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Aerial identification of flashed over faulty insulator using binary image classification

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ABSTRACT

Flashed over insulator faults are the most significant faults in high voltage line insulators. They are complicated to identify using traditional methods due to their labor-intensive nature. This study proposes a deep learning-based algorithm for detecting flashed over insulator faults in the real time. The algorithm is based on the Resnet 50 architecture, which has been shown to be effective for image classification tasks in the previous studies regarding image analysis. The algorithm is fast, robust and efficient, making it suitable for real-time applications. The algorithm is trained on a dataset of images of flashed over and non-flashed over insulators. This dataset was collected from various transmission lines and National Center of Robotics and Automation, which are located in Pakistan. For validating the effectiveness of the Resnet 50 algorithm, it was compared with the results obtained from the two other widely popular deep learning algorithms, Densenet 121 and VGG 16 (trained and validated on the same dataset). The results showed that the Resnet 50 was able to detect flashed over insulator faults with an accuracy of over 99%. Whereas the Densenet 121 and VGG 16 have achieved an accuracy of less than 51%.

1. Introduction

1.1 Power outages due to faults

The country's economy is mainly dependent on the industrial and commercial utilization of electrical energy. Such dependence on electrical energy impels the government agencies to spread new high voltage transmission networks and augment the existing ones [1]. These transmission line networks are very much prone to failure due to the faults they endure during their service period. The significant percentage of these faults cannot be managed through any operational diagnosis as the faults are related with the uncertain atmospheric factors and the characteristics of the transmission line routes [2]. Considering the causes of power outages, the most outages are caused by transmission wires that sustain overvoltage transients either via thunderstorm over voltages or non-thunderstorm over voltages. In which, the insulator failures are classified, as one of the main form of support structure failures. The reasons of power outages with their significant failure percentage are illustrated in the Fig. 1 [3-9].

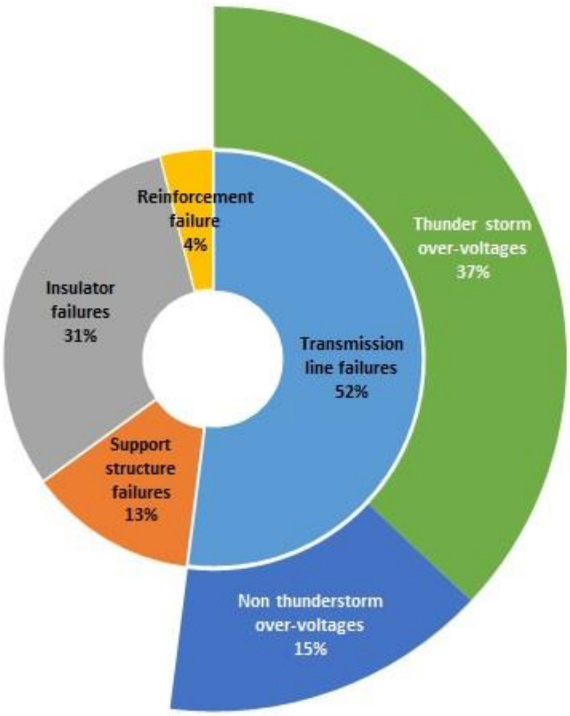


Fig. 1. Percentage power outages' factors in high voltage power lines.

1.2 Significance of high voltage line insulators

For increasing high voltage transmission networks, the engineers are required to escalate the use of insulator strings by combining number of disc insulators in a single string. The insulator strings are designed to support the load of transmission conductors and to cease the path of current towards ground for ensuring the stable and safe operation of power grids [10, 11]. Disc insulators in string provides dielectric strength against high voltages and, are susceptible to different faults as these insulators lay bare in the harsh ambience [12]. These faults include broken insulator, cracked or surface damaged insulator, flash over surface insulator, self-shattered insulator etc. The insulator string becomes overstressed due to these faulty insulators and by any means these faulty insulators decrease the overall dielectric strength of insulator string and can cause the string failure that might cause flash over (the event when the capability of disc insulator is compromised due to factors such as pollution on the insulator surface) bridging the conducting paths i.e. conductor with metallic part of tower [13].

