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Review on Machine Learning based Visual Inspection System

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ABSTRACT

This paper reviews the various approaches for visual inspection system using machine learning in various fields. In the first part of the paper, we present a general introduction to the visual inspection methods and areas where it is required. Basic idea of Machine learning, Artificial Intelligence and Deep Learning, also how they are useful in visual inspections. Research work of visual inspection domain on different products is summarized along with the technique they used, and accuracy gained with technique. Most commonly approach used is YOLO and CNNs for the batter results. Write the text from your article in different sections.

KEYWORDS

Cracks detection; Defect detection; Industry 4.0; Image processing; Machine learning; Sorting Classification; Visual inspection; YOLO.

1. INTRODUCTION

The Visual Inspection is a method of data collection, data analysis, quality control, and data verification. All types of industries used the visual inspection method for maintenance of facilities, visual scrutiny of products, structures and equipment using human senses like vision, hearing, touch, and smell, etc. In the area of visual, human eyes play the main role and like this machine has camera-based systems. These systems help to achieve high accuracy, quick data collection, and quality control. [1] Visual Inspection is a basic and old method of quick inspection. It is the process of looking for defects, flaws, misalignment, etc. This type of inspection does not require any special testing equipment, but it requires unique training so that the inspection person knows what to look for. In general, such a type of inspection taken place by looking or walking around inside of the machine, structure, boilers, etc. [2] Visual inspection is used for internal and external surface inspection of numerous structures, types of equipment, storage tanks, pressure vessels, etc.

A visual inspection can be categorized into Unaided Visual Inspection and Aided Visual Inspection. Unaided Visual Inspection is done without the use of any mechanical/optical device. [3] Aided Visual Inspection is done with the use of optical, electrical, or mechanical instruments. Optical Aids like Microscopes, Borescopes, Fiberscopes, Video Cameras and Mechanical Aids like Micrometers, Depth gauges, Feelers gauges, Weld gauges, Calipers, Thread pitch gauges. These instruments are used by a trained professional in industries. With the demand for high-speed work output, these processes need to be automated with the help of available resources. Under the Optical Aided system, video cameras are now loaded with high resolution and a lot of features.

These features can be extracted with a computer vision system and the decision could be taken by the computer system. This advancement in visual inspection will overcome the issues in existing methods. Some of the major issues with the manual inspection are A manual inspection needs a greater number of trained human assets to speed up the work. Multiple types of job work require differently trained persons for tasks. The probability of the mistake or error may be arising due to excessive workload. Sometimes it is dangerous to inspect errors in highly risky environments like in boiling chambers, tunnel inspection under construction, high altitude cracks in buildings or towers, etc. Training for the newly introduced type of error or defect, humans took a long time to learn the inspection method for minimizing the error rate.

Smart Inspection System with Computer Vision. Most of the advanced inspection systems are designed based on this block diagram. It represents an overview of how that system works. In Smart Inspection System process starts with image acquisition in which the targets object's image is acquired with a suitable camera sensor. Camera sensor selection is an important factor for the system. For example, applications like marking or sticker labels, error detection need a camera that can capture a clear image of text, and applications like fiber defect system need the microscopic image. Then this image is stored in the computer for further processing. With the help of a computer, different features are extracted from the acquired images. The method of feature extraction uses different kinds of software for image processing like MATLAB, Python, etc. These extracted features were further used by Machine Learning/Artificial Intelligence trained models to find out the error/defect in the target. Also, these extracted features play the main role in creating and training of Machine learning/Artificial Intelligence models. These ML/AL models are trained with large data set of errorless/defect less and error/defected images.

