Damage Analysis on ACSR Conductors Using X-Ray with A Deep Learning Approach

Hansen Manuturi Sianipar[a]*, Andigan Sitompul[a], Muhammad Faizin[b]
[a] PT PLN (Persero),
Jl. Duren Tiga Raya No.102, RT.8/RW.1, Duren Tiga, Kec. Pancoran, Kota Jakarta Selatan, Daerah Khusus Ibukota Jakarta 12760
[b] Department of Mechanical Engineering, Jenderal Soedirman University,
Jl. Raya Mayjen Sungkono No.KM 5, Blater, Kalimanah, Purbalingga, 53371, Indonesia
*E-mail: hansen.sianipar@pln.co.id

Abstract

Aluminum Conductor Steel Reinforced (ACSR) conductors are widely used in electrical transmission networks due to their high tensile strength and long-term durability. Despite these advantages, ACSR conductors remain vulnerable to internal degradation such as corrosion and wire breakage, which cannot be detected through conventional visual inspection. To address this limitation, this study employs nondestructive X-ray imaging to assess internal conductor conditions and classify them into three categories: normal, internal corrosion, and broken wires. A deep learning approach based on a Convolutional Neural Network (CNN) was developed to enhance the accuracy and consistency of defect identification. The research workflow involved systematic data collection, image pre-processing, and model training focused on learning structural strand patterns and density variations associated with internal damage. Model performance evaluation showed strong learning capability, with training loss decreasing from 1.35 to 0.35 and validation loss from 0.9 to 0.25. The model achieved nearly 90% validation accuracy, surpassing training accuracy and indicating excellent generalization. Overall, the integration of X-ray imaging and deep learning demonstrates high potential for rapid, reliable, and automated detection of internal ACSR conductor defects, supporting improved maintenance planning and decision-making for transmission line asset management.

Kata kunci: ACSR, Conductor, Deep Learning, X-Ray

Abstrak

Konduktor Aluminium Conductor Steel Reinforced (ACSR) banyak digunakan dalam jaringan transmisi listrik karena kekuatan tariknya yang tinggi dan daya tahan jangka panjangnya. Meskipun memiliki keunggulan ini, konduktor ACSR tetap rentan terhadap degradasi internal seperti korosi dan putusnya kabel, yang tidak dapat dideteksi melalui inspeksi visual konvensional. Untuk mengatasi keterbatasan ini, penelitian ini menggunakan pencitraan sinar-X non-destruktif untuk menilai kondisi konduktor internal dan mengklasifikasikannya ke dalam tiga kategori: kabel normal, korosi internal, dan putus. Pendekatan pembelajaran mendalam berbasis Jaringan Convolutional Neural Network (CNN) dikembangkan untuk meningkatkan akurasi dan konsistensi identifikasi cacat. Alur kerja penelitian ini melibatkan pengumpulan data sistematis, praproses gambar, dan pelatihan model yang berfokus pada pembelajaran pola untai struktural dan variasi kepadatan yang terkait dengan kerusakan internal. Evaluasi kinerja model menunjukkan kemampuan pembelajaran yang kuat, dengan kerugian pelatihan menurun dari 1,35 menjadi 0,35 dan kerugian validasi dari 0,9 menjadi 0,25. Model ini mencapai akurasi validasi hampir 90%, melampaui akurasi pelatihan dan menunjukkan generalisasi yang sangat baik. Secara keseluruhan, integrasi pencitraan sinar-X dan pembelajaran mendalam menunjukkan potensi tinggi untuk deteksi cacat konduktor ACSR internal yang cepat, andal, dan otomatis, mendukung peningkatan perencanaan pemeliharaan dan pengambilan keputusan untuk manajemen aset saluran transmisi.

Kata kunci: ACSR, Konduktor, Deep Learning, X-Ray

1. Introduction

Perusahaan Listrik Negara (PLN), the principal electricity provider in Indonesia, bears a significant obligation to ensure the safe and optimal functioning of all components within its power network. Among these components, the overhead conductor, particularly of the ACSR (Aluminum Conductor Steel Reinforced) variety, is vital for the transmission system. This type of conductor is prevalent in high-voltage and medium-voltage networks due to its distinctive blend of mechanical strength and electrical conductivity. A steel core provides the tensile strength, while aluminum strands serve as the primary electrical conductor. This combination renders ACSR both efficient and durable [1]. As years of operation accumulate and network load demands escalate, conductor conditions may deteriorate. Key factors contributing to this deterioration include extreme environmental conditions, temperature variations, increased current loads, and aging materials [2]. Consequently, reconductoring, replacing aging conductors with more advanced alternatives, has become crucial for maintaining an uninterrupted electricity supply [3].