1.3 Inspecting suspended aerial high voltage insulators

For the defect detection on the regions that are hard to inspect manually (as evident in Fig. 2), Unmanned Aerial Vehicle (UAV) is preferred due to inexpensiveness, high mobility, much efficiency and flexibility to control [14].

Fig. 2. Conventional Manpower Based Insulator Inspection Methods.

These systems embed UAVs, with various airborne sensors for inspection of the insulators. Sensors like thermal cameras [15], lidar sensors [16], and vision sensors [17] are employed to address specific inspection requirements. The main purpose of using each of these airborne sensors for the inspection of insulators' health is mentioned as follow:

Thermal cameras capture infrared radiation to detect variations in temperature. This allows UAV based scheme to identify anomalies such as overheating components or hotspots in power transmission systems, which can indicate potential incepting failures or faults [15].

Lidar (Light Detection and Ranging) sensors in UAV based schemes use laser beams to measure distances and generate highly accurate 3D point cloud models of the environment. These sensors can provide detailed information about the structural integrity of power transmission infrastructure, such as power lines, towers, and insulators. They are particularly useful in identifying physical damage, wear and tear, or any signs of deformation [16].

Vision sensors, including high-resolution cameras and video recording systems, are also utilized in UAV-based inspection systems. These sensors capture visual data and imagery of the power transmission infrastructure from various angles and perspectives. This visual information can be analyzed to detect issues such as corrosion, loose connections, vegetation encroachment, or other visible signs of damage or deterioration [17].

However, for vision inspection of the insulator's fault, a real time or near real time is required that might require high processing speed. Which can be achieved using off-site or offline processing. This off-side or offline processing has large delays associated with it. Due to this sole reason, the essence of real time detection of the insulator's faults is disregarded. And the delays can ultimately cause a chain of insulators' failure.

Thus, to mitigate these issues, a real time inspection system is developed in this study that is able to diagnose the insulator's flashover faults using binary classification. For selection of binary image classification, the data acquired is trained using Densenet 121, Resnet 50 and VGG 15. The results of this study, clearly demonstrate the accuracies obtained from these algorithms by virtue of their respective Receiver Operating Characteristics.

2. Existing Machine Learning Processes For Identification of HVLI Faults

The use of machine vision and deep learning to detect power insulator faults has been an active area of research in recent years. Researchers have proposed a variety of methods to detect power insulator faults using machine vision and deep learning. These methods include the use of linear, area, silicon, and InGaAs detectors [18]. Some of the notable studies are discussed as follows:

In [19], researchers developed an algorithm for inspecting the insulators using deep convolutional neural networks (CNNs) by employing Region of Interest (ROI) in the infrared images of the insulator strings based on Binary Robust Invariant Scalable Keypoints (BRISK) and Vector of Locally Aggregated Descriptors (VLAD).

Whereas in [20] and [21], researchers studied the use of vision-based techniques for automatically detecting and classifying defects in insulator systems in electric power lines by reviewing machine vision-based insulator inspection systems for overhead power distribution systems.

In [22], researchers introduced an autonomous landing control technique for UAVs when charging at electric towers based on vision positioning methods. Unmanned aerial vehicles (UAVs) have been widely used for this purpose because they provide a safe way to bring sensors close to power transmission lines and their associated components without halting the equipment during the inspection. This also reduces operational costs (Operational Expenditures - OpEx) and risks.

