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Advanced Classification Technique for Defect and Fault Detection in the Electrical Industry Using Image Data

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Abstract: Effective defect and fault detection in image data is essential for quality assurance, particularly in industries reliant on high-performing infrastructure, like power transmission insulator defects. So far, various methods based on machine learning techniques have been developed to detect defects in images captured using UAVs. In this study the advanced techniques used in image-based fault and defect detection evaluates with a primary focus on the electrical industry. A wide range of approaches are discussed for identifying faults and defect in power transmission line images and underscoring their impact on detection accuracy and adaptability to complex environments. In this paper, a new version of the Mask R-CNN network is presented, which has been redesigned in its head architecture to satisfy these limitations. To increase the accuracy of detection, in the classification branch, a series of fully connected layers with a rhombus structure have been used. The results of the experiments show that an accuracy rate of 98.81% and precision rate of 98.89% for detecting insulator defects in power transmission lines, which is higher than the existing compared methods and the cost and time of repairs will reduce.

Keywords: *Machine Learning, Deep Learning, Defect Detection, Fault Detection.*

1. Introduction

Defect Detection (DD) appears to have unfavorable working requirements because of failure in machine production design and equipment. Due to customary application, products efficiently disintegrate to weariness. DD raises the prices of processes by companies and compresses products that simulate the service lives. These limitations cause the expansive destruction of resources. To overcome these limitations, we needed to generate significant

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damage to people and safety [1]. A central competency is catching defects which companies maintain to enhance the grade of the simulated developments with no influencing presentation. In this context, there are evident benefits over manual detection in technologies with Automated DD. These technologies adjust an improper background and achieve high precision and efficiency in performance. The earlier studies on this scope decreased the exhibition price and enhanced the efficiency and quality of presentation and product for intelligent transformation in the industry.

DD and classification must be feasted on, just like individual issues associated with the specialization of artificial vision. The public objective of emulating mortal vision can be to determine and organize a topic. The mentioned objectives bonded together. We handle both classes and concentrate on the precise solutions that are intensely associated with visual processing techniques, particularly inspection techniques in industrial applications. Quality Control (QC) is an essential characteristic of the industrial exhibition sequence—some general strategies employed to evaluate the grade of a function. To Rely on the technique used to determine a defect on a surface/volume, QC strategies are categorized as detrimental or non-destructive (See Figure 1). Non-destructive testing aims at observing an element to DD without removing selections from it or perpetually impairing it.

Many researchers studied DD strategies in this context. We outlined an application of hyperspectral [2], pulsation range, infrared [3], etc. In DD for surface authors [4] utilizing computer vision in conjunction with image processing (IP) approaches. Approximating the results of ex-investigations, revealed that DD in surface founded on IP needs a real-time performance at a high level for industrial applications. For DD in fabric, researchers [5] [6] investigated the development of DD techniques typically employed in textile materials from the standpoint of DD expansion of the textile enterprise exhibition. Authors in [7] concentrated on a comparison of consequences received with commercially general non-experimental IR techniques to supply concerns for non-destructive DD. DD strategy is a superheated matter in the enterprise. DD strategy is a desirable issue in the enterprise. Nevertheless, researchers categorize product defect types [8], the major DD strategies, living supplies for DD, etc.

The visual-based procedure is the considerable typical DD method in the industry. Nevertheless, the classic visual assessment is a non-measurable approach with unstable and emotional effects. It caused authors to devise new automated DD techniques with challenging conditions because of the sophistication and individuality of detailed issues to decode. Nevertheless, a method relies on the fabric effects of the covers to observe the environmental requirements.

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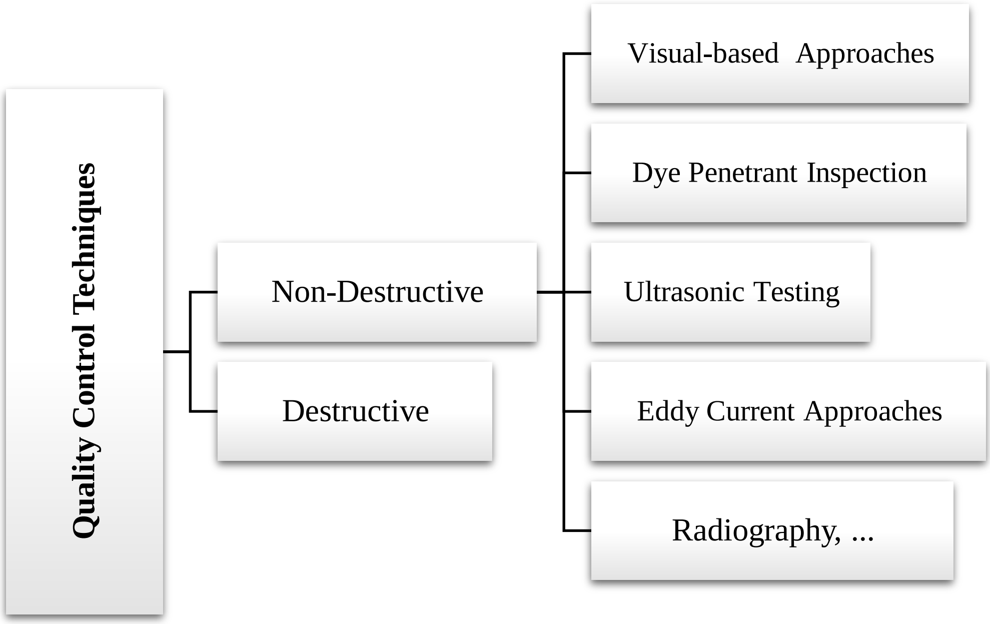

FIG 1: Classifiacation of the QC techniques

Defect definition and the classification of them are a manner in which sequence of personal determinations found. The principal features in DD rely on the desired precision and resolution of its approach; the scope of faults vary in industrial applications. It recommended to specify a quality criterion of the outcome in every industrial application before organizing and executing the automated system.

In this study, advanced techniques and machine learning approaches to detect faults and defects in power transmission lines based on images captured by UAVs or drones have been investigated and their impact on detection accuracy and compatibility with complex environments has been discussed. The goal of this paper is to improve the accuracy of insulator defect detection in power transmission lines. In this regard, a new version of R-CNN network has been presented. Therefore, the main contributions of this article are choosing the suitable network as the backbone in the R-CNN can increase the final accuracy of defect detection. Also a structure use in the arrangement of the fully connected layers in the classification branch of the R-CNN network, instead of the classic sequential structure, can improve the performance of the network detection. To reduce the effect of over-fitting in the Mask R-CNN, which is produced by training the network, a drop-out layer in the segmentation branch can be used in the middle of fully connected layer.

The rest of this article is organized as follows: In the next section present the taxonomy of defects that appear on metal characters. In the section 3, we present the defect and fault detection technologies and then in section 4 present the related works of the DD tecniqes. In

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the section 5 present the explanation of ategorization by method type. In the section 6, our proposed method is described with details. At the section 7, the experimental results from the improved mask R-CNN is compared with efficient existing methods in insulator defect detection scope. In the section 8, we discuss the precision and minimum error of the proposed methed and other research metheds. Conclusion and future works are given in the section 8.

