A New Classification of Existing Techniques for Error/Defect Detection in Image Processing

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ABSTRACT:
The detection of defects is important in quality control in manufacturing. These defects raise the costs incurred by enterprises, compress the service life of simulated products, and result in the expansive destruction of resources, thereby significantly harming people and their safety. Defect detection and classification need to be feasted as unique problems associated with the field of artificial vision. We categorize the defects like electronic components, pipes, welded parts, textile materials, etc. We express artificial visual processing techniques aimed at comprehending the charged picture in a mathematical/analytical manner. Recent mainstream and deep-learning techniques in defect detection are studied with their features, stability, and weaknesses explained. We resume with a survey of textural defect detection based on statistical, structural, and other methods. We investigate the application of ultrasonic testing, filtering, deep learning, machine vision, and other technologies utilized for defect detection to offer a new classification. In addition, high precision, high positioning, fast detection, and small objects through examination are the biggest challenges in applying quality detection.

KEYWORDS: Machine Learning, Deep Learning, Defect Detection.

1. INTRODUCTION

Due to failure in design and machine production equipment, the defect of the complex industrial processes, like internal holes, pits, abrasions, and scratches arise unfavorable working conditions. Products easily disintegrate and be inclined to weariness because of daily application. These defects raise the costs incurred by enterprises, compress the service life of simulated products, and result in an expansive destruction of resources, thereby generating significant harm to people and their safety [1]. Therefore, catching defects is a center competency that companies possess to enhance the quality of the simulated products without influencing production. Automated defect detection technology evident benefits over manual detection. It adjusts to an inappropriate environment and achieves with high precision and efficiency. The earlier research on this scope decreases the production cost enhance production efficiency and product quality for the intelligent transformation in industry.

Defect detection and classification need to be feasted as unique problems associated to the field of artificial vision. The general purpose of mimicking human vision is to determinate and organize a subject. These two objectives bonded together. We handle both classes and concentrate on the precise solutions that intensely associated to visual processing

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methods, particularly on inspection techniques in industrial applications. Quality control is an essential characteristic in the industrial production line. Some approaches employed to evaluate the quality of a process. Relying on the method used to determine a defect on a surface/volume, quality control strategies categorized as destructive or non-destructive (See Fig. 1). Non-destructive testing aims at observing an element to detect a defect without extracting samples from it or perpetually impairing it.

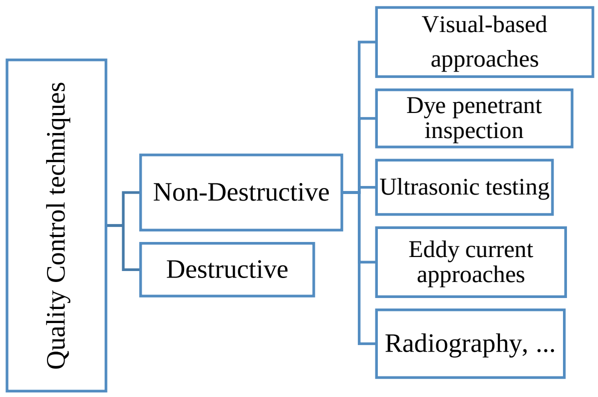

Fig. 1. Categorization of the quality control techniques.

Many researchers reviewed defect detection technologies to supply references for the application and research of defect detection technology. We outlined the application of hyperspectral [2], pulsation spectrum, infrared [3], etc. For surface defect detection, Xianghua Xie [4] contemporary advancements in surface detection utilizing computer vision and image processing techniques. By approximating of the findings of past investigations, it revealed that surface defect detection based on image processing needs high real-time performance in industrial applications. For fabric defect detection, researchers [5]-[6] investigated the application and development of defect detection methods typically employed in the textile fabrics from the standpoint of defect detection development of the textile industry production. Thermal imaging technologies employed in many industrial areas. I. Jorge Aldave [7] concentrated on the comparison of consequences received with commercially general non-experimental IR techniques to supply references for non-destructive defect detection. Defect detection technology is a hot topic in the enterprise. Defect detection technology is a desirable topic in the enterprise. Nevertheless, researchers categorize product defect types [8], the main detection techniques, summary of applications of defect detection technology, existing equipment for defect detection, etc. The review of the research status of relevant technologies have yet to be realized.

The visual based approach is one of the most common defect detection procedures in industry. Nevertheless, the traditional visual assessment is a non-measurable process with unstable and subjective outcomes. It caused authors to devise new automated defect detection systems with challenging requirements because of the complexity and individuality of any specific problem to decode. Nevertheless, a system relies on the fabric effects of the surfaces to observe the environmental requirements.

The definition of a defect and its categorization is a manner that effects on series of subjective decisions. The main features of a defect depend on the desired precision and resolution of the detection approach; the size of defects vary among industrial applications. It recommended to specify a quality criterion of the outcome in every industrial application before organizing and executing the automated system.

This study organizes the common defects of electronic elements, pipes, welding regions, and fabric textiles. It outlines the mainstream deep learning technology for defect detection with its application status to analyze the application situation of the major defect detection equipment, to supply reference for defect detection technology in approach and useful application.

This study contained as follows. In Sect. 2, we present a taxonomy of defects that appear on metal surfaces. In Sect. 3, we represent the defect detection technologies. In Sect. 4 and Sect. 5, we reviewed the existing machine learning and deep learning methods for defect detection. In Sect. 6, we express the challenges and finally concluded the conclusion.

2. TAXONOMY OF DEFECTS

In the industrial exhibition area, quality control strives at maintaining a quality level or at localizing the defects for further repair. Conventional detection techniques deal with regular, macro-sized and complex deviations of surface defects. Basically, every artificial optical defect detection method strived to detect defect and classified them for additional processing. For a reasonable classification, industrial applications require well-structured databases of the possible defect types. Due to the randomness and essence of the defects that can appear in the operation scenarios, showing such a general and complete database for a classifier is challenging way.

In this area, basically every application utilizes a material-based defect classifier. The proposed taxonomy of defects organized to two major groups: visible and palpable. It is worth mentioning that the categorization is basically and not sufficient for systems with specific conditions. It delivered a strong and reliable basis for a classification with artificial intelligence system. The essential assumption of this defect categorization is a hardly subjective decision. This decision is based on a threshold and a logical-based illustration of the size ratio of both the element and the defect. Thus, the structure of the proposed taxonomy organized by size ratios and spatial features.

3. DEFECT DETECTION TECHNOLOGIES

Product defect detection technology detects the surface and internal defects of outcomes. The defect detection technology guides to the detection technology of spot, pit, scratch, and color differences. Internal defect detection technology contains internal flaw detection, hole detection and crack detection [9]. Some techniques used to detect product quality. These consists deep [10], magnetic powder [11], eddy current testing [12], ultrasonic testing [13], and machine vision [14] detection methods. Moist magnetic particle detection combines the magnetic powder in all liquid media. Magnetic powder observes the location of defects via liquid force and the interest of the superficial magnetic domain [15]. The moisture detection technique has high sensitivity [16]. Dry Magnetic powder testing [17] connects magnetic powder onto the cover of the magnetized workpiece for defect detection. This technique employed for the local examination of defects in large casting, welding parts, and other features that are inappropriate for moist detection.

