# LiDAR-Based Object Recognition for Robotic Inspection of Power Lines

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Abstract: This article presents a novel technique using Light Detection and Ranging (LiDAR) sensors implemented in an autonomous robot for the multimodal predictive inspection of high-voltage transmission lines (*LaRa*). The method enhances the robot's capabilities by providing vertical perception and classifying transmission-line components using artificial-intelligence techniques. The LiDAR-based system focuses on analyzing two-dimensional (2D) slices of objects, reducing the data volume, and increasing the computational efficiency. Object classification was achieved by calculating the absolute differences within a 2D slice to create unique signatures. When evaluated experimentally with a k-nearest neighbors network on a Raspberry Pi on a real robot, the system accurately detected objects such as dampers, signals, and insulators during linear movement experiments. The results indicated that this approach significantly improves *LaRa*'s ability to recognize power-line components, achieving high classification accuracy and exhibiting potential for advanced autonomous inspection applications.

## 1 INTRODUCTION

The reliability and efficiency of power-line infrastructure are critical to modern society, necessitating regular inspection and maintenance to prevent outages and ensure safety. Traditional methods for inspecting power lines, which involve manual inspections or the use of manned helicopters, are labor-intensive, expensive, and often dangerous. The advent of autonomous robotic systems offers a promising alternative for performing detailed inspections while reducing human risks and operational costs.

Robotic systems offer unparalleled consistency and precision, perform repetitive tasks without fatigue, and operate in environments that are hazardous or inaccessible to humans. By automating the inspection process, these robots can conduct frequent and thorough assessments and identify potential issues before they escalate to critical failure (Yang et al., 2020). This proactive approach not only enhances the reliability of the power supply but also significantly reduces maintenance costs and minimizes downtime. Furthermore, the use of robots can alleviate safety risks associated with manual inspections, protect the well-being of maintenance personnel, and ensure compliance with stringent safety regulations.

Power-line inspections typically depend on manual processes that are time-consuming, labor intensive, and dangerous. These methods typically involve visual inspections conducted by personnel on foot or using specialized vehicles (Chen et al., 2021). Although they are effective, they are limited in their ability to access hard-to-reach areas—particularly in difficult terrain or adverse weather conditions. The effectiveness of traditional visual inspection methods relies heavily on the experience of the inspector, which limits their reliability for comprehensive integrity verification.

The emergence of autonomous robotic systems has provided a transformative solution for these challenges. Equipped with advanced sensing and navigation capabilities, these robots can perform detailed inspections of power lines, significantly reducing the need for human intervention and associated risks. Among the various available sensing technologies, Light Detection and Ranging (LiDAR) is the most promising. LiDAR systems use laser pulses to measure distances with high precision and create detailed three-dimensional (3D) maps of the environment. When integrated with advanced object-recognition algorithms, LiDAR-equipped robots can assess the conditions of power lines, insulators, and other critical elements with high reliability (Zhang et al., 2022; Qin et al., 2018).



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The complexity of a power-line environment presents unique challenges for object recognition. Factors such as varying weather conditions, dense vegetation, and the presence of multiple overlapping objects necessitate robust and adaptable recognition systems. Incorporating artificial intelligence (AI) into LiDAR-based robotic systems enhances their capability to recognize and classify objects in complex power-line environments. AI algorithms—particularly those based on machine learning—can be trained on vast datasets to identify various components and anomalies accurately. These algorithms learn to discern subtle patterns and features in LiDAR data, improving their accuracy and reliability over time. By continuously updating the models with new data, the system can adapt to changing conditions and maintain high performance. The combination of AI and LiDAR technology allows the development of intelligent inspection systems that not only detect issues but also predict potential failures, facilitate timely interventions, and reduce the likelihood of power outages.

This article presents an advanced technique for inspecting power lines wherein LiDAR sensors are used to accurately detect transmission-line components. The method was implemented in an autonomous robot for the multimodal predictive inspection of high-voltage transmission lines (*LaRa*) to enhance the capabilities of a multimodal inspection sensor. The integration of LiDAR technology provides vertical perception of the elements on adjacent transmission lines. Object classification was performed using various AI techniques with the aim of identifying the most precise method for evaluating actual transmission-line elements. The proposed approach concentrates on examining a single 2D cross-section of the object, which greatly minimizes the amount of data and enhances computational performance.