2. Taxonomy of detects

In the industrial exhibition area, CC strives to maintain a quality status or at localizing the defects for additional restoration. Traditional detection techniques vend with standard, macro-sized, and difficult deviations of character faults. Every artificial optical DD method strived to DDs and classified them for additional processing. For a reasonable classification, industrial applications require well-structured databases of the probable fault classes. Due to the randomness and essence of the defects that appear in the function systems, showing such an all-around and complete database for a classifier is difficult. Figure 2 shows the based steps of IP.

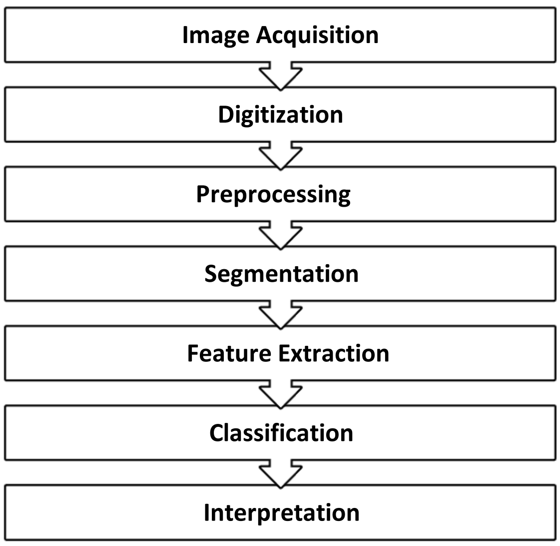

FIG 2: The steps of IP

In this area, every application utilizes a material-based fault classifier. The proposed taxonomy of defects is organized into two principal classes: observable and tangible. The classification is basically not sufficient in systems with detailed conditions. It delivered a dedicated foundation in the category of artificial intelligence systems. The essential hypothesis in DD classes is a hardly subjective decision. The decision is founded on a point and a logical-based illustration of the size balance of both the element and the fault. Thus, the design of the proposed classes is classified by dimension proportions and spatial components.

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3. Defect and Fault Detection Techniques

Development DD technology detects the cover and inner weaknesses of outcomes. The DD technology guides the detection technology of location, hole, scrape, and color contrasts. Internal DD technology contains an inner fault, spot, and crack detection (CD) [9]. Some techniques are employed to catch the development rate. These consist of profound [10], magnetic powder [11], vortex existing testing [12], ultrasonic testing [13], and machine vision [14] detection procedures. Moist magnetic particle detection combines the magnetic powder in all fluid media. Magnetic powder observes the area of faults via fluid force and the interest of the superficial magnetic domain [15]. The wetness detection method has increased sharpness [16]. Arid Magnetic powder testing [17] connects magnetic powder to the cover of the magnetized workpiece for DD. The technique is employed for the regional examination of faults in big casting, welding positions, and other features that are inappropriate for moist detection. Figure 3 shows an overview of DD techniques.

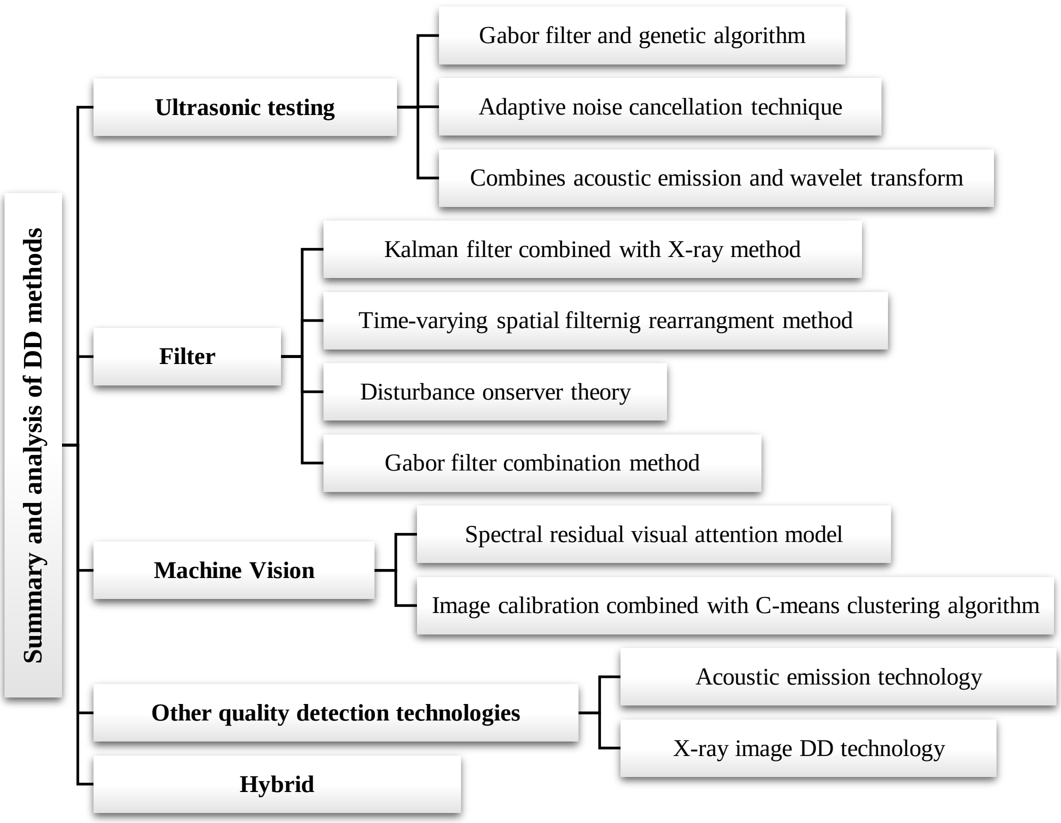

FIG 3: Overview and analysis of DD techniques

The constant magnetic particle detection technique notices faults in magnetic break or powder underneath the outer magnetic area [18]. This technique is employed to monitor the faults in the outer magnetic area. Some elements that affect the precision of magnetic powder testing

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include roughness and the profile of the difficulty selection, the geometrical features of faults, the specified magnetization approach, and the grade of operators [19]. The elements that affect the sensitivity of testing are reflecting reagents, the implementation of liquid, the rate of operators, and the impact of defects. Elements that affect the accuracy of the detection of vortex current are the parameters of the material and the shape of the test report [20].

The ultrasonic testing product is influenced by the gradient between the fault character and the ultrasonic propagation path [21]. If the curve is steep, the motion produced is robust, and the defect is efficiently caught. If the angle is flat, the signal returned is weak in which detecting make a leak straightforward. Thus, choosing the proper detection sensitivity and related search to decrease leakage detection is required [22]. The aspects that affect ultrasonic testing include projection direction, investigation effectiveness, sound connection grade, and device use commonness [23].

Device image detection includes of image purchase, DD, and variety. Because of objective, non-destructive, and low-cost attributes, device image is employed. Machine vision recognizes objects based on the color, texture and geometric features of objects. The rate of image acquisition defines the problem of IP.

The rate of the IP algorithm impacts the accuracy, mistake detection speed of DD, and category [24]. The deep learning (DL) approach is likewise a DD approach that is founded on IP , which utilized to acquire proper components in huge data [25]. Table 1 displays a comparison of employed development DD approaches. The conventional DD methods and the famous DL DD methods have their benefits. These methods are positively concentrated. Osmosis testing technology [26] is an applicable for DDs in positively porous and non-porous fabrics.