This block of the system helps to decide whether a target piece is defective or not. This result is further processed and stored in the database. In real-time these results help to sort or identify the defective items. This smart visual inspection system speeds up the process of visual inspection. For example, industries of bottles manufacturing want to sort cracked/defective bottles if they use a smart inspection system it will help the automation system to filter out the defective piece. In this paper, we identify the different methods of defect detection using a camera to create a visual inspection system. Machine Learning and Artificial Intelligence techniques were applied. A general idea of Artificial Intelligence, Machine Learning and Deep Learning is discussed in Section II, and Visual inspection system advantages and applications in section III. In IV section literature review of different researchers and their approach to visual inspection is discussed.

2. ARTIFICIAL INTELLIGENCE, MACHINE LEARNING AND DEEP LEARNING

2.1 Artificial Intelligence (AI)

Fields of AI, ML DL are interconnected. In general, Artificial Intelligence is a wider field of technology in which Machine Learning and Artificial Intelligence comes. According to Fig. 1 A part of machine learning is called deep learning. A subset of artificial intelligence is machine learning. The term Artificial intelligence came into existence between the 1950s-1970s. At that time digital data was not available in sufficient amounts. But nowadays we have a large amount of data.

In simple words "Artificial Intelligence is a technique which enables machines to mimic human behavior." With AI machines can learn from past and present experiences [4].

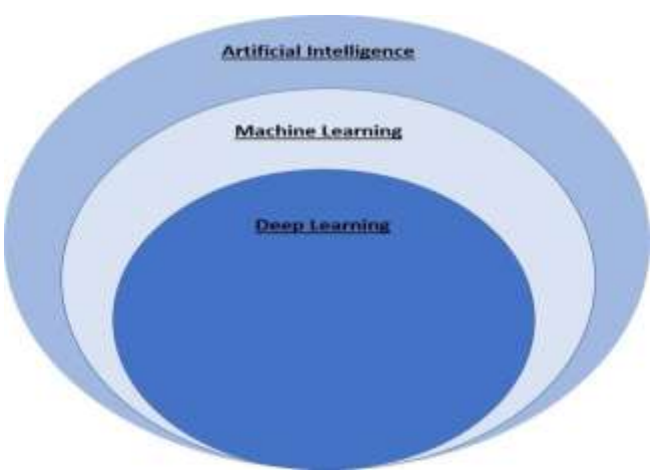

Fig. 1 Deep Learning Machine Learning Artificial Intelligence

AI-Based Machines can be trained to accomplish a specific task/work by processing a wide range of data and recognizing patterns. Some of the well-established examples of AI are Self-Driving Cars (Tesla), Manufacturing Robots, Disease Mapping, Social Media Monitoring Natural Language Processing Tool (NPL).

2.2 Machine Learning (ML)

Tool In late 1980s and early 1990s, machine learning emerged. How to train resilient versions of AI systems and huge complicated models more effectively was a concern in statistics. How to create a design and operational model of the brain for storing more closely related human behaviour was the problem that researchers in the field of neuroscience identified. Then, the emphasis on machine learning shifts away from symbolic-based techniques that were carried over from artificial intelligence and toward the techniques and models of statistics and probability theory. So, "Machine Learning is a subset of Artificial Intelligence technique which use statistical methods to enable machines to improve with experience." It assists the computer in acting and reaching data-dependent decisions necessary to complete a task. Algorithms used in these systems are built with the ability to learn and become more effective over time. Whenever they are exposed to the new data set [4]. Some examples of Machine learning are Netflix, the app knows what you want to watch, social media like Snapchat filters use augmented reality and ML for flower crown photos in real-time, Face detection attendance system using image processing and machine learning, Speech Recognition (ok google, Cortana), Medical Diagnosis, disease detection from X-Ray, MRI images, Market Trends prediction, Video Surveillance, Social Media Services.