An increasingly relevant method involves non-destructive testing techniques such as X-ray radiography. This approach allows for the identification of internal defects that external visual inspections might miss, thereby providing valuable support during evaluation processes and decision-making regarding reconductoring [4][5]. Structurally speaking, ACSR combines aluminum's high conductivity with the steel core's tensile strength [6]. Its resilience against mechanical stresses such as wind forces and span tension makes it suitable for extensive transmission lines. Nevertheless, prolonged use can lead to various forms of degradation [7]. Common issues include corrosion of the steel core, fatigue cracks in both aluminum and steel strands, wire abrasion from contact between strands or other components such as dampers, overheating from excessive current loads, and deterioration in humid or polluted environments. Research indicates that pitting corrosion on aluminum layers or loss of galvanization on steel cores can significantly diminish tensile strength. Moreover, friction among strands or with attached components may accelerate material wear. Elevated thermal conditions resulting from increased current can further weaken aluminum conductors, leading to sagging and an increased risk of mechanical failure [8][9].

In managing power assets effectively, severe conductor degradation presents several operational options: continued operation under close monitoring conditions; targeted repairs; or complete replacement through reconductoring [10]. Reconductoring frequently emerges as the most cost-effective and time-efficient solution, as it capitalizes on existing physical infrastructure such as towers and foundations without requiring new installations [11]. Decisions about conductor replacements should not rely solely on age or load levels; a comprehensive analysis of internal conditions, along with an estimation of remaining useful life, is vital for ensuring accurate reconductoring decisions [12][3]. Traditional visual or thermal inspections often fall short in identifying internal defects within the steel core or hidden layers of conductors [13]. Consequently, X-ray radiography has established itself as an excellent alternative method. X-ray imaging provides detailed insights into a conductor's internal structure while identifying issues such as broken strands or internal corrosion that are otherwise invisible externally [14][15]. Studies conducted by Manitoba Hydro reveal that much damage occurs primarily in the outer aluminum layers of ACSR 500 kV conductors [16]. Tools like LineVue and portable X-ray systems have demonstrated effectiveness in quickly assessing the condition of steel cores. Despite offering considerable advantages, field adoption of X-ray technology remains limited due to various technical challenges, including difficulties accessing tall transmission towers, complications during inspections on live lines, and a requirement for specialized skills to interpret X-ray images [17].

AI and computer vision technologies are increasingly used to analyze X-ray images. The unique visual characteristics of X-ray images differ significantly from those of standard optical photographs due to complex texture patterns arising from the arrangement of aluminum strands and steel cores, which are often challenging to discern manually [18]. Using AI applications for feature extraction, segmentation, defect identification, and damage classification, these tasks can be performed automatically, accelerating evaluation from hours to mere seconds and identifying defect patterns that human operators may overlook, especially in low-contrast scenarios. Portable X-ray technologies are lighter, safer, and capable of producing higher-resolution imagery than previous versions, making them more practical and suitable for field applications [19]. When integrated appropriately alongside AI capabilities, it facilitates smoother, standardized internal evaluations of conductors' states, which is of immense significance given Indonesia's expansive transmission development initiatives and PLN's commitment to ensuring all installed components uphold superior quality, free of defects. The evolution witnessed across both manual/automated inspection techniques signifies ongoing digital transformation permeating power network maintenance operations. While traditional manual methods retain relevance, especially during final result validations, AI-empowered automated solutions offer substantial potential to enhance speed and consistency/and objectivity throughout inspection, thereby fortifying asset management processes while supporting effective decision-making and reconductoring efforts alongside broader national power network upkeep activities. This research will provide significant contributions both technically, such as the development of inspection methodologies and X-Ray data interpretation, and operationally, such as the development of reconductoring procedures based on the real conditions of ACSR conductors. Thus, it is hoped that this research can help network operators and asset owners make more accurate and efficient decisions, extend the service life of conductors, and improve the reliability of the electricity transmission system.