The remainder of this paper is organized as follows. Section 2 discusses related work to clarify the contributions of the present study. Section 3 describes the concept of the *LaRa* inspection robot. Section 4 presents the proposed approach for LiDAR-based object recognition and the experiments. Finally, Section 5 presents conclusions.

# 2 RELATED WORK

The integration of LiDAR technology into robotic inspection systems has attracted considerable attention in recent years, with studies demonstrating its potential to revolutionize power-line maintenance (Alhassan et al., 2020). (Korki et al., 2019) discussed the challenges of using unmanned aerial vehicles (UAVs) in power¬line inspection and fault detection, along with solutions. They presented three conceptual designs that incorporate AI and efficient sensors for high-precision fault detection. These designs use thermal sensors and secure cloud-based communication for data transfer.

LiDAR sensors are widely used in UAV inspections of power lines to create detailed maps. (Chen et al., 2022) proposed a diffusion-coupled convolutional neural network for real-time detection of power transmission lines using UAV-borne LiDAR data. (Jenssen et al., 2018) addressed the limitations of the current manual and helicopter-assisted methods for power-line inspection, highlighting concerns regarding cost, speed, and safety. This review covers existing research on automating this process using UAVs, robots, and AI-driven vision systems, emphasizing the requirement for high accuracy. The proposed approach focuses on employing UAVs for inspection, utilizing optical images as primary data, and leveraging deep learning for analysis to advance autonomous vision-based inspections in the power sector.

(Paneque et al., 2022) discussed power-line inspection using a reactive-quadrotor-based online system. In contrast to traditional methods involving two-stage processes (data collection and offline analysis), this system constructs a real-time 3D map, evaluates data quality on the fly, and adjusts flight to enhance the resolution as needed. The use of LiDAR sensors for UAV inspection of transmission lines primarily focuses on creating maps for subsequent segmentation and classification, utilizing the sensor's capability for 3D depth perception in visual processing.

These studies highlight the transformative potential of LiDAR technology for power-line inspection and maintenance. They address critical aspects, including fault detection, UAV integration, advanced object recognition, multisensor fusion, and real-time monitoring, laying a solid foundation for further advancement. LiDAR sensors are typically used for surface mapping. This study introduces a novel approach involving LiDAR-based object recognition for power-line inspection, which can be integrated into a multimodal inspection approach as a complementary component.

# 3 *LaRa*: AUTONOMOUS ROBOT FOR MULTI-MODAL PREDICTIVE INSPECTION OF HIGH-VOLTAGE TRANSMISSION LINES

The inspection is performed autonomously using a mobile robot that moves over electrical cables. The autonomous robot for the multimodal predictive inspection of high-voltage transmission lines (*LaRa*) is designed to attach to the cable and move with precision, carrying the multimodal inspection system, as shown in Figure 1.

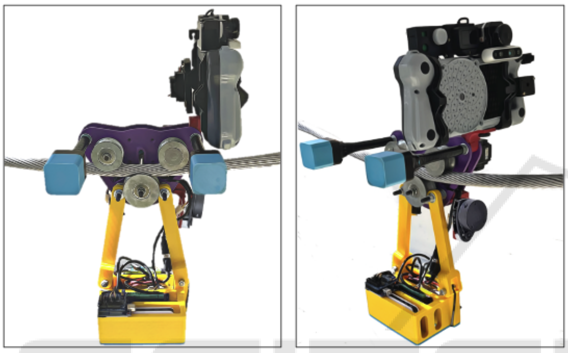

Figure 1: The Autonomous Robot for Multi-Modal Predictive Inspection of High-Voltage Transmission Lines.

Two wheels are used to ensure support on the electrical cable: one wheel is free, and the other is driven by a servomotor, as shown in Figure 2. The third wheel is part of a connecting rod–crank system that moves the non-actuated wheel toward the cable, maintaining a clamping pressure similar to that of a robotic claw. This wheel can also move linearly away from the cable, allowing the robot to be removed and perform obstacle suppression maneuvers.

