

A Convolutional Neural Network Ensemble Model for High-Voltage Insulator Surface Image Classification

Arailym Serikbay

Department of Electrical and Computer
Engineering
Nazarbayev University
Astana, Kazakhstan
arailym.serikbay@nu.edu.kz

Mehdi Bagheri

Department of Electrical and Computer
Engineering
Nazarbayev University
Astana, Kazakhstan
mehdi.bagheri@nu.edu.kz

Amin Zollanvari

Department of Electrical and Computer
Engineering
Nazarbayev University
Astana, Kazakhstan
amin.zollanvari@nu.edu.kz

Abstract—Power transmission lines use high-voltage insulators for both electrical insulation and mechanical support. In normal operating conditions, insulators are often exposed to outdoor contamination and stress from different weather conditions. These factors can lead to insulation malfunctions and power losses. Consequently, electricity grid operating companies must conduct regular check-ups and evaluations to minimize possible power outages. This paper introduces a new method that uses deep convolutional neural networks (CNNs) for high-voltage insulator surface image classification. Given the effective use of CNNs in computer vision, numerous pre-trained models are available for various classification tasks. Typically, researchers fine-tune these models on a specific dataset, and a single model is selected and used for the final prediction. In contrast with this “winner-take-all” approach, in this study, an ensemble of pre-trained CNNs is proposed to classify the type of pollution accumulated on the insulator surface. This focus is warranted because each pre-trained convolutional base operates as a feature extractor, and thus a combination of them as proposed in this study functions as a composite feature extractor. Our numerical results clearly show the superiority of the proposed ensemble technique over the common “winner-take-all” approach for classifying insulator surface contamination.

Keywords—convolutional neural network, ensemble learning, insulator surface contamination

I. INTRODUCTION

Transmission lines are essential for transmitting and distributing electricity to residential and industrial buildings. Most of the power-distributing and transmitting system components, including high-voltage insulators, were built many years ago and are now approaching the end of their expected operational lives. As a result, the existing power lines could cause deterioration issues, posing a risk to the overall integrity of the electrical distribution network [1]. Monitoring and analysing the condition of the high-voltage insulator as one of the main overhead transmission line components is a demanding task. To prevent future power outages and guarantee a sufficient electricity supply, authorities and power utilities should address these issues.

The efficient operation of high-voltage insulators can ensure a consistent electricity supply to consumers. The conventional techniques used to analyse the high-voltage insulator condition include on-foot visual inspection [1] and helicopter patrolling [2]. These methods are time-consuming and potentially dangerous, and inspectors cannot always

physically reach remote locations. Instead of visually inspecting with the naked eye, applying infrared [3-6] and ultraviolet cameras [7-8] can enhance on-foot visual inspection and helicopter patrolling. According to the Planck rule [3], all objects emit radiation with a wavelength inversely proportional to their temperature. This radiation is detected by infrared cameras and converted to a thermal image. A normal operating high-voltage insulator's thermal image should be uniform. Consequently, any temperature change can indicate surface pollution or partial discharge problems [4-6]. The electrical field around high-voltage insulators may ionize the air around them and lead to electrical discharge, which in turn causes ultraviolet light emission. Ultraviolet cameras can detect this radiation level, which indicates insulation degradation [7]. However, the infrared and ultraviolet camera's capabilities are limited by high-voltage insulator location accessibility, weather conditions, and the inability to reveal temperature-independent interior problems [8].

High-voltage insulators are prone to contamination due to the lack of protection and permanent exposure to adverse weather conditions. The mixture of dirt, dust, snow, and other contaminants forms a conducting layer on the insulator surface, resulting in the leakage of current and presenting a potential danger of power outages [9]. The issue of high-voltage insulator surface contamination in overhead transmission lines has been recognized for several years [10]. Hence, conducting on-time inspections and evaluations of the high-voltage insulator's condition is crucial to guaranteeing a safe and reliable power supply. The objective of this research is to classify high-voltage insulator surface contamination properly. In this regard, a high-voltage insulator dataset (HVID) is constructed consisting of insulator surfaces coated with water, snow, soil, and cement. Fig. 1 shows images of high-voltage insulators with different surface contaminations. After that, an ensemble of deep CNNs is proposed to classify the types of high-voltage insulator surface contamination. The success of CNN in computer vision has resulted in the use of numerous pre-trained models for various classification tasks. Typically, these models are fine-tuned using a dataset specific to a target task, and then the best model is selected during the model selection step for further prediction. In this study, it was suggested to use an ensemble of CNN models (base models) with our custom HVID. The convolutional base of these models forms a composite feature extractor, which can lead to better classification performance.

