Smart Quality Management System at the Manufacturing Sector using Deep Learning for Anomaly Detection

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An assembly line is a place where materials are put together and processed to check if the end product meets the quality standards. One of the biggest challenges faced by the manufacturing sector is quality management. Any newly built product is prone to have surface defects like scratches or dents or paint errors which might happened during the process of manufacturing and transportation. Currently such quality checks are being done manually using Human Vision. Now with the advent of IoT and Deep Learning techniques, we could build an anomaly detection system that recognize defects on the surface of the system by capturing photographs of the Automobile in the assembly line and sends it to an image processor system for validation. We were able to detect defects with 90% and above accuracy with the existing detection algorithms.

Keywords: Industry 4.0, Deep Learning, Surface defects, YOLO.

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1 Introduction

Industry 4.0 is a buzzing term that is used to show the process in the management of manufacturing sector. Industry 4.0 can be achieved with the help of latest domains like IOT, data analytics, Machine Learning, Deep Learning Etc. The adaptation of Industry 4.0 has proved to improve productivity, efficiency and pro-vide quality assurance in the product manufactured with cost effective solutions. Top companies are slowly adopting to industry 4.0 [1].

The first impression made by any product is the most important to grab the market [2]. But, due to some defects in the surface like scratches, dents made during manufacturing and transportation can bring huge economic losses sellers and the buyers. The manufacturing companies arrange for professional labor for doing regular inspections before the product is released to the market [3]. The Vehicles that don't qualify the inspection are sent back for repair. The classical approach is done as a random sampling of the products and observation of differences in the surface manually. This detection method is not sufficient for the latest improvements in the manufacturing sectors as human vision is not trustable or not fully guaranteed to detect the mistakes. For small surface mistakes it is impossible for human vision to identify them.

Automation of such processes have been of great interest of research where IoT combined with deep learning techniques are used to get low cost, real time system with high degree of precision to improve productivity and quality to a greater extent. This paper is summarized as related work in section 2 and proposed system in Sections 3 and 4. And finally experimental results as Section 5 followed by conclusion in Section 6.

2 Literature Review

In [4] multi-form Gabor and color Gabor is designed from a feature convolution kernel library. The detection accuracy is effectively improved as the feature extraction is optimal and the convolution kernel is trained and screened to replace the low level convolution kernel in the original network.[5] proposes an improved YOLOv3 surface defect detection method based on the YOLOv3 network model. The proposed method combines the batch normalization (BN, Batch Normalization) layer and theconvolutional layer thereby improving the forward reasoning speed of the model. It also reduces the model's defects and the training time of the dataset. It uses K-means clustering algorithm by optimizing it to determine the appropriate anchor boxes for the defect dataset using K-means++. In [6] an active laser detection system is proposed to obtain high-intensity cat-eye reflection images. YOLOv3-4L,which is an advanced version of YOLOV3 to detect the actual position of the target was introduced. In the YOLOv3-4L model, each image was resized to 608×608 to preserve image details.[7] proposes a supervised deep convolutional neural network. It is used to classify all the images in a collection of images. It providesHigh range crack detection performance when compared with features extracted with existing methodologies.In [8]videos are visually examined by adding up the pixel level classification confidence of various frames that has different illumination levels. A crack segmentaion algorithm is proposed which takes 685 pixel-level ground truth images with 37 cracks for evaluation. The end results has great improvement of 9% over the exisiting convolutional neural network based methodologies.In [9] a DeepCrack net is proposed which has the encoder–decoder architecture of SegNet. It fuses the convolutional features produced in the encoder network and in the decoder network at the same scale. They have trained a DeepCrack net on one crack dataset and evaluate it on three others. The experimental results demonstrate that DeepCrack achieves F -measure over 0.87 on the three challenging datasets in average and outperforms the current state-of-the-art methods. In [10], based on the saliency and statisticl features, a unsupervised crack detection algorithm is used.

Here the conspicuity map and spatial continuity of the candidate crack pixels are measured.[11] the proposed method consists of three steps. A geodesic shadow-removal algorithm to remove the pavement shadows while preserving the cracks anda crack probability map using tensor voting, which enhances the connection of the crack fragments with good proximity and curve continuity are being done.At the end,a set of crack seeds from the crack probability map is examined. A graph model shows the seeds and from which minimum spanning trees are got. Recursive tree-edge pruning is conducted to identify desirable cracks. The proposed methodology is evaluated on a collection of 206 real pavement images. The results show that the proposed method achieves a better performance than several existing methods.

