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Machine Learning and Deep Learning Approaches for Defect Detection in Manufacturing

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Abstract— ***In many manufacturing processes, quality control is the main component specially the casting and welding. The manual procedures of the quality control is time consuming, so to meet the high-quality product images demand, the utilization of the visual inspection systems is becoming more attractive. Different Artificial intelligence techniques showed outstanding performance in classification, detection and localization tasks. Network is training simultaneously for the detection of defects and segmentation resulting high accuracy. In manufacturing, product image defect detection is important and in this paper, different existing Machine Learning (ML) and Deep learning (DL) methods for detection of defects are surveyed. The product image defects are classified and different available techniques are discussed in this paper for the defect detection. Feature analysis and segmentation techniques are also surveyed. This paper summarize various Machine learning and deep learning techniques for defect detection. The equipment's functions and characteristics used for the detection of defects are also investigated.***

Index Terms— ***Quality control, Defect detection, Artificial Intelligence, Deep Learning, Machine Learning***

I. INTRODUCTION

Nowadays, with the advancement of technology, the quality control systems are equipped with the industrial process for not only to ensure the product image quality but also avoid defective product images cost. In the manufacturing, quality control is the fundamental component and to meet the growth targets, product image rate is increased by the manufactures while maintaining the limits of quality control [1, 2]. Recently, quality management systems are described as the technique for the manufacturing business performance. Different defects are introduced in the product image by the casting and welding. Early defect detection leads to the cost and time saving. The cost effective inspection is facilitated by utilizing the automated quality control. The faster inspection rates and higher quality demands are included by the automated inspection systems [3].

The artificial intelligence and machining techniques are developed with the time so the industrial product image quality requirements are increasing rapidly. In the manufacturing of industrial product images, there are machining defects [4]. There are disadvantageous effects of machined surface and industrial product image quality. For quality controlling and incrementing the commercial value, the product image analysis is the important process. The product image quality like detection of defects is tested by the machine vision technology. The defect detection accuracy is increased by effective detection methods developed by the researchers. Many techniques like "deep neural network (DNN), logistic regression (LR), deep belief network (DBN) and other methods" are used nowadays for detection of defects [5, 6]. Defects in different areas are shown in Fig. 1.

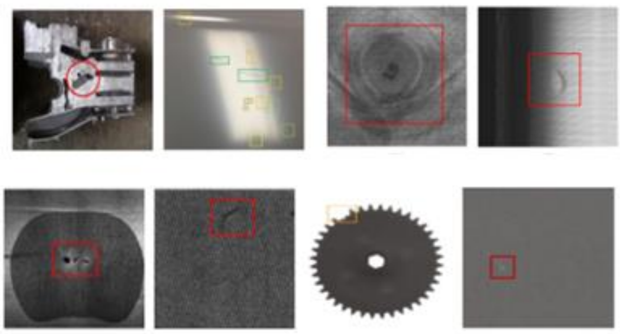

Fig. 1 Defects in different areas

The DNN based defect detection technique become popular with the advancement among various techniques. The product image features are learned automatically by the deep learning techniques from the large datasets through neural network (NN). Feature extraction is done automatically and has been successful in electronics field and other fields [7].

This paper reviews the defect detection techniques as the defects degrade the quality significantly. Technique is presented and designed for defect detection in various materials. The materials defects must be detected as soon as possible in any cases as the quality of product images are degraded. There should be inspection system for warning regarding the defect existence.

In Machine learning, deep learning (DL) and big data technique era, research has been conducted and the world of data-driven generation is shown because data amount is generated through different platform [8]. ML is the AI branch

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in which the computer systems learn directly from the collection of data from various sources and perform different tasks efficiently. ML and DL are the new technologies for assisting the social and economic addressing. The ML applications are shown in different fields and much to be done on data explosion available in various fields. The big data numbers generated through platforms are utilized by ML for improving efficiency and the available system performance [9, 10]. Types of machine learning are shown in Fig. 2.

