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SURFACE DEFECT DETECTION SYSTEM WITH MACHINE LEARNING

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ABSTRACT

Surface quality is the essential parameter for a product. In an industry, manual defect inspection is a tedious assignment. Consequently, it is difficult to guarantee the surety of a flawless steel surface. To meet user requirements, speed up the inspection process, and to improve the overall efficiency of the industry, Machine Learning based automatic surface investigation strategies have been proven to be exceptionally powerful and prevalent solution in the recent years. We have taken a traditional machine learning approach to resolve this problem. This project makes an attempt to enhance the performance of the model using Image preprocessing techniques and use these extracted features to train and build a machine learning model to segment and classify defect images. The input is taken from the NEU surface defect database. This database contains six types of defects including crazing, inclusion, patches, pitted surface, rolled-in-scale, and scratches.

Keyword – *Surface Defect, Machine Learning, Classification, Random Forest, Convolution neural network.*

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1. INTRODUCTION

Surface defect detection is an important part of industrial production, and has significant impact upon the quality of industrial products on the market. The traditional manual detection method is time-consuming, and its detection accuracy is easily affected by the subjectivity, energy and experience of the inspector which will compromise the following Customer satisfaction.

- Production cost.
- Effective utilization of resources.
- Inspection cost.
- Price fixation and advertisement
- Increasing sales.

Thus, it becomes necessary to implement an effective and efficient system of surface defect detection. This objective can be achieved by implementing Surface defect detection using Machine Learning technique

1.1 Objectives

- Proposed system is a real time application.
- Proposed system discovers strong rules hidden in these frequent item sets to predict and classify the defect accurately.
- Proposed system uses surface defect images to predict and classify new images.
- Proposed system makes use of "machine learning" to correctly predict defects on the metal surface.

1.2 Existing system

Current system is a manual process where they maintain defects and its types using books or ledgers. Humans do quality checking which can be tiring and inaccurate at times. Drawbacks of Existing System:

- Manual Process
- Time Consuming
- Expensive
- Inaccurate
- Lack of user satisfaction
- Less Efficient.

1.3 Proposed System

Proposed system is a real time application which is useful for industrial sector to identify and classify defects on metal surfaces. Quality check represents an important part of industrial production, so it is necessary to continuously improve within all possible and available opportunities and resources. Descriptive or predictive mining applied on historical data about occurred accidents in combination with other important information creates an interesting alternative with potentially useful and helpful outcomes for all involved stakeholders.
Proposed system provides a modern approach for quality check. Using machine learning and image segmentation the system provides accurate classification of the defects on the metal surface.

2. LITERATURE SURVEY

In the industrial production process, due to the deficiencies and limitations of existing technology, working conditions, and other factors, the quality of manufactured products is extremely easily affected. Among them, surface defects are the most intuitive manifestation of product quality being affected. Therefore, in order to ensure the qualification ratio and the reliable quality, product surface defect detection [1,2] is necessary. "Defect" can be generally understood as the absence, imperfection or area compared with the normal sample. The comparison between the normal sample and the defective sample of industrial products is shown in Figure 1. Surface defect detection refers to the detection of scratches, defects, foreign body shielding, color contamination, holes, and other defects on the surface of the sample to be tested, so as to obtain a series of relevant information such as the category, contour, location, and size of surface defects of the sample to be tested [3]. Manual defect detection was once the mainstream method, but this method is low in efficiency; the detection results are easily affected by human subjectivity and cannot meet the requirements of real-time detection. It has been gradually replaced by other methods. At present, some scholars have launched relevant research on surface defect detection, involving the latest methods, applications, key issues, and many other aspects [4]. Literature [5] summarizes the current research status of defect detection techniques such as magnetic particle inspection, penetrant inspection, eddy current inspection, ultrasonic inspection, machine vision, and deep learning [6,7]; compares and analyzes the advantages and disadvantages of the above methods; and combs the defect detection technology in electronic components, piping, welding parts, machinery parts, and the typical applications in quality control. From supervised learning model method, unsupervised learning model method [8], and other methods [9] (semi-supervised learning model method and weakly supervised learning model method), literature [10] analyzes surface defect detection methods based on deep learning, and then, three key problems of real-time, small samples, and comparison with traditional image processing-based defect detection methods in surface defect detection are discussed. After reviewing the automatic optical (visual) inspection (AOI) technology, literature [11] systematically described several steps and related methods used in the technology for surface defect detection. Literature [12] first lists the different objects in the field of defects; the mainstream technologies and deep learning methods used for defect detection are introduced and compared. After that, the applications of ultrasonic detection and deep learning methods in defect detection are analyzed. Finally, the existing applications are investigated and based on defect detection equipment, several challenges for defect detection are proposed, such as three-dimensional target detection, high precision, high positioning, rapid detection, small targets, etc. Through investigation, it can be found that in the field of surface defect detection of industrial products, there is currently little literature review on machine learning methods, and although some literatures summarize the problems and challenges in surface defect detection for industrial products, their solutions and directions are not systematic enough. In addition, in terms of datasets, there is still no comprehensive arrangement of industrial product surface defect detection datasets. Therefore, in order to solve the above problems, this paper firstly summarizes the research status of industrial product surface defect detection from the traditional machine vision method and deep learning method, after that, the key problems in the process of industrial surface defect detection, real-time problems, small sample problems, small target problem, unbalanced sample problem, are discussed, and some solutions for each problem are given.