TABLE 1: Comparison of standard DD techniques

Method	Advantages	Disadvantages
Ultrasonic Testing	- Easy to use - Strong penetration - High sensitivity - Automatic detection - Portable equipment	- Unsuitable for complex workpieces
Machine Vision Detection	- High precision - Automatic detection - Versatile applications	- Limited to surface detection
Magnetic Powder Testing	- Visualizes shape, size, and position - Suitable for various sizes - High precision - Low cost	- Difficult to automate - Influenced by geometric shape - Limited to ferromagnetic materials

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Osmosis Testing	- High sensitivity - Non-destructive to shape and material type	- Challenging for porous materials - Slow detection speed - Difficult to automate
Eddy Current Testing	- Non-contact - Fast detection - High sensitivity - Suitable for high-temperature environments	- Low detection accuracy - Limited deep detection - Not suitable for all materials
X-ray Testing	- Non-destructive - Strong penetration - No effect on material and structure - Easy operation	- Exposure to radiation

This table summarizes various non-destructive testing methods, highlighting their advantages and disadvantages. Each method has its unique strengths, such as portability and high sensitivity, while also facing challenges like limited applicability and difficulties in automation. Understanding these factors can guide the selection of appropriate testing techniques for specific applications in the electrical industry and beyond.

4. Related Works of DD Techniques

Most of the standard detection techniques ought to depend on manual service to conclude, the equipment product cost increased, which is not flexible and defined by the tools life and manufacturing accuracy. Creative DD methods, especially machine vision and DL techniques [27], control evolved as one of the important technologies for automating DD due to their versatility and absence of support on mortal service.

Corresponded to standard DD techniques, the latest technologies present more useful examination results and decrease costs. Though these nevertheless depend on large quantities of known data to guide standard updates and enhance assessment accuracy. In continuation, the current authors concentrate on the existing hybrid works in IP.

Authors in [28], presented a hybrid technique founded on machine learninig (ML) and optimization employing X-ray pictures for lung disease classification. The incredible development of ML controls revealed that it can serve at a masterful class in several complex jobs, like medical decision-making and IP. Their research aimed to take benefit of the potential of ML by creating a unique technique for lung disease identification. This goal is exceeded in their model, in which the finest probable detection of lung disease is utilized. Their proposed model consisted of 2 preliminary steps: a) the classification methods including bagging, voting chorus education, and promoting techniques, and b) optimization by Emperor Penguin

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Optimization (EPO). Their model in conjunction with the SVM constructed an accuracy of 97.50%. The results seem more than that of other hybrid models.

In [29], a hybrid ML technique using a multi-layer feed-forward NN (MLFFNN) model was offered to enhance DD for Lamb surge answers. The authors guided sixty-six simulations to describe a distinct damage scenario. The proposed model was strained and the highest value of accuracy was 99.94%.

Damage processing is an issue in which several techniques are handled to benefit IP. It exists two classes of Structural health monitoring (SHM): a) contact-based like sensors, and b) non-contact processes like photogrammetry. The authors in [30] concentrated on centers in IP. They employed several preprocessing techniques consisting image enhancement, image filtering, and dynamic response measurement. The authors concentrated on crack detection based on IP techniques and employed computer methods. They operated distinct IP strategies to catch shots and supply the primary format for a CD procedure based on IP. Their structure of images contains preprocessing, resizing, denoising, segmentation, and morphology. These efforts are aimed at the process of decision-making regarding the solemnity of a crack.

The authors in [31] concentrated on detecting defects in solar panels. Solar enclosures are disclosed to persistent and harsh atmospheric states that show regular losses or precise disorder of energy era. Existing methods are applied for detecting defects in terms of managing resources. Automatic designation of defects confirms that photovoltaic partitions are supported to evade power production issues. Hence, a DL algorithm called DenseNet was introduced by the authors. Experimental results achieved more increased accuracy compared with other living NN architectures. In [32] authors attempted to focus on developing a progressive system. In this system, DL approaches are applied to detect anomalies in road traffic. Their analysis aims to operate the possibility of DL techniques for the sophistication of road traffic monitoring. The proposed system operated Super-Resolution Generative Adversarial (SRGAN) and Convolutional NN (CNN) models to categorize the images obtained from the dataset. This study obtained better results employing CNN and SRGAN with equal accuracy, precision, recall, f1-score, and ROC of 100%.

Acoustic emission is a dependable manner for corruption detection, regardless, the classification of these acoustical emission calls by only ML methods in its babyhood. Authors in [33] suggested an approach employing a mixed approach to integrate the detection of corrosion with ML methods to accurately forecast the corrosion severity levels. To estimate, five Deteriorating harshness classes in multi-class problems were conducted and tested based on mass failure that happened during revved pollution testing. The highest results based on Naive Bayes, BP-NN, and RBF-NN demonstrated an accuracy of 90.4%, 94.57%, and 100%, respectively.

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For modern manufacturing, authors in [34] proposed an architecture founded on DL and computer vision to consider the texture roughness of machined steel automatic features. In this architecture, for object detection tasks, two popular DL architectures were developed, Faster R-CNN Inception v2 and Faster R-CNN ResNet50. For rapid, accurate, and real-time inspection, the acquired results indicate the possibility of the presented mixed technique rather than other methods. Further, the standard qualified operating Faster R-CNN Inception v2 materializes as the better option in terms of detection accuracy.

For error detection in this scope, some works are of concern. Table 2 shows the comparison of the related woeks. In [35], authors discover various important applications in this context. The greatest significance of these cases was that they were difficult to investigate while being available. Nevertheless, the designation of enclosure systems removes valuable understandings needed in the procedure. They present a hierarchical topology algorithm to identify enclosure systems with heightened efficiency and accuracy. The algorithm recognized all styles of entire enclosures and was optimized for hydrate titles in large-scale systems. Moreover, they applied the benefit of the algorithm for the designation of enclosures upon automated limitations to defeat.

In 2022, the rapid detection of premature deterioration could be an encouraging approach to roadway supervision. Earlier CD authorizes preventative actions to be carried out to evade crack and potential defeat. Regarding the improvement in IP in considerate engineering, the standard optical examination superseded by semi or automatic processes. The method of catching things from the images is a whole location of any IP procedure. The accuracy speed of the category relies laboriously on the grade of the effects received from the segmentation phase. The significant challenge is the detection of delicate, periodic filmy cords breaks that are planted into the textured backdrops. There is even a requirement for additional advancement. The theoretical residents are operating on image markers of damages, whereas there is no current presently no formal system. The publications examination shows the record of action and performance of living analyses and concentrates on the significant styles of techniques in the specialization of image segmentation, i.e. thresholding, edge, and data-driven-based procedures. The study supplies useful details for students performing these methods that produce a complete despair detection method for images with changing requirements [36].

In [37], authors indicated device arrangement post-laser processing in CD. Scanning electron microscopy (SEM) pictures were operated to invent a process for crack markers. Because of the emotional and time-consuming manual inspection of SEM pictures, they show a procedure to determine cracks from an SEM in MATLAB programming. IP algorithms were employed to segment crack parts from further texture defects and afterward to remove crack information. The outcomes demonstrate victorious segmentation of cracks from SEM pictures with a

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designation accuracy more significant than 95 %. In [38], the authors suggest two methods, i.e. digital IP and DL-based. They complete cover crack assessment methods and endeavor their interpretations in view by reaching the outcomes across four additional kinds of cover crack picture datasets.

