Segmentation and Defect Classification of the Power Line Insulators: A Deep Learning-based Approach

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Abstract—Power transmission network physically connects the power generators to the electric consumers extending over hundreds of kilometers. There are many components in the transmission infrastructure that requires a proper inspection to guarantee flawless performance and reliable delivery, which, if done manually, can be very costly and time taking. One of the essential components is the insulator, where its failure could cause the interruption of the entire transmission line or widespread power failure. Automated fault detection of insulators could significantly decrease inspection time and its related cost. Recently, several works have been proposed based on convolutional neural networks to deal with the issue mentioned above. However, the existing studies in the literature focus on specific types of fault for insulators. Thus, in this study, we introduce a two-stage model in which we first segment insulators from the background images and then classify its state into four different categories, namely: healthy, broken, burned, and missing cap. The test results show that the proposed approach can realize the effective segmentation of insulators and achieve high accuracy in detecting several types of faults.

Index Terms—Transmission Lines, Insulators, Convolutional Neural Networks, Image Classification, Segmentation, Defect Detection.

I. INTRODUCTION

A. Background and Motivation

The smart grid is a concept that is used to describe a novel structure for the power grid where smart communication and control facilities should provide better reliability and resiliency toward the network where operations become more automated [1]–[4]. Smart grids as a new design for power grids also involve three main sections of generation, transmission, and distribution. There exist many challenges toward automation of all of these three sections. However, as the transmission section typically covers several kilometers, the induced challenge proceeds even more severe.

Even though transmission lines at first glance may be the most important component of a transmission grid considering insulation control rule, insulators also play an important role as they mechanically secure wires in transmission sections. For instance, if any of the insulators become faulty or defected, it will directly influence the total usage and the span life of transmission lines. Consequently, it is of great importance to detect insulator faults timely to guarantee the safety of transmission lines and, as a result reaching better reliability for the entire power grid [5].

Considering the long length of transmission grids manual inspection of their regular operation, for example, through helicopters and human experts impose great difficulty and colossal time consumption. Thus, several experiments have tried to consider automating inspecting power transmission systems visual task [6], [7]. Specifically, considering the danger involved in the task for humans, unmanned aerial vehicles (UAVs) have proven to be a useful tool in the inspection of power transmission grid components. Fig. 1 shows a UAV while it is inspecting the transmission lines insulators.

Generally, the taken images through the inspection carried out by UAVs includes different backgrounds such as mountains, grass field, tower and others, which can vary related to the time of inspection as well. Thus, processing the taken images will be rather challenging and complicated.

Fig. 1: A UAV inspecting transmission line insulators [8].

B. Literature Review and Contributions

Two different practices exist while processing insulators images, first segmenting them and the second to detect defects. In recent years, some studies have focused on these tasks [9]–[12]. In [9], a detection approach for transmission line insulators and their missing cap fault based on Faster Regions with a convolutional neural network is introduced. The given approach consists of a convolutional neural network (CNN) followed by a region proposal network and an object detector. Detection of the insulator images with the complex aerial background is also carried out in [10]. The model involves classic architecture of five modules of convolution and pooling, two modules of fully connected layers. The detection of the insulator is done along with and the recognition of the explosion fault of insulators. Similarly, in [11] cascading structure of CNN is proposed for the segmentation and fault detection of insulators. The proposed network only detects the missing cap defect of the insulators. A transmission network insulator recognition is investigated in [12] where the segmentation algorithm is based on CNNs is proposed. In this study, the data-set is only utilized to segment and recognize the insulators, and no defect detection is considered in the process.
Note that the aforementioned studies either only focus on segmentation tasks or consider the limited types of defects, for instance, missing cap. However, there are several common defects that can happen to any insulators. The most common types of faulty insulators can be categorized as broken, burned, and missing cap ones. Example of which are shown in Fig. 2.

![Healthy](image) ![Broken](image) ![Burned](image) ![Missing cap](image)

Fig. 2: Modes of failure

C. Paper Contributions and Organization

Our main contribution is the proposal of a two-stage model that involves both segmentation and detection tasks for faulty insulators detection. Both tasks are based on the use of state-of-the-art unsupervised learning methods. Thus, insulators’ defect detection can be naturally automatized, given an image of it. We leverage the most recent developments on CNN for proposing an architecture and training the network on the problem of defect detection. For doing so, the algorithmic framework first segments the insulators from the taken images, and then it detects insulators defects if there is any. In our work, not only do we classify the faulty insulators, but also types of fault would be the output of the two-stage model, which separates our work from the studies carried out in the existing literature.