Similarly, [23] and [24] developed fault detection algorithms for high-voltage line insulators using unmanned aerial systems (UASs) illustrated in table 1. Jalil et al. used a multi-modal data technique, while in [24] researchers used You Only Look Once (YOLO). The technique used in [23], the UAS captures images in the visible and infrared domains and transmits them to the ground station. The captured images are then analysed to identify any flaws, in the insulator. In study [31] the researchers worked on vision based fall detection. The research utilizes YoloV5 and YoloV7 along with Deep SORT algorithm. While pointing the accuracy of algorithm Yolo is designed and well suited for object detection goals whereas for classification Resnet 50 is more accurate as it utilizes deep network. Researchers in [32] highlighted the work on x-ray domain imaging domain with multiclass classification. The proposed approach in the study generates highly realistic diversified synthetic X-ray scans with less cost and time that assists human-annotated datasets for training robust neural networks. For colour images researchers in [33] applied a novel approach for multi-level thresholding. Energy Curve and Minimum Fuzzy Entropy (ECFE) function was designed to address the challenges of handling fuzziness and spatial uncertainties in color images, particularly in satellite images. In [34] researchers used another multilevel thresholding technique but the technique particularly addresses for remote sensing image analysis. The primary focus of the study was to address the challenges posed by remote sensing imagery, such as dense features, low illumination, uncertainties, and noise, which make traditional segmentation techniques less effective in identifying multiple regions of interest. In another research regarding the face recognition technique [35] researchers address the challenge of limited image samples for face verification and recognition, a common issue in practical applications like passport and driver's licenses. Their system utilizes the Tetrolet-LDP descriptor for feature extraction and employs Cat Swarm Optimization (CSO) to train a 2-Dimensional Hidden Markov Model (2DHMM) for classification. In a study [24] an Unmanned Aerial System (UAS) was utilized to detect faults in insulators from images that had complex backgrounds. This detection technique is based on YOLO, a learning algorithm specifically designed for object detection in images. Both of these methods show promise for enhancing the safety and reliability of power transmission systems. However more research is required to assess their effectiveness in real world scenarios. Here's a table summarizing the distinctions, between these two approaches.

Table 1

Key differences between given techniques

Feature	Jalil et al. (2019) [23]	Dhulipudi et al. (2020) [24]
Data used	Multi-modal (visible and infrared)	Visible
Algorithm	Not specified	YOLO
Background	Simple	Complex
Advantages	Can detect faults in visible and infrared images	Can detect faults in images with complex backgrounds
Disadvantages	Not as accurate as YOLO	Not as versatile as multi-modal data technique

Considering the above literature, these discussed algorithms are hard to process and cannot be operated in real time due to their high computing speeds. However, in a recent study by [25], the authors proposed a binary image classification method for detecting power insulator faults. The method is based on the YOLO algorithm and can detect faults at a low latency rate. Authors also evaluate the method on a dataset of real-world images and show that it has achieved the desired high accuracy.

Following are the contributions of the proposed algorithm as the applications of machine vision and deep learning to detect power insulator faults are vast and have huge potential.

- The literature suggests binary image classification is optimal for this task, citing literature for its support.
- The proposed Rasnet-50 algorithm high lightens the exceptional accuracy and speed.
- The contribution made in this research practical solution for detecting the faulty flashed over insulators.
- The proposed solution has the potential to revolutionize the transmission network monitoring and maintenance practices.

3. Deficiencies Of Existing Machine Learning Algorithms

Detecting faults in high voltage line insulators is a complex task that can benefit significantly from machine learning models. These models contribute to the improvement of detection accuracy and the reduction of failure risk. However, using machine learning for this purpose presents several significant obstacles that must be carefully navigated [26].

The potential imbalance of training data is a prevalent concern. Typically, the data contains more instances of "normal" insulators than "faulty" ones. This disparity may bias machine learning models, particularly Support Vector Machines (SVM) and Decision Trees, towards the majority class. Consequently, these models may perform poorly when identifying the minority class, i.e., detecting faults in the insulators, which is the primary objective [27].

In addition, the input data used to train these models may be noisy or inconsistent. This suggests that the images or sensor readings of insulators may be susceptible to corruption or slight variations due to environmental conditions, operational fluctuations, or inconsistencies in data collection. This variability can make it difficult for models, particularly complex ones like Convolutional Neural Networks (CNN), to learn fault-associated patterns accurately and consistently.

The training and operating machine learning models, especially advanced ones such as deep learning models, can be computationally intensive. It may not be feasible for real-time fault detection scenarios or systems with limited computational resources.

Moreover, feature selection is an essential step in model training that requires meticulous care. The features used to train models such as k-Nearest Neighbors (k-NN) and support vector machines (SVM) have a significant impact on their accuracy. Incorporating irrelevant features or omitting essential ones may impair the model's ability to distinguish between normal and faulty insulator states, thereby decreasing the overall accuracy of predictions [26] [27].