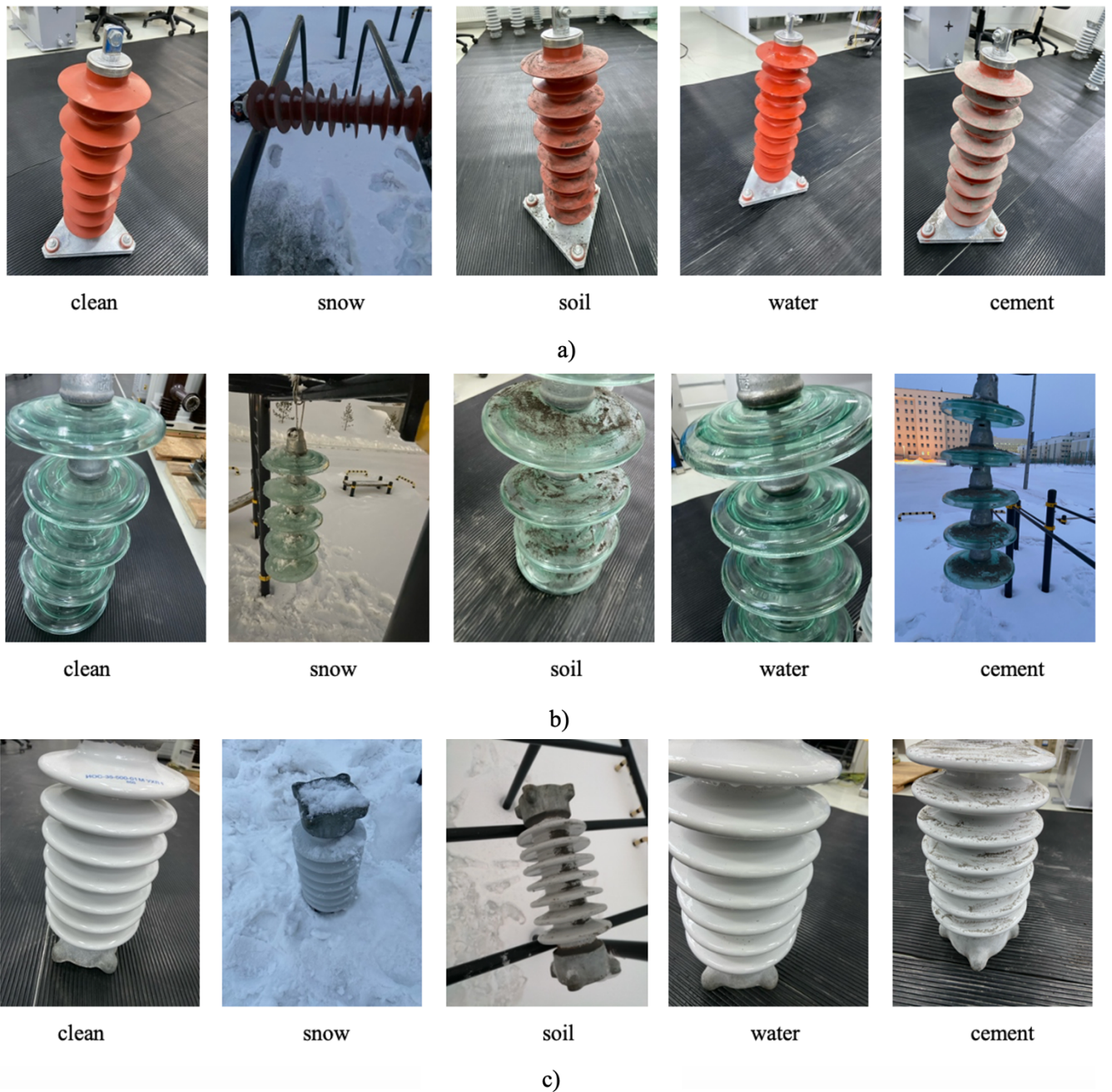


Fig. 1. High-voltage insulator surface contamination types: a) polymeric, b) glass, and c) ceramic insulators.

The paper is organized as follows: Section II provides an overview of the existing research results on high-voltage insulator condition analysis. Section III outlines the details of the proposed ensemble learning method. Section IV presents the custom insulator dataset details, training results, and the robustness test of the final selected model for daytime and nighttime lighting. Section V concludes and summarizes the main findings.

II. RELATED WORKS

Traditional high-voltage insulator condition analysis procedures employ various methods to interpret primary data, such as images, sounds, or electrical measurements, which are collected by electricity maintenance specialists. The methods include visual inspection on foot [11], thermography [12], ultraviolet [13], ultrasonic [14], electrical tests based on

partial discharge [15], leakage current [16], flashover voltage [17], and resistance [18].

Traditional methods for analyzing the condition of high-voltage insulators are time-consuming, expensive, and prone to human error due to the large amount of data involved and the requirement for an expert powerline maintenance professional [19]. To avoid the constraints of traditional approaches, a hybrid strategy is proposed, analyzing collected data (images, electrical, etc.) with artificial intelligence methods [20].

One of the novel approaches used in high-voltage condition monitoring is the integration of computer vision techniques with drones, which enables the development of more comprehensive hybrid methods. In this regard, drones were used in various condition-monitoring solutions such as visible-light RGB cameras [21], RELIFO [22], YOLO [23], and Raspberry Pi [24].

Many engineering tasks now use advanced approaches, such as deep learning. These advancements help to overcome the limitations of conventional techniques. In this regard, researchers have conducted many studies on the assessment of high-voltage insulator conditions using various deep-learning techniques [25–26]. Particularly, CNNs are highly efficient for image classification tasks because of their effective feature extraction function [27]. However, a large training dataset is often required to build an accurate CNN model in complex classification tasks. That being said, transfer learning can be used to alleviate this problem by using pre-trained CNN models trained on substantially large datasets and fine-tuning them based on smaller datasets collected for different but related tasks.