2. Materials and Methods

The research begins with collecting data on transmission cable components that frequently experience failures, obtained through interviews with field engineers, along with real-time measurements of vibration, temperature, and cable tension for deeper analysis. The collected data is processed using Excel to support the development of a machine-learning-based feasibility analysis model designed to predict potential cable failures while also calculating ampacity and dynamic line rating (DLR). The predictive results are then integrated with reconductoring analysis to determine whether the 150 kV transmission cable remains suitable for operation or requires replacement. This comprehensive assessment relies on standardized SOPs to ensure every step is performed consistently and accurately, supported by historical failure data, operational parameters, and technical specifications. Once feasibility is evaluated, the study compares reconductoring options using traditional conductors versus advanced high-temperature low-sag (HTLS) conductors to improve transmission capacity and reliability. By combining predictive modeling with strategic reconductoring recommendations, the research aims to provide an effective and efficient solution for enhancing PLN's transmission system performance, thereby supporting the strengthening of Indonesia's electrical infrastructure and the nation's ongoing clean energy transformation.

2.1 Aluminium Conductor Steel Reinforced (ACSR)

This study uses Aluminum Conductor Steel Reinforced (ACSR) cables, which are widely used for overhead distribution and transmission. These cables consist of Galvanized Steel Wire with Grease on the inner layer and Stranded All Aluminum Conductor (AAC) on the outer layer. These cables comply with the SPLN 41-7: 1981 standard, which is designed to increase current-carrying capacity and durability in transmission systems. ACSR (Aluminum Conductor Steel Reinforced) cable is often used in high-voltage electricity distribution and transmission networks. The composition of this cable consists of two main parts: an inner layer of galvanized steel wire (Galvanized Steel Wire with Grease), which provides mechanical strength to support the cable, and an outer layer of All Aluminum Conductor (AAC), which provides high electrical conductivity. This cable is designed to withstand harsh environmental conditions and is widely used in overhead lines. In this study, ACSR cables are used to evaluate their effectiveness in 150 kV transmission systems and the potential for replacement with HTLS conductors to increase capacity and reliability [20].

The specifications of the ACSR cables described show significant technical capabilities for supporting the operation of electricity transmission and distribution systems, especially on 150 kV lines. The combination of the mechanical strength obtained from Galvanized Steel Wire with Grease and the good electrical conductivity of All Aluminum Conductor (AAC) makes this cable an optimal choice for overhead line applications. The technical data listed in the table provide a clear picture of the current capacity, resistance, and cable strength, which are important for determining maintenance needs and reconducting decisions.

Table 1. ACSR Cable Specification

Nominal Size	Actual Size	No. of Wire	Approx. Overall Diameter	Approx. Net Weight	DC Resistance at 20°C	Current Carrying Capacity	Calculated Breaking Force	Standard Length
16/25	15.3/27.5	6/1/180	1.80	5.40 kg/km	18.790	100 A	5,950 N	2000 m
25/4	24/8	6/1/225	6.80	9.80 kg/km	10.230	120 A	9,200 N	2000 m
35/4	34.3/8.0	6/1/225	8.10	14.00 kg/km	8.340	135 A	12,650 N	2000 m
44/52	43.0/13.7	6/1/276	9.60	17.80 kg/km	0.5946	205 A	17,170 N	2000 m
51/68	51.2/29.8	6/1/286	11.70	22.30 kg/km	0.5644	225 A	43,800 N	2000 m
70/12	69.9/11.4	6/1/267	11.70	24.10 kg/km	0.4130	260 A	26,860 N	2000 m
95/65	96.5/56.3	3/2/320	13.60	35.70 kg/km	0.3053	315 A	35,750 N	2000 m
105/75	105.7/57.5	3/2/320	13.60	40.50 kg/km	0.2992	335 A	39,350 N	2000 m
120/20	121.6/68.0	3/2/315	15.50	46.50 kg/km	0.2374	370 A	45,650 N	2000 m
150/25	127.9/29.8	6/1/333	15.50	59.60 kg/km	0.2259	385 A	56,700 N	2000 m

To determine the feasibility of a 150 kV transmission cable in an electrical system, several technical parameters need to be tested to assess whether the cable can continue to function correctly or requires repair measures, such as reconductoring. The feasibility analysis of this cable involves several important aspects, including insulation resistance testing, temperature measurement, ampacity, dynamic line rating (DLR), partial discharge (PD), and sag and tension analysis. Insulation resistance testing assesses the condition of the cable insulation layer, which is very important to prevent leakage current that can cause interference. Temperature measurements are taken to ensure that the cable operates within safe temperature limits. Ampacity measures a cable's capacity to conduct current without degrading in quality. DLR considers local weather conditions to more accurately assess cable transmission capacity. Partial discharge (PD) is used to detect potential damage to the cable's connection or insulation. Finally, sag and tension analysis are important for evaluating whether the cable can withstand high loads without degrading or being damaged.