The constant magnetic particle detection method notices defects in magnetic break or powder under the external magnetic field [18]. This method employed to monitor the defects in the external magnetic field. Some elements effect on the precision of magnetic powder testing contain roughness and the profile of the test piece, the geometrical features of defects, the specified magnetization approach, and the quality of operators [19]. The factors that affect the sensitivity of testing are imaging reagents, the performance of fluid, the quality of operators, and the impact of defects. Factors that affect the accuracy of the detection of vortex current are the parameters of material and the shape of the test piece [20].

The ultrasonic testing product influenced by the angle between the defect surface and the ultrasonic propagation direction [21]. If the angle is vertical, the signal produced is strong and the defect is efficiently detected. If the angle is horizontal, the signal returned is weak in which detecting make a leak straightforward. Thus, choosing the proper detection sensitivity and corresponding search to decrease leakage detection is necessary [22]. The factors influence ultrasonic testing contain projection direction, investigation effectiveness, sound connection quality, and instrument operating frequency [23].

Machine vision detection consists of image acquisition, defect detection, and classification. Because of accurate, non-destructive, and low-cost characteristics, machine vision is employed. Machine vision recognizes objects based on the color, texture and geometric features of objects. The quality of image acquisition defines the difficulty of image processing. The quality of the image processing algorithm impacts the accuracy, error detection rate of defect detection, and classification [24]. The deep learning approach is likewise a defect detection approach that is based on image processing, which utilized to acquire proper features in massive data [25]. Table 1 displays a comparison of employed product defect detection approaches.

Table 1. Comparison of standard defect detection techniques

Method	Advantage	Disadvantage
Ultrasonic testing	Easy to use Strong penetration High sensitivity Automatic detection Portable equipment	Unsuitable for complex work pieces
Machine vision detection	High precision Automatic detection Many applications	Surface detection only
Magnetic powder testing	Visualization in shape, size, and position Suitable for any size High precision Low cost	Difficult automatic detection Influenced by geometric shape and test pieces Limited to ferromagnetic materials

Osmosis testing	High sensitivity Affectless on shape and material type	Difficult detection for porous materials and automatically Slow detection speed
Eddy current testing	Non-contact detection Fast detection speed High sensitivity Automatic detection Suitable for high temperature environments	Low detection accuracy Difficult detection for deep detection Limitation for applicable materials Not-visualization for shape and size
X-ray testing	Non-destructive detection Strong penetration Affectless on material and structure Easy operation	Radiation affects

The traditional defect detection methods and the popular deep learning defect detection methods have their benefits. These methods are positively concentrated. Osmosis testing technology [26] is an applicable for detecting defects in highly absorbent and non-porous materials.

Most of the traditional detection techniques need to depend on manual assistance to complete, the equipment product cost increased, which is not adaptable and defined by the equipment life and manufacturing accuracy. Creative defect detection methods, especially machine vision and deep learning techniques [27], have evolved as one of the important technologies for automating defect detection due to their versatility and lack of support on human assistance.

Corresponded to traditional defect detection techniques, the new technologies present more useful examination results and decrease costs. Though these nevertheless depend on large amounts of known data to guide model updates and enhance inspection accuracy.

3.1. Artificial Visual Processing Techniques

The primary purpose of visual-based approaches is to comprehend the world both natural and artificial illustrations. The procedure in the latter is to recognize images to look for a mathematical/logical connection between the input and representations. This connection is a change from the input to the model to reduce the information included in the image to appropriate information for the application domain.

Image representation approximately separated into four levels, as depicted in Figure 3. The order of image presentation and the background functions/algorithms facilitated as low and high-level image processing. Low-level processing techniques do not employ prior knowledge about the content of the image. It means that the techniques that belong to this group applied to every image. This group contains: (1) image compression; (2) pre-processing; (3) sharpening; and (4) edge extraction techniques.

The higher-level processing techniques are complicated and work above the mathematical model of the image by selecting classifiers and where imitating the human understanding is required.

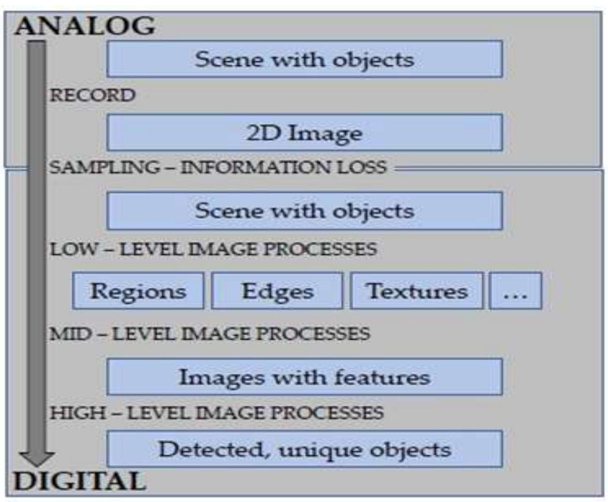

Fig. 2. The hypothetical levels of image presentation for image analysis. The modification from the analog to the digital domain consequences in some information loss.

As illustrated in Fig. 2, to achieve the level of the picture with content, several features of the image have to be conveyed. Two different principles devote for unaffectedly emerging visual statements. The one achieved about the object to be found. The second performed with no given information about the object; but with knowledge on the environment. Most non-destructive visual examination techniques to find surface irregularities apply textures, performed by low-level processes. These principles can be replicated in artificial systems, but utilizing distinct methods. To identify particular defects on a surface, a descriptor database of the possible defects must be installed.

Textural Defect Detection: Surfaces supply unique information for artificial visual detection. The latter utilize various types of texture analysis because the general task of defect detection is a surface analysis problem. The favorable and accurate method to represent a texture is to extract its unique features, although this turns out to be a demanding task.

3.2. The Traditional Method for Defect Detection Technology

Non-destructive defect detection of outcomes is utilized in manufacturing to analyze the advantages and disadvantages of diverse algorithms and enable to comprehension of the algorithms. We concentrate on the application status by the combination of classical defect detection and different algorithms. Figure 3 illustrates the diverse defect detection techniques and their affiliated performance results or outlines for non-destructive defect detection.

The ultrasonic defect detection techniques utilized to detect the defects in the internal structure of the sample. Thus, the results contemplated in the performance of the ultrasonic signal [28]. The results, as illustrated in [29], indicates that the ultrasonic defect detection techniques have the advantages of fast detection speed and simple operability. They also have special advantages in detecting defects in the internal material and structure as well as the size of the product. However, this method is unsuitable for workpieces with complicated structures with low detection efficiency.

Ultrasonic methods are ineffective for catching defects on the upper surface of the sample since a nonlinear relationship exists between the defect position and the signal obtaining the time, which shows to the defect to be arranged to the unaffected pass lock end [30].