In [39], the authors' attending position concentrates on specifying the cracks utilizing IP and defeating the routine distinction approach by operating appropriate ML algorithms. To address this goal, Basalt Fiber Reinforced Polymer/Glass Fiber Reinforced Polymer and Steel bars were applied. The testing pictures were utilized for IP and defeat pattern recognition in Python programming. Operating six ML classifiers, the defeats in the systems were categorized into three categories i.e., compression, flexure, and shear. It seemed that the SVM classifier presented the most useful rendition with 100% accuracy. In [40], the authors deliver a study of image CD processes in IP. A complete examination of these procedures is conducted to accentuate the most profitable automatic methods for CD.

In [41], the authors present a technique that utilizes an acclimated performance of the segmentation algorithm to glimpse breaks in 2-D pictures. Their technique exploits the Gaussian cumulative density function (CDF) to overwhelm the weakness in clangorous circumstances. The presented algorithm was stretched on 300 pictures including a range of commotion examples of different clangor requirements. The confirmation effects were pledging for the detection of level cracks with precision of 79.21%, recall of 89.18%, and F1 score of 83.90%.

In [41], the authors examine the necessary measures affected by DD utilizing IP, ML, and AI for DD from a space. In [42], the authors give effect in IP strategies to drive ahead the analysis specialization by studying accomplishments in the issued documents. So, developed IP strategies can be devised and new methods in the IP methods can be oriented. In [43], the authors conduct a comprehensive study of the current publications and recognize the circumstances in the prospective investigation. They complete the report with study movements for the destiny of this location, like data grade issues, tiny entity detection and ingrained application.

In [44], the authors suggested a technique for DD using a DL and the ME process. The presented technique can examine the ME process to advise to user of the process when strange printing is caught. In [45], the authors utilized PBSR to improve the explanation of MSI. They suggested the presented channel by utilizing a spirit picture. Finally, they revealed the possible relevance of PBSR in a clinical environment by combining structural from a patient examination of a puppy liver. In [46], the authors offered an IP system to remove components from pulsation movements, founded on the seeing expression model. The removed components are provided into a light classifier for the category. The highest accuracy was 99.7%.

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In [47], a technique is presented to implant the picture union surveillance The authors improve the appearance and catch the picture unions, consequently improving the post-transmission grade of the photo. Enhancing photos contains techniques like employing a filter and growing difference to enhance the optical grade of pictures [48]. In [49], the convolutional NN and traditional IP algorithm were connected to create segment groups and compute group numerals. The outcomes showed a mark segmentation of 0.878 in duration, a precision of 0.936, and an accuracy of 86%. In [50], the authors proposed an investigation using R-CNN, SSD, VGG16, and Yolov4 DL representatives with IP and used a hybrid method for the automated decision. The presented mixed approach for the disease diagnosis qualified and tried utilizing 1040 pictures. The highest accuracy was 96.47%. In [51], the authors show a technique for catching designation errors in pictures with semantic segmentation. They offered a conscientious method for error detection.

Advances in recent years in the processing and capabilities of computer networks have led to the accumulation of a considerable portion of data. Also, the increased efficiency of the automatic method of recovery and knowing the basic difference between man and machine, i.e. interpreting photos and texts, has become a basic requirement. The purpose of any recovery system is to deliver relevant information at the right time to the right user. Images are of particular importance as a form of document that can convey a significant amount of information. In this article, we will review the concepts, applications, and methods of image recovery based on content by combining color and texture features [49].

In [50], in today's world, quality control - automatically in the manufacturing industry to enhance the rate of the product is of particular importance because its use makes it possible to detect defective areas on the product surface, more easily and with high accuracy. This goal requires effective DD algorithms, corresponding to the speed of the production line. In general, character DD techniques can be studied from two perspectives: 1) feature extraction methods, and 2) DD methods. All review articles study and review these techniques from the perspective of feature extraction methods. However, the intention of this article is to study surface DD techniques from the point of view of DD methods, unlike other review articles, because the number of these methods is large and it is difficult to describe all of them in this article. In this article, only a few methods of surface DD techniques have been reviewed and the strengths and weaknesses of these methods have been stated. In the end, these methods have been compared.

A DL Model was introduced in [52] to address the DD issue. The pictures are involved with Gray Scale Quantization Algorithm (GSQA) to remove the elements. Removed components are qualified with a DL representative to further categories of neurons. Each category has been developed to calculate Defect Class Support (DCS). At the trial stage, the information picture was used with additional procedures, and the elements removed expired via the standard

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introduced. The resulting coating produces a numeral of DCS discounts utilizing which the process determines the category of fault the fault in the picture. The highest outcome was 97% for accuracy value.

Table 2 provides a comparative summary of recent studies on defect detection techniques across various fields, focusing on the suggested methods, associated parameters, and results. This table highlights a range of approaches from structural and statistical methods to model-based techniques, showcasing their adaptability to different parameters, including resource detection, crack identification, and image authentication.

TABLE 2: The summary pf related work

Author(s) / Year	Suggested method	Parameters and variables	Advantages / Result
[35] Liu et al. 2022	HTR algorithm efficiently and accurately recognizes cage structures.	Resources, gas storage, transport, separation, water desalination, refrigeration.	HTR algorithm efficiently identifies complete cages, hydrates in large-scale systems, and unique topological isomers of cages. Validated for clathrate hydrate identification under mechanical loads.
[36] Kheradmandi et al. 2022	Research analyses image segmentation algorithms for automated distress detection in pavement images under various conditions.	Image segmentation, irregular dark lines cracks	Research analyses image segmentation algorithms for automated distress detection in pavement images under various conditions.
[37] Hazzan and Pacella 2022	SEM images developed for crack identification method.	SEM images aid in crack identification and quantification.	Achieved over 95% segmentation accuracy in identifying and quantifying cracks in SEM tungsten carbide microstructure using various laser processing parameters.
[38] Yadhunath et al. 2022	Computer vision techniques for surface crack inspection.	Surface crack	Presents two approaches for surface crack inspection systems: digital image processing (IP) and deep learning (DL) for enhanced inspection capabilities.
[39] Aravind et al. 2021	Uses IP and ML algorithms to identify cracks and validate techniques.	Confusion matrix, accuracy, precision, recall scores	Achieved 100% accuracy in identifying failure patterns using support vector classifiers, outperforming other ML classifiers.
[40] Munawar et al. 2021	Review of image-based crack detection techniques implementing IP and/or ML.	Crack detection, possible defects	Analyzed various IP and ML techniques for defect detection, highlighting promising automated approaches for infrastructure maintenance.
[41] Safaei et al.	New method detects cracks using adapted weighted neighborhood pixels segmentation algorithm and	Detect cracks	The proposed algorithm is efficient, processing images in less than 3.15 seconds