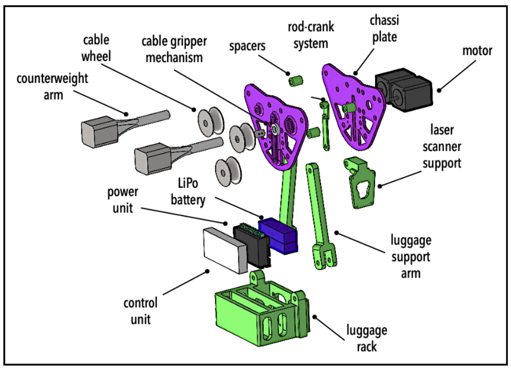


Figure 2: Exploded view of *LaRa* robot.

The cable-gripper system is mounted on a structure consisting of two parallel plates separated by fixed spacers. Between these plates, a connecting rod–crank system moves the fixing wheel at the bottom of the cable. The motors are fixed to the front part of the claw, which interferes with the stabilization of the system on the cable, leading to rotation around the cable and potential falls.

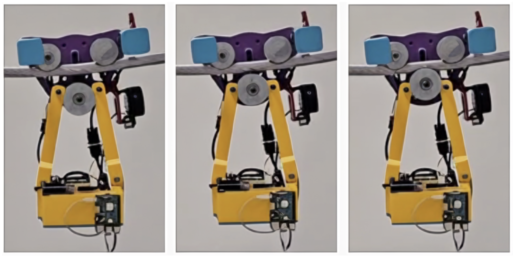

Figure 3: Cable-gripper system in action.

The *LaRa* robot features a lower luggage rack fixed with two articulated arms to ensure that the weight is always directed toward the gravitational force at the center of the cable gripper. The luggage rack houses the electronic control system, motor power, control system, and battery of the robot.

The center of mass of the system is aligned with the cable center, which is achieved by introducing two counterweight arms. One of these arms also serves as a support for the attachment of the multimodal inspection sensor.

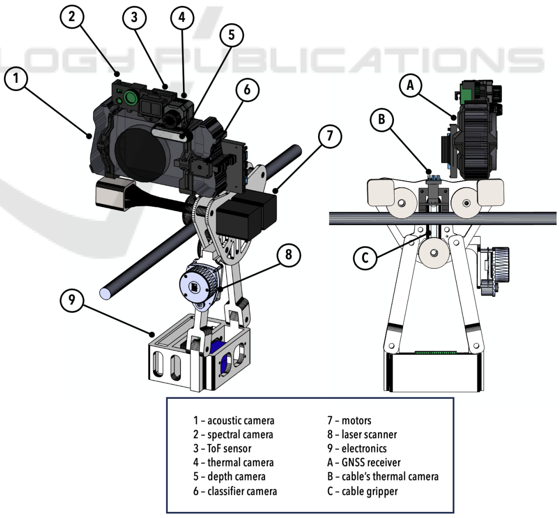


Figure 4: Modules of *LaRa* robot.

High-voltage transmission lines are inspected using a multimodal sensor specially designed for predictive inspection. The sensor consists of several subsensors (Figure 4), including an acoustic camera, a spectral camera, a ToF sensor, a thermal camera, a depth camera, and a classifier camera. All the sensors are integrated into a stacked inspection map. This approach is detailed in a previous work (*hidden for blind review*).

The *LaRa* robot also features a specially placed LiDAR sensor (Figure 4, item 8) to track objects in a plane below the robot. This information is crucial for analyzing the distance between transmission-line elements and vegetation. It is also correlated with the acoustic faults detected in the robot's interior plane.

## 4 THE LiDAR-BASED OBJECT RECOGNITION

We investigated the development of a classification system for LiDAR sensors in autonomous inspection robots. For power lines, LiDAR-based recognition was employed to introduce perception into the interior plane of the robot, identify elements in the lower cables, and measure the distance between the elements and vegetation, as shown in Figure 5.

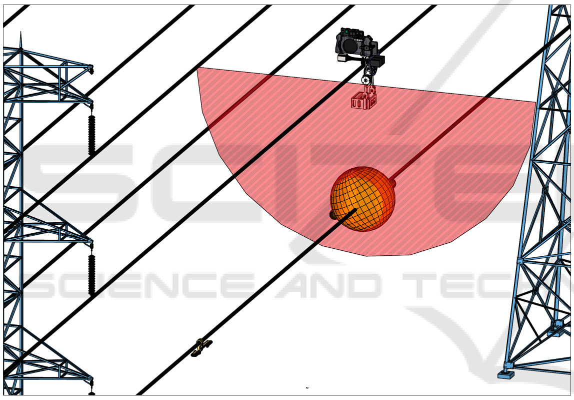

Figure 5: Proposed approach for LiDAR-Based Object Recognition.