The development of an accurate classifier model for monitoring the condition of high-voltage insulators represents a significant step forward in minimizing power losses and ensuring the stability of power supply systems. Traditional methods [11–18] face challenges such as high electrical risks, elevated costs, lengthy inspection times, and limited access to remote locations [19]. Regarding the advanced techniques, using pre-trained CNN models to classify images generally follows the common “winner-take-all” approach. Specifically, these models are fine-tuned using data collected for a specific purpose, and the best model is determined and used for making the final predictions. Upon selecting the final model, all other models and their extracted features are discarded. This work introduces an innovative approach to overcoming these limitations by employing advanced techniques to create a highly efficient classifier model. Instead of using this standard approach, an ensemble of pre-trained CNNs is proposed for high-voltage insulator surface condition classification.

III. METHODOLOGY

The ensemble learning method improves output prediction by combining multiple individual models, known as base models [28]. The idea behind the ensemble approach takes advantage of a diverse and comprehensive feature set, leading to more accurate output prediction. In this paper, 7 pre-trained CNN models are used as base models: DenseNet121 [29], EfficientNetB0 [30], InceptionResNetV2 [31], MobileNetV2 [32], ResNet50V2 [33], VGG16 [34], and Xception [35], as they have a proven history and are widely used in various classification tasks [29–35]. Instead of

selecting a single base model for predicting a high-voltage insulator surface contamination type, an ensemble of these models is proposed to determine the class of output based on a soft-voting applied to the output of these models. At the same time, we propose selecting the optimal subset of pre-trained CNN models for identifying the high-voltage insulator surface pollution type instead of selecting only one model as a final classifier. Thus, the proposed approach involves assessing a total of 127 subsets, covering all possible combinations of seven pre-trained CNN models. The ensemble model subset with the highest validation accuracy is selected as the best classifier model. Fig. 2 demonstrates the overall procedure.

Several ensemble learning methods have been used by researchers in the field of high-voltage insulator condition monitoring [37] (see Table I).

IV. RESULTS AND ANALYSIS

A. Experimental Dataset

In this paper, we have built an HVID with ceramic, polymer, and glass insulators composed of 3752 images. Data was collected in indoor and outdoor environments during both daytime and nighttime periods. To achieve different contamination surfaces, a pre-contamination technique is used and simulated different contamination profiles with cement, soil, snow, and water. The HVID was divided into training (70%), validation (15%), and test (15%) sets.

Following the split of HVID into subsets, several data augmentation techniques [36] have been used to expand the training data subset. For more detailed information about data augmentation methods and the HVID size, refer to Figs. 3 and 4. The simulations were carried out with GPUs (T4 x2).

B. Experimental Results

Fig. 5 shows the validation accuracy of individually trained models. The best individually trained model is VGG16 with 92.0% accuracy. The results of ensemble model selection among 127 model subsets show that the EfficientNetB0-VGG16 ensemble model achieved the highest validation accuracy of 94.4%. Thus, the selected ensemble model outperformed the best separately trained VGG16 model by about 2.6% on the validation set. The results also show that 20 ensemble models achieved a validation accuracy higher than VGG16, which was the top-performing base model.

TABLE II. ENSEMBLE LEARNING METHODS USED IN HIGH-VOLTAGE INSULATOR CONDITION ANALYSIS.

Reference	Task	Technique	Performance
[37]	Contaminated composite insulators (condition analysis)	Stacked generalization, random subspace, bagging, boosting, and more	RMSE: 1.06×10^{-3}
[38]	ESDD, humidity, voltage, and leakage current are examples of contaminated insulators.	Random forest and crisscross optimization with XGBoost	Accuracy: RF: 0.838,
[39]	Contaminated composite insulators (ultrasonic data)	The ensemble model uses stacked generalization with SVR and a Gaussian kernel.	RMSE: 0.002, R^2 : 0.998
[40]	Insulators with missing caps	The multi-level perception ensemble uses SSD, with MobileNet serving as the base model.	AP: 0.9226, Recall: 0.9369, Precision: 0.9123
[41]	Contaminated, drilled, and broken porcelain insulators	The ensemble extreme learning machine method was optimized using PSO.	Mean Accuracy: 0.98; 600% faster than other methods