Table 2. Cable Eligibility Based on Parameters

Parameter	Cable Eligibility	Required Actions
Insulation Resistance	> 10 MΩ (eligible) < 1 MΩ (not eligible)	If the resistance < 1 MΩ, it needs to be replaced or reconditioned by the cable.
Cable Temperature	70–90°C (feasible) > 90°C (unfeasible)	Cables whose operating temperature is more than 90°C require further evaluation or replacement.
Ampacity	According to the required capacity (feasible) Exceeding capacity (not feasible)	If the ampacity does not meet the existing load, it is necessary to reconductor.
Dynamic Line Rating (DLR)	DLR according to design capacity (feasible) DLR is lower than design (not feasible)	If the DLR is lower, it needs evaluation and reconductoring.
Partial Discharge (PD)	No discharge or very low (feasible) High PD (not qualified)	High PD indicates insulation degradation that requires replacement of cables or connections.
Sag and Tension	Sag within safe limits, voltage as per standard (feasible) Excessive sag or too high tension (not feasible)	Conductor replacement or reconductoring to overcome the problem of sag and excessive tension.

The following table 2 presents the indicators or parameters used to assess whether the cable is still suitable or no longer suitable for use, based on the results of the tests carried out. This table provides guidance on the limits of the accepted values for each parameter, as well as the steps that need to be taken based on the test results. Using the parameters and indicators listed in Table 2, we can clearly determine the condition of the cable whether it is still suitable for use or needs to be corrected. If the test results show that one of the parameters is outside the specified limit, then reconconductoring measures are a step that needs to be considered to maintain the reliability of the transmission network. This table becomes a very important guide for technical decisions in the process of maintenance and repair of transmission cables.

2.2 Damage Analysis and Reconductoring

X-ray micro-tomography scanners generally consist of an X-ray source, a rotating specimen stage, a light-conversion scintillator, a light imaging device (usually using a CCD-based video camera), and a controller computer. This prototype system has been used to study a variety of organs, including coronary arteries, vasorum, and bone. In addition to these purpose-built scanners, several commercial micro CT scanners are now available, based on similar technical principles. In a nutshell, the scan is performed by rotating the specimen at a specified angle along the path of the X-ray beam, then acquiring an X-ray transmission image at each viewpoint. The three-dimensional image is reconstructed from multiple angles using tomographic reconstruction algorithms, such as Feldkamp's modified filtered backprojection. The reconstructed image consists of cubic voxels (typically ranging from 1 to 20 µm per side, depending on the optical magnification of the micro-CT setup), each voxel having a grayscale value representing X-ray attenuation at its corresponding location in the specimen.

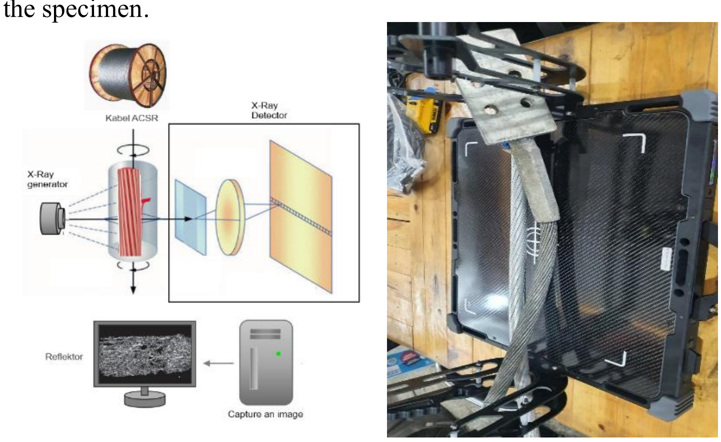

Figure 1. Design of the Reconducting Scheme on ACSR Cables Using X-Ray

Based on Figure 4. Explains that the X-ray scanning system is used to analyze the condition of ACSR (Aluminum Conductor Steel Reinforced) cables. The process begins with an ACSR cable positioned in an X-ray path generated by an X-ray generator. These X-rays are directed at the cable and pass through the cable material, interacting with its internal structure. After passing through the wire, the intensity-reduced X-rays will be received by the X-ray detector which converts the radiation into a digital image. These detectors are essential for capturing information regarding the internal structure of the cable that is invisible to the naked eye, such as hidden damage or defects. The reflectors contained in the system help to reflect unabsorbed X-rays, improving the quality of the resulting image by clarifying contrast and reducing noise. The resulting images from the detector are then processed by a computer, which processes the data and produces a two-dimensional (or three-dimensional) image that describes the condition of the cable in detail. Using this X-ray technology, damage analysis of ACSR cables can be performed in a non-destructive manner, allowing to detect problems such as corrosion, cracks, or other structural changes that may affect the performance of the cables in power transmission.