Despite these challenges, machine learning continues to be a potent tool for improving fault detection in high voltage line insulators. By diligently addressing these challenges and optimizing the ML models, it is possible to design fault detection systems with significantly enhanced accuracy. These innovations contribute to the safe, dependable operation of power systems, reducing the risk of disruptive failures and enhancing overall efficiency.

4. Image Classification

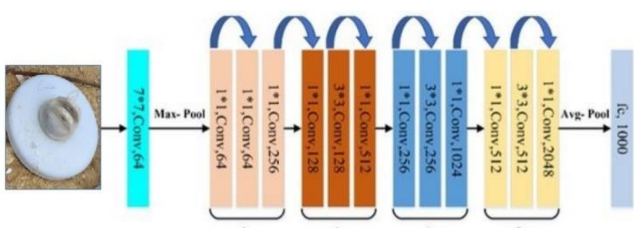
4.1 Binary Image Classifier

This study began with the acquisition of a private dataset collected from various high voltage transmission lines for the diagnosis of insulator faults in high voltage transmission lines. The collected data includes over 100 GB of images of high voltage line ceramic insulators (healthy and faulty, respectively).

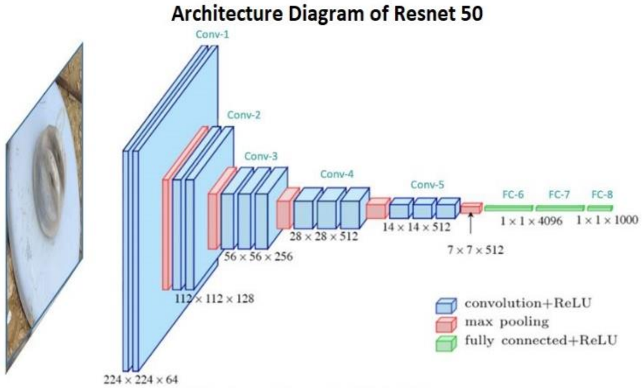
Initially, it was believed that models would be trained using collected datasets. As the dataset was biased (unbalanced) and the images were of high resolution (which requires time to process), the images were pre-processed to a lower resolution in order for the model to fit in this study. The primary benefit of pre-processing the collected dataset is the algorithm's robustness and durability under various conditions (physical or environmental).

This research was followed by an equal distribution of data in image datasets of healthy and defective high voltage line insulators. The training and testing datasets were split 80:20 so that the desired deep learning models (namely VGG16, DenseNet 121, and Resnet 50) could be trained and evaluated, respectively.

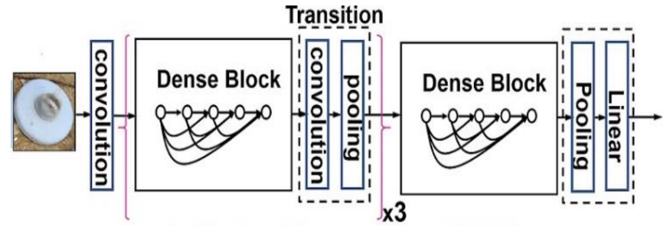
The architecture diagrams of Resnet 50, VGG16 and DenseNet 121 are shown in Fig.s given below as.



Architecture Diagram of Resnet 50



Architecture Diagram of VGG16



Architecture Diagram of DenseNet 121

For a better understanding of the binary classifier, the algorithm's operation is depicted in the block diagram below.