The denser the allocation of the real position of the effect, the higher the confidence of the “trailing” spectacle of the direct access wave signal on the map. The machine vision-based defect detection techniques are appropriate for the detection of surface defects in products, which has reached up to 88.60% accuracy in binary defect detection problems [31]. The accuracy of defect detection over scratches, gaps, hierarchies, pitting, edge cracks, crusting, and inclusions achieve 95.30% [32]. The defect detection techniques based on filtering has a strong ability to explain the disruption signal and detection of the tool defect inside the machine.

To the categories of defect detection techniques for mechanical products, several other technologies are unrestricted like the X-ray image defect detection technology [33], Pulse magnetoresistance approach [34], and Acoustic emission technology [29].

Statistical Approaches: Statistical methods concentrate on study the spatial allocation of pixel values in a registered image. In this classification, it is achievable to calculate numerous publications and methods, varying from low-level to higher-order statistics, like histogram statistics, autocorrelation, local binary patterns (LBP) and others. Histogram effects and statistics support for both higher and low procedures with low computational cost. These functions include operations from statistics. It contains other histogram comparison statistics utilized for texture features, like L1 and L2 norm, EMD distance, divergence, Chi-square, and the normalized correlation coefficient. The technique catches defects by reviewing whether the distribution of the monitored data is distinct from a baseline recorded allocation in an adaptive manner.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (1)$$

$$Specificity = \frac{TN}{(TN + FP)} \quad (2)$$

$$Detection\ Success\ Rate = \frac{(TP + TN)}{(TP + FN + TN + FP)} \quad (3)$$

where TP, TN, FN and FP devoted for true positive, true negative, false negative and false positive, respectively.

Structural Approaches: Structural Approaches (SA) concentrate on the spatial location of the texture components. These extracted from the texture and defined as texture primitives. Using spatial setup rules to texture primitives result in a dynamic texture model. The texture primitives are simple grey-scale regions, line features or individual pixels. These elements used in a mixture with placement rules which emanated from the geometric associations or spatial statistics of these primitives.

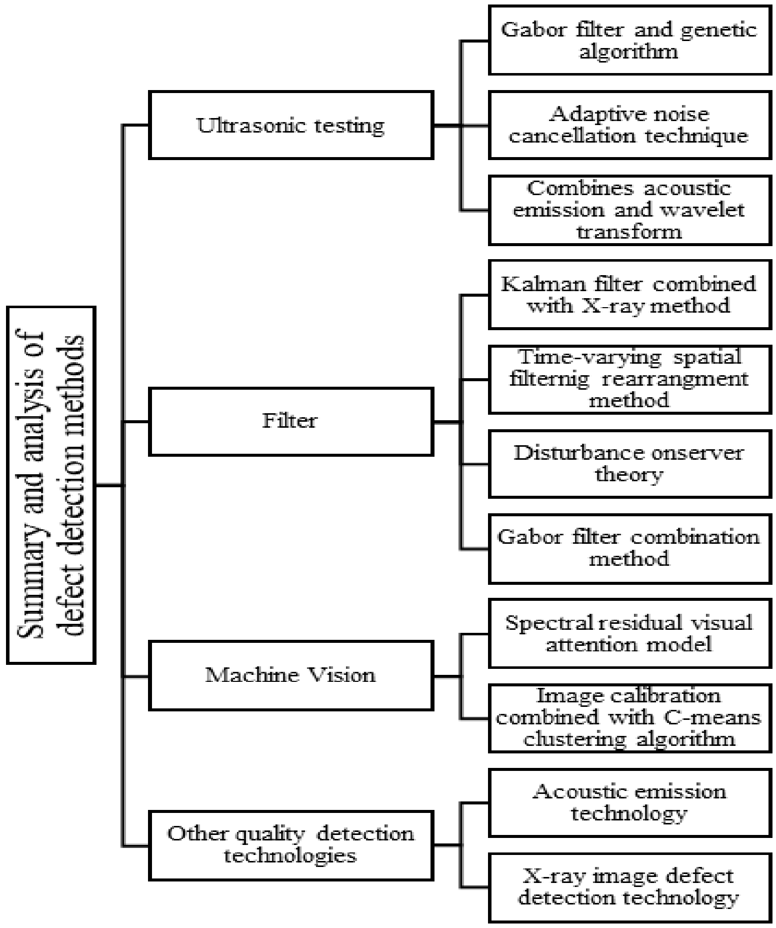

Fig. 3. Overview and analysis of defect detection techniques.

Filter-Based Approaches: Images represented by glimpsed features like edges, textures and regions (Fig. 3). Purifying these characteristics is one of the prematurely tries in image processing scope. It is a low-level process, and the edges diagnosed as spatial premature passion modifications in the image [35]. To drag edges, it employed some filters in the spatial part, like Sobel, Robert, Canny, Deriche, Laws and Laplacian filters. In most issues, working in this part implicates noise and difficulties to discover a plain kernel. Thus, converting the images into the frequency part with Fourier Transformation (FT) provides the power to efficiently filter the noise as represented in [35]. The fundamental logics converted the image into Fourier part and then filtered. After it, these logics reconverted into the spatial scope. The contrasts between the initial and processed images regarded as possible faults based on the involved procedure in the conversion [36].

The Fourier conversion relies on the whole image. These effects yielded it incapable to localize defects in the spatial part. The considerable solution is to use a FT for spatial reliance. If the window function be Gaussian, it results in the Gabor transform. The Gabor transform (GT) tries the optimal combined localization in these parts [37]. Two types of methods are of concerned. First one when some filters stowed in predetermined frequencies and directions to protect all conceivably emerging frequencies in the image and compute the correlation [38]. Nevertheless, this method is intensive to gain high distinction quality. Second one involves the performance of the optimal filters to associate with the selected recognition region, whereas acquiring the optimal sets is difficult [39].

With equivalent effects to the Gabor transform, Wavelet Transform (WT) illustrations employed as defect detectors [40]. WTs established on short waves of changing frequency and restricted period reached wavelets and supply provincial information from any directions on any input image [41].

Model-Based Approaches: Techniques based on model organized into three groups: (1) fractal, (2) autoregressive, and (3) random field models. Fractals recreate an effective role in the characterization of the natural surfaces, these firstly conveyed by Mandelbrot [42]. The primary idea of the autoregressive model (AR) is to describe texture characteristics based on the linear dependences of pixels [43].

Markov random fields techniques integrate both statistical and structural information of context conditional commodities like pixels relying on their neighbor pixels [44] and classification problems [45].

Table 2. A preference of most typically used textural defect detection approaches.