Supervised learning, unsupervised learning, and reinforcement learning are three different types of machine learning. A learning model or function that maps inputs to outputs depending on specified input-output pairings is created through the process of supervised learning. Then output function is used to predict the outputs for new inputs.[5] Algorithms are trained on labelled data sets. Data needs to be labelled accurately for better results. In this learning, the algorithm is provided with training data set (a small part of the large data set) and training begins. Training data sets are provided with labelled data so that algorithm got the idea of the problem, solution, and data point. Then algorithm finds out the link between the inputs and outputs. Then this solution is deployed for the complete data set, and it starts making decisions. Unsupervised Learning is a method deal with unlabelled data sets. Only a large data set is provided an algorithm is implemented on it. It finds out the hidden features out of the data sets. The algorithm automatically identifies the relationships between the data points without any human input. The development of these hidden structures is what increases the diversity of unsupervised learning [6].

For example, finding out the different customer.

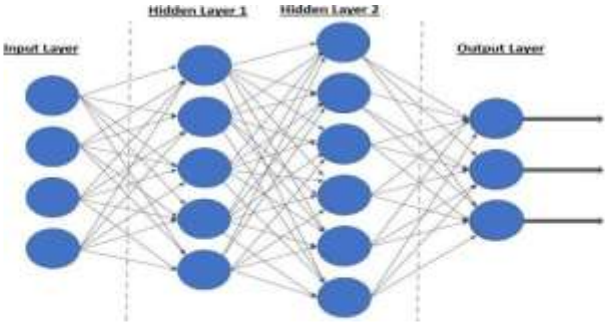

Fig. 2 Artificial Neural Network Structure

segments out of big data set. The Reinforcement Learning approach draws its influence from how people learn things from an early age. It provides an algorithm that uses a technique of exploration and learning to grow and learn in new environments. In Algorithm agent begins with trying and exploring the provided environment. Whenever an agent wins or reaches up to its target algorithm rewards it and if it loose then the agent got punished. So, the idea of the algorithm is to achieve maximum rewards and fewer punishments, while exploring the environment it learns to form its old wins and losses. Over the time system got trained on its own. Some of the examples of reinforcement is identifying the shortest or most efficient route between two points. So, the system will be rewarded for finding less distance in among all. The system is programmed to provide the most effective and appropriate solution to the issue.

2.3 Deep Learning (DL)

Artificial neural networks were created because of deep learning, a type of machine learning that promotes the activity of the brain's neurons. All we need to do is connect the data between all the neurons that are made and adjust them according to the data pattern, the extra neurons that are added to the larger data size automatically add readings to many output levels. Thus, it allows the system to learn how to create a complex map without relying on any algorithm. An in-depth learning algorithm can be considered as the emergence of a complex and complex mathematical transformation of machine learning algorithms. Its algorithm monitors data with a logical structure like how one can draw conclusions. This can be achieved by using both supervised and unsupervised learnings. In-depth study is a layered structure of an algorithm called the neural network (ANN) (Fig 2). Artificial neural networks were created because of deep learning, a type of machine learning that promotes the activity of the brain's neurons [7]. Deep learning methods in the domain of visual inspection become so much popular, that it allows the system or machine to learn by simply providing some sampler image set. It helps the system to improve performance with time.

