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Image-Based Defect Detection and Lifespan of Manufactured Processes using Deep Learning: A case study

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Abstract:
The identification of flaws in manufactured goods is a crucial part of quality control in production. The manufactured products must satisfy two things viz., the industry specifications and customer specifications and accordingly the defects are classified. Defects through human inspection is too demanding and may always calls for an additional defect known as overlook defects. The advent of machine vision and learning made the human efforts simpler and the journey from human's to machines for quality control is proved to be a successful learning curve and highly demanding as well. The technique of machine vision and image annotation brought the change required in the field of quality control. This paper provides an insight of deep learning techniques for defect identification with a case study. To begin, defects and its significance is brought forward that might appear in manufactured products and then the characteristics, benefits, and shortcomings of customized approaches are put forth. The article, outlines the fundamental concepts and methodologies of deep learning with machine vision approach such that defects in manufacturing can be identified. A fractional order singular value decomposition (FSVD) algorithm with deep neural networks is adopted for defect detection and python platform is used for its implementation.
Keywords: Deep Learning, Defect Detection, Manufacturing Processes, Convolutional Neural Networks, Image Analysis, Automation, Artificial Intelligence

I. Introduction

In today's contemporary manufacturing industry, assuring the quality of the products being produced is of the utmost significance in order to keep a competitive edge and keep customers happy. The identification of flaws in the items being created while they are still in the process of being produced is an essential step in reaching high-quality standards [1, 2]. Traditional techniques of defect identification often depend on manual inspection, which may be laborious, subjective, and fraught with the potential for making mistakes. Deep Learning (DL) methods, which are a subset of artificial intelligence, have recently emerged as potentially useful tools for automating the identification of defects in production processes. This article presents a thorough insight into the use of DL approaches for identifying image-based defects in a variety of industrial domains. These gains have been made possible as a result of research conducted using deep learning. Artificial Neural Network (ANN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Perceptron (MLPs) are the major focus of attention in the research world since they have shown extraordinary performance in image processing tasks [3, 4].

The various defects in the manufacturing are classified as critical, major and minor. These are based on industry standards/ specifications and customer specifications. Critical defects call for total rejection of products, major defects are made into acceptable ones by correcting the identified defects whereas, minor defects are based on customer visual inspection and can be accepted with minor defect corrections or without it [5]. The stages of defects identifications are:

- early stage (pre-production), wherein, the raw material can be inspected.
- At the time (on-production), wherein, the average production defect is evaluated and corrections can be recommended.
- Finishing (pre-shipment), wherein, last minute defect inspection is done.

All the products are subjected to tables of acceptable quality levels (AQL) and are processed accordingly.

In manufacturing, the detection of defects is of the utmost importance for a number of reasons that have direct bearing on product quality, satisfaction of customers, operational efficiency, and overall success of businesses. The significance of defect detection can be understood through the following key points:

Assurance of Product Quality: Defects in manufactured products can lead to quality that is compromised, which in turn can have an effect on the product's ability to function, reliability, and durability. It is essential to ensure that products meet or exceed quality standards in order to keep the reputation of the brand intact and continue to build trust among customers.
Satisfaction of Customers: The sale of flawed products can result in customer dissatisfaction, which can then lead to unfavorable reviews, product returns, and a reduction in customer loyalty. The customer experience can be improved, and long-term relationships can be strengthened when products are consistently delivered without defects [6, 7].
The early identification and correction of manufacturing flaws results in significant cost savings because it eliminates the need to produce defective products. This results in less waste, which in turn lowers production costs, and it eliminates the costs that would otherwise be associated with rework, repairs, or product recalls.
Efficiency in Operations: Effective defect detection processes help streamline production workflows by identifying problems at an early stage, before they become more serious. Because of this, disruptions are kept to a minimum, resource utilization is maximized, and overall manufacturing efficiency is improved.
Compliance with Regulations: Many different types of businesses must adhere to stringent quality and safety regulations. The failure to detect defects could result in the company not complying with applicable regulations, which could result in financial and reputational harm to the business.
Management of the Supply Chain: Defective components or products can spread throughout the supply chain, affecting subsequent processes and the products that are ultimately produced. The integrity of the supply chain can be maintained as well as the prevention of the spread of defects through early defect detection.
Reduced Warranty Claims: Defects identified before products reach the market reduce the likelihood of warranty claims and associated costs. This is especially relevant for industries with extended warranty periods.
Brand Reputation: Consistently delivering high-quality products reinforces a positive brand image and enhances market competitiveness. On the other hand, a reputation for producing defective items can be detrimental to a brand's standing.
Long-Term Cost-Effectiveness: Investing in effective defect detection systems might involve upfront expenses, but it ultimately leads to long-term cost savings by preventing defects from reaching customers and avoiding costly corrective actions [8, 9].
Continuous Improvement: Defect detection provides valuable feedback for process improvement. Analyzing defects can help identify root causes, refine manufacturing processes, and implement corrective measures to prevent future occurrences.
Safety and Reliability: In industries where safety is paramount, such as aerospace or medical devices, defects can have severe consequences. Rigorous defect detection ensures the safety and reliability of critical products.
Innovation and Research: Efficient defect detection allows manufacturers to focus on innovation, research, and development rather than being burdened by recurring quality issues.
The objective of the article is to elaborate on defects and significance, highlight the traditional defect detection technologies, deep learning methodology with a case study and result presentation. The article is organized as follows: Section I, introduces defects and its significance, section II, presents, a traditional and deep learning technology, section III, presents methodology with a case study and section IV concludes the work.

II. Traditional approaches for defect Detection

Manufacturing defects may be of external and internal in nature. External defects can be visualized but, minute external, internal and deep internal requires a combination of traditional as well as computer vision techniques. The defect-detection technology refers to the tools used to locate and analyze surface flaws on a product, such as blemishes, indentations, scratches, and color variations. Internal fault identification, hole detection, and crack detection technologies make up the bulk of the tools used to identify these problems. The most sought after traditional techniques viz., magnetic powder testing, eddy current testing, ultrasonic testing and machine vision are highlighted along with a brief on deep learning [10].

The wet magnetic particle detection method combines the magnetic powder with a liquid medium (water, oil, etc.). If liquid pressure and an external magnetic field are present, magnetic powder may pinpoint the precise location of faults [10, 11]. The technique for detecting moisture is very sensitive, and the liquid medium may be reused several times. Sticking magnetic powder to the surface of a magnetized work piece is part of the fault identification process known as magnetic powder testing. This technique is used to inspect flaws in big castings, welding pieces, and other components on a more local level when wet detection cannot be used [10, 12]. Continuous magnetic particle detection is a technique for detecting flaws in magnetic powder or solution while an external magnetic field is being applied to the system. The technique may find use in the area of defect identification in external magnetic fields of devices. The accuracy of magnetic powder testing is affected by a number of variables, including the test piece's roughness and profile, the flaws' geometrical properties, the magnetization technique used, and the expertise of the operators. Factors including imaging reagent performance, osmotic fluid effectiveness, operator quality, and flaws may all impact the sensitivity of an osmosis test. The accuracy of an eddy current detection might be affected by many factors, such as the kind of coil used, the type of material used, and the shape of the object being tested [10, 13].

The results of an ultrasonic inspection might be impacted by the angle between the defect's surface and the direction of the ultrasonic waves. The reflected signal is strong and defects are readily apparent at a vertical angle. When the angle is horizontal, the returning signal is attenuated, making a leak obvious. Therefore, minimizing the risk of leaking detection requires careful consideration when choosing the detection sensitivity and associated probe. The operating frequency of the instrument, the quality of the sound contacts, the probe's efficiency, and the direction of sound projection are all crucial elements in ultrasonic testing [10, 14, & 15].

The three main phases of machine vision detection are picture capture, feature extractions, defect detection using features, and defect categorization. Machine vision is used extensively because of the many benefits it provides, such as speed, precision, no destructiveness, and cheap cost. Machine vision relies heavily on an object's color, texture, and shape in order to correctly recognize it. The complexity of the image processing rises when a high-quality picture is captured. Therefore, the precision and error rate of defect identification and classification are greatly influenced by the quality of the image processing technology. The deep learning technique is not only a learning method, but also a defect detection method, and it is based on image processing, a technology often used to acquire meaningful features from huge amounts of data. In summary, defect detection in manufacturing is not only about ensuring product integrity but also about optimizing operations, safeguarding customer satisfaction, and maintaining a competitive edge in the market. Implementing robust defect detection processes contributes to overall business sustainability and growth [10, 16, 17, & 18].