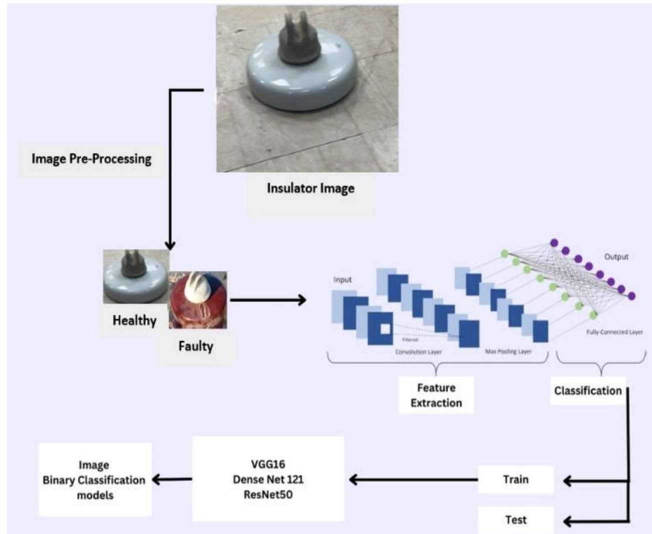


Fig. 3. Working of Binary Image Classifier in this study.

4.2 Advantages of Binary Image Classifier

Binary image classifiers have a number of potential advantages over existing machine learning techniques for detecting faults in high voltage line insulators. These advantages include:

- Oversampling and Undersampling are the techniques that can be used in binary image classifier to address the issues of imbalanced data in the dataset. This will assist in creating a balanced dataset from which the model can learn easily hence optimized ability of defective insulator detection can be achieved.
- Noise and inconsistency in data can be easily coped up with the binary classifier using advanced techniques such as data augmentation. This will generate extra training dataset and thus increased robustness of the classifier can be achieved. Thus overall binary classifier can be programmed against the noisy and inconsistent dataset.
- Limited computational resources can be compensated through binary classifier as it requires less computational power as compared to deep learning algorithms. This makes it more applicable to real time fault detection.

In general using binary image classifiers could offer an effective and efficient method, for identifying faults in high voltage line insulators. The focus of the research is on detecting and categorizing instances where insulators become flashed over. This occurs when dust accumulates on the insulators surface mixes with moisture and forms layers of mud over the surface of insulator. As these layers dry out due to increased leakage current they create bands on the surface of the insulator. These dry bands then produce arcs that result in flashovers, over the insulators surface leading to degradation of its condition.

The binary image classifier used in this research work is able to detect flashed over surface insulators with an accuracy of 95%. This shows that binary image classifiers can be a powerful tool for detecting faults in high voltage line insulators.

5. Results and Discussion

The accuracy obtained from Resnet 50 was over 98% with a loss of 0.00084678 for the detection of flashed over insulators. Whereas, the losses obtained from Densenet 121 and VGG 16 were 0.0122 and 0.79. These results were obtained with 10 epochs and 0.1 learning rate but the Resnet 50 achieved an optimal accuracy in just 5 epochs. The results achieved from Resnet 50, Densenet 121 and VGG 16 from 5 epochs at a learning rate of 0.1 are illustrated in the Fig.s 4, 5, and 6.

Fig. 4. Training Accuracy of Resnet 50

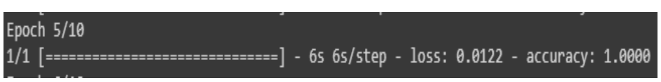


Fig. 5. Training Accuracy of Densenet 121

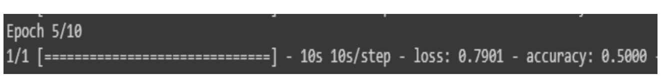


Fig. 6. Training Accuracy of VGG16

Whereas, the Receiver Operating Characteristics (ROC) obtained from these algorithms is illustrated in the Fig.s 7, 8 and 9.