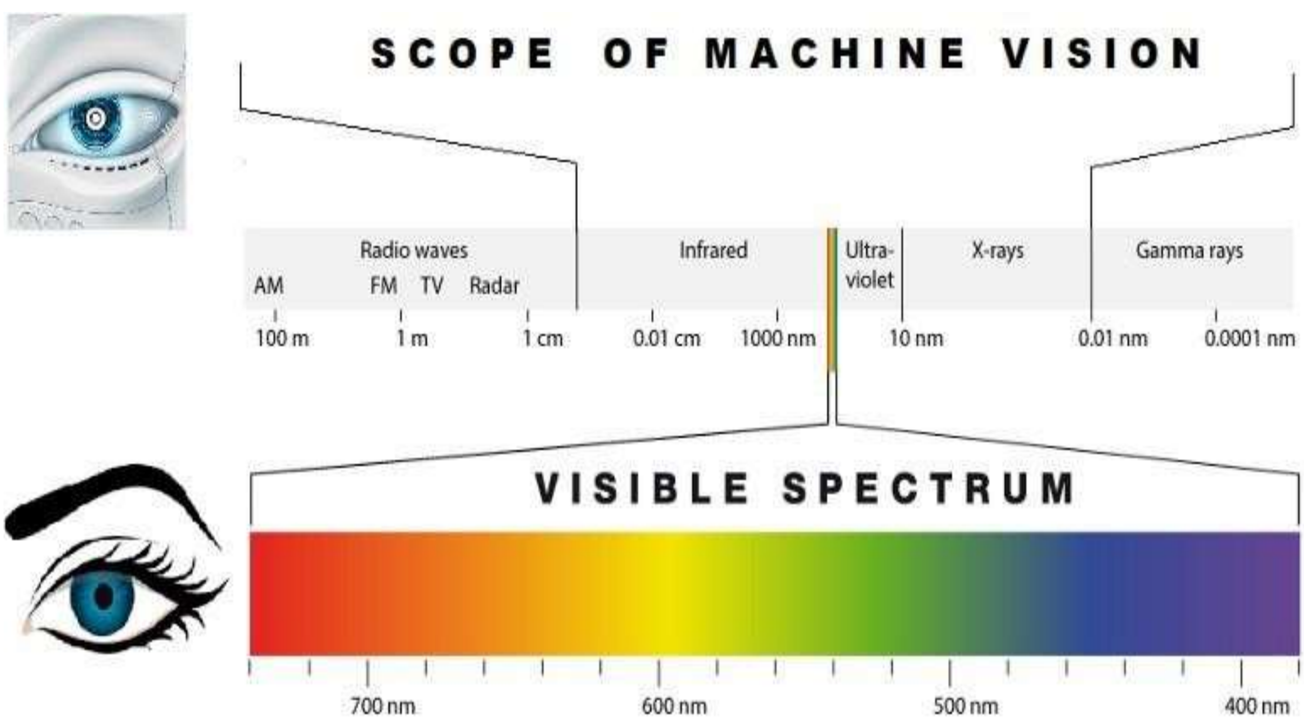

Fig. 3 Computer Vision and Human Visible Spec

3. VISUAL INSPESECTION SYSTEM

Computer vision vs Human Vision Computer/ Machine vision has high optical resolution with the help of various technologies and equipment used for target image acquisition. In comparison with human eyesight, computer vision has a wider spectrum of visual perception along with ability to do observation in X-Rays, UV, and Infrared spectrum as shown in Fig. 3.[8] Advantages are Faster Observation as well as conclusion are made extremely faster with the speed of hardware used in application. The machine/computer has high speed of processing the data with large memory capacity. Reliability: These systems have less error rate and reliable results. Accuracy: With the help of artificial intelligence on achieving the more accurate models for prediction. Faster autonomous system will be developed with high accuracy and such system always learning from the new data. Accuracy always increasing in constant learning.

4. LITERATURE REVIEW

L.Song, X. Li, Y. Tang et al. (2018) [9] have proposed D- CNN (Deep Convolution neural network) technique for the micro-level defects in metal screws. For this task clear images of screws were captured using a camera, and then these images used for the training the deep learning. Then all collected images were processed for the CNN training and result in an output trained model used for testing. According to the experiment results, 98% accuracy was achieved. The average detection time for each image is 1.2s. In the experimental setup, they have used a computer, industrial camera, a bright light source with a controller, and a stand for camera holding and object placement. Future applications for this technology include industrial production, quality control inspection for items like bottle cap flaw identification and mobile phone screen flaw detection, among others.

Y. J. Cha, W. Choi, G. Suh et al. (2018) [10] have pro- posed a computer vision-based a strategy to get around the shortcomings of skilled human resources' visual inspection techniques. Visual inspection of structural damage, such as cracks in the steel or concrete, is done either on-site or remotely with the aid of image technology. In this paper, they proposed a faster approach for visual inspection using convolutional neural networks based on regions. Steel delamination, bolt corrosion, medium steel corrosion, and high steel corrosion are among the five forms of damage that it can identify. Using the database, the Faster-RCNN architecture is changed, trained, validated, and tested. The proposed system can produce images with a resolution of 500x375 pixels in 0.03 seconds. More damaged and undamaged photos could be put into the database in subsequent scopes to boost accuracy and resilience.