The rest of the paper is organized as follows. Section II introduces the detection approach based on CNN. Section III presents data preparation for the experiments. Experiments are described in section IV. Finally, conclusions are depicted in section V.

II. DETECTION APPROACH

In this section, the utilized CNN structures and further details of network models, applied augmentations, loss function and performance metrics are introduced.

A. CNN Preliminaries

CNN is a special type of neural network that has proven effective in computer vision applications. State-of-the-art results can be achieved in segmentation and classification tasks [13]. Compared to computer vision algorithms that do not take advantage of CNNs, much less pre-processing is required. More importantly, such networks are able to learn characteristics from data, which otherwise would have to be individually accounted for [14].

Even though CNNs have been proposed in different architectures - to increase their efficiency for specific tasks or datasets, three different types of layers are used without exception, each with a specific propose: convolutional, pooling, and fully connected (linear) layers. The convolutional layers aim to extract feature maps of the input images by applying filters over the different regions of images. For instance, with $k$ filters, each filter having weight and bias of $w_i$ and $b_i$, respectively, the convolution of an image patch, $x_n$, can be written as follows:

$$f_{i,n} = \sigma(W_i x_n + b_i),$$

where $\sigma$ is the activation function. Besides rectified linear units (ReLU), sigmoid, or softmax activation functions, a multitude of different options exist, all having their individual advantages. These are applied on a layer’s output neurons (e.g., after a convolutional layer). After a number of convolutional layers, pooling layers are commonly applied in prominent network architectures to reduce the size of particular dimensions. Max-pooling and average-pooling are two examples. Pooling layers, alongside reducing dimensions' sizes, perform denoising when utilized on images. Fully connected layers are generally the last layers of CNNs, possessing a similar structure compared to the traditional neural networks [15].

B. Performance Metrics

Intersection over Union (IoU) metric (2) is used for the segmentation problem (first stage of our framework). It is defined based the true positive (TP), true negatives (TN), false positive (FP) and false negative (FN)

$$\text{IoU} = \frac{TP}{(TP + FP + FN)} = \frac{\sum_{i=1}^{N} 1\{\hat{y}_i = y_i = 1\}}{\sum_{i=1}^{N} 1\{\hat{y}_i = y_i = 1\} + 1\{\hat{y}_i = 1 ; y_i = 0\} + 1\{y_i = 0 ; \hat{y}_i = 1\}} (2)$$

where $N$ is the number of samples, $\hat{y}_i$ is the predicted label, and $y_i$ is the true label for sample $i$.

For the classification problem, second stage, we use accuracy metric defined in (3).

$$\text{Acc} = \frac{TP + TN}{(TP + TN + FP + FN)} = \frac{1}{N} \sum_{i=1}^{N} 1\{\hat{y}_i = y_i\} (3)$$
C. CNN Structure

As discussed in the introduction section, the insulators' classification requires two different yet closely related stages. First, segmentation from the background image and only then apply the classification network to determine their states (possible states are depicted in Fig.2). Note that even though a single network may also be suggested to perform regarding the task mentioned above, in this paper, we propose a modular detection algorithm, as presented in Fig 3 to deal with the problem in hand.

The structure includes two distinct yet well-known CNNs (see Fig.5). The first network is utilized in the first stage segmenting the insulators, and the second network outputs the state of the insulator provided with the segmented insulator as input. Using two networks in serial allows for more straightforward implementation, as the segmentation and classification stages can be fine-tuned individually. Furthermore, a modular system facilitates replacing components in the data processing step.

A CNN architecture that has proven effective for segmentation applications is the so-called UNet [16]. To classify the insulators’ states, a VGG-like architecture is used [17]. First, a batch of input images is passed to the UNet. Its output is a batch of binary images, also known as as masks. Let \( i(x,y) \) denote an input image and \( m \) denote the UNets output. If pixel \( i(x,y) \), with \( x, y \in W, H \) is part of an insulator, \( m(x,y) = 1 \), else \( m(x,y) = 0 \). Hence, \( i \circ m \) yields an image with only the insulator(s) left. This reduces noise on the classification stage, because the image to classify only contains the component of interest.