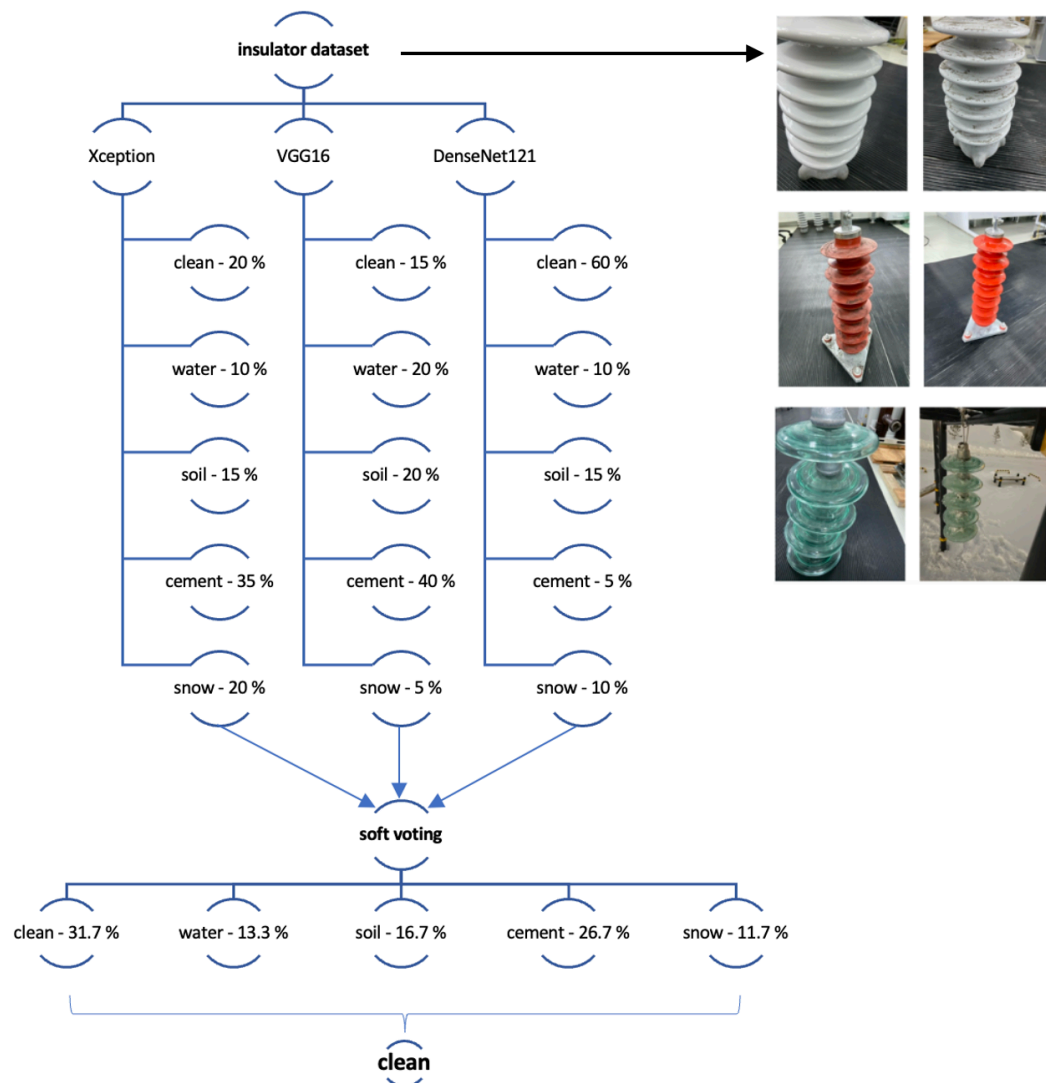


Fig. 2. A concept of soft-voting ensemble method.

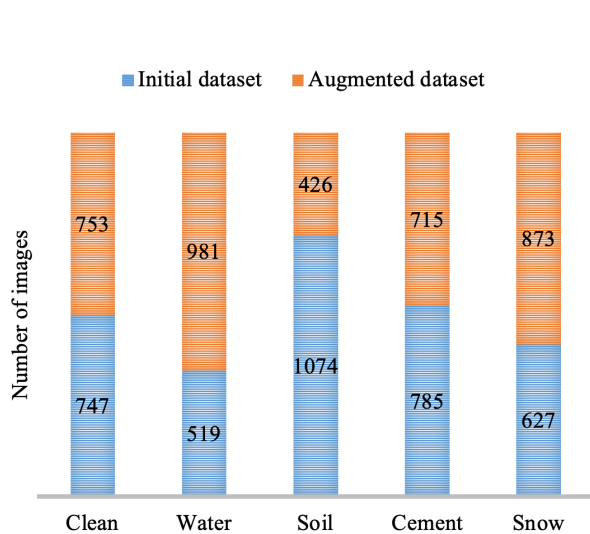


Fig. 3. Initial and augmented HVID.

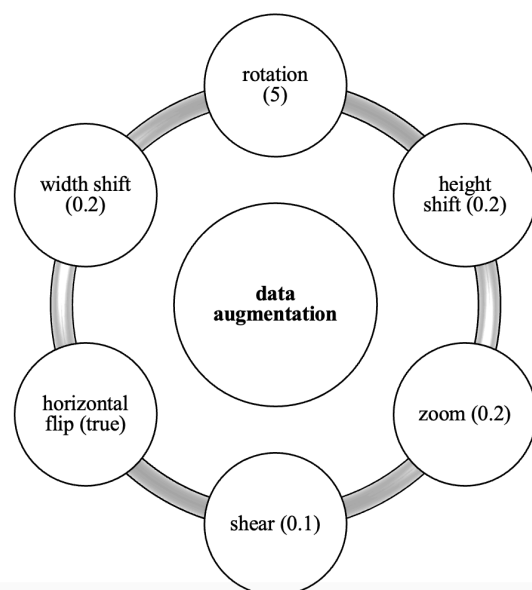


Fig. 4. Data augmentation techniques.