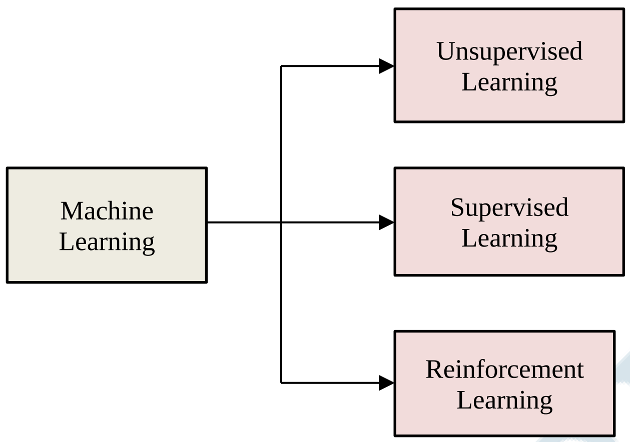

Fig. 2 Different types of machine learning

II. LITERATURE SURVEY

Author presented the complex transfer learning (TL) methods which enable the SLS process defects automatic classification by utilizing the small datasets in this paper [11]. The VGG16 and the Xception CNN model are used with pre-trained weights from the Product image-Net dataset and an adapted classifier good and defective product image data classification during part manufacturing. The performance of the model is evaluated and compared by the known performance metrics. The Accuracy, Precision, Recall, F1-Score and AUC value are achieved by the VGG16 model architecture. The CNN defect detection results show the effectiveness of the model for additively manufactured parts. Author verifies the steel surface defect detection algorithm based on machine vision for the problem of defect detection in steel product image [12]. The network with multi-scale fusion is trained based on target features. The deformable convolution network replaces the conventional convolution network for the target complex features. The proposed method trained the deep learning network model shown by the experimental results. The small target defects are identifies by the detection method. Author developed a machine vision system for quality inspection of the packaging [13]. An inspection camera is consisted in the vision system for the product image package capturing. The misplaced, missing and damaged labels or sealing problems is identifies by product image analysis software with Machine Learning. The system accuracy and speed development utilizing machine learning reached 120pcs/minute while requiring less time and labour than existing inspection methods. Author briefs the existing techniques in optical illumination, product image acquisition and product image analysis in visual inspection field [14]. The machine vision is introduced the industrial defect detection in latest development. The deep learning applications play important role increasingly for further visual inspection development. Thus, deep learning application is detailed described in classification, localization and segmentation. To improve the product image quality and manufacturing defects is vital [15]. The existing product image processing, computer vision and machine learning techniques are discussed and utilized for defect detection. The benefits and limitation of existing algorithms are highlighted to find a better solution. Author discussed the most efficient approach for detection of defects in manufacturing process. An automatic defect detection system is presented in artificial intelligence based on deep learning technology utilizing to get 2D and 3D information of target objects simultaneously [16]. Due to the cast product image surfaces characteristics, the conventional 2D detect detection system success rate is affected by the illumination location. The feature fusion data is generated by the photometric stereo system. The automatic inspection machines defect detection performance is improved by this dataset. The proposed method detection accuracy is 62.58% as shown by the experimental results. The detection performance is improved by the presented technique by utilizing the deep learning technique. Author surveys the state of the art deep-learning methods for detection of defects. Initially the product image defects are classified into categories and then the defects deep learning methods are reviewed with their characteristics and limitations. Then the defect detection applications are analyzed and summarized [17]. To further understand the difficulties, existing equipment characteristics are investigated. Finally, the existing system achievements and limitations are outlined along with the challenges on the detection of defects. Author discussed the deep Learning has shown the remarkable results in the computer vision applications. Both accuracy and processing time is outperformed by deep learning models [18]. The higher and higher accuracy is achieved by the deep learning models on the complex testing datasets. The structured and analytical overview of popular object detection models is offered for detection of defects such as Region based CNNs, YOLO (You only look once) and cascaded architectures [19]. A specific method is proposed by the author for defect detection during web material product image.. A comprehensive survey of artificial intelligence in 3D printing is presented in this paper by author [20]. The slicing prefabrication is accelerated through the parallel algorithms and the planning is intelligently optimized. Many more researchers have worked on this in previous years, some of their work is tabulated in Table 1.

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Table 1 Different research articles of this work in previous years

Sr. No	Title	Methodology adopted	Key Findings	Demerits	Reference
1.	An efficient method for defect detection during the manufacturing of web materials	Present a method for detection of a specific defect that occurs during the web materials product image on.	An analysis of how the method accesses the input data is performed for time reduction for detection. Verification of both the proposed method and the data structure are done by the various experiments.	High complexity	[21]
2.	Real Time Quality Assurance and Defect Detection in Industry 4.0	Automated product image-based systems	In a wide variety of industries, quality assurance systems are utilized. Automated product image-based systems achieve quality standards.	Carried-out research is limited by the inputs. Defect detection and quality assurance systems are potentially supported by the obtained findings.	[22]
3.	Detection and Segmentation of Manufacturing Defects with Convolutional Neural Networks and Transfer Learning	Convolutional Neural Networks and Transfer Learning	Simultaneously performs defect detection and segmentation. Higher defect detection accuracy than training on defect detection alone	High prediction accuracy. Reduced training time.	[23]
4.	Applications of artificial intelligence and machine learning in metal additive manufacturing	Existing equipment 's functions and characteristics utilized for detection of defect.	Summarize high precision, high positioning, rapid detection, complex background and object association.	Limited information about the defect detection. Rely on large amounts of learned data.	[24]
5.	Surface Defect Detection Methods for Industrial Product images: A Review	Machine learning methods in surface defect detection is summarized.	Industrial surface defects are summarized comprehensively.	Some methods is not enough or not up-to-date	[25]
6.	A Survey on Recent Applications of Machine Learning with Big Data in Additive Manufacturing Industry	Machine Learning is a growing field of Artificial Intelligence (AI) are the widely used techniques in industries as well as in academics.	Recent applications of Machine Learning with Big Data are explored in the field of additive manufacturing. ML with Big Data significance is elaborated in industry.	Computational Complexity. Based on the large datasets.	[26]
8.	An optical system for identifying and classifying defects of metal parts	Automated optical system	An automated optical system for detection and classification of aesthetical defects. Visualize information related to quality and product image.		[28]