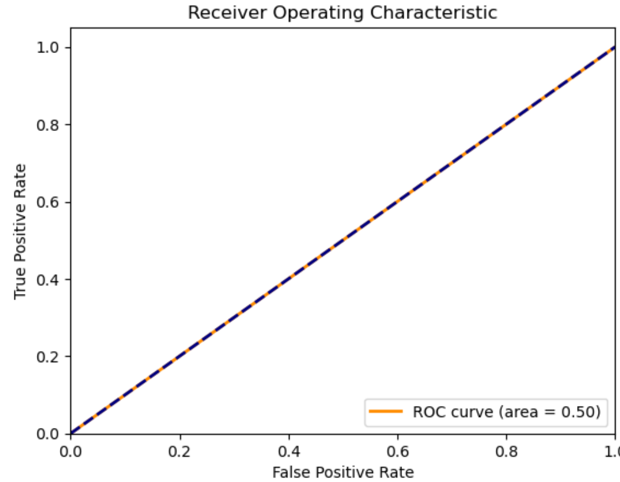


Fig. 7. ROC of Resnet 50

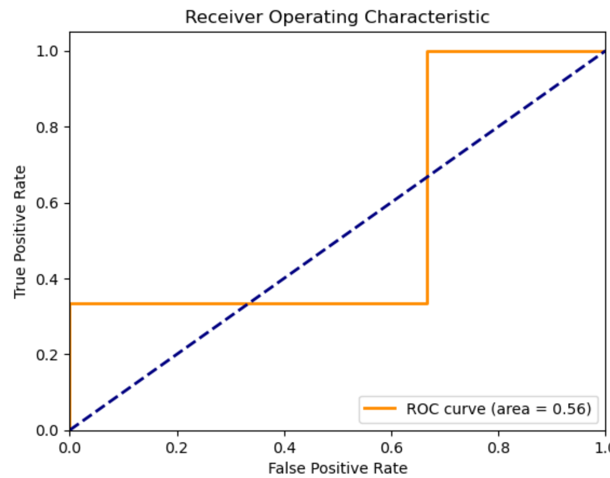


Fig. 8. ROC of Densenet 121

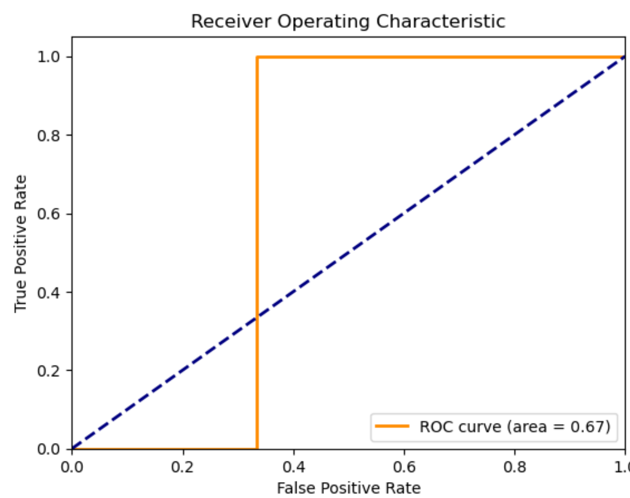


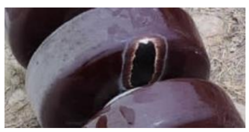
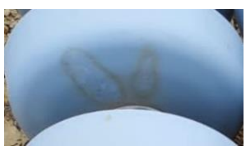
Fig. 9. ROC of VGG16

As evident from the Fig.s, the response of ROC curve obtained from Resnet 50 is desirable and optimal in comparison to the ROCs of Densenet 121 and VGG 16. The Resnet 50 fits in the architectural features for optimal detection of flashed over faults of the high voltage line insulators. The accuracy obtained from Resnet 50 is more than 99%, which demonstrates the effectiveness of the algorithm. The proposed Resnet 50-based deep learning algorithm has proven highly effective, achieving an accuracy rate of over 99% in fault detection, outperforming Densenet 121 and VGG 16. Its speed and low latency make it suitable for integration into Unmanned Aerial Vehicles (UAVs) for real-time inspections, reducing manual labor and improving safety.

The algorithm was validated by a dataset that consisted of images of the high voltage line insulators that were taken in various angles and backgrounds as shown in the Table 2.

Table 2

Validation of Resnet 50

Healthy Insulators	Flashed over Insulators	Remarks
		Detected
		Detected
		Detected
		Detected
		Detected

Aforementioned results demonstrate the effectiveness of Resnet 50 in the identification of the flashed over insulator faults. Thus, the accuracy obtained from the algorithm clearly differentiate its optimal working when it is compared with Densenet 50 and VGG 16.