Four machine-learning models were tested to develop a more reliable method for object recognition. The analysis was conducted using Orange (Demšar et al., 2013; Demšar and Zupan, 2012)—an open-source platform for data visualization and machine learning—and the virtual experiment platform CoppeliaSim (Coppelia Robotics) (Rohmer et al., 2013) for simulation of robotics systems. A Hokuyo LiDAR sensor was configured to perform 158 readings within a 50° field of view. The sensor was attached to a simple model of the inspection robot, and both the sensor and robot were controlled and configured using a Robot Operating System (ROS). Three distinct scenes were created, each containing one of the analyzed objects, with variations in distance and angle, as shown in Figure 6. To collect the data, a Python script recorded the sensor readings as the robot moved through each scene.

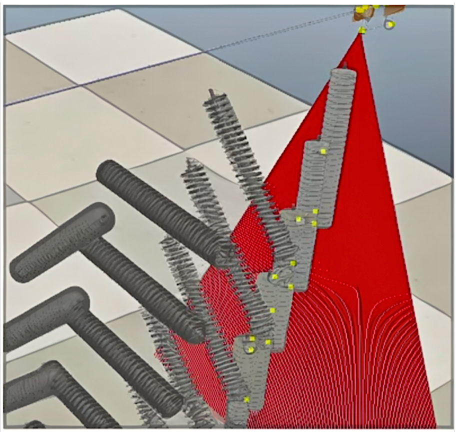

Figure 6: Creation of the dataset in a virtual environment.

Four machine-learning models were tested to develop a more reliable method for object recognition. A composite technique was employed to compare the results of k-nearest neighbors (kNN), decision tree, random forest, and neural network models, as shown in Figure 7.

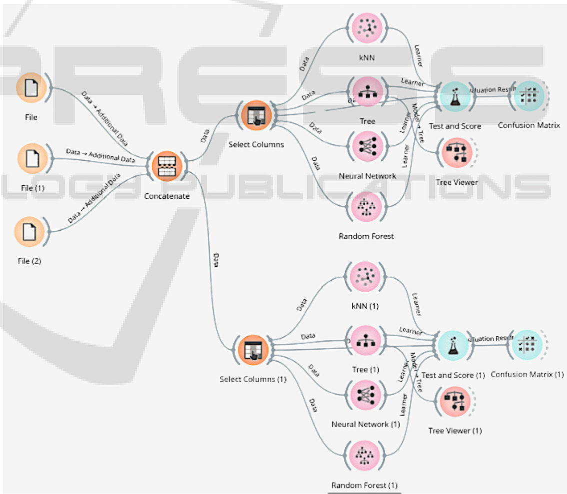


Figure 7: Analysis of Machine Learning methods.

A confusion matrix—a fundamental tool in machine learning and data analysis—was used to evaluate the performance of the classification model by comparing the predictions made by the model with real data. The comparison between the machine-learning models was based on the confusion matrix, as shown in Table 1 for the random forest model, Table 2 for kNN, Table 3 for the decision tree, and Table 4 for the neural network.

The random forest model had the highest scores across all metrics: it had an area under the ROC curve (AUC) of 0.963, a classification accuracy (CA)

Table 1: Confusion Matrix of Random Forest.

| | Damper | Isolator | Wire marker | Σ |
|---|---|---|---|---|
| Damper | 334 | 5 | 9 | 348 |
| Isolator | 14 | 868 | 28 | 910 |
| Wire marker | 11 | 93 | 170 | 274 |
| Σ | 359 | 966 | 207 | 1532 |

Table 2: Confusion Matrix of KNN.

| | Damper | Isolator | Signaler | Σ |
|---|---|---|---|---|
| Damper | 314 | 25 | 9 | 348 |
| Isolator | 8 | 875 | 27 | 910 |
| Wire marker | 6 | 163 | 105 | 274 |
| Σ | 328 | 1063 | 141 | 1532 |

Table 3: Confusion Matrix of Decision Tree.

| | Damper | Isolator | Wire marker | Σ |
|---|---|---|---|---|
| Damper | 317 | 17 | 14 | 348 |
| Isolator | 26 | 793 | 91 | 910 |
| Wire marker | 10 | 100 | 164 | 274 |
| Σ | 355 | 910 | 269 | 1534 |