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Author(s) / Year	Suggested method	Parameters and variables	Advantages / Result
2021	Gaussian cumulative density function.		for county-level pavement maintenance projects.
[42] Klára et al. 2019	PBSR enhances spatial resolution of MSI by guiding high-resolution features from one modality to reconstruct low-resolution images.	Linear interpolation (LI), image fusion (IF)	PBSR outperformed linear interpolation and image fusion in improving MSI resolution, validated using phantom images and mouse cerebellum samples.
[43] Zhang et al. 2018	Increases MSI resolution and validates its performance using phantom images and mouse cerebellum samples.	Machine fault diagnosis, remaining service life prognosis	Developed an IP method for extracting features from vibration signals, achieving high classification accuracy with a sparse representation-based classifier.
[44] Kuo-Lung Hung 2017	New image authentication technique embeds image block directions for verification.	Variability, error image transmission, detect transmission error	Proposed a novel image authentication technique to address malicious image modifications and error transmissions, improving image quality post-transmission.
[45] Liu et al. 2016	Review of literature on component detection and diagnosis (DD), identifying future research challenges.	Reliability, safety, sustainability of power transmission	Summarizes techniques and methodologies for component detection and DD diagnosis, highlighting future research trends and data quality issues.
[46] Meng et al. 2016	Develops a webcam-based failure detection method for manufacturing processes.	Spaghetti-shape error, abnormal printing detection	Achieved 97% accuracy in detecting errors using CNN for real-time monitoring of 3D printer processes.
[47] Kosti and Vasovi 2015	Reviews recent advancements in IP systems for future research.	Review Articles	Analyzes advancements and new techniques in IP systems, providing insights for future research directions.
[48] Lukac, R. et al 2014	Focuses on machine vision and image enhancement.	Image enhancement, machine vision	Discusses techniques for enhancing images and understanding image meaning for various applications, including robotics.
[49] Wu et al. 2023	Combines algorithms to calculate the number of bunches in two periods using CNN and image-processing algorithms.	Bunch detection, target segmentation, accuracy rate	Achieved target segmentation MIoU of 0.878 and final bunch detection accuracy rates of 76% during challenging harvest periods.
[50] Adem et al. 2023	Utilizes Faster R-CNN, SSD, VGG16, Yolov4 DL models for disease detection in sugar beet.	Accuracy rate	Hybrid method for automatic leaf spot disease detection achieved a classification accuracy rate of 96.47% using a dataset of 1040 images.

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Author(s) / Year	Suggested method	Parameters and variables	Advantages / Result
[51] Rottmann et al. 2023	Develops deep neural networks (DNNs) for semantic segmentation.	Accuracy rate	Addresses issues in annotation acquisition for semantic segmentation datasets, enhancing DNN performance through uncertainty quantification.
[52] Prabhakaran et al. 2023	Real-Time Multi Variant DL Model (RMVDM) and Gray Scale Quantization Algorithm (GSQA) for defect detection.	Accuracy rate	Method achieves around 97% accuracy in defect detection and localization with less time complexity, enhancing performance in identifying defects like cracks and dust.

According to the comparison made in Table 2, the references show different methods for defect and error detection in image processing, ranging from classical image segmentation techniques to advanced deep learning (DL) models. Key insights are offered into methods like the HTR algorithm, which excels in recognizing complex cage structures and is validated for clathrate hydrates under mechanical stress [35], and deep learning-based approaches, which achieve high accuracy in real-time defect detection and disease identification [50, 52]. Statistical techniques, such as image segmentation and pattern recognition, are instrumental in automated pavement distress detection and image quality improvement [36, 39]. Filter-based methods, including image fusion and pixel enhancement, improve visual clarity and assist in diagnosing faults [41, 48]. Overall, Table 2 illustrates how each method, parameter set, and resulting accuracy rate are tailored to meet the specific requirements of diverse applications, emphasizing the balance between algorithmic efficiency, precision, and computational feasibility across these studies.

Table 3 provides a cohesive overview of the diversity in defect detection methodologies across various studies. The approaches are categorized by distinct method types (Statistical, Structural, Filter-Based, and Model-Based) each addressing specific aspects of image processing and defect / error identification with parameters. Structural methods, like the HTR algorithm and SEM imaging, emphasize physical feature identification for accuracy in applications such as cage and crack detection [35, 37]. Statistical approaches are commonly applied in studies focusing on irregularity identification in textures and patterns [36, 39]. Filter-based methods, as seen in pixel enhancement and segmentation techniques, improve image clarity, ideal for maintenance tasks [41, 48]. Model-based approaches leverage advanced deep learning models to achieve high accuracy and adaptability in complex data processing, such as automated disease detection and defect localization [38, 50, 52]. The table showcases the various strengths and results across methods and also underscores their unique contributions to enhancing precision, efficiency, and robustness in image processing applications.

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TABLE 3: A cohesive overview of the diversity in defect detection methodologies

Ref. No.	Author(s) / Year	Suggested Method	Method Type	Parameters
[35]	Liu et al. (2022)	HTR algorithm	Structural	Resources, gas storage, transport
[36]	Kheradmandi et al. (2022)	Image segmentation	Statistical	Irregular dark lines cracks
[37]	Hazzan and Pacella (2022)	SEM images	Structural	SEM images
[38]	Yadhunath et al. (2022)	Computer vision	Model-Based	Surface crack
[39]	Aravind et al. (2021)	IP and ML algorithms	Statistical	Confusion matrix, accuracy
[40]	Munawar et al. (2021)	Review of crack detection	Statistical	Possible defects
[41]	Safaei et al. (2021)	Weighted segmentation	Filter-Based	Crack detection
[42]	Klára et al. (2019)	PBSR image fusion	Filter-Based	Linear interpolation, image fusion
[43]	Zhang et al. (2018)	Wavelet transform	Filter-Based	Machine fault diagnosis
[44]	Kuo-Lung Hung (2017)	Image authentication	Model-Based	Variability, error image transmission
[45]	Liu et al. (2016)	Literature review	Statistical	Reliability and sustainability
[46]	Meng et al. (2016)	Webcam detection	Model-Based	Spaghetti-shape error detection
[47]	Kosti and Vasovi (2015)	Review of IP systems	Statistical	Review articles
[48]	Lukac, R. et al. (2014)	Image enhancement	Filter-Based	Image enhancement techniques
[49]	Wu et al. (2023)	CNN and image processing	Model-Based	Bunch detection
[50]	Adem et al. (2023)	DL models	Model-Based	Accuracy rate
[51]	Rottmann et al. (2023)	DNNs	Model-Based	Accuracy rate
[52]	Prabhakaran et al. (2023)	RMVDM, GSQA	Model-Based	Accuracy rate

In terms of suggested method, the references propose diverse methods for image analysis, including traditional image processing techniques and deep learning algorithms. References

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[35-38, 41] focus on structural analysis methods that utilize feature extraction to detect cracks and structural defects in images, typically applying segmentation or recognition algorithms for precise identification. Alternatively, references [39, 50, 51, 52] leverage machine learning and deep learning models, such as convolutional neural networks (CNN), to enhance accuracy and automate defect detection, supporting applications that require high-level classification and pattern recognition.

In terms of evaluation, [35] and [39] focus on accuracy and classification metrics, emphasizing the reliability of ML and algorithmic approaches in real-world applications. For instance, [45] highlights challenges related to power transmission reliability, emphasizing safety metrics. Other studies, such as [46], achieved a 97% accuracy rate in detecting failures in 3D printing, demonstrating CNN's applicability in error detection. Research of [49] focused on segmentation accuracy, achieving notable performance improvements in target detection tasks. These parameters (accuracy, precision, and response time) provide a comparative framework to evaluate the robustness, effectiveness, and suitability of different methods across various image processing applications.