III. Methodology

Image preprocessing is an essential step that must be taken before using deep learning techniques for the purpose of improving the efficiency of fault identification. A correct preprocessing helps improve the quality of the input pictures, lowers noise, increases essential features, and prepares the data for an effective training and inference procedure for the model. Listed below are some of the picture preprocessing methods that are often used for defect identification in manufacturing processes [10, 19].

Image Resizing and Scaling: Image resizing to a constant resolution guarantees consistency throughout the dataset while reducing the amount of computational complexity involved in the process. When training, it is helpful to scale the values of the pixels to a certain range, such as [0, 1], to assist avoid numerical instability.

Normalization: To reduce the impact of illumination fluctuations and improve model convergence, normalization helps offset such effects by first removing the mean from the pixel values and then dividing those results by the dataset's standard deviation.

Enhancing Contrast: Methods such as histogram equalization or adaptive histogram equalization may be used to improve picture contrast, which in turn makes flaws more visible against background noise.

Noise Reduction: Gaussian blur, median filtering, or bilateral filtering are three techniques that may assist decrease noise in photos, particularly those that were acquired under difficult settings or with noisy sensors.

Edge Detection: Utilizing edge detection techniques (such as Canny and Sobel) allows one to highlight borders and edges, which often serve as early warning signs of flaws in a product.

The use of different thresholding algorithms may divide the picture into binary sections, isolating probable defect areas that can then be analyzed further.

Morphological procedures: Dilation, erosion, opening, and closure, may be used in image morphology to assist eliminate tiny noise or smooth out imperfections in the picture.

Converting a picture to a different color space (such as RGB, HSV, or LAB) might assist accentuate certain characteristics or flaws that could be more noticeable in certain color channels. This is accomplished via the process of color space conversion [20].

Augmentation: Adding changes of the original pictures to the dataset (such as rotations, flips, and shears), as part of the augmentation process, helps to enhance the variety of training samples and improves model generalization.

Data Augmentation: Defect Generation: Adding artificial flaws to pictures that are otherwise defect-free may assist to get a more balanced dataset and make it possible for the model to train more efficiently.

Analysis of the Histogram Conducting an analysis of the image's histogram may provide light on the manner in which pixel intensities are distributed and direct modifications to improve contrast.

Methods: That Are Adapted Locally Applying local adaptive methods (such as CLAHE, which stands for contrast limited adaptive histogram equalization) is one way to improve contrast while also taking into account regional differences in illumination.

Image Registration and Alignment: In situations in which photos are recorded from a variety of angles or locations, image registration and alignment may assist to standardize the orientation and scale of the images by bringing them to the same level of consistency.

Cleaning the data involves removing any artifacts, labels, or annotations that might potentially interfere with the fault identification process. This helps to increase the accuracy of the model. It is essential to keep in mind that the selection of preprocessing methods is contingent on the particular aspects of the defect detection issue, the nature of the manufacturing process, and the quality of the input pictures. Experimentation and careful adjustment of the preprocessing processes are often required in order to acquire the best possible results when utilizing deep learning for fault identification [21].