D. Loss Functions

Weighted Binary Cross-Entropy (4) is used for the segmentation and detection problems.

\[
BCE = -\frac{1}{N} \sum_{i=1}^{N} w_1 \cdot y_i \cdot \log(p(\hat{y}_i)) + w_2 \cdot (1 - y_i) \cdot \log(1 - p(\hat{y}_i))
\]

Also, the mean square error (5), is used as loss function for segmentation of insulators.

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} \| y_i - \hat{y}_i \|^2
\]

III. DATASET PREPARATION

In order to mimic the real-world behavior of how data is actually captured for analysis through the UAVs, we utilized directly the high-quality videos given by UAVs. These videos are taken by several companies throughout the world and are publicly accessible [8], [18]. This gives an advantage to our model. When training is completed, the network can recognize several types of insulators utilized in different locations and companies all over the world. We rendered the videos to image sequences frame by frame. Therefore, the input images are high quality images captured in these videos. In the next step of the preparation, we created ground truth for the segmentation task. The original number of insulators images was 119 however, with the augmentation tools, it was increased to 9520. To do so, we used different types of augmentations by albumentation [19] such as HorizontalFlip, VerticalFlip, BrightnessContrast, and others, complete list of which is given in Table II. Also, some augmented images are shown in Fig.4. We have three types of defects: missing cap, broken cap, and burned cap samples of which are depicted in Fig.2. We also have separate types of augmentation applied for these images to have a sufficient number of images for this task. The number original images and augmented are specified in Table II.

| Data       | Classification | Segmentation |
|------------|----------------|--------------|
| Before augmentation | 46          | 119          |
| Validation-set | 14          | 14           |
| After augmentation | 3680       | 9520         |
| Train-set   | 14           | 14           |
| Validation-set | 14          | 14           |

IV. EXPERIMENTS

As mentioned in the previous section, the structure of the CNN to detect faults includes two different CNNs. As shown in the illustration, the output of the UNet (a binary mask) is passed to the VGG, alongside the input image, for classification. Thus, the classification returned by the VGG is dependent on the segmentation result of the UNet. Training UNet is straightforward as it can be trained by considering the available ground truth of the target masks. However, for training the classification network two approaches can be investigated:

- Training UNet and VGG independently
- Training VGG on UNet’s (trained) output

In the remainder of this subsection, we first investigate UNet (segmentation) training and its performances and then the result of both approaches for classification stage training are discussed.

1) UNet training: Since, the original dataset is captured from several videos with different background and number of the images is rather low, we propose training to be carried

\[\text{TABLE I: Number of insulator images before augmentation} \]

| Augmentation Types | Probabilities |
|--------------------|--------------|
| VerticalFlip       | p=0.5        |
| HorizontalFlip     | p=0.5        |
| ElasticTransform   | p=0.5        |
| GridDistortion     | p=0.5        |
| OpticalDistortion  | p=0.8        |
| Transpose          | -            |
| RandomRotate90     | p=0.5        |
| CLAHE              | p=0.8        |
| RandomBrightness   | p=0.5        |
| RandomContrast     | p=0.5        |
| RandomGamma        | p=0.8        |
2D Convolution + ReLU + Batch norm
Segmentation: U-Net Classification: VGG
Input
× Multiplication
Maxpool (scalefactor = 2)
Upsample (scalefactor = 2)
Linear + ReLU
Channels
(3, 16, 3)
(16, 32, 16)
(32, 64, 32)
(64, 128, 64)
(128, 256, 128)

Fig. 3: Structure of the fault detection algorithm

Fig. 4: Examples of the augmentation results

in two sequence which guarantees a better training result and performance in the end. These two sequences are depicted in Fig. 5. As can be seen from this figure in the second sequence lower losses are achieved for the validation set. Note that the depicted loss is calculated over batch thereby including some fluctuation. However, only the best performance is saved and utilized in the next steps. Several stage of the training and the related outputs are depicted in Fig. 6. We also investigated a threshold where UNet can preform its best performance considering maximum IoU metric as shown in Fig. 7. The Trained segmentation network could reach the IoU of 0.795 in segmenting the insulators from the main images. Some of the final segmentation network results and produced masks are depicted in Fig. 8. As can be seen, the trained UNet performs satisfactory in segmentation of power transmission insulators.