5. Explanation of Categorization by Method Type

The categorization of methods (statistical, structural, filter-based, and model-based) provides a structured way to understand how each approach addresses defect detection in image processing. Statistical methods focus on data analysis and inferential statistics, typically involving various algorithms for analysis and prediction. Structural methods involve the physical and functional structure of the subject matter, often utilizing methodologies for inspection or measurement. Filter-Based methods enhance images or data through various filtering techniques, improving quality or feature extraction. Lastly, model-based methods use sophisticated DL models, which are often the most accurate due to their ability to learn from vast datasets, providing scalable solutions in real-time applications.

According to the following tables, the references employ a range of methods, each contributing uniquely to defect detection and image analysis. Statistical approaches, represented in [36, 39, 40, 43, 45, 47], leverage data-driven analysis to identify patterns and defects, relying heavily on algorithms that assess variance, error rates, or probabilistic modeling to inform detection results. Structural methods, evident in [35, 37, 38, 41], utilize feature-based analysis to identify structural irregularities in images. These methods emphasize recognizing physical attributes, making them well-suited for applications involving spatial pattern recognition and defect localization. Filter-based approaches, used in [41, 42, 44, 48], apply neighborhood and pixel-density filters to refine image quality and identify structural anomalies. By focusing on enhancing image clarity, these methods are particularly useful for initial image preprocessing in defect detection. Model-based approaches, seen in [39, 43, 46, 49-52], predominantly utilize

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machine learning and deep learning models, such as CNNs, for their adaptability to complex data and high precision in large datasets. These approaches excel in handling complex patterns, offering high accuracy and scalability.

Evaluation Parameters: The key evaluation parameters include accuracy, precision, recall, and processing time. Accuracy serves as a core metric in references [39, 46, 50, 52], which is critical for validating the defect detection capabilities of models. For image quality, resolution enhancement is evaluated in [42, 49] by parameters such as segmentation performance and mean Intersection over Union (MIoU). Additionally, processing speed is highlighted in [41, 43] for assessing the computational efficiency in large-scale applications where quick results are crucial.

Results and Advantages: The results show strong outcomes across methods. For instance, the deep learning models in [39, 50, 52] achieve high accuracy rates, demonstrating the efficacy of CNN-based techniques in precise defect detection. In traditional methods, [35, 41] yield rapid processing with minimal computational demand, making them suitable for high-throughput environments without intensive resource requirements. These findings illustrate the potential of both traditional and advanced methods to meet different project needs.

Limitations and Challenges: Despite positive results, some limitations arise. Structural and simpler image processing methods in [36, 38] face challenges in recognizing complex defects or handling diverse environments, suggesting that additional refinement is needed. Additionally, the deep learning approaches in [50, 52] demand large datasets and high computational resources, posing implementation challenges and increasing costs. These limitations highlight the trade-offs between traditional and model-based approaches, emphasizing the importance of aligning the chosen method with project requirements for optimal results.

6. The proposed insulator defect detection approach

Convolutional Neural Network (CNN) is a type of deep artificial neural network (ANN) which is used in data analysis and image recognition. Therefore, CNNs are the fundamental tools for different computer vision problems such as image segmentation [53]. The classical architecture of CNNs consists of three main layers: convolutional, pooling, and fully connected layers. Sequential combination of these layers, enables the CNN to learn how to identify and recognize the object of interest in an image. In a complex situation with multiple objects in input image, classical CNN architecture isn’t optimal. R-CNN is a state-of-the-art dee p architecture and stands for region-based CNN [54]. R-CNN architecture utilizes bounding boxes across the object regions, which then evaluates convolutional networks independently on all the Regions of Interest (ROI) to classify multiple image regions into different classes.

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Fast R-CNN is an improved version of R-CNN architectures with two stages: region proposal network (RPN) and simple CNN. RPN is a neural network that proposes multiple objects that are available within a particular image [55]. Features are extracted in RPN, using RoIPool (Region of Interest Pooling) from each candidate box and performs classification and bounding-box regression. RoIPool is an operation for extracting a small feature map from each extracted RoI. Fast R-CNN is faster than R-CNN because high number of necessary region proposals to feed the next CNN stage is not needed. Image Segmentation is the process of partitioning input image into multiple continues sets of pixels called segments. This segmentation is used to locate objects and boundaries (lines, curves, etc.). Hence, visual surface defect detection can be categorized as image segmentation problem, where two type of regions called defect and non-defect, should be segmented.

Mask R-CNN is a type (CNN) which is used generally for image segmentation [56]. Maks R-CNN was developed first time based on Faster R-CNN architecture. While Faster R-CNN has two outputs, class label and a bounding-box offset, Mask R-CNN is the addition output called object mask. Mask R-CNN perform pixel-wise instance segmentation alongside object detection. This is achieved through the new output mask, which generates precise segmentation masks for each detected object. This enables fine-grained pixel-level boundaries for accurate segmentation.

The main goal in this paper is to diagnose defect in power transmission lines. In the analysis of aerial images, we face two problems, insulator segmentation and defect detection. Therefore, the Mask R-CNN network can be a suitable option due to the three outputs as bounding box, mask and label.

In this paper, an improved version of the Mask R-CNN network is presented, with the aim of increasing the accuracy of defect detection in power transmission lines. In the first phase, to increase the accuracy of insulator segmentation, the backbone of the Mask R-CNN is changed. In the second phase, to increase the final accuracy of defect detection, the structure of the network head is improved. The architecture of the proposed Mask R-CNN is shown in the Figure 4.

The backbone is the first box in the Improved Mask R-CNN that is used to extract feature maps. In most of the papers and various applications, ResNet has been used as the backbone of Mask R-CNN [57]. ResNet is superior to most CNNs because it uses residual units, which allows deep layers to directly learn from shallow layers and improve the network's convergence. Due to the fact that in some aerial images, there is more than one insulator in the image and also the size of the defects are not the same, in this paper, ResNet-101 is used as the backbone of Mask R-CNN.

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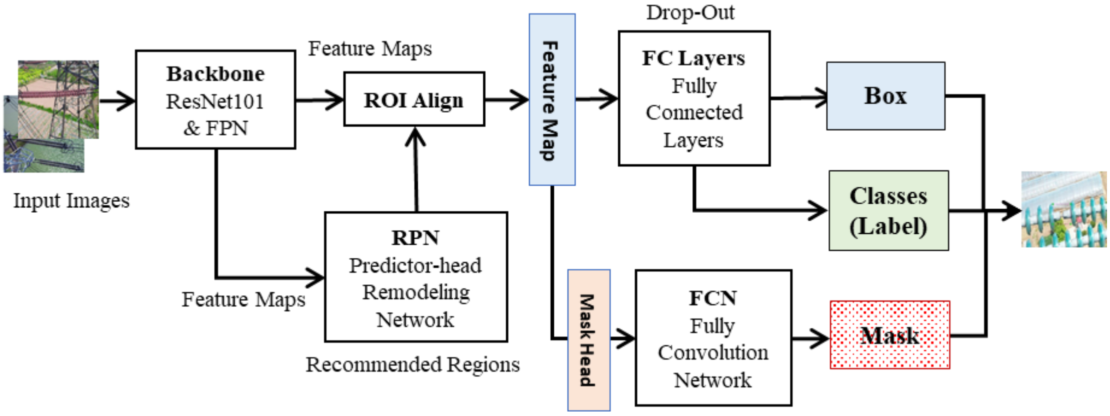

FIG 4: The architecture of the improved Mask R-CNN

ResNet-101 has 101 layers, therefore, in complex problems such as insulator defect detection, it can provide higher accuracy. The architecture of the ResNet-101 is shown in the Figure 5 with details such as layer types and output size of internal feature maps. In order to extract feature maps, a pre-trained ResNet-101 which is trained on COCO dataset is used and final fully connected layer in this network is removed.