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III. SEGMENTATION METHODS

i. Supervised Method

"The accurately labelled data obtained in the training phase is utilized by the supervised methods to decide the unlabelled data of testing phase. The training and testing are the two phases included in the supervised method. A model is designed in which extracted features of data points are mapped to the classes [29]. The classes of the unlabelled data are determined by utilizing the model in the testing phase. The human intervention is required by the training phase to demonstrate the results variability. The performance of the supervised classification is much better than the unsupervised classification in terms of accuracy. Some of the classifiers are detailed in this section."

a. K-nearest model

"The comparison of new unlabelled problem instances with a collection of labelled samples in the training set is done by the memory-based supervised learning algorithm which is k-NN algorithm. There are two stages in k-NN classification model [30]."

1. "Identification of nearest neighbours for an unlabelled instance.
2. Determination of the instance class using neighbours."

b. Support Vector Machine (SVM)

"The product image is splitted by SVM into two classes and a hyper-plane is getting which is the best classifier. The hyper-plane has the maximum distance the nearest data point [31]."

ii. Unsupervised Method

The training data is not required by the unsupervised segmentation with homogeneous attributes. The algorithm automatically decides the number of classes. Clustering and Active Contour Models are included in the unsupervised methods [32].

a. Clustering

"The unlabelled product image data is partitions into clusters as it is unsupervised method for the segmentation of product image. The common characteristics are shared by the pixels in clustering. The hard clustering and soft clustering are the two types of clustering. A data point is either belongs to a cluster or not in the hard clustering [33, 34]. The probability of data points belonging to a cluster is in soft clustering whereas in k-means clustering. In Fuzzy C-Means clustering, at the same time, single data can belong to two or more clusters."

b. K-means Clustering

"In the pixel based method, the segmentation is done by utilizing k-means clustering and the procedure is done in the following steps:

1. K-means n1(1), n2(1),…,nk(1) are corresponding to the product image K-cluster.
2. Distance between each observation xi, i = 1,2,…,m, Where xi= d-dimensional real feature vector.
3. Calculation at tth iteration, means mj(t) , j = 1,2,…,k for each cluster. x1 = belongs to that cluster whose mean has the least distance with x1.
4. The new means are calculated at each iteration so, a cluster of observations is formed

The procedure is repeated until the new means do not change. Hence, the product image is finally partitioned into k clusters."

c. Fuzzy C-means Clustering

"FCM clustering algorithm works on the assigning membership values uij to each feature data point xi,i = 1,2,…,n, xi ∈ℝd principle. The centres of the clusters cj, j = 1,2,…,k. Where, k < n depending upon the Euclidean distance of the data point. The following properties are satisfied by the membership values [35]. The major disadvantages of the standard FCM algorithm are that it uses the non-robust Euclidean distance and it is sensitive to noise. The second limitation is dealt by designing algorithms incorporating spatial information into account by many researchers."

d. Active Contour Models (ACM)

"ACM is often called Deformable Models which is a model-based segmentation technique for segmentation. By incorporating a-priori knowledge of the object, connected and continuous model is built for a specific anatomic structure. The evolution of the surface is involved in the deformable models with the function such that the structure of the original object is matched with it. The significant variability of biological structures is accommodated with the deformable models. The parametric ACMs and geometric ACMs are the main classifiers of it."

e. Parametric active contour model

"The active contour models have been widely used and also known as snakes which are gradient descent method based. In order to minimize the defied energy functional, this method tracks the boundary by matching the deformable model to the product image curve. The elasticity and rigidity of the curve are controlled by the parameters involved in the energy functions. There is deformation which is resisted by the internal forces and the initial contour is pushed by the external forces. The model has few limitations though its implementation is simple."