2.3 Machine Learning Application Image Acquisition

Figure 2. This method uses an X-ray imaging system to analyze the internal structure of Aluminum Conductor Steel Reinforced (ACSR) cables and detect damage, material degradation, and corrosion in the steel core and aluminum coating. The system scheme consists of an X-ray generator, an X-ray detector, a reflector, and an image processing computer, all directly connected. The ACSR cable is slowly moved using two hasps to adjust its position along the scan path. The generator emits an X-ray beam through a cable specimen, which is then captured by a detector and converted into a digital image using an optical reflector connected to a computer system. The images obtained show the internal structure of the conductor as a two-dimensional cross-section, which can then be reconstructed into a three-dimensional model using a tomographic algorithm. In principle, this process is similar to X-ray micro-tomography (micro-CT), in which the scanning system comprises an X-ray source, a rotating specimen stage, a light-conversion scintillator, and a CCD-based imaging device. The cable specimen is rotated at various angles to the X-ray beam to obtain transmission images from different directions. The images were then reconstructed using Feldkamp's filtered back-projection algorithm to produce a three-dimensional visualization of voxels measuring 1–20 μm per side, where each voxel has a grayscale value representing the level of X-ray attenuation at a given position. This value correlates with the density and condition of the conductor material, making it easier to identify microcracks, corrosion, and deformation.

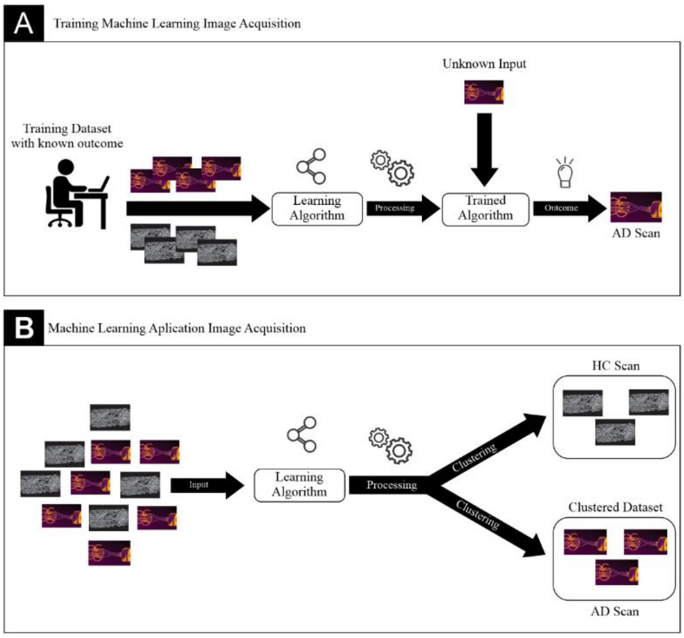

Figure 2. Workflow Machine Learning Application Image Acquisition

The next stage includes integration with machine learning algorithms as shown in parts A and B of the figures. In stage A (Training Machine Learning Image Acquisition), the scanned image with known damage conditions is used as a training dataset. This dataset is processed through learning algorithms such as Convolutional Neural Network (CNN) to form an image classification model. The trained model is then used to recognize new inputs from the actual scan results, resulting in an AD Scan (Anomaly Detection) output that indicates a potential corruption. Meanwhile, phase B (Machine Learning Application Image Acquisition) describes the application of the model to the actual dataset of field inspection results. The images produced from X-ray scanning are entered into the machine learning system to be clustered into two main categories, namely HC Scan (Healthy Conductor) and AD Scan (Anomaly Detection). This process generates a clustered dataset that describes the distribution of healthy and damaged areas along the ACSR cable. Thus, this method enables a data-driven reconduction process, where only the part of the cable that shows an indication of damage will be replaced or repaired, thereby improving the cost efficiency and maintenance time of the transmission network. Clustering is an unsupervised machine learning technique that groups images based on similarity. In this figure, the output of the clustering process is divided into two major groups:

a. HC Scan (Healthy Conductor / Normal Condition)

This cluster includes images that represent conductors in normal operating condition. The algorithm identifies no significant structural damage, no bird-caging, no corrosion, and no elongation. These images are visually consistent and present no patterns that correlate with known defect signatures.

b. AD Scan (Abnormal / Defective Conductor)

The clustered dataset classified as AD Scan contains images that show patterns aligned with defective conditions. The figure lists several categories of buruk (damaged) conductors:

K1 –Stranded broken wires

K2 –Internal or external corrosion

These images typically show irregularities in the X-Ray density map or abnormal heat concentration in the thermal scan.