Layer name	Output size	101-layer
Conv1	112×112	7×7, 64, stride 2
Conv2_x	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 1\times1, & 64 \\ 3\times3, & 64 \\ 1\times1, & 256 \end{bmatrix} \times 3$
Conv3_x	28× 28	$\begin{bmatrix} 1\times1, & 128 \\ 3\times3, & 128 \\ 1\times1, & 512 \end{bmatrix} \times 4$
Conv4_x	14 × 14	$\begin{bmatrix} 1\times1, & 256 \\ 3\times3, & 256 \\ 1\times1, & 1024 \end{bmatrix} \times 23$
Conv5_x	7 × 7	$\begin{bmatrix} 1\times1, & 512 \\ 3\times3, & 512 \\ 1\times1, & 2048 \end{bmatrix} \times 3$
	1 × 1	**Average pool, 1000-d fc, softmax**

FIG 5: The internal architecture of ResNet-101 with details

One of the branches at the head of the Mask R-CNN has the task of detecting the label of the input image. In the problem of detecting defects, there are two classes of normal insulator and defective insulator. A network of multiple fully connected layers in series format is responsible for extracting the final features for label recognition. Finally, a softmax layer does the classification task. In the classical Mask R-CNN architecture, several fully connected layers

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with equal dimensions are proposed. The possibility of learning and training is available in Mask R-CNN. In power transmission lines, possible defects are quite different from the background point of view. Therefore, the use of layers with equal dimensions may cause the features that have a high discriminative power to classify the label to be affected by the background features and reduce their efficiency in the last layer. Therefore, in our proposed improved version Mask R-CNN, a rhombus-shaped structure is used to design the fully connected layers series in the label detection branch. In the rhombus-shaped structure, first in some layers, the output size of the convolution layers increase alternately, and then in the next layers until the end of the structure, the output size of the layers decreases periodically.

7. Experimental Results

The proposed transmission line insulator defect detection method is implemented in the software environment of Python 3.11, TensorFlow 2.15, Keras 2.15 and windows 10. A physical computer with 16 core CPU, 16 GB RAM and GPU RTX 4060 is used to implement proposed deep network. In order to train proposed model, hyper parameters are selected as follows: 1000 Epoch, Batch_size:8, and confidence: 0.3. Learning rate is selected as 0.001 for first 900 epochs, and it is reduced to 0.0001 for final 100 epochs. To increase the speed of convergence, the weights of pre-trained Mask R-CNN on COCO dataset are used [58].

7.1. Datasets

Insulator Defect Image Dataset (IDID) contains 7568 images of power transmission lines with natural background, which are categorized into three groups including normal insulation, defective insulation due to Flash over and defective insulation due to Shell-Broken. This database contains 2636 images of completely normal insulators and 1140 images of insulators with defective coating and 2004 images of insulators of power transmission lines that have been damaged by Flash over [59].

7.2. Performance evaluation metrics

In the experiments, to evaluate the performance of the proposed method, some benchmark common metrics such as accuracy (A), precision (P), recall (R), F_1 score and Mean Squared Error (MSE) are performed. The accuracy, precision, recall, F_1 score, and MSE calculating equations are as follows:

$$\text{Accuracy} = (TP+TN) / (TP+FN+FP+TN) \tag{1}$$

$$\text{Precision} = TP / (TP+FP) \tag{2}$$

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Recall = TP / (TP+FN) (3)

$$F_1\,Score == 2 * \frac{(Recall * Precision)}{(Recall + Precision)} = 2 \times \frac{P * R}{P + R} \quad (4)$$

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(y_i - y_i)^2 \quad (5)$$

Where true positive (TP) shows the number of samples which are correctly labeled, TP + FP is the total number of positioned targets, and $TP + FN$ is the total number of actual targets. In many cases, F_1 score as independent metric, which represents the harmonic average of precision and recall.

7.3. Results of the proposed method

The proposed deep neural network in this paper provides three outputs, including class label, bonding-box and object mask, for each input objective image. Therefore, the effectiveness of the presented method has been evaluated in two fields of insulator segmentation in power transmission lines and defect detection.

As mentioned above, the first phase of the improved Mask R-CNN is insulator segmentation. The bounding box segmentation branch in the proposed network is used for this aim. In some articles, the defect classification is done without examining the insulator in the image. These methods usually analyze the entire input image for labeling. One of the advantages of the method presented in this paper is insulator segmentation. This branch in the presented deep network can improve the background knowledge of the repairman, reduce the costs and reduce the dependence of the UAV to high zoom. In this respect, the performance of the proposed approach is evaluated on IDID dataset. The grand-truth of all the images of dataset is available. Therefore, in order to evaluate the efficiency of the proposed network provided for insulator segmentation, the output of the bounding-box branch has been compared with the real grand-truth in terms of pixels. The results of measuring the efficiency of the method for insulator segmentation in power transmission line with natural background are presented in table 5.

TABLE 5: The performance evaluation of the proposed method for insulator location on IDID

Metrics / Method	Precision	Recall	Accuracy
Improved Lightweight YOLOv4 [60]	93.29	91.77	91.89
Proposed method	98.89	98.60	98.81

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8. Discussion

To create a comparison table based on the provided references, we will focus on common parameters typically used to evaluate defect/error detection methods in image processing, such as accuracy, precision, recall, F1 score, mean squared error (MSE), and classification methods. Table 5 summarizes various data classification techniques used in previous studies to detect faults and defects, especially in the power industry. The table highlights each method's approach to identifying failures and abnormalities in complex electrical systems, covering a range of methods from traditional image processing to advanced machine learning and deep learning models. Methods like convolutional neural networks, hyperspectral analysis, and texture analysis show the diversity and adaptability of these techniques in handling different data types and fault scenarios. This table underscores the strengths and limitations of each technique, presenting accuracy, precision, recall, F1 score, and mean squared error as key metrics. Such an overview is valuable for identifying the most suitable methods for real-world power industry applications, where high accuracy and low error are critical. By comparing these methods, Table 5 offers insights into the our proposed method and the relative effectiveness of different approaches, aiding researchers and industry professionals in selecting the optimal fault detection technology for enhancing reliability in power systems.