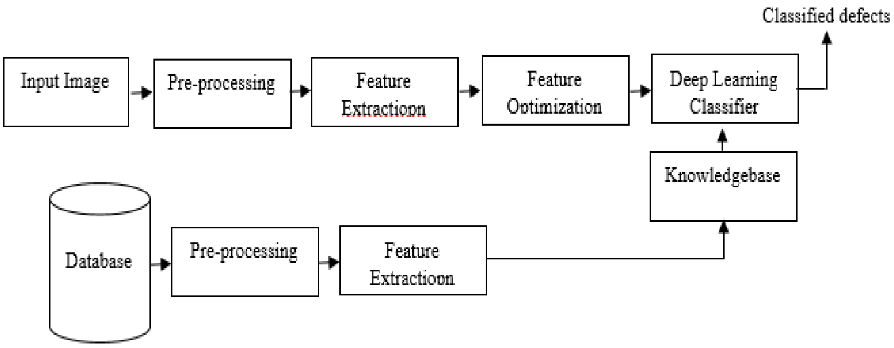

Figure 1: Image processing block schematics for defect detection

The block schematics for the work flow is shown in figure 1. As shown, the flow has data collection, preprocessing, feature extraction, optimization and deep learning classifiers. This paper focuses on a surface deformation [22] case study using fractional order singular value decomposition (FSVD) algorithm based on deep learning classifier. The case study highlight the practical advantages of automation powered by deep learning (DL), such as higher inspection speed, improved accuracy, and decreased operating expenses. The case study highlights its use in industrial applications.

AI-ML (Artificial intelligence and machine learning) and deep learning (DL) have become the defacto algorithms that are applicable in almost all sorts of fields. Machine learning approach is based on learning from experimental data (dataset) and predicting the result for the input, based on the comparison with the dataset. Deep learning uses artificial neural network (ANN) and performs complicated operations based on large dataset. Artificial neural networks come with a single hidden layer whereas, deep neural networks have many hidden layers. Incorporation of number of hidden layers allows the DNN to perform classification with maximum accuracy. Thus these are used in image based classification objectives [23]. Artificial neural networks and deep neural networks are represented structurally as shown in figure 2.

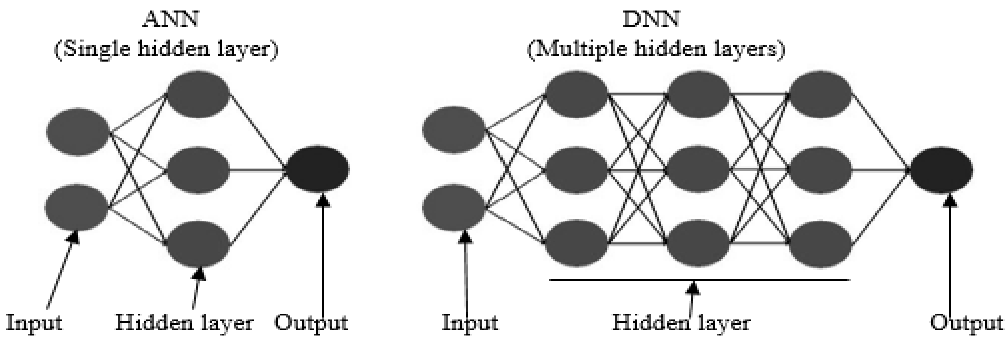

Figure 2: ANN and DNN Architecture

The algorithmic steps are given in the flow as shown in figure 3.

Step A

Initialize the dataset;

Pre-process the dataset images;

(convert color images to grey; removal of noise, image resize and convert to processable format);

Get the features;

Reduce the feature dimension using PCA;

Build the dataset matrix;

Step B
Get the input image;
Pre-process the input image;
Get the features of the input image & its matrix;
Reduce the feature dimensions;

Step C
Post the features on to the DNN classifier;
Apply least distance criteria;
Compare and get the classified image as per the defects;
End

Figure 3: Algorithmic flow

IV. Case Study and Result

A surface deformation case study is conducted on an automotive tires and results are tabled according to the deformation defects with respect to the industry and simulated standards. The defect class is classified and lifetime of the tire based on its deformation property is predicted. Standard images are collected from respective company websites and some third party websites and placed them into dataset and testing images. The dataset features and the query input image features matrix is created and the simulated observations are placed in the tabular form. The feature grey level matrix for the dataset and the input query image is compared and the defects and the lifetime is classified.

The sample dataset images and the input query images are shown respectively in figure 4 and 5. The industry standards are tabled in table I and II whereas, the simulated observed values for grey levels are placed in table III.