Approach	Method	Reference
Statistical	Histogram Co-occurrence matrix Local binary pattern Other gray level statistics Auto-correlation Registration-based	[46] [47] [48] [49] [50] [50] [51] [49] [52] [53] [54]
Structural	Primitive measurement Edge features Skeleton representation Morphological operations	[55] [56] [57] [58] [59]
Filter based	Spatial domain filtering Frequency domain analysis Joint spatial/spatial frequency	[60] [61] [62] [63] [64]
Model based	Fractal model Random field model Texem model Auto-regressive	[65] [66] [67] [68]
Other	Color texture analysis	[67] [63] [55]

4. MACHINE LEARNING FOR DEFECT DETECTION TECHNOLOGY

Here, the main direction is the emerging authority of the machine learning techniques. These techniques employed in all fields of product defect detection. The defect detection technology split into two major types: surface defect detection [69] and internal fault diagnosis [70]. Surface defect detection is equivalent to 'visual' detection, understanding from the target characteristics in an image with the benefit of deep learning image processing technology to organize and discover product defects, whereas internal defect diagnosis is equivalent to 'Auditory' detection, the diagnosis of defects in rotating parts like directions by means of modal analysis utilizing digital signals in the time or frequency part. We discovered the defect detection procedures and improved feature extraction [71]. Because Tool Condition Monitoring is a challenging, authors proposed a new ML-based method to describe failure symptoms of cutting tools in the time-frequency domain in 2024. This investigation concerns five cutting tools, and the results validated utilizing the Fast Fourier Transform, Short-time Fourier Transform, Empirical Mode Decomposition, and Variation Mode Decomposition methods. These methods applied to demonstrate that the suggested methodology better recognizes failure symptoms corresponded to other methods. One benefit of the suggested method is to regrade a lower order of the system results in time–frequency domain [72]. The canonical correlation analysis (CCA) is an issue for the lack of robustness against outliers. The authors in 2024 suggested a method to overcome this issue. The rendition and benefits of the suggested methods illustrated with two case studies. The results of two case analyses demonstrate that the RCCA and RSCCA methods have high robustness against outliers, and the robust FDD method is able to produce reliable results even if using the low-quality training data with outliers [73].

5. DEEP LEARNING FOR DEFECT DETECTION

Deep learning technology evolved to completed success in object detection, intelligent robot, and other fields. Deep learning has a type of neural network structure with multiple convolutions layer.

By integrating low-level characteristics to construct a conceptual high-level presentation of attribute, the data were sufficiently advanced in abstract ways like edge and shape to enhance the significance of the deep learning algorithm [74].

Thus, many researchers attempt to employ deep learning technology to defect detection of product and enhanced the product quality [75]- [76].

Table 2 outlines the benefits and drawbacks of deep learning techniques typically employed in product defect detection. It especially contains convolutional neural network (CNN) [77], autoencoder neural network [78], deep residual neural network [79], full convolution neural network [80], and recurrent neural network [81].

Table 3. Deep learning defect detection techniques.

Method	Advantage	Disadvantage
Convolutional neural network	Strong learning ability High-dimensional data High-order features	Increase the network depth
Auto encoder neural network	Good representation ability Good robustness	Consist the dimension of the input
Depth residual neural network	Better classification performance Not-overfitting	Cooperate with deeper depth
Full Convolutional neural network	Extracting the feature with any size image Obtaining the high-level semantic prior knowledge	Low speed of model
Recurrent neural network	Learning the essential features with fewer sample data	Overfitting phenomenon due to increasing the number of iterations

Deep learning is one of the quickest developing fields in computer sciences due to its capability to translate approvingly complex problems [82]. The decadent collection of classic machine learning methods resulted in the expansion of deep learning that earned its motivation from statistical learning. Most of the methods noted in the earlier sections regarded as traditional solutions, where the emphasis is on the explicitly planned features which can be contesting to represent in complex issues.

Nevertheless, deep learning utilizes data presentation learning to accomplish tasks and convert data into abstract expressions that promote the features learned for systems. This capability of deep learning overwhelms the condition of complex characteristics. Both deep and traditional machine learning exist data-driven artificial intelligence methods capable to successfully model deterministic directions, which are impossible to humans and connections between input and output. Deep learning disposes the capability of executing feature learning, model structure and model training by choosing various kernels and optimizing parameters.

A number of suitable investigations issued on defect detection explanations utilizing deep learning [83]- [84].

In 2015 Ren et al. [85] presented a technique by integrating the region proposal network (RPN) and Faster Region-based Convolutional Neural Network (Faster R-CNN) for object detection to develop about cost-free region suggestions. In [86], the authors employed a Faster R-CNN-based visual inspection approach to notice and categorize five defect classes with 90.6%, 83.4%, 82.1%, 98.1%, and 84.7% average precisions.

Their procedure completed the task especially faster than a traditional CNN based approach, which is essential for real-time implementation. Wang et al. [87] conceived a more rapid R-CNN algorithm to translate the speed problem of CNNs and to find short defects in complex products where they gained 72% detection and 81% classification accuracy. Liu et al. [88] presented a defect detection approach based on semantic segmentation. They employed a development and elongation of CNN called Fully Connected Networks (FCN). They converted the comprehensively combined layer of a CNN into a convolution layer. They acquired 99.6% accuracy on the German DAGM 2007 dataset. Lately, Kumar et al. [89] employed a deep convolutional neural network (DCNN) to catch and organize defect in tailors and performed and average of 86.2% testing accuracy, 87.7% precision and 90.6% recall.

Li et al. [90] connected Gabor filters and Pulse Coupled Neural Network (PCNN) for fabric defect detection and reached 98.6% accuracy. This factor is one of the most important factors by utilizing CNNs. To decrypt this problem, Yang et al. [91] designed a profitable and strong approach as virtual defect rendering to decode the problem of small datasets.

In a current study, Yang et al [27], designed a DCNN based system to catch and categorize defects to appear during laser welding in battery manufacturing. But they offered a novel model contacted Visual Geometry Group (VGG) model to enhance the efficiency of defect classification. Their examination on 8000 examples with a 99.87% accuracy confirmed that the pre-trained VGG model has small model size, lower defect positive rate and shorter training time and foretelling time. It is recognized that their model is favorably appropriate for quality assessment in an industrial environment.

CNN is a feedforward neural network. CNN consists of one or more convolutional layers and related layers and associated weights and pooling layers [92]. Publications is a famous LeNet convolution neural network configuration. LeNet network configuration utilized to detect defects in two conditions: (1) develop a complex multi-layer CNN structure, employ various network configuration to additional image content characteristics, and comprehensive end-to-end training to detect defects in images [93]- [94]; (2) integrate CNN with CRF model, prepare CNN with CRF energy function as restriction or optimize network prediction results with CRF.

Autoencoder network primarily contains two steps: coding and decoding. In the first step, the input signal transformed into a coding signal for feature extraction; in the second step, the feature information is converted into a reconstruction signal. After it, the reconstruction error is underestimated by modifying the weight and bias to discover the defect detection [95]. The contrast between autoencoder networks and other machine learning algorithms is that the learning objective of the autoencoder network is not for classification, whereas for characteristic learning [96]. It has a powerful capability of autonomous learning and favorably nonlinear mapping. It learn nonlinear metric procedures to translate the problem of segmentation of difficult background and foreground regions [97].

The deep residual network counts a residual module on the basis of the convolutional neural network. The residual network is represented by effortless optimization and enhances the accuracy by improving the network depth [98], CNN, Generative Adversarial Networks [99], etc. As the depth of the network grows, the extraction characteristic grows, whereas it is effortless to yield the activation function not to combine.