The EfficientNetB0-VGG16 ensemble model was evaluated on the test set and reached 93.3% accuracy. For the sake of comparison, the VGG16 model achieved 90% accuracy on the test set. This result shows the effectiveness of using an ensemble of pre-trained CNN models compared with individually fine-tuned models.

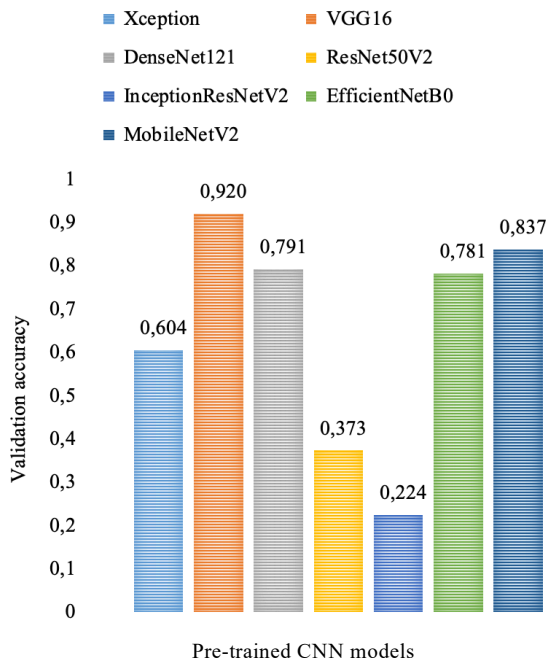


Fig. 5. Base pre-trained CNN models validation set accuracy.

C. Testing Model Robustness

In real-world implementation, inspectors may need to monitor insulators at any time during the day. Ensuring accurate model performance in both (day and night) conditions is essential for practical applications. The HVID has both daytime and nighttime images. We divided this dataset into two subsets, further denoted as D-HVID with the daytime high-voltage insulator images and N-HVID with the nighttime high-voltage insulator images. For more detailed information about HVID divisions and examples, please refer to Figs. 6 and 7.

The selected final ensemble classifier, EfficientNetB0-VGG16, was tested on D-HVID and N-HVID separately and had 95.4% and 83.9% accuracies, respectively (see Table II). One can note that it performs better with D-HVID than with N-HVID images.

Next, we conducted a daytime- and nighttime-specific model selection. In this regard, the D-HVID was first randomly split into 70% training, 15% validation, and 15% test sets. Then the same model training steps as for HVID were repeated. Table II shows that the EfficientNetB0-VGG16-DenseNet121 model had the highest validation accuracy for daytime images. On test data, this model achieved 88.1% for HVID, 96.8% for D-HVID, and 43.2% for N-HVID. This suggests that training a D-HVID-specific model naturally leads to better results on daytime images (see Table II).

