both segmented and top-tied insulators, in which six transformation parameters were considered: rotation, translation, brightness, shear, horizontal flip and changes of scale.
3. A few loose electric conductors were then introduced on the augmented data of top-tied insulators (12.5% of the augmented images – wires combination) and on free insulators (37.5% of the augmented data – free conductors), as shown in Fig. 7.
4. Random background patches taken from outdoors photographs were introduced as background for the whole resulting images.

This procedure was iteratively repeated at each of the 100 epochs used for training the CNN architectures and, since the procedure occurs randomly, a total of more than 48,000 modified images were generated for training purposes.

4.2. CNN architectures and transfer learning

The Convolutional Neural Networks (CNNs) are a powerful deep learning model, with some similarities to Multilayer Perceptron (MLP). The CNNs demonstrated excellent performance in several applications, especially in computer vision related tasks. In a typical CNN, the model architecture presents a series of convolutional, pooling and fully connected layers [12].

Considering the convolutional layers, there are several types of kernels to convolute the images and their corresponding activation maps. During the forward stage, a new set of activation maps is generated. Assuming a bi-dimensional image $I_{in}$ and the filters weights $W$, the filtering generalization would be formulated in a compact form as

$$Y = W * I_{in}.$$  (1)
where $Y$ is the computed matrix and $*$ is used as bi-dimensional convolutional operation for the entry in row $x$ and column $y$. Placing $J$ and $K$ as the filter dimensions, the equation that represents the convolution will be obtained as

$$Y[x, y] = \sum_{j=-J}^{J} \sum_{k=-K}^{K} W[-j, -k] Y_{m}[x + j, y + k].$$

(2)

For the subsampling stage, pooling layers can be used to reduce the dimensions of the activation maps as well as the network parameters. For this task, the most common approaches are max-pooling and average-pooling. The fully connected layers, on the other hand, are commonly allocated at the final stages of Convolutional Networks and correspond to the majority of CNN parameters (around 90%). The output layers usually employ sigmoid or Softmax-type activation functions.

The experiments were conducted using three well-known CNNs: VGG-19, Inception-v3 and ResNet-50. These models are pre-trained networks and may be used to accelerate the learning process and improve classification rates. The three exploited architectures are described as follows.

**VGG-19.** The VGG model earned first and second place in the 2014 ImageNet classification competition with a groundbreaking depth of 16 and 19 layers (VGG-16 and VGG-19, respectively), interleaving convolution and max-pooling layers [22].

**Inception-v3.** The Inception CNN, on the other hand, was the product of much engineering and tweaking to produce a network less complex than VGG yet supposedly presenting higher performing on the dataset evaluated by the authors [23]. This work used the version presented as “v3”.

**ResNet-50.** This model introduced residual blocks. Traditionally, two consecutive layers $f$ and $g$ receive input $x$ and are intertwined as $f(g(x))$. Residual blocks are structured as $g(f(x) + x)$ making training faster because gradients flow more directly since both layers are now directly differentiable relative to $x$. Furthermore, prior to any training, they already start to produce the identifying function since weights are initialized such that $f(x) \approx 0$ therefore $f(x) + x \approx x$. This also allows for more layers to be used; the version used here is ResNet-50 that contains 50 layers [24].

Transfer learning techniques were used to perform fine-tuning of these pre-trained networks [22]. The networks weights were frozen during training, with the exception of the dense layers, and of two convolutional layers for the specific case of VGG-19. Also, the last layer was replaced in order to classify material/design classes (softmax) and/or defect classes (sigmoid). As a matter of illustration, the VGG-19 adaptation architecture is shown in Fig. 8. The trained models and respective code are made available together with the dataset (see Section 3).

### 4.3. Multi-task learning

Even when the goal is a specific classification task, it is becoming a common practise to learn additional objectives because this also benefits the main task at hand [25]. Multi-task learning makes use of the intrinsic relation between individual learning tasks to improve classification performance. Therefore, in this work, we experimented not only with individual learning tasks based on separated assignments (material only − Type 1, and defect only − Type 2), but also a multi-task learning that jointly combines both tasks at the same time (Type 3).

In each case of the three learning tasks, the loss function ($\mathcal{L}$) to be minimized was the cross-entropy, defined as follows. For $N$ observations and $K$ classes, the model outputs a probability $\hat{p}_{i,k}$ for each observation $i \in \{1, \ldots, N\}$ and class $k \in \{1, \ldots, K\}$, which is contrasted against the true label $y_{i,k}$ which is 1 when the observation $i$ belongs to class $k$ and 0 otherwise.

$$\mathcal{L}(y, \hat{p}) = -\frac{1}{NK} \sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \log(\hat{p}_{i,k}).$$

(3)

In the multi-task case, the final loss $\mathcal{L}'$ combines the two losses, for material ($\mathcal{L}^{(m)}$) and defect ($\mathcal{L}^{(d)}$), as a simple unweighted sum,

$$\mathcal{L}'(y, \hat{p}) = \mathcal{L}^{(m)}(y, \hat{p}) + \mathcal{L}^{(d)}(y, \hat{p}).$$

(4)

Adam [25] with a low learning rate was used as the CNN optimizer. Learning rates higher than $10^{-4}$ were found to be harmful.