Figure 4: Sample Dataset Images

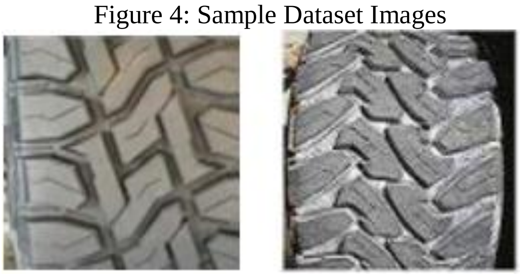

Figure 5: Sample input images

The thread wear and temperature standards which are in use in tire industry are given in table 1 and 2.

Table I: Tire & Thread Width Standards

Tire type	Thread width	Life span
Good tire	10/32" to 11/32"	80,000 to 100,000 miles
Average deformed tire	6/32" to 8/32"	30,000 to 50,000 miles
Badly deformed tire	2/32" of remaining thread depth	30,000 miles or below

Table II: Temperature and Speed Grade Standards

Temperature grades	Temperature Range	Speed range in mph	Tire type
A	29.1ºC – 38.7ºC	Above 115	Good tire
B	40.5ºC – 45.3ºC	100- 115	Average tire
C	46.2ºC – 49.9ºC	85-100	Badly deformed tire

Table III: Simulated grey level standards, defects and, lifespan

Tire type	Grey level variations	Lifespan
Good tire	Max. 21.88 – 35.02	80,000 to 100,000 miles
Average tire	Max. 38.77 to 45.25	30,000 to 50,000 miles
Badly deformed tire	Max. 47.03 to 78.03	30,000 miles or below

CASE I: Tire with zero defect

Input Image

Classified Image and defect

Zero defect

Table IV: Simulated Feature Matrix for zero defect

32.283	0	0	0	0	0	0	0	0	0	0	0
0	8.628	0	0	0	0	0	0	0	0	0	0
0	0	6.832	0	0	0	0	0	0	0	0	0
0	0	0	5.835	0	0	0	0	0	0	0	0
0	0	0	0	5.693	0	0	0	0	0	0	0
0	0	0	0	0	5.56	0	0	0	0	0	0
0	0	0	0	0	0	5.417	0	0	0	0	0
0	0	0	0	0	0	0	4.807	0	0	0	0
0	0	0	0	0	0	0	0	4.619	0	0	0
0	0	0	0	0	0	0	0	0	4.456	0	0
0	0	0	0	0	0	0	0	0	0	4.238	0
0	0	0	0	0	0	0	0	0	0	0	3.998

As can be seen from the simulated table IV and grey level observed simulated table III, it is evident that the tire under question is a good tire with zero defect and having a lifespan range of 80,000 to 100,000 miles.

CASE I: Tire with abnormal defect

Input Image

Classified Image and defect

Badly deformed

Table V: Simulated Feature Matrix for Badly deformed tire

56.683	0	0	0	0	0	0	0	0	0	0	0
0	13.286	0	0	0	0	0	0	0	0	0	0
0	0	12.405	0	0	0	0	0	0	0	0	0
0	0	0	11.900	0	0	0	0	0	0	0	0
0	0	0	0	11.642	0	0	0	0	0	0	0
0	0	0	0	0	10.549	0	0	0	0	0	0
0	0	0	0	0	0	10.453	0	0	0	0	0
0	0	0	0	0	0	0	9.873	0	0	0	0
0	0	0	0	0	0	0	0	9.783	0	0	0
0	0	0	0	0	0	0	0	0	9.552	0	0

0	0	0	0	0	0	0	0	0	0	9.447	0
0	0	0	0	0	0	0	0	0	0	0	9.173

Table V predicts that, the tire under consideration falls under bad deformation category and its lifespan also falls below 30,000 miles.

V. Conclusion

Research into defect-detection technology is an important area of study with major real-world consequences for improving the quality of industrial products. This article examines the use of neural network with deep learning technology for detecting product defects under complex manufacturing processes. A conventional and machine learning approaches have been considered and simulated results are placed. The image based deep learning approach have been put forth with due tabulations and simulations. It is very much evident from different literature study that, every image has its matrix form, that can be utilized to get required useful features for further manipulations. The article has utilized this fact and presented its results in its simplest form. Inclusion of dynamic processing instead of static is a futuristic aspect and 3D aspects can be tested with this criterion.

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