Table 4: Confusion Matrix of Neural Network.

| | Damper | Isolator | Wire marker | Σ |
|---|---|---|---|---|
| Damper | 329 | 10 | 9 | 348 |
| Isolator | 12 | 862 | 36 | 910 |
| Wire marker | 9 | 118 | 147 | 274 |
| Σ | 350 | 990 | 192 | 1532 |

of 89.6%, an F1 score of 0.891, a precision of 0.892, a recall of 0.896, and a Matthews correlation coefficient (MCC) of 0.812. This suggests that it is exceptionally effective for distinguishing between classes, making accurate predictions, and maintaining a strong correlation between the observed and predicted classifications. The neural network model also performed well, with an AUC of 0.906, CA of 87.3%, F1 score of 0.866, precision of 0.868, recall of 0.873, and MCC of 0.771, which were close to those of the random forest model. Both the kNN and decision tree models exhibited good performance but lagged behind the top two models. The kNN model had an AUC of 0.907, CA of 84.5%, F1 score of 0.828, precision of 0.840, recall of 0.845, and MCC of 0.718. The decision tree model achieved similar metrics, with an AUC of 0.907, CA of 83.2%, F1 score of 0.831, precision of 0.831, recall of 0.832, and MCC of 0.701. The evaluation results for these methods are presented in Table 5.

Table 5: Comparison of machine learning models.

| Model | AUC | CA | F1 | Prec | Recall | MCC |
|---|---|---|---|---|---|---|
| kNN | 0.907 | 0.845 | 0.828 | 0.840 | 0.845 | 0.718 |
| Tree | 0.907 | 0.832 | 0.831 | 0.831 | 0.832 | 0.701 |
| Neural Network | 0.906 | 0.873 | 0.866 | 0.868 | 0.873 | 0.771 |
| Random Forest | 0.963 | 0.896 | 0.891 | 0.892 | 0.896 | 0.812 |

kNN is a simple and intuitive lazy-learning algorithm, meaning that it does not require an explicit training phase, which can be beneficial for real-time or dynamic datasets where the model must adapt quickly with extensive retraining. This model exhibited strong performance, indicating that it is a reliable and accurate choice for classification tasks. Furthermore, it has relatively few parameters to tune, making it simpler to optimize than more complex models such as neural networks or random forests. For small to moderately sized datasets, kNN can be computationally efficient and quick to implement and is adequate for embedding in hardware; therefore, the KNN method was selected for object recognition.

The kNN approach was extended for applications in real *LaRa* robot. A new dataset was created using the RPLiDAR A1 LiDAR sensor from Slamtec, which was configured similarly to the simulation and pointed perpendicular to the cable, 1.1 m from the ground. Three types of real objects were analyzed: insulators, wire markers, and dampers, as shown in Figure 8.

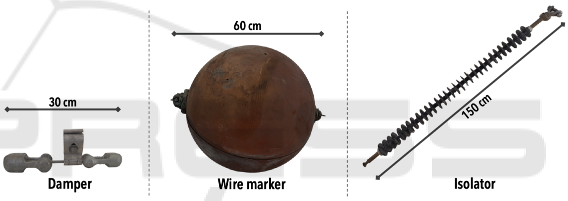


Figure 8: Objects of power lines: damper, wire marker and isolator.

The *LaRa* robot was coupled to a real power-line cable (i.e., a Grosbeak cable for 380 kV) fixed in a laboratory structure that provided the same distance to objects as a real transmission line. Four datasets were created—one for each class analyzed (nothing, wire marker, damper, and insulator)—and merged in Orange. The data captured by the sensor were processed to reduce noise; the information above 1.1 m was considered noise, as illustrated in Figure 9.

The kNN model was trained using the scikit-learn library in Python with six neighbors, as determined by the simulations. The trained model was saved in a file and converted to .csv for use in C/C++ code. The Euclidean method was used to calculate the distances in the kNN model. Each new reading from the LiDAR sensor was transformed into a vector of 159 elements and compared with the distances of the kNN model, and the class with the highest frequency among the first six distance sums was returned.

The code was implemented on a Raspberry Pi 3 running Raspbian with ROS Noetic, which was equipped with a 3.2-inch LCD to show the classifications. The LiDAR sensor and the code

Figure 9: Dataset acquisition.

communicated using the ROS, which facilitated integration of the system components.