IV. MACHINE LEARNING AND DEEP LEARNING IN DEFECT DETECTION

Demand of machine learning and its trends is increasing rapidly which are now utilized in all the fields of defect detection of products. There are two main categories of defect detection technologies that are surface detect detection and

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internal fault diagnosis. There is similarity in defect detection and visual detection that is target feature learning by the deep learning for classification and localization of the defects whereas the fault diagnosis in rotating parts utilizing the digital signals. Features extraction is also done as the defect-detection is the complex method. Defect detection by deep learning methods are surveyed and presented in the Table 2.

Table 2 Defect detection by deep learning methods

Methods	Performance
Machine learning [36]	The "ICA, Gabor filter, and RF" need approximately 0.097, 0.265 and 0.014 s, respectively.
CNN [37]	99.00% of recognition rate for different datasets and the time is 1.2ms
Deep CNN [38]	The 86.20%, 87.70%, and 90.60% are the average testing accuracy, precision, and recall rates respectively.
Deep neural networks [39]	All three metrics performance on the validation data reflect the adversarial training superiority.
Machine learning (ML) Technique [40]	99.4% of accuracy.
Fully Convolutional Neural Network [41]	Accuracy 99.14% a batch of 50 images required only 0.368 s.
Few-shot Learning [42]	97.25% accuracy rate
3D active stereo omnidirectional vision sensor [43]	The detect defects highest accuracy is 97.00%. The recognition time of a single image is 0.19 s.
Support vector machine and CNNs [44]	"Accuracy is 87.00%, precision value is larger than 87.00% and the recall rate is larger than 89.00%.

a) **CNN for product defect detection:** It consists of one or more convolutional and fully connected layers, as well as associated weights [49]. Defect can be detected by the Le-Net network structure in two different situations: one is to design a complex multi-layer CNN structure and complete end-to-end training to detect defects in images [50, 51], the other situation is to combine and train CNN with CRF model and optimize the network prediction results and to achieve the product defect detection.

b) **Full CNN for product defect detection:** The connection between any two nodes between two adjacent layers is the fully connected layer. The weight values are more which means that the network will take up more memory and calculations. The convolution layer generates the feature map which is mapped into a fixed-length feature vector. The full CNN can accept any sized input image and use the de-convolution layer to sample the feature map. It recover the same size of the input image and prediction can be generated for each pixel, while retaining the spatial information in the original input image, and finally feature map of the upper sampling pixel by pixel classification is done.

V. IMAGE FEATURE EXTRACTION AND CLASSIFICATION

"In computer vision and image processing, image feature extraction and classification based on time-frequency composite weighting Feature extraction is a concept. It refers to the computer utilization for image information extraction and determines whether each image points belong to the feature extraction of image. The feature extraction purpose is the division of the points on the image into different subsets, which are often isolated points, a continuous curve, or region. There are usually many features to describe the image."

"The classification of features can be done according to different criteria, such as point features, line features, and regional characteristics according to the features representation on the image data. According to the feature extraction region size, it can be divided into global feature and local feature. The image features used in some feature extraction methods include color feature and texture feature, analysis of the current situation of corner feature, and edge feature."

"For multi-frame blurred images, the time-frequency composite weighting algorithm is a frequency-domain and time-domain weighting; simultaneous processing algorithm based on blurred image data."

a) Application of deep convolution neural network in image classification

"After obtaining the feature vectors from the image, the image can be described as a fixed length vector and then a classifier is needed to the feature vectors classification. In general, a common CNN consists of input layer, convolution layer, activation layer, full connection layer, and final output layer from input to output."

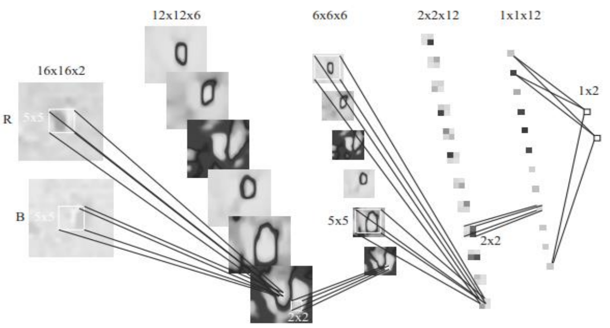

Fig. 3 Defect detection by CNN architecture

In order to investigate the CNN pre-training on the error rates, the convolutional layers' filter banks are initialized with the weights of sparse auto-encoders trained weights in unsupervised manner."

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VI. CONCLUSION

In product production, quality of the industrial quality is important and the defect-detection has practical significance for the product quality insurance. The comprehensive overview is presented in this paper for the defect detection technologies in industrial processes. Different Artificial intelligence techniques showed outstanding performance in classification, detection and localization tasks. Network is training simultaneously for the detection of defects and segmentation resulting high accuracy. The investigation helps the researchers and industrial enterprises to understand the product research progress in the traditional methods of defect detection and deep learning.

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