3. Results and Discussion

3.1 Deep Learning Based Classification of ACSR Cable Defects

Figure 3 demonstrates how X-ray imaging combined with deep learning can be applied to detect and classify structural defects in Aluminum Conductor Steel-Reinforced (ACSR) cables. These conductors are widely used in overhead transmission systems for their strength and conductivity, yet they remain vulnerable to hidden deterioration such as internal corrosion and broken strands issues that cannot be identified through visual inspection alone. As a result, X-ray–based nondestructive evaluation is essential for uncovering internal anomalies before they develop into serious failures. The figure offers a direct visual comparison between healthy ACSR cables and two major defect categories, highlighting the clear differences in internal structure observable through X-ray imaging and underscoring the need for automated, deep learning–assisted inspection to ensure consistent identification. In the top row, the image labeled “Internal corrosion” shows a cable whose steel core contains irregular textures, non-uniform density patterns, and darker regions indicative of material degradation from moisture, chemical exposure, or prolonged oxidation. This type of corrosion weakens the steel core which bears most of the tensile load and can reduce mechanical strength over time. Next to it, the “Normal” image depicts a cable with smooth, symmetric aluminum and steel strands, free of voids, fractures, or discoloration, serving as the reference condition during model training. The third image, “Broken wires,” illustrates a snapped strand with a clear gap and sharp edges, typically resulting from fatigue, excessive tension, vibration, or ice loading. Because even a single broken strand can worsen over time, early identification is critical.

The second row includes two additional “Normal” examples, showing intact aluminum strands wrapped consistently around the core. These variations in lighting and imaging angle demonstrate why the deep learning model must be robust enough to recognize defect-free cables under different visual conditions. The third image in this row, labeled “Internal corrosion,” provides another view of degraded internal strands, this time with measurement overlays, indicating that quantitative assessments can complement visual inspection. Deep learning models learn to detect subtle variations in brightness, texture, and density from such examples.

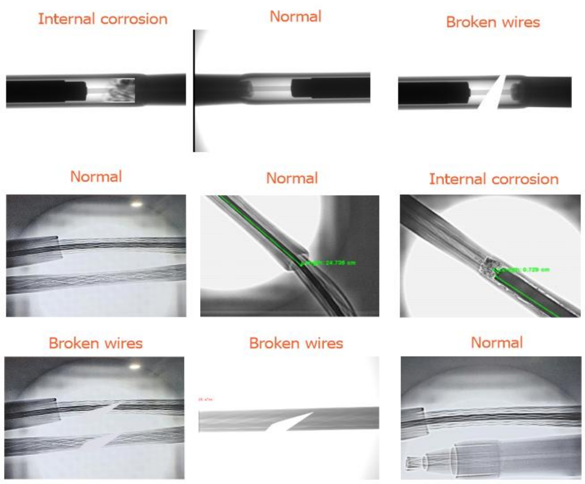

Figure 3. Classification of ACSR Cable Defects

The bottom row begins with two “Broken wires” images, each showing clear strand separation, misalignment, and abrupt discontinuities—signs of severe structural damage that threaten conductor performance and safety. Deep learning systems can reliably flag these defects by recognizing distinctive edge features and sudden intensity changes in the X-ray images. The final image labeled “Normal” again presents a cable with uniform internal structure, reinforcing the appearance of a defect-free sample.

Clustering algorithms such as K-means, DBSCAN, or hierarchical clustering group images based on similarity metrics derived from their feature representations or deep learning embeddings. When applied to ACSR cable imagery, clustering typically forms three dominant groups corresponding to normal, corroded, and broken-wire samples. Normal strands cluster tightly because of their relatively consistent structure and low variability in texture. Corroded samples form a separate cluster characterized by intermediate variation, with microstructural and density irregularities producing greater intra-cluster spread. Broken-wire images tend to occupy a distinct region of feature space, often separated by large distances due to the high-contrast, high-gradient discontinuities introduced by physical fracture. These clusters not only validate the separability of the three main defect categories but also help identify ambiguous samples, transitional cases, or previously unseen defect conditions. For example, an image situated between the corrosion and broken-wire clusters might represent a cable transitioning from early damage to structural failure. Detecting such borderline conditions is particularly valuable for preventive maintenance planning. Furthermore, the integration of deep learning, feature learning, and clustering creates a comprehensive methodology that leverages the strengths of each analytical dimension.