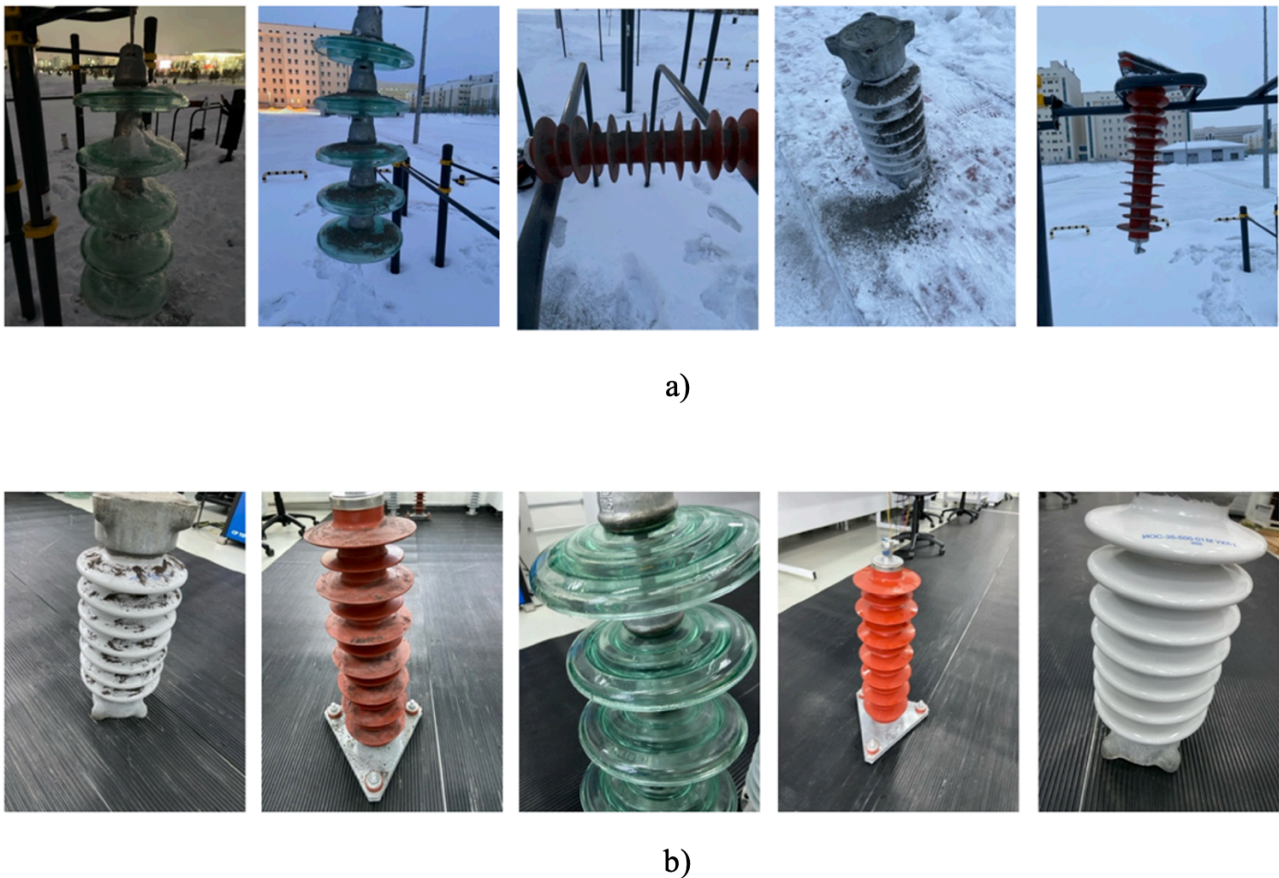


Fig. 6. The D-HVID and N-HVID images for a) daytime and b) nighttime.

TABLE II. TEST ACCURACY OF THE BEST ENSEMBLE CLASSIFIER WITH THE HIGHEST VALIDATION ACCURACY

		The best ensemble classifier with the highest validation accuracy	HVID		
			D-HVID + N-HVID	D-HVID	N-HVID
HVID	D-HVID + N-HVID	EfficientNetB0-VGG16	0.933	0.954	0.839
	D-HVID	EfficientNetB0-VGG16-DenseNet121	0.881	0.968	0.432
	N-HVID	Xception-DenseNet121	0.331	0.232	0.908

TABLE III. TEST ACCURACY OF THE BEST BASE CLASSIFIER WITH THE HIGHEST VALIDATION ACCURACY

		The best base classifier with the highest validation accuracy	HVID		
			D-HVID + N-HVID	D-HVID	N-HVID
HVID	D-HVID + N-HVID	VGG	0.900	0.944	0.825
	D-HVID	VGG	0.875	0.966	0.383
	N-HVID	Xception	0.326	0.205	0.878

For N-HVID the same steps were repeated, including data splitting and model subset selection steps. Here, the Xception-DenseNet121 model reached the highest validation accuracy. The selected ensemble model showed 33.1%, 23.2%, and 90.8% test accuracies for HVID, D-HVID, and N-HVID images, respectively. From these investigations, it becomes clear that the lighting has a huge impact on both the model selection as well as classifier performance (see Table II).

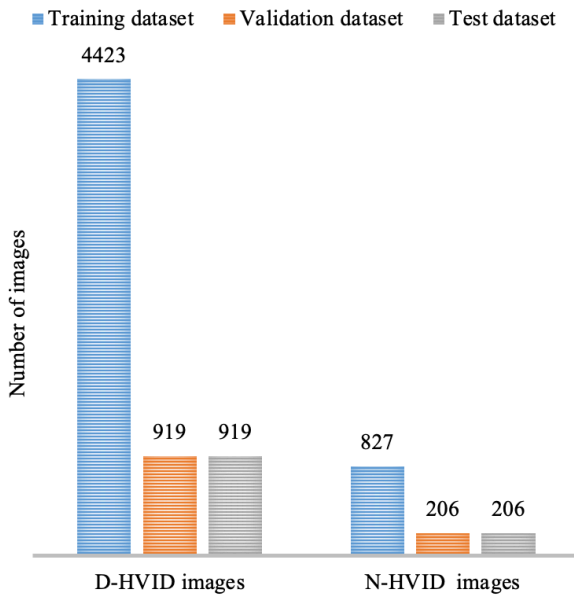


Fig. 7. The dataset for daytime and nighttime.

The primary focus of this paper is to compare the base model's accuracy to the ensemble model. Table III demonstrates that all three ensemble models outperformed the corresponding base models regardless of lighting conditions. What emerges from the results reported here is that an ensemble model performs better than a base model, regardless of lighting conditions. The results indicate that if the daytime of deploying the classifier is known beforehand, training the ensemble classifier with images from a similar time of day could enhance performance.

V. CONCLUSION

This research aims to provide an accurate high-voltage insulator surface pollution classifier model. In this paper, an ensemble of seven pre-trained CNN models is studied: DenseNet121 [29], EfficientNetB0 [30], InceptionResNetV2 [31], MobileNetV2 [32], ResNet50V2 [33], VGG16 [34], and Xception [35]. Because the convolutional base of each model serves as a valuable feature extractor, an ensemble of these models is proposed rather than a single model. The results of ensemble model selection show that a combination of EfficientNetB0 and VGG16 performed better than the best base model and reached 93.3% test accuracy. Compared to other ensemble methods used for high-voltage insulator condition analysis (see Table I), such as Random Forest and crisscross optimization, which reported an accuracy of 83.8% for contaminated insulators [38], or ensemble learning methods achieving RMSE as low as 0.002 [39], the ensemble of pre-trained CNN models in this study shows competitive performance. The results show the possibility of using an ensemble CNN model to accurately classify images of high-voltage insulator surfaces into different contamination classes. Also, it was examined how daytime and nighttime lighting affect classifier performance. This analysis showed that if the time of deploying the classifier is known in advance, training the ensemble classifier with images collected from a similar time of day could improve the classification performance.