The purpose of the deep residual network is to optimize the increasing number of network layers with residual while improving the network structure. The output and input segment dimensions of the convolution layer in the residual unit are identical. Then via the activation function, the loss is decreased.

The completely connected layer is a relation between any two nodes between two bordering layers. A thoroughly connected neural network employs a completely connected operation. There are more additional weight values, which indicate that the network takes up more memory and calculations [100]. During the analysis of the totally connected neural network, the feature map developed by the convolution layer mapped into a fixed-length feature vector. The entire convolution neural network obtains the input image of any size, and utilizes the deconvolution layer to sample the feature map of the last convolution layer. It retrieves to the same size of the input image. In that case, a prediction developed for each pixel, while maintaining the spatial information in the original input image. Eventually categorizes the feature map of the upper sampling pixel by pixel.

The recurrent neural network utilizes the recurrent convolution process to substitute the convolution operation on CNN. The contrast is that the recurrent neural network does not achieve the pooling layer operation to remove the features behind the recurrent operation for removing the input layer features. While it utilizes the recurrent convolution operation to process the features of the samples.

For error detection in this scope, some works are of concern. Table 2 shows the comparison of the related works. In [101], Clathrate hydrates find diverse significant applications including, but not limited to, future energy resources, gas storage and transport, gas separation, water desalination, and refrigeration. Studies on the nucleation, growth, dissociation, and micro/nanoscale properties of clathrate hydrates that are of utmost importance for those applications are challenging by experiments but can be accessible by molecular simulations. By this method, however, the identification of cage structures to extract useful insights is highly required. Herein, we introduce a hierarchical topology ring (HTR) algorithm to recognize cage structures with high efficiency and high accuracy. The HTR algorithm can identify all types of complete cages and is particularly optimized for hydrate identification in large-scale systems composed of millions of water molecules. Moreover, topological isomers of cages and n × guest@cage can be uniquely identified. Besides, we validate the use of HTR for the identification of cages of clathrate hydrates upon mechanical loads to failure.

In 2022, the prompt detection of early decay in the pavement could be an auspicious technique in road maintenance. Admittedly, early crack detection allows preventive measures to be taken to avoid damage and possible failure. With regards to the advancement in computer vision and image processing in civil engineering, traditional visual inspection has been replaced by semi-automatic/automatic techniques. The process of detecting objects from the images is a fundamental stage of any image processing technique since the accuracy rate of the classification will depend heavily on the quality of the results obtained from the segmentation step. The major challenge of pavement image segmentation is the detection of thin, irregular dark lines cracks that are buried into the textured backgrounds. Although the pioneering works on image processing methodologies have proven great merit of such techniques in detecting pavement surface distresses, there is still a need for further improvement. The academic community is already working on image-based identification of pavement cracks, but there is currently no standard structure. This literature review establishes the history of development and interpretation of existing studies before conducting new research; and focuses heavily on three major types of approaches in the field of image segmentation, namely thresholding-based, edge-based, and data driven-based methods. With comparison and analysis of various image segmentation algorithms, this research provides valuable information for researchers working on enhanced segmentation strategies that potentially yield a fully automated distress detection process for pavement images with varying conditions [102].

In [103], Laser processing of cutting tool materials particularly cemented carbides can induce many surface defects including porosity, balling, and micro-cracks. When present in the microstructure of cutting tools, micro-cracks can lead to chipping and early failure. The detection and identification of cracks can be used to predict tool performance post laser processing. To develop a method for crack identification scanning electron microscopy (SEM) images were used. The manual review of SEM images is subjective and time consuming. This study presents a method to identify and quantify cracks from an SEM microstructure of tungsten carbide (WC) in MATLAB. Image processing algorithms were used to segment crack regions from other surface defects and the background microstructure; and subsequently to extract crack geometry and information. The results show successful segmentation of cracks from SEM images with an identification accuracy greater than 95 % across a range of different laser processing parameters.

In [104], the construction of a building involves tremendous investments of time, money, and emotion. Therefore, every stakeholder involved in the process starting from construction companies to the tenants wants to make sure that a structure is built well and that it can serve its purpose without any safety hazards. While the majority of factors concerning a building's safety are evaluated manually, there are factors like detecting visible structural damage that might incur a severe investment of time via manual inspection. Therefore, the need of the hour is to engineer automated systems that with the help of computer vision techniques will detect visually discernible defects in buildings. The paper proposes two approaches, namely digital image processing-based and deep learning-based that deal with creating surface crack inspection systems and attempt to showcase their performances in perspective by comparing their results across four different types of surface crack image datasets.

In [105], one of the major challenges in the construction industry is the detection of cracks in concrete structures and identification of failure types of these structures that lead to their degradation. Manual quality checks are prone to human error, and require longer response time and specialist experience and knowledge. Therefore, visualizing the cracks and identifying failures in concrete structures using computer techniques is now a preferred option. The present work focuses on identifying the cracks using image processing and failure pattern recognition technique by employing suitable machine learning algorithms, and validating the techniques using Python programming. For this purpose, M30 grade geopolymer and conventional concrete beams were cast using Basalt Fiber Reinforced Polymer/Glass Fiber Reinforced Polymer and Steel bars. The beams were subjected to four-point static bending test by varying the shear span to the effective depth ratio. The experimental images were used for image processing and failure pattern recognition in Python language. Employing six machine learning classifiers, the failures in the structures were classified into three classes namely, flexure, shear, and compression. The machine learning classifiers were also adopted to determine the confusion matrix, accuracy, precision, and recall scores. It was found that among the six classifiers used, the support vector classifier gave the best performance with 100% accuracy in identifying the failure patterns.

In [106], annually, millions of dollars are spent to carry out defect detection in key infrastructure including roads, bridges, and buildings. The aftermath of natural disasters like floods and earthquakes leads to severe damage to the urban infrastructure. Maintenance operations that follow for the damaged infrastructure often involve a visual inspection and assessment of their state to ensure their functional and physical integrity. Such damage may appear in the form of minor or major cracks, which gradually spread, leading to ultimate collapse or destruction of the structure. Crack detection is a very laborious task if performed via manual visual inspection. Many infrastructure elements need to be checked regularly and it is therefore not feasible as it will require significant human resources. This may also result in cases where cracks go undetected. A need, therefore, exists for performing automatic defect detection in infrastructure to ensure its effectiveness and reliability. Using image processing techniques, the captured or scanned images of the infrastructure parts can be analyzed to identify any possible defects. Apart from image processing, machine learning methods are being increasingly applied to ensure better performance outcomes and robustness in crack detection. This paper provides a review of image-based crack detection techniques which implement image processing and/or machine learning. A total of 30 research articles have been collected for the review which is published in top tier journals and conferences in the past decade. A comprehensive analysis and comparison of these methods are performed to highlight the most promising automated approaches for crack detection.