Orange was used to evaluate the accuracy of the model by employing data collected from an actual sensor. For this evaluation, the F1 score was selected because of the imbalance between the classes in the dataset. The F1 score is a performance metric that combines precision and recall and provides a harmonic mean of these two metrics. It is particularly useful when there is an imbalance in classes because it offers a more balanced view of the model's performance.

For our dataset, when the kNN model was used with six neighbors, the F1 score was 0.938, with an accuracy of 94%. Table 6 presents the confusion matrix, indicating the percentage of correct classifications for each class. The matrix revealed that the most significant errors occurred in the classification of the damper. This is because the damper was significantly smaller than the other objects.

Table 6: Confusion Matrix of kNN in real model.

| | None | Isolator | Wire marker | Damper | Σ |
|---|---|---|---|---|---|
| None | 98.5% | 1.7% | 0.0% | 2.0% | 201 |
| Isolator | 0.5% | 91.7% | 1.5% | 15.1% | 239 |
| Wire marker | 1.0% | 3.9% | 98.5% | 0.7% | 269 |
| Damper | 0.0% | 2.6% | 0.0% | 82.2% | 131 |
| Σ | 197 | 230 | 261 | 152 | 840 |

## 4.1 Evaluation

The proposed approach was evaluated within an experimental framework in which the kNN model embedded in the Raspberry Pi controlling the *LaRa* robot was used to detect objects in the lower plane. A linear movement experiment was performed on the robot cable in a round-trip path passing through elements such as dampers, signals, and insulators. The recognition system obtained 50 classification samples for each object at different distances as the robot moved along the cable, as shown in Figure 10.

The proposed method performed classification

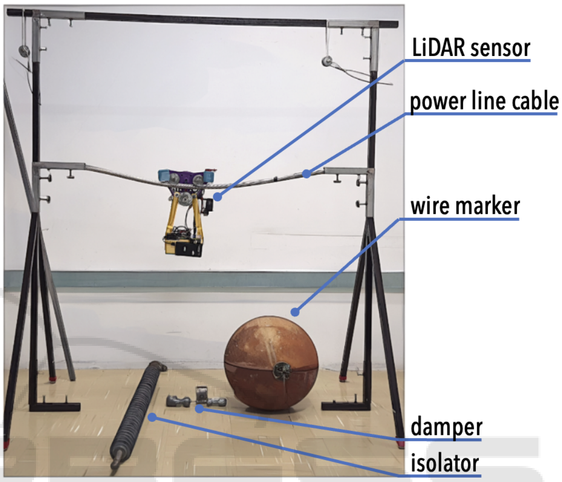


Figure 10: Objects of power lines: damper, wire marker and isolator.

and returned the average of the six closest distances to each reading. When the sensor-captured data were consistent with the training data, the average distance of the readings was below 1, indicating high classification certainty. This metric was adopted to analyze whether the model was capable of correctly identifying objects and maintaining the expected proximity between the sensor readings and training data. The evaluation results are shown in Figure 11, and the output data are presented in Table 7.

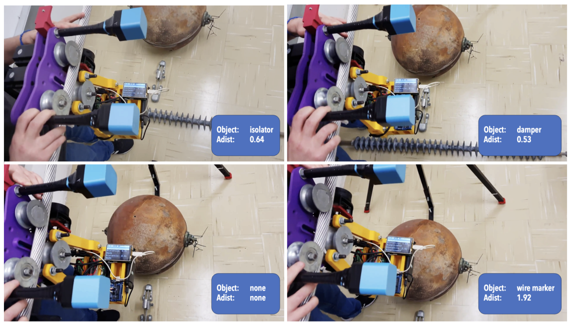

Figure 11: Experimentation of LiDAR-Based Object Recognition.

Table 7: Overall evaluation.

| | Recognitions | Efficiency | Mean A.distance | Deviance |
|---|---|---|---|---|
| Damper | 46 | 92.00% | 0.44 | 0.07 |
| Isolator | 48 | 96.00% | 0.61 | 0.14 |
| Wire marker | 50 | 100.00% | 1.41 | 0.34 |
| Mean | 48 | 96.00% | 0.82 | 0.18 |

The experimental analysis was summarized and graphically presented using boxplots. These graphs provide a visual summary that can help identify the central tendency, variability, and symmetry of the data, along with potential outliers, as shown in Figure 12.