3. METHODOLOGY

Classification is one of the most popular machine learning techniques to predict the class of new samples, using a model inferred from training data. In general, classification is defined as a learning method that maps or classifies data instances into the corresponding class labels that are predefined in the given dataset. Data classification is a two-step process; first one is the learning step where a classification model is constructed from a given dataset; the data from which a classification function or model is learned is known as the training set, and second one is a classification step where the model is used to test or predict the class labels for a separate unseen given data; the data set that is used to test the classifying ability of the learned model or function is known as the testing set. We have used to Random Forest classifier for image classification. Dataset will be given to the classifier as input where it classifies the defect as crazing, inclusion, patches, pitted surface, rolled-in-scale, and scratches

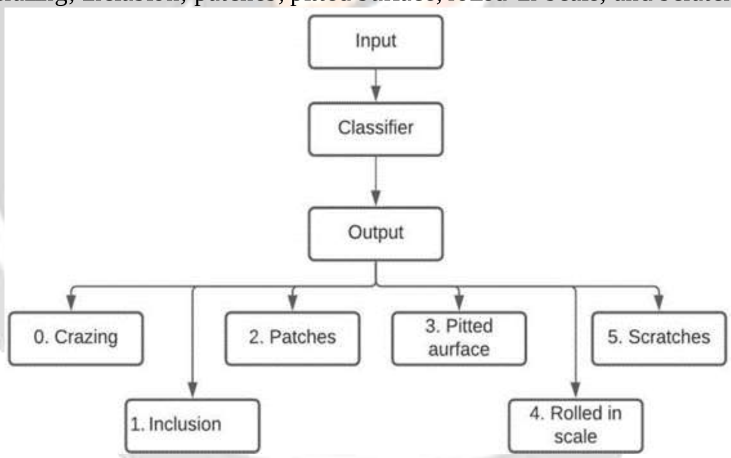

Figure 1: Classification

3.1 Model 1

<u>Classifier 01:(Random Forest):</u>

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given data set and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of over-fitting.

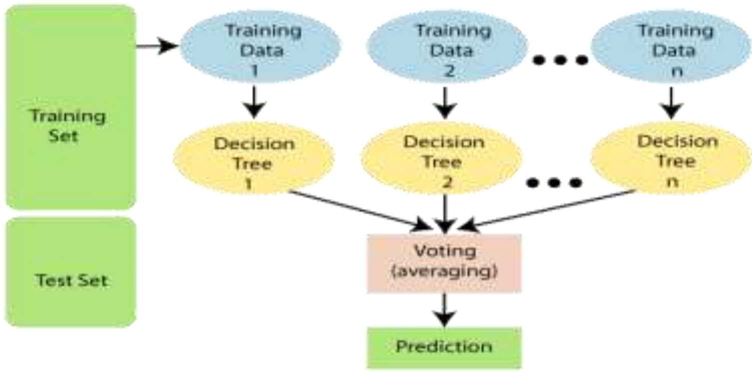

Figure 2: Random Forest

How does Random Forest algorithm work?

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase. The working process can be explained in the below steps:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes

The accuracy acquired by using the model: 65-70%.

3.2 Model 2:

Classifier 02 (CNN):

A Convolution neural network, or CNN, is a deep learning neural network sketched for processing structured arrays of data such as portrayals. CNN are very satisfactory at picking up on design in the input image, such as lines, gradients, circles, or even eyes and faces. This characteristic that makes convolution neural network so robust for computer vision. CNN can run directly on a underdone image and do not need any pre-processing. A convolution neural network is a feed forward neural network, seldom with up to 20.The strength of a convolution neural network comes from a particular kind of layer called the convolution layer.

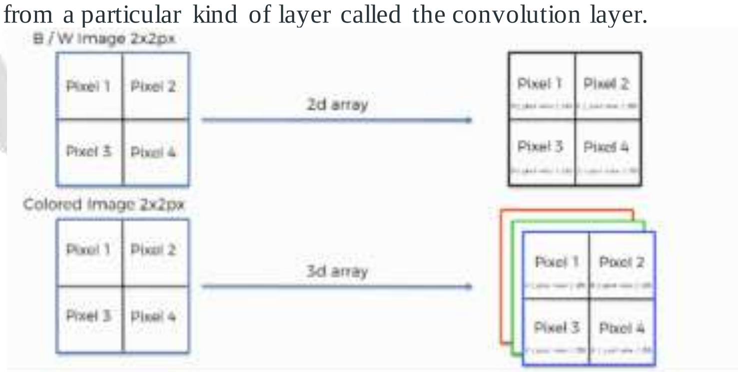

Figure 3: Convolution neural network

Before getting into the details of this operation, you should first keep in mind that the way black & white images are scanned differs in one major way from how colored images are. We're going to examine each of them separately, but first, let's look at the similarities.