3 Proposed Methodology

3.1 Convolutional neural networks CNN

Convolutional neural networks (CNNs) are done using Convolutional computation. It has a deep structure deep structure that helps learning structured and translation-invariant information from input images. The CNN Layer consists of the Input Layer, Conolutional Layer,the Pooling Layer and the output layer. Grey Processing, data augumentation and Normalization of the input images are done using the input layer. Convolutional operations are carried out by the Convoutional layer to ensure that the forward and backward transmission of information is done precisicely in each and every layer. Nonlinearity is introduced after the convolutional layer using the Activation layer which gives a better representation of learning ability. Then subsamplethe feature maps is done by the Pooling layer which reduces the overhead to a greater extent. It could also mitigate the overfitting phenomenon. The Average,max pooling strategies are commonly being used as the pooling functions. The Output layerused the SoftMax function for classification tasks to present the results to the applications.It helps to identify the probability ofan input in each category, thereby obtaining the results for classification.

3.2 YOLOv5 Algorithm

The YOLO algorithm uses the convolutional neural networks to detect objects in instantaneous time. The algorithm uses a single neural network for the entire image, then divides the image into different sections and indicates boundary boxes and probabilities for each section. We could find YOLOv5 with four variations - YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x. YOLOv5 works with the architec-ture of CSPDarknet53 where the SPP layer is the backbone, PANet the Neck and YOLO the detection head .YOLO is selected as the main algorithm for our case as it follows a single stage detector.

4 System Design

4.1 Architecture

Figure 1 illustrates the overall architecture of the System: (1) Image Acquisition Sys-tem where a camera connected to the Raspberry pi is being used to gather the images of the automobile ready for the Quality analysis in the manufacturing sector. These images are stored in the cloud and are used as the test data. (2) Image Processing System where training dataset acquired from various data sources are used to develop a model using the Yolo V5 algorithm.

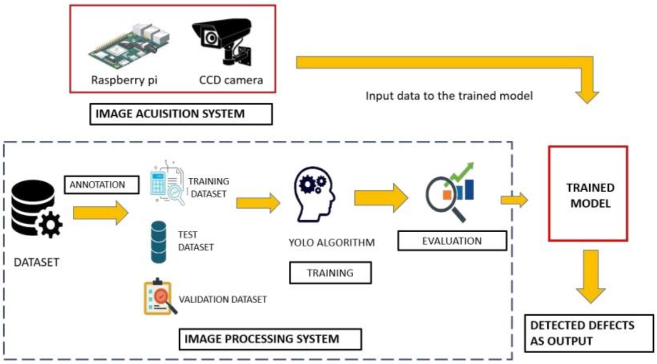

Fig. 1. Architecture Diagram

4.2 Methodology

The Back-bone and PANet of the YOLOv5 network helps in the feature extraction. Multiscale information extraction is also taken care of by the Back-Bone and PANet.The result is passed to an enhancement system to lessen the problem of extracting small areas of defects using Spatial attention. The less defective features are suppressed by Channel attention.

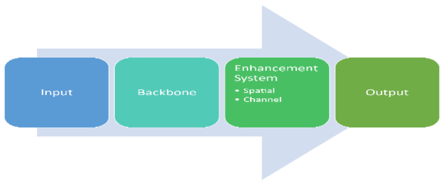

Fig. 2. Methodology

5 Experimental Results

A public dataset is used that contains 1000 images. The images contain bounded rectangles that label the defects. Here we train our model with images that has defects like scratch, dent, solvent popping, water spotting etc. The voluminous dataset is cleaned by re-moving the junk images.The small defects present in the images in the dataset are annotated using roboflow. Annotation is done by drawing a rectangular boundary box around the defects.Then the annotated images are pre-processed so that all the images are resized to same size.After pre-processing it is augmented. In this augmentation step we add noise to images. Adding noise helps in expanding the size of the dataset and also adding known amount of noise enables us to test the performance efficien-cy and robustness of an algorithm. In roboflow after these steps, the dataset is divided into 3 groups. The three groups are the training,testing and validation set.Then these three sets are trained using yolov5 algorithm so that it detects the defects effectively. Now the image captured by the image acquisition system which consists of Raspberry pi and a CCD camera is given as input to our trained model. The yolov5 trained model detects the defects in the captured image if any is present.

Fig. 3. Result

The proposed algorithm was able to differentiate normal and paint defects.The mean average precision (mAP)and the AUC are used as evaluation metrics. Initially the precision,recall are calculated, where Precision(P) is TP/(TP+FP) and Recall(R) is TP/(TP+FN).[TP=True Positive,FP=False Positive ,FN =False Negative].

The P-R curve is got from the calculated P and R. The calculated P-R curve is called the ROC curve. The area that is covered by the ROC curve is called as the AUC.The area under the P-R curve represents the mAP which is the mean of different average precisions(AP).

6 Conclusion

An Smart Quality Management system using YOLOv5 is used which detects specific paint defects. Evaluations are performed on the public datasets. The proposed meth-od is applicable for idetifying paint defects with great accuracy and thereby improve the Quality at the Manufacturing Sector.

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