Additionally, Faster-CNN will be used in conjunction with drones to replace human-based visual assessment on hazardous situations.

T. Wang, Y. Chen, M. Qiao et al. (2017) [11] have proposed a Deep convolution neural network that can automatically extract necessary and crucial elements for defect detection with less knowledge of the image beforehand, and this system is also noise-resistant at the same time. They made use of the DAGM data set, which consists of six distinct groups that vary from one another in terms of backdrop texture. The experiment's proposed model successfully assigned the image sample to the appropriate image class. The model had achieved the accuracy of the 99.8% of correct detection on provided dataset. They also guarantee real-time detection with this model.

L. Ma, Y. Lu, X. F. Nan et al. (2018) [12] have proposed a Deep Convolution neural network-based automatic surface detection approach for mobile phones. They had used the linear industrial array camera for image acquisition, and then these images were automatically segmented into already specific sizes and used the Google Net network to reduce the number of parameters. Then CNN is trained and tested. They had also used the sliding window technique to detect the defects or regions of interest in large-size images. The accuracy of the proposed method is 99.5%. The detection accuracy is more than the manual visual inspection.

L. Qui, X. Wu, Z. Yu et al. (2019) [13] have proposed a Deep learning approach for computer/machine vision's pixel-wise surface defect segmentation algorithm. Proposed method is divided into 3 parts/stages: 1) Stage-1 Segmentation 2) Stage-2 Detection 3) Stage-3 Matting In the first stage for pixel-wise detection, they used a Fully convolution network. Based on visual observation, they choose F-CNN. Defects like this are locally connected and the geometrical layout of the entire defect area has some bearing on defect detection. Then in stage 2, Detection is divided into a region of interest extraction and region of interest classification. In stage-3 matting, the defective area's contour is fine-tuned using a guided filter. Additionally, they suggested a technique to increase the algorithm's effectiveness. In their results, they can process 25 images of size (512 x 512) per second with an accuracy of more than 99%. This proposed method is weaker in the detection of the structural defect than the texture defect.

G. Hu, J. Huang, Q. Wang, et al. (2019) [14] have proposed an automatic defect detecting in fabrics using deep convolution generative adversarial network (DCGAN). They had used a new encoder component which helps in extending the approach to standard DCGAN. This encoder rebuilds the target image flawlessly, and when it is subtracted from the original image, a residual map can be created to show any potential faults. Their approach may produce a map of the target image's immediate vicinity, with each pixel's value indicating the likelihood of flaws there. Their method is not like the model training technique like collect the defective samples and then train the model. This approach is not sensitive to the illumination or brightness changes or blurring effect. This gives the approach high flexibility to the detection of different types of defects. The proposed method can be used in fabric industries.

D. Tabernik, S. Sˇela, J. Skvarcˇ et al. (2019) [15] have proposed a segmentation-based method for locating surface cracks. Their architectural layout makes it possible to train the model using less samples. Training with a small number of samples helps to boost up the speed of the training. They have also compared this model with the existing commercial software. On a recently constructed dataset of the actual quality control setup, they had conducted the experiment. Then the system can learn from the 25-30 defective images instead of a large data set. This technique can assist businesses in deploying systems with a minimal amount of erroneous data. They divided their strategy for this experiment into two parts. A segmentation network that has been trained on images with flaws is used in the first stage, followed by pixel-by-pixel labelling of the defect. They added a second decision network in the following stage to forecast the remaining anomalies in the entire image. They also deployed the system on semi-furnished industrial products, i.e., electrical commutator (fractured surface). In future scope, they mentioned that can be tested and deployed on complex data set related to visual inspection from the real-world application.