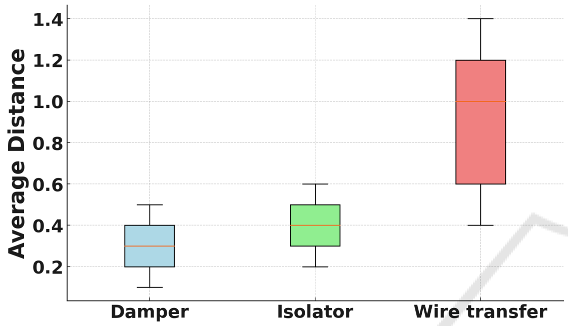


Figure 12: Boxplot of average distances.

## 5 CONCLUSIONS

This paper presents a novel approach for detecting and classifying elements along power lines using a LiDAR sensor. In contrast to traditional methods that process entire 3D point clouds, this method focuses on analyzing a single two-dimensional (2D) slice of an object, significantly reducing the data volume and increasing the computational efficiency.

Object classification was achieved by calculating the absolute differences between consecutive values within a 2D slice of the LiDAR point cloud. These differences were aggregated to create a unique signature for each object, allowing effective categorization. The results indicated that the kNN classification system can introduce the capability of power-line object recognition to a *LaRa* autonomous inspection robot equipped with a LiDAR sensor, achieving accurate identification of different classes of objects.

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## REFERENCES

Alhassan, A. B., Zhang, X., Shen, H., and Xu, H. (2020). Power transmission line inspection robots: A review, trends and challenges for future research. *International Journal of Electrical Power & Energy Systems*, 118:105862.

Chen, C., Jin, A., Yang, B., Ma, R., Sun, S., Wang, Z., Zong, Z., and Zhang, F. (2022). Dcpld-net: A diffusion coupled convolution neural network for real-time power transmission lines detection from uav-borne lidar data. *International Journal of Applied Earth Observation and Geoinformation*, 112:102960.

Chen, M., Tian, Y., Xing, S., Li, Z., Li, E., Liang, Z., and Guo, R. (2021). Environment perception technologies for power transmission line inspection robots. *Journal of Sensors*, 2021(1):5559231.

Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinovič, M., Možina, M., Polajnar, M., Toplak, M., Starič, A., et al. (2013). Orange: data mining toolbox in python. *the Journal of machine Learning research*, 14(1):2349–2353.

Demšar, J. and Zupan, B. (2012). Orange: Data mining fruitful and fun. *Inf. Družba IS*, 6:1–486.

Jenssen, R., Roverso, D., et al. (2018). Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning. *International Journal of Electrical Power & Energy Systems*, 99:107–120.

Korki, M., Shankar, N. D., Shah, R. N., Waseem, S. M., and Hodges, S. (2019). Automatic fault detection of power lines using unmanned aerial vehicle (uav). In *2019 1st International Conference on Unmanned Vehicle Systems-Oman (UVS)*, pages 1–6. IEEE.

Paneque, J., Valseca, V., Martínez-de Dios, J., and Ollero, A. (2022). Autonomous reactive lidar-based mapping for powerline inspection. In *2022 International Conference on Unmanned Aircraft Systems (ICUAS)*, pages 962–971. IEEE.

Qin, X., Wu, G., Lei, J., Fan, F., Ye, X., and Mei, Q. (2018). A novel method of autonomous inspection for transmission line based on cable inspection robot lidar data. *Sensors*, 18(2):596.

Rohmer, E., Singh, S. P., and Freese, M. (2013). V-rep: A versatile and scalable robot simulation framework. In *2013 IEEE/RSJ international conference on intelligent robots and systems*, pages 1321–1326. IEEE.

Yang, L., Fan, J., Liu, Y., Li, E., Peng, J., and Liang, Z. (2020). A review on state-of-the-art power line inspection techniques. *IEEE*

*Transactions on Instrumentation and Measurement*, 69(12):9350–9365.

Zhang, Y., Dong, L., Luo, J., Lu, L., Jiang, T., Yuan, X., Kang, T., and Jiang, L. (2022). Intelligent inspection method of transmission line multi rotor uav based on lidar technology. In *2022 8th Annual International Conference on Network and Information Systems for Computers (ICNISC)*, pages 232–236. IEEE.