3.2 Analysis of Training and Validation Curves

Figure 4. Training And Validation Algoritma

According to figure 4. Training and validation the loss curves show that the model learns effectively from the training data, with the training loss starting high at around 1.35 and decreasing sharply during the first several epochs before gradually stabilizing near 0.35 by epoch 30. The validation loss follows a similar downward pattern, starting near 0.9 and steadily dropping to about 0.25, consistently staying below the training loss which indicates excellent generalization and minimal overfitting, as an overfitted model would show rising validation loss while training loss keeps falling. The accuracy curves further support this, with the training accuracy rising from roughly 40% to about 86%, while the validation accuracy climbs even higher, reaching nearly 90% despite some normal fluctuations. The fact that validation accuracy surpasses training accuracy is unusual but positive and can be attributed to regularization techniques like dropout, differences in dataset difficulty, or details of the accuracy calculation process. In the context of X-ray image analysis for ACSR reconductoring, these results demonstrate that the model is highly reliable in identifying internal defects such as strand fractures, faulty splices, or corrosion within the steel core an essential capability for non-destructive evaluation during transmission line maintenance. Because reconductoring decisions rely on precise detection of internal structural issues, the consistently low validation loss and high accuracy confirm that this machine learning model is well-suited for automating and accelerating the inspection process, ensuring improved reliability, safety, and long-term performance of ACSR conductors in the power grid.

3.3 Edge Detection of X-ray–based damage analysis on ACSR

Edge detection in the context of X-ray–based damage analysis on ACSR (Aluminum Conductor Steel-Reinforced) cables, as illustrated in the figure 5. Serves as a crucial pre-processing and feature-enhancement step that enables a deep learning model to discriminate between normal conductor conditions and various forms of degradation such as internal corrosion and broken wires; in this figure, the edge-enhanced representations highlight the structural discontinuities, intensity gradients, and subtle texture variations that would otherwise be difficult to perceive in raw radiographic images, and by converting X-ray scans into high-contrast boundary maps, the algorithm isolates the physical geometry of the wires, serrations, voids, and corrosion artefacts while suppressing irrelevant low-frequency background noise. The top row shows three distinct classes internal corrosion, normal, and broken wires represented through high-contrast line drawings generated by an edge detector (likely Canny, Sobel, or a comparable gradient-based operator); in the "internal corrosion" sample, the interior steel core region displays irregular, clustered edge responses caused by heterogeneous density changes produced by rust or material decay; these lead to noisy and fragmented lines and a more chaotic internal pattern, allowing both humans and machine classifiers to recognize the onset of internal degradation. In contrast, the "normal" image in the top row contains smooth, continuous outlines of the aluminum strands and steel core, with minimal intensity fluctuation; the edges appear clean and uninterrupted, reflecting uniform density distribution typical of healthy ACSR structure. The "broken wires" example exhibits abrupt discontinuities along the outer strands where the edge detector captures sharp geometrical breaks, misalignment between segments, and jagged line terminations indicative of physical fracture.