In [107], cracks considerably reduce the life span of pavement surfaces. Currently, there is a need for the development of robust automated distress evaluation systems that comprise a low-cost crack detection method for performing fast and cost-effective roadway health monitoring practices. Most of the current methods are costly and have labor-intensive learning processes, so they are not suitable for small local-level projects with limited resources or are only usable for specific pavement types. This paper proposes a new method that uses an adapted version of the weighted neighborhood pixels' segmentation algorithm to detect cracks in 2-D pavement images. The method uses the Gaussian cumulative density function (CDF) as the adaptive threshold to overcome the drawback of fixed thresholds in noisy environments. The proposed algorithm was tested on 300 images containing a wide range of noise representative of various pavement noise conditions. The method proved to be time and cost-efficient as it took less than 3.15 s per 320 × 480 pixels' image for a Xeon (R) 3.70 GHz CPU processor to generate the detection results. This makes the proposed method a perfect choice for county-level pavement maintenance projects requiring cost-effective pavement crack detection systems. The validation results were promising for the detection of medium to severe-level cracks (precision = 79.21%, recall = 89.18%, and F1 score = 83.90%).

In [107], in addition to causing damage to vehicles, road defects are one of the main causes of vehicle accidents which lead to loss of human lives. Many methods of detecting defects have been introduced over the years to reduce the consequences of these defects. One of these methods is image processing. Use of image and video processing has many applications in medicine, science, agriculture, and defect detection in structures. It has been used for defect detection on roads because timely detection and analysis of defect is very important for road serviceability and safety of the people. Detection of a defect by image processing broadly follows some of the basic steps which include feature extraction, edge detection, morphological operators, and training of data. Different approaches are used for various kinds of defect detection and analysis which have replaced the manual inspection method of roads saving time and resources. This chapter discusses the basic steps involved in defect detection using image processing along with existing systems that use machine learning and artificial intelligence for the detection of defects from a distance. To write this chapter, papers on the topic of image and computer vision-based defect detection systems have been consulted.

In [108], image processing is a subset of digital signal processing that has different applications and benefits in different fields. Digital processing is in fact the digital image processing that can be performed with the help of computer science, programing, and artificial intelligence. Image processing is one of the applications and subsets of artificial intelligence that, as its name suggests, processes digital images and displays a certain output with specific information based on predefined training. Nowadays, the applications of image processing technology in various fields of science, technology have caused a lot of attention in order to expand the capabilities of arterial intelligence in different engineering challenges. This paper presents recent development and applications in image processing systems in order to move forward the research field by reviewing and analyzing recent achievements in the published papers. As a result, advanced image processing systems in different applications can be developed and new techniques in the image processing systems can be introduced.

In [109], the widespread popularity of unmanned aerial vehicles enables an immense amount of power lines inspection data to be collected. How to employ massive inspection data especially the visible images to maintain the reliability, safety, and sustainability of power transmission is a pressing issue. To date, substantial works have been conducted on the analysis of power lines inspection data. With the aim of providing a comprehensive overview for researchers who are interested in developing a deep-learning-based analysis system for power lines inspection data, this paper conducts a thorough review of the current literature and identifies the challenges for future research. Following the typical procedure of inspection data analysis, we categorize current works in this area into component detection and defect detection diagnosis. For each aspect, the techniques and methodologies adopted in the literature are summarized. Some valuable information is also included such as data description and method performance. Further, an in-depth discussion of existing deep-learning-related analysis methods in power lines inspection is proposed. Finally, we conclude the paper with several research trends for the future of this area, such as data quality problems, small object detection, embedded application, and evaluation baseline.

In [110], the material extrusion (ME) process is one of the most widely used 3D printing processes, especially considering its use of inexpensive materials. However, the error known as the "spaghetti-shape error," related to filament tangling, is a common problem associated with the ME process. Once occurring, this issue, which consumes both time and materials, requires a restart of the entire process. In order to prevent this, the user must constantly monitor the process. In this research, a failure detection method which uses a webcam and deep learning is developed for the ME process. The webcam captures images and then analyzes them by machine learning based on a convolutional neural network (CNN), showing outstanding performance in both image classification and the recognition of objects. Sample images were trained based on a modified Visual Geometry Group Network (VGGNet) model and the trained model was evaluated, resulting in 97% accuracy. The pre-trained model was tested on a 3D printer monitoring system for its ability to recognize the "spaghetti-shape-error" and was able to detect 96% of abnormal deposition processes. The proposed method can analyze the ME process in real-time and inform the user or halts the process when abnormal printing is detected.

In [111], mass spectrometry imaging (MSI) and histology are complementary analytical tools. Integration of the two imaging modalities can enhance the spatial resolution of the MSI beyond its experimental limits. Patch-based super-resolution (PBSR) is a method where high spatial resolution features from one image modality guide the reconstruction of a low-resolution image from a second modality. The principle of PBSR lies in image redundancy and aims at finding similar pixels in the neighborhood of a central pixel that is then used to guide reconstruction of the central pixel. In this work, we employed PBSR to increase the resolution of MSI. We validated the proposed pipeline by using a phantom image (micro-dissected logo within a tissue) and mouse cerebellum samples. We compared the performance of the PBSR with other well-known methods: linear interpolation (LI) and image fusion (IF). Quantitative and qualitative assessment showed advantage over the former and comparability with the latter. Furthermore, we demonstrated the potential applicability of PBSR in a clinical setting by accurately integrating structural (i.e., histological) and molecular (i.e., MSI) information from a case study of a dog liver.

In [112], machine fault diagnosis and remaining service life prognosis provide the basis for condition-based maintenance and are key to operational reliability. Accurate assessment of machine health requires effective analysis of vibration data, which is typically performed by examining the change in frequency components. One limitation associated with these methods is the empirical knowledge required for fault feature selection. This paper presents an image processing approach to automatically extract features from vibration signals, based on visual word representation. Specifically, a time-frequency image of vibration signal is obtained through wavelet transform, which is then used to extract "visual word" features for recognizing fault-related patterns. The extracted features are subsequently fed into a sparse representation-based classifier for classification. Evaluation using experimental bearing data confirmed the effectiveness of the developed method with a classification accuracy of 99.7%.

In [113], the advent of the 3G communications era has led to a trend of digital media information being transmitted through wireless networks. The variability and high error rate of the wireless communications environment often cause loss of information. Images transmitted in a noisy channel environment tend to be obstructed by unexpected information, which decreases the quality of the image. Therefore, it is an intensive research topic to repair error images and increase their post-transmission quality. Image authentication technique is a mechanism to deal with the malicious image modification problem. However, it can also be used to solve the problem of error image transmission. In this paper, a new image authentication technique is proposed to embed the image block directions as the verification information. At the receiver, the information is then extracted to detect transmission error and incorporated with a newly interleaving prediction method to repair the erroneous regions of the image. In this way, it can not only repair the image, but also detect the image blocks that are erroneous, thus enhancing the post-transmission quality of the image.

In [114], image processing has two main branches: image enhancement and machine vision. Improving images includes methods such as using a blur filter and increasing contrast to improve the visual quality of images and ensure that they are displayed correctly in the target environment, such as a printer or computer monitor. While machine vision deals with methods that can be used to understand the meaning and content of images to be used in tasks such as robotics and image axis.