Both types of images are similar in the following respects:

- Each pixel contains 8 bits (1 byte) of information.

- Colours are represented on a scale from 0 to 255. The reason for this is that bits are binary units, and since we have 8 of these per byte, a byte can have any of 256 (2^8) possible values. Since we count 0 as the first possible value, we can go up to 255.
- In this model, 0 is pitch black and 255 is pure white, and in between are the various (definitely more than 50!) shades of grey.
- The network does not actually learn colours. Since computers understand nothing but 1's and 0's, the colours' numerical values are represented to the network in binary terms.

Now let's delve into the major difference that we mentioned above.

Black & white images are two-dimensional, whereas colored images are three-dimensional. The difference this makes is in the value assigned to each pixel when presented to the neural network. In the case of two-dimensional black & white images, each pixel is assigned one number between 0 and 255 to represent its shade.

On the other hand, each pixel inside a colored image is represented on three levels. Since any color is a combination of red, green, and blue at different levels of concentration, a single pixel in a colored image is assigned a separate value for each of these layers.

That means that the red layer is represented with a number between 0 and 255, and so are the blue and the green layers. They are then presented in an RGB format. For example, a "hot pink" pixel would be presented to the neural network as (255, 105, 180).

Once images are processed, pooling takes place and the image is classified.

In this module, the output of the CNN model is displayed.

The CNN model classifies input image as one among the 6 defects (Crazing, Inclusion, Patches, Rolling, Pitched Surface, Scratches)

The accuracy acquired using CNN: 90-95%.

4. CONCLUSION

We have clearly observed that both in image classification and segmentation, machine learning approach performs very well. The Classification model built in this project can be deployed in hot-rolled steel industry, for real time detection of the defects in the product. In the production line the images of the product (rolled steel) are continuously captured and fed into the ML model. If this image is flagged as a defect image, then it is obvious that there is a defect in the product. So, this part of the product has to be taken for further processing, by assessing the defect levels, quality engineers should decide whether the product has to re-worked or discarded. However, the initial quality inspection, which if done manually would have been painstakingly time consuming and expensive. This can be automated with machine learning as discussed in this project.

5. REFERENCES

[1] De Vitis, G.A.; Foglia, P.; Prete, C.A. Row-level algorithm to improve real-time performance of glass tube defect detection in the production phase. IET Image Process. 2020, 14, 2911–2921. [CrossRef]

[2]. Rasheed, A.; Zafar, B.; Rasheed, A.; Ail, N.; Sajid, M.; Dar, S.H.; Habib, U.; Shehryar, T.; Mahmood, M.T. Fabric Defect Detection Using Computer Vision Techniques: A Comprehensive Review. Math. Probl. Eng. 2020, 2020, 8189403. [CrossRef]

[3] Jain, S.; Seth, G.; Paruthi, A.; Soni, U.; Kumar, G. Synthetic data augmentation for surface defect detection and classification using deep learning. J. Int. Manufact. 2020, in press. [CrossRef]

[4]. Ma, Y.; Li, Q.; He, F.; Liu, Y.; Xi, S. Adaptive segmentation algorithm for metal surface defects. Chin. J. Sci. Instrum. 2017, 38, 245–251.

[5] Li, S.; Yang, J.; Wang, Z.; Zhu, S.; Yang, G. Review of Development and Application of Defect Detection Technology. Acta Autom. Sin. 2020, 46, 2319–2336.

[6] Ma, S.; Wu, N.; Li, X. Deep learning with big data: State of the art and development. CAAI Trans. Intell. Syst. 2016, 11, 728–742.

[7] Zhang, Z.; Pang, W.; Xie, W.; Lv, M.; Wang, Y. Deep Learning for Real-time Applications: A Survey. J. Softw. 2020, 31, 2654–2677

[8] Yu, W.; Zhang, Y.; Yao, H.; Shi, H. Visual inspection of surface defects based on lightweight reconstruction network. Acta Autom. Sin. 2020, 41, 1–12.

[9] Liu, J.; Liu, Y.; Luo, X. Research and development on deep learning. Appl. Res. Comput. 2014, 31, 1921–1930+1942.

[10] Tao, X.; Hou, W.; Xu, D. A Survey of Surface Defect Detection Methods Based on Deep Learning. Acta Autom. Sin. 2020, 47, 1017–1034.
[11] Lu, R.; Wu, A.; Zhang, T.; Wang, Y. Review on Automated Optical (Visual) Inspection and Its Applications in Defect Detection. Acta Opt. Sin. 2018, 38, 23–58.
[12] Yang, J.; Li, S.; Wang, Z.; Dong, H.; Wang, J.; Tang, S. Using Deep Learning to Detect Defects in Manufacturing: A Comprehensive Survey and Current Challenges. Materials 2020, 13, 5755.