### 4.4. Evaluation

#### 4.4.1. Pipeline training

To evaluate the impact of the main design options of the proposed model, different variations were considered to train the classifier. On top of training directly from the raw ICS images, these approaches were introduced progressively:

A: Data augmentation as previously described is activated (details present in item 2 of topic 4.1).
B: Fine-tuning of the last two convolutional layers of the CNNs. In the case of VGG-19, the chosen layers were $C_{n-1}$ and $C_n$ (illustrated in Fig. 8).

C: Image segmentation of the training dataset from the masks described in topic 4.1.

D: Background addition with random patches taken from outdoor environments, according to item 4, of topic 4.1.

E: Addition of top tie and free electric conductors on the training images according to item 3 of topic 4.1.

F: Multi-Task training according to the type 3 setting (insulator type and conformity status) described in topic 4.3.

Z: Combination of A, B and C.

4.4.2. Test

Conventional test. This test was implemented using the original DOPL images acquired outdoors.

Stress test. To simulate a more realistic scenario and the use of mobile robots for image acquisition, test images were also augmented to make them more challenging. This procedure involved the following combined transformations: rotation, brightness, shear, shift, zoom magnification, zoom reduction. These dimensional changes were similar to those performed in the training stage, but more intensely applied.

Ensemble test. This procedure was essentially composed of two stages: classification process and score-level fusion. Each test image went through six isolated data augmentation tasks (the same cited for the stress test stage). A prediction was obtained for each transformed image and the ensemble decision was based on the simple majority voting scheme.

4.4.3. Performance evaluation metrics

In order to evaluate the prediction of insulator material, accuracy (Acc) was used, i.e., the percentage of times the network produced the correct output. The output of the neural network is a value $p_{i,k}$ that provides a probability for each observation $i$ of class $k$. This is discretized into a one-hot encoding matrix by defining $\hat{y}_{i,k}$ to be 1 for the class $k$ such that $\hat{p}_{i,k} = \max\{\hat{y}_{i,k}\}$ and 0 otherwise. For $N$ samples and $K$ classes (in this case, $K = 4$), accuracy may be defined as

$$\text{Acc} = \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \hat{y}_{i,k}. \tag{5}$$
Furthermore, Confusion Matrices (CMs) are produced whereby each element of the matrices $M_{j,k} = \sum_{i=1}^{N} y_{i,j} \hat{y}_{i,k}$. In the perfect case (no classification errors), CM is zero for all elements except the diagonal. This matrix allows the identification of which classes the model is facing more difficulties.

For defect classification, given the biased ratio of normal insulators relative to defective ones (class imbalance), F1-score was used as is typically done for class imbalance. Taking $k = 0$ and $k = 1$ to be the negative and positive classes, respectively, the following parameters are defined as shorthands $TP = \sum_{i=1}^{N} y_{i,1} \hat{y}_{i,1}$ (true positives), $FP = \sum_{i=1}^{N} y_{i,0} \hat{y}_{i,1}$ (false positives), and $FN = \sum_{i=1}^{N} y_{i,1} \hat{y}_{i,0}$ (false negatives), with F1 being defined as

$$F1 = \frac{2TP}{2TP + FN + FP}.$$  \hspace{1cm} (6)

For visual analysis, we used ROC curves that are two-dimensional graphs where $TPR = TP/Cp$ (True Positive Rate) is plotted on the vertical axis and $FPR = FP/Cn$ (False Positive Rate) is plotted on the horizontal axis, with $Cp$ and $Cn$ corresponding to positive and negative conditions, respectively. The ROC chart describes the relationship between the benefits (TP) and the costs (FP). Areas under the ROC curve (AUC) close to one indicate high discrimination performances. When the area is one, the curve is flattened at the top of the graph, corresponding to 100% sensitivity (TPR) and 100% specificity (1–FPR).

5. Results

Results are summarized in Table 1, corresponding to the best accuracy for all evaluated CNN architectures. We considered cases of a single output and the MTL setting. VGG-19 achieved the best performance for all conditions evaluated. For component classification, the best approach was Type 1 (component only training) with an Acc of 92%. For defect detection, the Type 3 approach presented the best result, with Acc and F1 values of 85% and 0.75, respectively.