In [115], robots first detect the number of banana bunches when making judgements on sterile bud removal and estimating weight for harvest in the field environment. Banana bunches are complex in shape, arranged in a nonlinear helical curve along the stalk, and have different growth states in different periods, with bunches widely spaced in the early period and densely arranged in the harvest period. Deep Learning nor classical image-processing algorithms alone can detect and count bunches in both periods. Therefore, these algorithms were combined to calculate the number of bunches in the two periods. For counting bunches in the debudding period, the convolutional neural network Deeplab V3 + model and classic image-processing algorithm were combined to finely segment bunches and calculate bunch numbers, providing intelligent decision-making for judgment on the timing for debudding. To count bunches during harvest, based on deep learning to identify the overall banana fruit cluster, the edge detection algorithm was employed to extract the centroid points of fruit fingers, and the clustering algorithm was used to determine the optimal number of bunches on the visual detection surface. An estimation model for the total number of bunches, including hidden ones, was created based on their helical curve arrangement. The results indicated a target segmentation MIoU of 0.878 during the debudding period, a mean pixel precision of 0.936, and a final bunch detection accuracy rate of 86%. Bunch detection was highly challenging during the harvest period, with a detection accuracy rate of 76% and a final overall bunch counting accuracy rate of 93.2%. Software was designed to estimate banana fruit weight during the harvest period. This research method provided a theoretical basis and experimental data support for automatic sterile bud removal and weight estimation for bananas.

In [116], leaf spot disease, which causes 10 − 50% loss in sugar beet yield, causes great damage on the leaves. This disease physiologically appears as individual circular spots on the sugar beet leaves and over time spreads to the entire leaf, resulting in complete death of the leaf. Therefore, in our study, Faster R-CNN, SSD, VGG16, Yolov4 deep learning models were used directly, and Yolov4 deep learning model with image processing was used in a hybrid way for automatic determination of leaf spot disease on sugar beet and classification of severity. The proposed hybrid method for the diagnosis of diseases and identifying the severity were trained and tested using 1040 images, and the classification accuracy rate of the most successful method was found to be 96.47%. The proposed hybrid approach showed that the combined use of image processing and deep learning models yield more successful results than the analysis made using only deep learning models. In this way, both the time spent for the diagnosis of leaf spot disease on sugar beet will be reduced and human error will be eliminated, and the relevant pesticides will be sprayed to the plant at the right time.

In [117], the authors present for the first time a method for detecting label errors in image datasets with semantic segmentation, i.e., pixel-wise class labels. Annotation acquisition for semantic segmentation datasets is time-consuming and requires plenty of human labor. In particular, review processes are time consuming and label errors can easily be overlooked by humans. The consequences are biased benchmarks and in extreme cases also performance degradation of deep neural networks (DNNs) trained on such datasets. DNNs for semantic segmentation yield pixel-wise predictions, which makes detection of label errors via uncertainty quantification a complex task. Uncertainty is particularly pronounced at the transitions between connected components of the prediction. By lifting the consideration of uncertainty to the level of predicted components, we enable the usage of DNNs together with component-level uncertainty quantification for the detection of label errors. We present a principled approach to benchmark the task of label error detection by dropping labels from the Cityscapes dataset as well as from a dataset extracted from the CARLA driving simulator, where in the latter case we have the labels under control. Our experiments show that our approach is able to detect the vast majority of label errors while controlling the number of false label error detections. Furthermore, we apply our method to semantic segmentation datasets frequently used by the computer vision community and present a collection of label errors along with sample statistics [118] .

The Problem of Photovoltaic (PV) defects detection and classification has been well studied. Several techniques exist in identifying the defects and localizing them in PV panels that use various features, but suffer to achieve higher performance. An efficient Real-Time Multi Variant Deep Learning Model (RMVDM) is presented in this article to handle this issue. The method considers different defects like a spotlight, crack, dust, and micro-cracks to detect the defects as well as localizes the defects. The image data set given has been preprocessed by applying the Region-Based Histogram Approximation (RHA) algorithm. The preprocessed images are applied with Gray Scale Quantization Algorithm (GSQA) to extract the features. Extracted features are trained with a Multi Variant Deep learning model where the model trained with a number of layers belongs to different classes of neurons. Each class neuron has been designed to measure Defect Class Support (DCS). At the test phase, the input image has been applied with different operations, and the features extracted passed through the model trained. The output layer returns a number of DCS values using which the method identifies the class of defect and localizes the defect in the image. Further, the method uses the Higher- Order Texture Localization (HOTL) technique in localizing the defect. The proposed model produces efficient results with around 97% in defect detection and localization with higher accuracy and less time complexity.

6. CHALLENGES

High precision, high positioning, fast detection, and small object through examination are the most challenges in the application of quality detection [119]- [85] (See Table 4).

7. CONCLUSION

Industrial product quality is a significant portion of product production. The research on defect detection technology has excellent functional significance to guarantee product quality. This article supplies a complete outline of the research status of product defect detection technology in complicated industrial processes. We approximated and studied traditional defect detection and deep learning techniques and completely outlined the empirical results of defect detection methods. Integrated with the actual application conditions and the result of artificial intelligence technology, the defect detection tools examined and studied. Via analysis, we discovered that 3D object detection, high precision, high positioning, and rapid detection are the challenges of industrial research. We suggested that implanted sensor equipment, online product defect detection, 3D defect detection, etc. are the evolution directions in the field of industrial product defect detection. We consider that the study will aid industrial businesses and researchers comprehend the research progress of product defect detection technology in the field of deep learning and traditional defect detection.

This article provides a review of defect detection methods represented in more than 100 scientific assistances. A substantial part of works is based on statistical statements and employs statistical or filter-based procedures. The Gabor filter is one of the utilized techniques. Nevertheless, most of the investigations offer detailed restrictions, being heavily conditional on the pattern, material and texture. Cracking the segmentation and windowing problems of coinciding objects is a ponderous topic closed by some investigators. Images having color features reproduce the complexity of these problems.

Neural networks are a strong approach utilized in artificial image processing. These almost decode every classification problem. Nonetheless, the major disadvantage is the needed large amount of training samples. In artificial image processing, this issue effortlessly cracked with labeled datasets. Regardless, in other fields like robotics, it is a challenging problem. Enhancing the training efficiency and intersection qualification of neural networks is a continuous research area. It is noted that large neural networks employed for deep learning need considerable computational resources, which direct to an inevitable parallelization of the challenges [120].

In artificial image processing, various textural databases are known for testing. Although some investigations do not supply sufficient results due to the scarcity of testing samples and regular inconsistency of such databases, there is a tremendous demand for designing general defect detection techniques able to deal with any type of defect on every kind of material and able to show a general and dedicated defect description system. To this purpose, deep learning is the emerging field that decodes the generality need and hyper-complexity of problems without drastically increasing computational costs.

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Table 4. Research Related Summary.