ACKNOWLEDGMENT

The authors acknowledge support for this study from the Collaborative Research Project (CRP), Nazarbayev University under Grant 211123CRP1604, and in part by the Faculty Development Competitive Research Grant (FDCRG), Nazarbayev University under Grant 201223FD8811.

REFERENCES

- [1] A. Salem, K. Lau, W. Rahiman, Z. Abdul-Malek, N. Mohammed, S. Al-Gailani, R. Abd Rahman, and S. Al-Ameri, "Pollution Flashover Voltage of Transmission Line Insulators: Systematic Review of Experimental Works," *IEEE Access*, vol. 10, pp. 10416–10444, 2022.
- [2] M. Ahmed, J. Mohanta, and A. Sanyal, "Inspection and identification of transmission line insulator breakdown based on deep learning using aerial images," *Electric Power Systems Research*, vol. 211, 2022.
- [3] T. Britannica, "Planck's radiation law," *Encyclopedia Britannica*, 2024.

- [4] Z. Abdin, A. Kumar, "Design of early fault detection technique for electrical assets using infrared thermograms," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 753–759, 2014.
- [5] H. He, W. Lee, D. Luo, and Y. Cao, "Insulator Infrared Image Denoising Method Based on Wavelet Generic Gaussian Distribution and MAP Estimation," *IEEE Transactions on Industry Applications*, vol. 53, no. 4, pp. 3279–3284, 2017.
- [6] L. Jin, Z. Tian, J. Ai, Y. Zhang, and K. Gao, "Condition evaluation of the contaminated insulators by visible light images assisted with infrared information," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 6, pp. 1349–1358, Jun. 2018.
- [7] F. Lv, H. Jin, S. Wang, and H. Li, "Fault Diagnosis Based on Ultraviolet Imaging Method on Insulators," 2012 Second International Conference on Intelligent System Design and Engineering Application, Sanya, China, pp. 1426–1429, 2012.
- [8] F. Bologna, N. Mahatho, and D. Hoch, "Infra-red and ultra-violet imaging techniques applied to the inspection of outdoor transmission voltage insulators," *IEEE AFRICON 6th Africon Conference in Africa*, George, South Africa, vol. 2, pp. 593–598, 2002.
- [9] J. Sun, G. Gao, G. Wu, X. Cao, and G. Zhu, "Influence of pollution distribution on insulator surface on flashover characteristics," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 21, no. 4, pp. 1637–1646, August 2014.
- [10] A. Baker, M. Farzaneh, R. Gorur, S. Gubanski, R. Hill, G. Karady, and H. Schneider, "Insulator Selection for AC Overhead Lines With Respect to Contamination," *IEEE Transactions on Power Delivery*, vol. 24, no. 3, pp. 1633–1641, July 2009.
- [11] E. Da Silva Domingues, "Improved Condition Monitoring of Composite Insulators," Aug. 2012.
- [12] Z. A. Jaffery and A. K. Dubey, "Design of early fault detection technique for electrical assets using infrared thermograms," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 753–759, 2014, doi: 10.1016/j.ijepes.2014.06.049.
- [13] S. He, et al., "Detecting contaminated insulators by UV imaging technology," 2010, pp. 74–77.
- [14] C. Yuan, et al., "Ultrasonic phased array detection of internal defects in composite insulators," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 23, no. 1, pp. 525–531, 2016.
- [15] J. Wang, et al., "Evaluation on partial discharge intensity of electrical equipment based on improved ANFIS and ultraviolet pulse detection technology," *IEEE Access*, vol. 7, pp. 126561–126570, 2019, doi: 10.1109/ACCESS.2019.2938784.
- [16] Z. Tingtao, L. Tianyu, C. Ke, and H. Xiaoguang, "On-line monitoring system of insulator leakage current based on ARM," in 2011 6th IEEE Conference on Industrial Electronics and Applications, Beijing, China, 2011, pp. 365–369, doi: 10.1109/ICIEA.2011.5975610.
- [17] X. Jiang, et al., "Effect of inverted T arrangement on AC pollution flashover characteristics of insulator strings," *High Voltage*, vol. 4, no. 2, pp. 97–104, Jun. 2019.
- [18] "The Basics of Insulation Resistance Testing and Why It's So Important," Vitrek, July 27, 2023. [Online]. Available: <https://vitrek.com/the-basics-of-insulation-resistance-testing-and-why-its-so-important/>. [Accessed: Aug. 22, 2024].
- [19] Y. Liu, et al., "Optical Imaging Technology Application in Transmission Line Insulator Monitoring: A Review," *IEEE Trans. Dielectr. Electr. Insul.*, 2024, doi: 10.1109/TDEI.2024.3351093.