The performance of the VGG models was further discretized according to the different training pipeline specifications (stages A, B, C, D, E, F and Z). Fig. 9a shows the Acc of Type 1 CNN for 100 training epochs. This graph shows that all the proposed implementations provided improvements in model accuracy compared to the case without IG (first point of the graph). Fig. 9b displays the results of the Type 3 model used for defects identification due to the implementation of realistic details (D and E). In contrast to the previous graph, the addition of top ties and free conductors decreased the Type 3 model precision. Apparently, feature E produces overlaps in defective areas of the component images, as can be seen in Fig. 13d, which shows image samples after stages D and E.

In both graphs of Fig. 9b, it is possible to see that the background addition stage (D) seems to present considerable influence on performance. This step increased precision by 39 and 61 percentage points for insulators and defects classification, respectively. The implementation of the data augmentation stage (A), on the other hand, has turned the model more ro-
bust, bringing stress test values closer to conventional test values. The Ensemble tests improved the models stability, getting closer to the best test values, reaching Acc of 91.5% for Type 1 and 84.5% for Type 2.

Fig. 10 illustrates ROC curves for Type 1 VGG-19 without the image generator (Fig. 10a) and the same model with the addition of A,B,C,D and E training pipeline stages (Fig. 10b). The proposed techniques improved the ROC curves (higher sensitivity and specificity values) and consequently increased AUC to values above 0.98.

Heat-maps are compared for the models with and without background introduction stage (D) in Figs. 11 and 12. These heat-maps $h_{x,y}$ are produced by normalizing the gradient $g_{x,y,c}$ of the sum of the output classes (predicting material) relative to each input pixel and color,

$$g_{x,y,c} = \frac{\partial \sum_k \hat{y}_k}{\partial x_{x,y,c}}. \quad (7)$$

The gradient is made mono-chromatic by choosing the maximum absolute color for each pixel and then normalizing it,

$$h_{x,y} = \frac{\max_c \|g_{x,y,c}\|}{\max_{x,y,c} \|g_{x,y,c}\|}. \quad (8)$$

The heat-map is then blended using a 40–60 proportion on the red-channel. The models that produced these gradients used average-pooling instead of max-pooling to avoid gradients being too coarse. The heat-map makes clearer the previous result.
Fig. 13. Examples of insulator misclassification.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Intact</th>
<th>Defective</th>
</tr>
</thead>
<tbody>
<tr>
<td>PGI</td>
<td>469</td>
<td>32</td>
</tr>
<tr>
<td>CPI</td>
<td>29</td>
<td>465</td>
</tr>
<tr>
<td>GGI</td>
<td>19</td>
<td>19</td>
</tr>
<tr>
<td>CBI</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>89.5%</td>
<td>89.9%</td>
</tr>
</tbody>
</table>

(a) Insulator class (b) Defect

regarding background addition. The model that has never seen the background before (Fig. 11) was more easily distracted by it, while the model trained by introducing realistic backgrounds (Fig. 12) was more focused on the object of interest.

Table 2 presents the Confusion Matrix for Type 1 and Type 2 models considering the best pipeline configurations. Both models present sensitivity and precision values above 80% and 64%, respectively. Misclassifications are caused by certain image features, such as aggressive differences in shape and texture, intense brightness variation and image overlaps. Figs. 13a, b and c show examples of images for which the proposed models present classification errors. These examples illustrate possible room for improvement through the upgrading of the IG (by providing a larger set of information for the training dataset) as well as the integration with segmentation and multi-view techniques focused on improving the robustness of the computer models classification.

6. Conclusion

Evaluating the integrity of electrical insulators is very important for assuring power distribution lines safe operation. A promising methodology was presented for automatic inspection of insulators found in Overhead Power Distribution Lines using deep learning, digital image processing and data augmentation. Two main classification tasks were considered, the discrimination of insulator type and the identification of defects. Few research or benchmarks exist for this application. For that reason, a data-set was collected containing 2560 images, and 480 segmentation masks were produced. Part of the photographs were taken inside a studio with controlled conditions, while other part was acquired at a specially-built realistic-looking distribution line. The VGG-19 deep-learning architecture achieved the best classification performances: the single task VGG-19 (Type 1) presented overall accuracy of 92% for component classification and the multi-task learning
VGG-19 (Type 3) obtained accuracy and F1 of 85% and 0.75, respectively. Another point of interest in this work was the development of an Image Generator designed to build training datasets. The Image Generator was able to digitally edit the dataset collected in a photographic studio and produce a new set of images with the desired features of realistic environments. Such implementation provided gains of 66 percentage points in component classification and 61 percentage points in non-conformity identification, considering the test dataset obtained in the didactic overhead power line. In future studies, we intent to expand the types of insulators evaluated simultaneously, inserting, for instance, hybrid and suspension types. The Image Generator could also be used for object identification and segmentation. A further refinement of the classification techniques aims to discriminate the type of defect presented by the components.

Declaration of Competing Interest

None.

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Supplementary material

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