X. Xu, H. Zheng, Z. Guo et al. (2019) [16] have proposed a convolution neural network for the defect detection and inspection for the roller bearings. Their approach was focused on smaller the data set to reduce the computation time and generate effective results for the defect detection. They employed label dilation to solve the issue of an unbalanced distribution of classes. They suggested a (SSDA) semi-supervised data augmentation method to increase the dataset in a more efficient and regulated manner. As a result of the experiment, the SDD- CNN model achieves more accuracy than the original CNN. In the experimental setup, raw roller images were captured using a monocular camera with a customized light source setup. The shape of the defects was extremely unobservable, and the occurrence of defects is very low, which makes the task more tedious. So, they used label dilation and then a semi supervised data augmentation approach. Their model for inspection v3 with a deep transfer learning strategy achieved 99.56%.

J. Li, Z. Su, J. Geng et al. (2018) [17] have proposed a method of steel strip defect detection using YOLO. They have improved the YOLO network and made it 27 convolution layers network. For steel strip, they have produced a data collection with six different forms of surface flaws or defects. Defects in steel strips have more complex features due to different production lines. They have trained the network in 50000 iterations on the six types. Old algorithms mainly focused on defect classification, but they can't help in locating the defect. But the modified network can obtain the position and size of the defect. In the future, if the same network is feed with a large amount of data set more accuracy could be achieved. The proposed convolutional YOLO detection achieves good results in terms of recall rate of 95.86%, map of 97.55%, and detection rate of 99. Recognition speed of 83 FPS is also realized.

Z.Zhao, B. Li, R. Dong et al. (2018) [18] have proposed a defect detection framework with positive samples to reduce the complexity of labelling the samples as positive and negative samples. They have used the positive samples, or we can say defect-free samples and labelled. The basic idea of the proposed work is to take a sample image, if it has defects then repair the defects and regenerate an output sample image. Then the comparison could be drawn between the input and reconstructed image to find out the exact defect areas. They used GAN (Generative Adversarial Networks) LBP (Local Binary Pattern) for local contrast in images, as well as an autoencoder for imperfect image reconstruction. In this approach, the autoencoder fixes the image to the nearby sample of a successful case. You are not required to ascertain the precise nature of the fault. Thus, the repair map's information can be learned by the network. Many faults are produced during training and fed to the model to be trained. Artificial flaws and data-enhancement techniques are used in training. The model can then automatically fix the flaws and develop.

T.Brosnan, D.Sun et al. (2004) [19] have reviewed an inspection approach based on computer vision for food product's quality and safety standards. Most of the work is in the domain of inspection and grading of fruits and vegetables. The hardware setup is consisting of a camera, illumination, product Graber board, computer hardware, and software. Applications discussed in this paper are: i) Bakery Products ii) Meat and Fish iii) Vegetables iv) Fruit v) Prepared consumer food vi) Grain vii) Food container inspection.

V.Adibhatla, H.Chih, C.Hsu et al. (2020) [20] have proposed for quality inspection of printed circuit boards (PCB) using YOLO you only look once. The network was trained using a well-characterized data set of 11000 images and a network of 24 convolutional layers, two fully connected layers. For data collection they had used an automated optical inspection system to obtain the RGB format images, then further it converted to JPEG images. An interface was developed for labelling the images for defected and non-defected. In the experiment, they had used the Tiny-YOLO-v2 model with high-end GPU-Nvidia TITAN V with the Kera's framework on operating system Linux. The use of early stopping criteria has been implemented and helps achieve high validation accuracy. Tests with batch sizes of 8, 16, and 32 yield accuracies of 95.88%, 97.77%, and 98.79%, respectively. Further in this research other types of defects could be introduced to make a fully functional industry-oriented system.