Author(s) /Year	**Suggested method**	**Parameters and variables**	**Advantages / Result**
[101] 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.
[102] Kheradmandi and Mehranfar 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.
[103] Hazzan and Pacella 2022	SEM images developed for crack identification method.	SEM images aid in crack identification and quantification.	Study uses MATLAB to identify and quantify cracks in SEM tungsten carbide microstructure, segmenting regions and extracting geometry information. SEM crack segmentation accuracy over 95% achieved using various laser processing parameters.
[104] Yadhunath et al. 2022	Computer vision techniques	Surface crack	The paper presents two approaches for surface crack inspection systems: digital image processing and deep learning.
[105] Aravind et al. 2021	Work uses image processing and machine learning algorithms to identify cracks and validate techniques.	Determine the confusion matrix, accuracy, precision, recall scores	Experimental images were processed and failure pattern recognition in Python using six machine learning classifiers. Support vector classifiers achieved 100% accuracy in identifying failure patterns, outperforming the other classifiers.
[106] Munawar et al. 2021	This paper provides a review of image-based crack detection techniques which implement image processing and/or machine learning	Crack detection, possible defects	Image processing and machine learning techniques analyze infrastructure parts for defects, improving performance and crack detection robustness. This paper provides a review of image-based crack detection techniques which implement image processing and/or machine learning. A total of 30 research articles have been collected for the review which is published in top tier journals and conferences in the past decade. A comprehensive analysis and comparison of these methods are performed to highlight the most promising automated approaches for crack detection.
[107] Safaei et al. 2021	New method detects cracks in 2-D pavement images using adapted weighted neighborhood pixels segmentation algorithm and Gaussian cumulative density function as adaptive threshold	Detect cracks	The proposed algorithm, tested on 300 images, is time and cost-efficient, taking less than 3.15 seconds per 320x480 pixels image. It is ideal for county-level pavement maintenance projects requiring cost-effective crack detection systems.
[108] Klára Ščupáková, et al.	Patch-based super-resolution (PBSR) enhances the spatial resolution of MSI by guiding high-resolution features from one	Linear interpolation (LI) image fusion (IF)	This study uses PBSR to improve MSI resolution, validated using phantom images and mouse cerebellum samples. PBSR outperformed linear interpolation and image fusion, showing advantages

Author(s) /Year	Suggested method	Parameters and variables	Advantages / Result
2019	modality to reconstruct low-resolution images.		in quantitative and qualitative assessments. It has potential clinical applicability in integrating structural and molecular information.
[109] Zhang et al. 2018	This paper presents an image-processing approach for extracting features from vibration signals using visual word representation. It uses PBSR to increase MSI resolution and validates its performance using phantom images and mouse cerebellum samples.	Machine fault diagnosis, remaining service life prognosis	This paper presents an image processing method for automatically extracting features from vibration signals using visual word representation. The method uses wavelet transform to recognize fault-related patterns and uses a sparse representation-based classifier for classification accuracy.
[110] Kuo-Lung Hung 2017	New image authentication technique embeds image block directions for verification.	Variability, error image transmission, detect transmission error	The image authentication technique addresses malicious image modification and error transmission issues. This paper proposes a new image authentication technique embedding image block directions for verification, extracting information to detect transmission errors, and incorporating an interleaving prediction method to repair erroneous regions, improving image quality post-transmission.
[111] Liu et al. 2016	Review of literature on component detection and defect detection, identifying challenges for future research.	Maintain the reliability, safety, and sustainability of power transmission	This paper summarizes literature techniques and methodologies, including data description and method performance. It reviews current works in component detection and defect detection diagnosis, identifying challenges for future research. Discusses deep-learning analysis methods for power lines inspection, identifies future research trends, and discusses data quality issues.
[112] Meng et al. 2016	Research develops webcam-based failure detection method for ME process.	Spaghetti-shape error, abnormal printing is detection	Webcam uses CNN for image classification and object recognition. The trained image model achieved 97% accuracy and was tested on a 3D printer monitoring system to detect "spaghetti-shape-error" and 96% abnormal deposition processes. The method analyses ME processes in real-time and informs users or halts them.
[113] Kosti and Vasovi 2015	Recent advancements in image processing systems reviewed and analyzed for future research.	Review Articles	Recent advancements in image processing systems reviewed and analyzed for future research. Advanced image processing systems developed; new techniques introduced for various applications.
[114] Lukac, Rastislav and Karl Martin 2014	Machine vision	Image enhancement, machine vision. Improving images	Image processing consists of two branches: image enhancement and machine vision. Enhancing images involves using blur filters and increasing contrast to enhance visual quality and display in the target environment. Machine vision focuses on understanding image meaning for tasks like robotics and image axis.
[115] Wu et al. 2023	Deep Learning	Bunch detection, target segmentation, accuracy rate	These algorithms combined to calculate the number of bunches in the two periods. The convolutional neural network Deeplab V3 + model and classic image-processing algorithm. The results indicated a target segmentation MIoU of 0.878 during the debudding period, a mean pixel precision of 0.936, and a final bunch detection accuracy rate of 86%. Bunch detection was highly challenging during the harvest period, with a detection accuracy rate of 76% and a final overall bunch counting accuracy rate of 93.2%.

Author(s) /Year	Suggested method	Parameters and variables	Advantages / Result
[116] Adem et al. 2023	Faster R-CNN, SSD, VGG16, Yolov4 deep learning models	Accuracy rate	Leaf spot disease appears as individual circular spots on the sugar beet leaves and over time spreads to the entire leaf, resulting in complete death of the leaf. Faster R-CNN, SSD, VGG16, Yolov4 deep learning models were used directly, and Yolov4 deep learning model with image processing was used in a hybrid way for automatic determination of leaf spot disease on sugar beet and classification of severity. The proposed hybrid method for the diagnosis of diseases and identifying the severity was trained and tested using 1040 images, and the classification accuracy rate of the most successful method was found to be 96.47%.
[117] Rottmann et al. 2023	deep neural networks (DNNs)	Accuracy rate	Annotation acquisition for semantic segmentation datasets is time-consuming and requires plenty of human labor. In particular, review processes are humans can easily overlook time consuming and label errors. The consequences are biased benchmarks and in extreme cases also performance degradation of deep neural networks (DNNs) trained on such datasets. DNNs for semantic segmentation yield pixel-wise predictions, which makes the detection of label errors via uncertainty quantification a complex task.
[118] Prabhakaran et al. 2023	Real-Time Multi Variant Deep Learning Model (RMVDM), Gray Scale Quantization Algorithm (GSQA), Multi Variant Deep learning	Accuracy rate	The method considers different defects like a spotlight, crack, dust, and micro-cracks to detect the defects as well as localizes the defects. The image data set given has been preprocessed by applying the Region-Based Histogram Approximation (RHA) algorithm. The preprocessed images are applied with Gray Scale Quantization Algorithm (GSQA) to extract the features. Extracted features are trained with a Multi Variant Deep learning model where the model trained with a number of layers belongs to different classes of neurons. Each class neuron has been designed to measure Defect Class Support (DCS). Further, the method uses the Higher- Order Texture Localization (HOTL) technique in localizing the defect. The proposed model produces efficient results with around 97% in defect detection and localization with higher accuracy and less time complexity.
[46] Hor et al. 2015	Combining color and texture features	High efficiency of the automatic method of recovery	Recovery systems aim to provide relevant information to users, with images being crucial for conveying significant information.