2) VGG: Since the prediction for the proposed network structure is computed as \( \hat{y} = \text{VGG}(\text{U-Net}(x), x) \), the classification result is dependent on the output of the segmenting unit. Two different types of training were conducted. First, the VGG was trained on the ground truth segmentation mask. The obtained loss through the explained regime is shown in Fig. 9. Stochastic gradient descent was chosen as an optimizer method, with a learning rate of 0.008 and a momentum of 0.26. Furthermore, a multiplicative scheduler was employed multiplying the learning rate by 0.98 after every global step. With the exogenous ground truth the obtained classification network accuracy is 0.92.

As shown in Table 3, however, utilizing both independently trained networks yields a mere 21% accuracy. This suggests that classification, as outlined, highly depends on the result of segmentation network. Training these components independently leads to poor outcomes. Secondly, the classifier was trained on segmentation results produced by the trained U-Net. Improved results were obtained by training the classifier on the output of the segmentation stage, as specifics proceeding of CNN could be considered. Note that getting acceptable training result proved difficult, due to limitations (especially in size) of the created dataset. Moreover, the dataset is very diverse. Thus, several training approaches were investigated.

3) Pre-training: CNNs are non-convex functions. The training success can be highly dependent on the starting point of the optimization. Rather than initializing the network randomly, a starting point can be supplied by loading model weights. In the following, pre-training means setting the model’s weights to the result obtained by training the VGG on ground truth data. This had positive effects on the consecutive training on segmentation results.
4) Reset and Alteration: The training was conducted in two nested for-loops, looping over outer and inner epochs. After looping over all inner epochs, adjustments were made to the optimizer. The first technique that proved successful was resetting the solver to its initial state. This prevented diminishing improvements when a local minimum was reached, or the learning rate became too small. This regularly facilitated finding an even better solution after a reset. Secondly, it was tried alternating between optimizers with different settings, in the same manner. This technique, however, turned out to be less effective.

For instance, the obtained loss values in training are depicted in Fig. 10a where no pre-training or solver resetting is utilized. It is clear increasing training iteration has no effect in decreasing validation loss. While applying these two, as shown in Fig. 10b, could lead to much better results as the minimum validation loss gradually decreases over training iterations. A better comparison is provided in Fig. 10c in which the minimum losses achieved by each investigated approach are demonstrated. Finally, the acquired accuracy by the combination of the aforementioned approaches is concluded in Table III. As can be observed in Fig. 2 the data set’s pictures are fairly diverse meaning that they include several types of insulators with dissimilar backgrounds, that is why the classification accuracy is limited to 0.78. However, if our proposed approach including the utilization of CNN and training approach is utilized by a specific transmission company, the diversity is noticeably reduced. Thus, we also evaluated the proposed approach on a more homogeneous data set. We ran 20 training epochs initializing the network with previous weights and obtained an accuracy of 93% as also reported in Table III which is quite satisfactory for the aforementioned classification problem.

TABLE III: The obtained accuracy results for different training regime of VGG based on UNet outputs (4800 global iterations)

| # Training | Pre-trained | Reset | Alternating | Acc  |
|------------|-------------|-------|-------------|------|
| 1          | x           | -     | -           | 0.42 |
| 2          | -           | x     | -           | 0.5  |
| 3          | x           | -     | x           | 0.71 |
| 4          | x           | x     | -           | 0.78 |

Performance on homogeneous data set 0.93

Separated VGG and UNet training 0.21

V. CONCLUSION

Insulators are known to be a vital component of the energy transmission systems. Yet, on the other hand, they are exposed to electrical, mechanical, and environmental stresses leading
to different kinds of defects. In this study, we focused on investigating approaches based on the deep learning techniques to detect and classify defected insulators. In doing so, we utilized state-of-art CNNs such as UNets and VGG modified to match the task in hand. We had three different defects. Namely, insulators with broken, burned, and missing cap. The results showed despite the lack of a large input dataset successful performance of the trained UNet in the segmentation task of insulators and the trained VGG as the second stage network in reaching a high IoU and a proper accuracy while classifying insulators into the possible considered classes.

![Training loss](image1)

(a) No pre-training and no solver reset

![Training loss](image2)

(b) Pre-training and solver reset

![Training loss](image3)

(c) Training on homogeneous data set using previously obtained weights as a warm start

Fig. 10: VGG training on UNet

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