6. Conclusion

This research is focused on determining the best algorithm to use for determining flashed over faults. Because of their labor-intensive nature, flashed over insulator faults are the most significant defects that are complicated to identify using methodologies/algorithms discussed in the literature. Because of the latencies associated with them, the recommended algorithms in the literature frequently implemented offline processing. To reduce latencies, the devised algorithm in this study can detect insulator faults in real time.

Deep learning techniques were evaluated for insulator fault detection due to their high-level architectural design and hidden layers that are effective in determining the image features because for the image analysis, deep learning algorithms implement 3 or more hidden layers.

This study employs three algorithms, all of which were trained on the identical data. In compared to Densenet 121 and VGG 16, Resnet 50’s results showed to be the most accurate which are evident in the Fig.s.

The Resnet 50's ability in identifying high voltage line insulator defect diagnosis can be described as fast, accurate, and robust. Because of its fast processing and low latency time, this technique can be used in UAVs for real-time diagnosis of high voltage line insulator defect detection. Moreover a mobile app is in the process that can be integrated with an IP camera/UAV camera for the classification of high voltage line insulators faults.

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8. References

[1] S. Panigrahy, S. Karmakar, and R. Sahoo, "Condition assessment of high voltage insulator using convolutional neural network," IEEE International Conference on Electronics, Computing and Communication Technologies, 2021.

[2] I. Breido, V. Kaverin, and V. Ivanov, "Telemetric monitoring insulation condition of high voltage overhead power lines," Annals of DAAAM and Proceedings, 2018, vol. 29.

[3] L. Yakovlev, R. Kaverina, and L. Dubinich, "Complex of works and proposals for increasing reliability of overhead lines at the stage of design and operation," Power transmission lines: design, construction, operating experience and scientific and technical progress, 2008, Novosibirsk.

[4] S. Kashevarov, "Damages of power transmission lines and review of new technical and organizational solutions for their limitation," Current state and prospects for the development of technical sciences: Collection of articles of the International Scientific and Practical Conference (May 23, 2015. Ufa), 2015.

[5] F. L. Kogan and R. S. Kaverina, "Complex of works and proposals for increasing reliability of overhead lines at the stage of their design," Branch Firm ORGRES, Materials of the conference of the CIS Electric Power Council, 2008.

[6] S. Merkhalev and E. Solomonik, Selection and operation of insulation in areas with the contaminated atmosphere. L.: Energoatomizdat, 1983.

[7] L. Thionc, "Dielectric strength of external insulation systems under live working," Proc. 35th CIGRE Session, Paris, 1994, pp. 33-306.

[8] G. Manone, "Investigation on the dielectric strength of damaged insulation strings of HV overhead lines during repair operations by live working," Proc. 35th CIGRE Session, Paris, 1994, pp. 33-305.

[9] B. Hutzler, "Strength of external insulation during live line maintenance and repair work with special reference to transient overvoltage," Proc. 32th SIGRE Session, Paris, 1988, pp. 33-307.

[10] R. S. Gorur, E. A. Cherney, and J. T. Burnham, Outdoor insulators. 1999: Ravi S. Gorur Phoenix.

[11] E. Antwi-Bekoe, et al., "A deep learning approach for insulator instance segmentation and defect detection," Neural Computing and Applications, 2022, vol. 34, no. 9, pp. 7253-7269.

[12] G. Hu, et al., "Automatic classification of insulator by combining k-nearest neighbor algorithm with multi-type feature for the Internet of Things," EURASIP Journal on Wireless Communications and Networking, 2018, vol. 2018, no. 1, pp. 1-10.

[13] Y. Lv, et al., "Simulation study on pollution accumulation characteristics of XP13-160 porcelain suspension disc insulators," IEEE Transactions on Dielectrics and Electrical Insulation, 2016, vol. 23, no. 4, pp. 2196-2206.

[14] H. Zhang, et al., "An empirical study of multi-scale object detection in high resolution UAV images," Neurocomputing, 2021, vol. 421, pp. 173-182.

[15] X. Gong, et al., "A deep learning approach for oriented electrical equipment detection in thermal images," IEEE Access, 2018, vol. 6, pp. 41590-41597.