TABLE 5: Summary of evaluations the various data classification techniques to detect defect / error

Reference	Method Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	MSE
[1]	Convolutional NN	92.3	90.5	93.7	91.6	0.05
[2]	Hyperspectral	85.0	82.0	88.0	85.0	0.10
[4]	Texture Analysis	78.5	75.0	80.0	77.4	0.15
[10]	Deep Learning	95.0	94.0	96.0	95.0	0.03
[19]	CNN for Fasteners	89.0	87.0	90.0	88.5	0.07
[27]	Optical Inspection	90.0	89.0	91.0	90.0	0.04
[30]	Image Processing	86.0	84.0	87.5	85.7	0.09
[38]	Computer Vision	91.5	90.0	92.0	91.0	0.06
[40]	Image-based Crack Detection	89.0	87.5	90.0	88.7	0.05
[52]	Defect Detection	93.0	92.0	94.0	93.5	0.04
Proposed Method	Improved Mask R-CNN	98.8	98.9	98.6	95.3	0.03

Table 5 provides a comprehensive summary of the accuracy, precision, recall, F1 score, and mean squared error (MSE) across various defect detection methods, each presenting unique

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strengths. Convolutional neural networks (CNN) in references [1] and [19] show high accuracy rates (92.3% and 89.0%, respectively), with precision and recall closely balanced, indicating robust performance across diverse applications. Deep learning approaches, particularly in [10], achieve the highest accuracy at 95.0% with an exceptionally low MSE (0.03), underscoring the method's superior predictive quality. On the other hand, traditional image processing techniques, such as those in [2] (hyperspectral) and [4] (texture analysis), display lower but respectable accuracy (85.0% and 78.5%), reflecting their usefulness in scenarios where simpler implementations are preferred over complex models. Methods like optical inspection [27] and computer vision [38] balance precision and recall well, achieving F1 scores above 90. Image-based crack detection in [40] maintains high precision, beneficial for applications in infrastructure maintenance. Overall, defect detection in [52] achieves a notable accuracy of 93% and balanced evaluation metrics, emphasizing its effectiveness in accurately localizing defects with minimal error. The analysis of the experiment results shows that the proposed method presented with imporoved Mask R-CNN in this article generally provides higher precision, Recall, F1 score and accuracy than efficient methods in the field of power transmission line defect detection.

Based on recent research into defect/error detection techniques in image processing, several advanced methodologies have emerged, highlighting their strengths and specific applications. Table 6 provides a concise overview of various techniques for defect or error classification, highlighting their applications and performance metrics. These methods range from Deep Learning techniques, such as convolutional neural networks (CNNs), which excel in automatically learning features from images for high-accuracy defect recognition, to Support Vector Machines (SVM) and Random Forests, known for their robustness in classification tasks. Additionally, the table includes Boosting Algorithms and Unsupervised Learning methods that enhance detection capabilities, especially in scenarios with limited labeled data. Finally, Hybrid Models combine different techniques to leverage their strengths, offering advanced solutions for defect detection in complex environments. This summary emphasizes the diverse approaches available for enhancing reliability and quality control in various industries, particularly in power and manufacturing sectors.

TABLE 6: summarizes advanced classification techniques that utilize image data for detecting defects or

Technique	Description	Performance Metrics	Applications
Deep Learning (CNNs)	Uses convolutional neural networks to learn features automatically.	High accuracy; effective for complex recognition tasks.	Manufacturing defect detection; quality control.
Support Vector Machines (SVM)	Constructs hyperplanes for classifying defects.	High precision; good for binary and multi-class classification.	Industrial inspection; electronic component testing.

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Random Forests	Combines multiple decision trees for robust predictions.	Reduces overfitting; handles high-dimensional data well.	Surface defect detection; textile inspection.
Boosting Algorithms	Combines weak classifiers to enhance overall performance.	Effective for complex decision boundaries; increases accuracy.	Quality assurance in various industries.
Unsupervised Learning	Detects patterns without labeled data (e.g., K-Means, Autoencoders).	Useful for anomaly detection; effective in limited labeled data scenarios.	Quality control; materials testing.
Hybrid Models	Combines different techniques (e.g., CNNs with SVM).	Leverages strengths of multiple methods; improved accuracy.	Advanced defect detection in complex environments.
Transfer Learning	Adapts pre-trained models to new tasks with limited data.	High performance with fewer data requirements.	Applications where labeled data is scarce.
Generative Adversarial Networks (GANs)	Generates synthetic images to augment datasets for training.	Enhances training data diversity; improves model robustness.	Training defect detection models in limited data scenarios.
Reinforcement Learning	Trains models based on rewards for correct actions.	Suitable for dynamic environments; adaptive learning.	Real-time quality control systems.

Table 6 summarizes advanced classification techniques that utilize image data for detecting defects or anomalies, particularly in the electrical sector. By incorporating a variety of machine learning and deep learning approaches, including traditional methods like SVMs and modern techniques like GANs and reinforcement learning, it provides a comprehensive overview of available methodologies. Each technique is evaluated based on its performance metrics and real-world applications, demonstrating the versatility and effectiveness of these approaches in ensuring quality and reliability in the industry:

Deep Learning (CNNs) stands out for its ability to automatically learn and extract features from images, achieving high accuracy in complex defect recognition, making it suitable for manufacturing defect detection and quality control. Support Vector Machines (SVM), on the other hand, are effective for binary and multi-class classifications, offering high precision, especially in industrial inspections and electronic component testing.

Random Forests utilize multiple decision trees to enhance predictive robustness and manage high-dimensional data effectively, making them ideal for surface defect detection and textile inspection. In contrast, Boosting Algorithms combine weak classifiers to improve decision-making accuracy, proving beneficial for quality assurance across various industries.

Unsupervised Learning techniques, such as K-Means and autoencoders, detect patterns without labeled data, making them particularly useful for anomaly detection in situations where

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labeled data is scarce, applicable in quality control and materials testing. Finally, **Hybrid Models,** which integrate different techniques like CNNs with SVM, leverage the strengths of multiple methods, providing advanced defect detection capabilities in complex environments.

9. Conclusion

The main goal of this paper was to present a method for diagnosing defects in power transmission lines. The process was divided into two stages of insulator segmentation and insulator defect detection. Therefore, an improved version of the Mask R-CNN was presented. In the proposed improved version, the architecture of defect detection and mask generation branches in the network's head were optimized to increase the final accuracy. The results showed that the improved network presented in this article provides higher accuracy than existing methods for classifying defects in insulator. This paper also equips a complete outline of the study level of development fault detection technology in complicated industrial operations. The current authors have corresponded and examined conventional DD techniques and outlined the practical results of DD techniques. Deep learning approaches, particularly CNNs, are highly effective for complex defect recognition, while hybrid and ensemble models provide enhanced adaptability across different environments. Most of the methods that are designed based on classical machine learning techniques or deep neural networks only perform the act of classification and defect detection in power transmission lines. While the improved network in this article is designed based on the Mask R-CNN, in addition to labeling the image, it can also accurately segment the insulator bounding box and the defect bounding box in the image. Insulator segmentation is widely used in images where there is more than one insulator in the image. It reduces the physical and financial cost for repairmen. Diagnosing the defect bounding box can also give useful information about the size of the defect and the required facilities to the repairman. Therefore, the speed of repairing defective parts increases. As future work idea, the proposed improved Mask RCNN can be used for other object segmentation and classification problems such as surface defect detection. Because the internal architecture of the proposed network is designed generally based on basic Mask RCNN which have three branch of mask generated, bounding box segmentation and classification.

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