- [20] O. Surucu, S. A. Gadsden, and J. Yawney, "Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances," *Expert Syst. Appl.*, vol. 221, 2023, Art. no. 119738.
- [21] A. Muhammad, A. Shahpurwala, S. Mukhopadhyay, and A. H. El-Hag, "Autonomous drone-based powerline insulator inspection via deep learning," *Proc. Iberian Robot. Conf. Cham, Switzerland: Springer*, pp. 52–62, 2019.
- [22] L. Matikainen, M. Lehtomaki, E. Ahokas, J. Hyypä, M. Karjalainen, A. Jaakkola, A. Kukko, and T. Heinonen, "Remote sensing methods for power line corridor surveys," *ISPRS J. Photogramm. Remote Sens.*, vol. 119, pp. 10–31, Sep. 2016.
- [23] C. Ma, Y. Fu, D. Wang, R. Guo, X. Zhao, and J. Fang, "YOLO-UAV: Object Detection Method of Unmanned Aerial Vehicle Imagery Based on Efficient Multi-Scale Feature Fusion," *IEEE Access*, vol. 11, pp. 126857–126878, 2023.
- [24] D. Waleed, S. Mukhopadhyay, U. Tariq, and A. H. El-Hag, "Drone-Based Ceramic Insulators Condition Monitoring," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–12, 2021.
- [25] Z. Zhang, B. Zhang, Z. Lan, H. Liu, D. Li, L. Pei, and W. Yu, "FINet: An Insulator Dataset and Detection Benchmark Based on Synthetic Fog and Improved YOLOv5," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–8, 2022.
- [26] B. Wang, M. Dong, M. Ren, Z. Wu, C. Guo, T. Zhuang, O. Pischler, and J. Xie, "Automatic Fault Diagnosis of Infrared Insulator Images Based on Image Instance Segmentation and Temperature Analysis," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 8, pp. 5345–5355, Aug. 2020.
- [27] J. Liao, H. Xu, X. Fang, Q. Miao, and G. Zhu, "Quantitative Assessment Framework for Non-Structural Bird's Nest Risk Information of Transmission Tower in High-Resolution UAV Images," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–12, 2023.
- [28] H. Zhou, "Ensemble Methods: Foundations and Algorithms," Chapman & Hall/CRC, 2012.
- [29] G. Huang, Z. Liu, L. Van Der Maaten, and Q. Weinberger, "Densely connected convolutional networks," *Proc. 30th IEEE Conf. Comput. Vis. Pattern Recognition*, pp. 2261–2269, 2017.
- [30] M. Tan, and Q. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," 36th Int. Conf. Mach. Learn., pp. 10691–10700, 2019.
- [31] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognition*, pp. 2818–2826, 2016.
- [32] A. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, Andreetto, and H. Adam, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," 2017.
- [33] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, "Inception-V4 Inception-Resnet and the Impact of Residual Connections on Learning," 2017.
- [34] K. Simonyan, and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 3rd International Conference on Learning Representations, ICLR Conference Track Proceedings, pp. 1–14, 2015.
- [35] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition*, pp. 1800–1807, 2017.
- [36] C. Shorten, and T. Khoshgoftaar, "A Survey on Image Data Augmentation for Deep Learning," *J Big Data* 6, vol. 60, 2019.
- [37] S. F. Stefenon, R. Bruns, A. Sartori, L. H. Meyer, R. G. Ovejero, and V. R. Q. Leithardt, "Analysis of the ultrasonic signal in polymeric contaminated insulators through ensemble learning methods," *IEEE Access*, vol. 10, pp. 33980–33991, 2022, doi: 10.1109/ACCESS.2022.3161506.
- [38] J. Zhang, H. Wang, Z. Zhang, X. Li, and F. Dong, "An insulator pollution degree detection method based on crisscross optimisation algorithm with blending ensemble learning," in *Proc. 2022 4th Int. Conf. Electr. Eng. Control Technol. (CEECT)*, Shanghai, China, 2022, pp. 83–87, doi: 10.1109/CEECT55960.2022.10030659.
- [39] S. F. Stefenon, R. B. Grebogi, R. Z. Freire, A. Nied, and L. H. Meyer, "Hybrid wavelet stacking ensemble model for insulators contamination forecasting," *IEEE Access*, vol. 9, pp. 66387–66397, 2021, doi: 10.1109/ACCESS.2021.3076410.
- [40] H. Jiang, X. Qiu, J. Chen, X. Liu, X. Miao, and S. Zhuang, "Insulator fault detection in aerial images based on ensemble learning with multi-level perception," *IEEE Access*, vol. 7, pp. 61797–61810, 2019, doi: 10.1109/ACCESS.2019.2915985.
- [41] S. F. Stefenon, R. B. Grebogi, R. Z. Freire, A. Nied, and L. H. Meyer, "Optimized ensemble extreme learning machine for classification of electrical insulators conditions," *IEEE Trans. Ind. Electron.*, vol. 67, no. 6, pp. 5170–5178, 2020, doi: 10.1109/TIE.2019.2926044.