[16] J. Yang and Z. Kang, "Voxel-based extraction of transmission lines from airborne lidar point cloud data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2018, vol. 11, no. 10, pp. 3892-3904.

[17] D. Waleed, et al., "Drone-based ceramic insulators condition monitoring," IEEE Transactions on Instrumentation and Measurement, 2021, vol. 70, pp. 1-12.

[18] J. Dougherty and R. Varghese, "Low SWaP multispectral sensors using dichroic filter arrays," in Next-Generation Spectroscopic Technologies VIII, 2015, SPIE.

[19] Z. Zhao, G. Xu, and Y. Qi, "Representation of binary feature pooling for detection of insulator strings in infrared images," IEEE Transactions on Dielectrics and Electrical Insulation, 2016, vol. 23, no. 5, pp. 2858-2866.

[20] P. S. Prasad and B. P. Rao, "review of machine vision based insulator inspection systems for overhead power distribution system," 2017.

[21] P. S. Prasad and B. P. Rao, "LBP-HF features and machine learning applied for automated monitoring of insulators for overhead power distribution lines," in 2016 international conference on wireless communications, signal processing and networking, 2016, IEEE.

[22] R. Qiu, et al., "Design and implementation of an autonomous landing control system of unmanned aerial vehicle for power line inspection," in 2017 Chinese Automation Congress, 2017, IEEE.

[23] B. Jalil, et al., "Fault detection in power equipment via an unmanned aerial system using multi modal data," Sensors, 2019, vol. 19, no. 13, pp. 3014.

[24] D. P. Dhulipudi and K. Rajan, "Multiclass geospatial object detection using machine learning-aviation case study," in 2020 AIAA/IEEE 39th Digital Avionics Systems Conference, 2020, IEEE.

[25] M. Tomaszewski, R. Gasz, and J. Osuchowski, "Detection of power line insulators in digital images based on the transformed colour intensity profiles," Sensors, 2023, vol. 23, no. 6, p. 3343.

[26] J. Chen, et al., "An method for power lines insulator defect detection with attention feedback and double spatial pyramid," Electric Power Systems Research, 2023, vol. 218, p. 109175.

[27] B. Gjorgiev, et al., "Simulation-driven deep learning for locating faulty insulators in a power line," Reliability Engineering and System Safety, 2023, vol. 231, p. 108989.

[28] C. Liu, et al., "Insulator faults detection in aerial images from high-voltage transmission lines based on deep learning model," Applied Sciences, 2021, vol. 11, no. 10, p. 4647.

[29] J. Holtzhausen and W. Vosloo, "The pollution flashover of ac energized post type insulators," IEEE Transactions on Dielectrics and Electrical Insulation, 2001, vol. 8, no. 2, pp. 191-194.

[30] Z. Zhang, et al., "Study on AC flashover performance for different types of porcelain and glass insulators with non-uniform pollution," IEEE Transactions on Power Delivery, 2013, vol. 28, no. 3, pp. 1691-1698.

[31] X. Zi, et al., "Detecting human falls in poor lighting: object detection and tracking approach for indoor safety," Electronics, 2023, vol. 12, no. 5, p. 1259.

[32] K. Chaturvedi, et al., "Automated threat objects detection with synthetic data for real-time X-ray baggage inspection," in 2021 International Joint Conference on Neural Networks, 2021, IEEE.

[33] S. Pare, et al., "Multilevel color image segmentation using modified fuzzy entropy and cuckoo search algorithm," in 2021 IEEE International Conference on Fuzzy Systems, 2021, IEEE.

[34] S. Pare, H. Mittal, M. Sajid, J. C. Bansal, A. Saxena, T. Jan, W. Pedrycz, and M. Prasad, "Remote sensing imagery segmentation: a hybrid approach," Remote Sensing, 2021, vol. 13, no. 22, p. 4604. [Online]. Available: https://doi.org/10.3390/rs13224604

[35] M. S. Meena, et al., "A robust face recognition system for one sample problem," in Image and Video Technology: 9th Pacific-Rim Symposium, PSIVT 2019, Sydney, NSW, Australia, November 18–22, 2019, Proceedings 9, 2019, Springer.