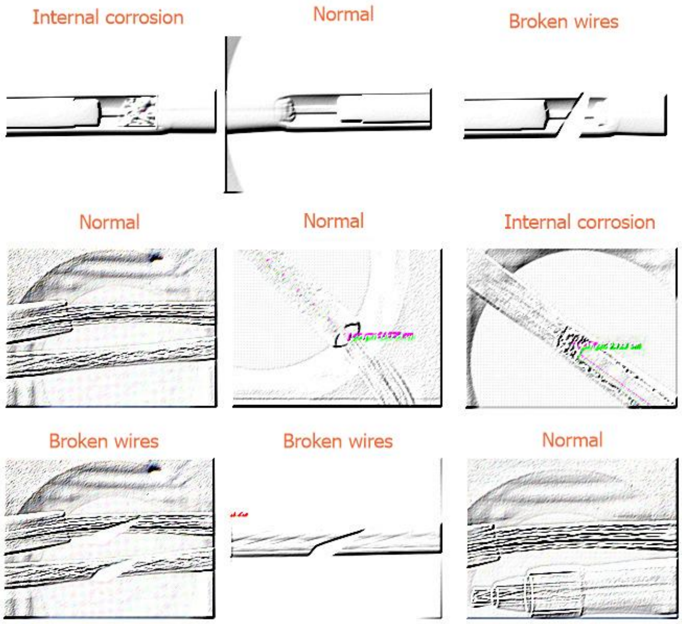

Figure 5. Edge detection in the context of X-ray

In the middle row, the first two images ("normal" and "normal") again demonstrate consistent and parallel strand patterns: the edge detection emphasizes the uniform layer geometry of the aluminum wires, producing long, stable line segments without fragmentation; these regular patterns allow a neural network to learn what an intact conductor looks like at multiple scales. The third image in the middle row, labeled "internal corrosion," shows disrupted intensity around the cable core where the edge detector outlines scattered micro-features tiny spots, pits, and granular structures caused by corrosion byproducts accumulating inside the steel reinforcement; these irregular edges contrast sharply with the smooth patterns found in healthy cables, and the presence of radially irregular shapes helps the model distinguish corrosion even when the surface appears visually intact. In the bottom row, the two "broken wires" samples emphasize how edge detection reveals structural failure: the algorithm outlines abrupt wire deviations, open gaps between strand endpoints, and inconsistent spacing, all of which serve as strong indicators of mechanical damage; in broken wire regions, the edges terminate suddenly or diverge sharply, forming discontinuous line segments, whereas in normal zones the lines remain parallel, symmetrical, and contiguous.

The final image ("normal") reaffirms the appearance of a healthy conductor: stable repeating contours, uniform thickness, and evenly spaced edges that show the cable's structural integrity. Collectively, these edge-enhanced images highlight how edge detection isolates meaningful structural cues continuity versus discontinuity, smoothness versus roughness, and uniformity versus irregularity that correlate strongly with physical cable health. In a deep learning workflow, these processed images serve multiple roles: (1) they act as direct input to classification models, enabling convolutional neural networks to focus on shape-related anomalies rather than being distracted by X-ray luminance variation; (2) they provide auxiliary channels for multimodal models that combine raw X-ray data with gradient-extracted features, improving robustness against noise; (3) they facilitate interpretability by allowing engineers to visualize precisely which physical features the model relies on for decision-making. Edge detection aids in distinguishing internal corrosion from external structural defects because corrosion generally produces diffuse, irregular edge patterns inside the cable core, whereas broken wires produce sharp, localized geometric discontinuities. The figure also demonstrates how edge detection enhances fault localization: corrosion zones appear as clusters of heterogeneous micro-edges within the cable interior, while broken wire zones manifest as stark breaks in the outer layers. The consistent labeling across the images shows that edge-based features remain reliable even under variations in orientation, magnification, and X-ray contrast, which is essential for real-world ACSR inspection where cables may be imaged under diverse conditions. Ultimately, the figure showcases how edge detection transforms raw X-ray scans into structured representations that make subtle mechanical and material defects more detectable, providing a solid foundation for deep learning algorithms tasked with automating the diagnosis of ACSR cable health.

4. Conclusion

In conclusion, this study highlights the of integrating X-ray imaging, deep learning classification, clustering analysis, and edge detection techniques for nondestructive evaluation of Aluminum Conductor Steel-Reinforced (ACSR) cables. The visual results in Figure 3 confirm that internal corrosion, broken wires, and normal conductors exhibit distinct radiographic patterns that can be effectively captured and differentiated using deep learning, providing a solid foundation for automated defect identification. Model performance, as shown in the training and validation curves, further reinforces the reliability of the proposed method. The training loss decreases sharply from approximately 1.35 to 0.35 by epoch 30, while the validation loss drops from about 0.9 to 0.25 and remains consistently lower than the training loss. This behavior indicates excellent generalization and minimal overfitting. Similarly, the accuracy curves show strong improvement, with training accuracy rising from roughly 40% to 86% and validation accuracy reaching nearly 90%. Although it is uncommon for validation accuracy to exceed training accuracy, this positive outcome can be attributed to regularization techniques such as dropout or variations in dataset complexity. In the context of X-ray based ACSR analysis, these results confirm that the model can reliably detect subtle internal defects such as strand fractures, steel-core corrosion, or splice anomalies supporting the need for accurate and fast nondestructive inspection. This capability is essential for guiding reconductoring decisions and ensuring long-term conductor performance. Clustering results also validate the clear separability between normal, corroded, and broken-wire samples, while identifying transitional cases that may represent early degradation stages. Additionally, the edge detection outputs highlight structural features, enhance defect visibility, and improve interpretability by emphasizing boundary discontinuities and texture irregularities.

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