G. Mahalingam, K. Gay, K. Ricanek et al. (2019) [21] have designed a PCB-METAL, dataset of a high-resolution image data set of the printed circuit board, which can be used for the various types of computer vision applications. They showed how to detect an IC in this paper. As a contribution to this dataset, they provide a freely accessible dataset of high-resolution photographs along with component text and bounding box annotations in XML format. They applied deep learning-based object detection for component detection. The testing set of the images are exclusive from the training data set. They experimented with three distinct methods, starting with YOLO object detection using just one convolutional neural network. They employed YOLO V3 to make predictions. The second method, Faster-RCNN, combines a detection network with fully convolutional features from the RPN Region Proposal Network. Retina Net represents the third method. It computes a features map over the image using a backbone that forms a single, cohesive network. They provided a public dataset of high-quality images for other researchers. More work can be done on this type of data set in the future.

J. Li, J. Gu, Z. Huang et al. (2019) [22] have proposed an improved YOLO -V3 algorithm by adds one output layer to it. In the process of training, they used the dataset of real PCBs and virtual PCB's photos build on the simulation software. This helps them increase the size of training data. Then they used a clustering algorithm for electronics components. In the field of autonomous robots for components assembly in PCB target detection is a core task. Due to the number of electronics components are available with lots of variation in design it is a bit difficult to achieve accuracy. They had proposed an improved YOLO V3 algorithm with virtual PCBs and actual PCBs. Yolo has a good detection speed. The proposed method increased the mAP of the original YOLO V3 from 77.08% to 93.07% and improved the detection accuracy.

Table. 1 Comparative performance of Different Methods and techniques

	Particulars	Method/Approach	Detection
1	Micro-level defects in metal screws [9]	Deep Convolution neural network (DCNN)	98%
2	Structural damage, cracks in the steel or concrete [1 0]	Faster-RCNN	90.6%
3	DAGM defect dataset [11]	Deep Convolution neural network	99.80%
4	Surface detection approach for mobile phones [12]	Deep Convolution neural network	99.5%
5	Defects In Fabrics [14]	Deep convolution generative adversarial network (DCGAN)	Detection accuracy improved
6	Locating surface cracks [15]	Segmentation-based deep-learning	>99%
7	Defect detection and inspection for the roller bearings [16]	Convolution neural network (CNN)	99.56%
8	Defects In Steel Strips [17]	You only look once (YOLO)	99%
9	Quality inspection of printed circuit boards (PCB) [20]	You only look once (YOLO), Tiny YOLO -V2	98.79%
10	Printed Circuit Board, IC -Chips [21]	YOLO V3, Faster-RCNN	Detection accuracy improved
11	Printed Circuit Board [22]	YOLO V3	93.07%

5. CONCLUSION

In summary, this paper Most of the methods of defect detection on various objects follow the same pattern of gathering fine images and creating a data set with defected and non- defected images and training a model for defect detection. To gain continuous improvement, the model needs to be fed with the fresh type of defected images and retrain itself for new defects. For the experimental and application-based setups, the major part is the type of camera sensor. Based on the type of application and environmental condition finding out the defects in concrete walls and bridge needs a camera sensor that can adapt to the frequent brightness/contrast changes on the other hand application like finding the defects in screws needs a camera sensor that provides high-resolution images. In the most of research work, Deep Convolutional Neural Networks are used for defect detection/ features extraction from the set of images/videos and image classifications. This further helps in creating image data set for defected and defect-free images.

YOLO algorithm for object detection and recognition is much more useful to be used in industrial applications due to its speed, high accuracy, and learning capabilities. Modern Visual inspection methods are useful in increasing productivity and filtering out the defected products. In integration with Industry 4.0 it can be implemented on large scale in industries for various applications. Train a model from a high-resolution images data set needs more processing power and time on the local system. Cloud computing-based CPU, TPU can be used. For microlevel visual inspection controlled environmental setup is required along with immune to the industrial noise. Trained models can find out the defected areas or defected items but not categorized whether the defect can be repairable or not. In addition to the detection of defects, it can be categorized as repairable and nonrepairable.

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