Detection of Wheel Discoloration using R-CNN

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Abstract - *Wheel defects on the haul trains of the railway network has been spotted as a vandalization in the railway infrastructure. The reasons for the wheel defects are due to the effect of temperature and the defects present in the railway wheel may cause vibrations and noise emissions where it cannot be averted and leads to a huge upturn in the cost. This paper utilizes a method by the machine learning technique to discern the wheel flaws in the railway wagon wheel using the R-CNN algorithm. The R-CNN algorithm uses the Selective Search technique for detection purpose and in this technique, the image (X-Ray) is segmented into few regions, then the segmented regions are processed by the CNN features. This algorithm helps to perceive the different types of wheel defects and also the location of the particular defect. To assess the performance of this technique, erecting multiple data sets by using train and test images of the wheel and done based on 2-D representation. Secondly, this algorithm spots the location of the defect present in the railway wagons wheel, this may be either at the circumference or the surface area of the wheel. These are advantageous for detection purposes and they are detected during the maintenance session where it aids to discern at the lower cost and it is also robust.*

***Key Words*: Machine Learning, Deep Learning, Railway safety, Railway Accidents, Railway Infrastructure, Artificial Neural Networks.**

1. INTRODUCTION

The railway wheel of the haul train is the gathering of two wheels fixed to the axle by interference fit and they rotate along the axle without any independent relative movement. The wheel parts are categorized into Hub, Disc, Tyre where the defects can be present over these parts of the wheel. These wheel defects are caused due to the effect of temperature which may lead to the thermal cracks in the wheel and the wheel defects are cataloged as manufacturing defects, normal wear and tear and so on. The prior detection of the flaws on the wheel is one of the indispensable parts in preventing impairment to the railway infrastructure and also the rolling stock. Since the damage occurs, it leads to additional cost for maintenance and repair and also it reduces the lifetime of the rolling stock. The life span of the infrastructure gets shortened and cannot be utilized for the assumed period.

Another important effect caused by wheel defects is vibration and noise emissions. It is one of the major parts of the railway network where it should be mitigated to maintain the system in a good way [1]. So, therefore, proposing a method to detect the flaws in the wheel of the freight trains to avoid such problems and to improve the performance of the railway system. The technique is to make use of R-CNN (Region-based Convolutional Neural Network) algorithm to get the machines to be trained up the wheel defects with the help of the machine learning methods. By using this technique, the type of defect and the location of such type of defect can be identified with limited cost when compared to doing it by the usage of sensors where it takes the process to be completed with the huge increase in the expenses of money.

2. RELATED WORKS

Table-1: Survey based on various research paper in Defect Detection

NAME	AUTHOR	PUBLISHED ON	DEMERIT
Sensor systems of detecting defects in wheel of railway vehicles running at operational speed	Nencho Nenov, Emil Dimitrov, Vasil vasilev, and Petyo Piskulev	"Sensor based systems used for monitoring the moving of railway wheels" in October 2011.	The implementation of the sensor is a tedious and complex process [2].
Nondestructive Testing of Train Wheels Using Vertical Magnetization and Differential-Type Hall-Sensor Array	Jinyi Lee,Myoungki Choi, Jongwoo Jun, Seokjin Kwon, Joo-Hyung Kim, Jungmin Kim, and Minhhuy Le	"A differential-type Hall-sensor array and vertical magnetizers used to improve the detection system" in September 2012.	Radiographic Testing (RT) is expensive and strenuous to implement. The detection capability of the sensor has rapidly decreased

			according to the increase of liftoff [3].
Railway Wheel Flat and Rail Surface Defect Detection by Time-Frequency Analysis	Bo Liang, Simon lwnicki, Gu Feng, Andrew Ball, van Tung Tran, Robert Cattley	"Time frequency analysis of vibration in railway wheel for early detection of wheel flats and railway surface defects" in January 2013 [4].	Information based on time like spikes and high-frequency cannot be detected easily by using Fourier transform. It is more time taking process.
Wheel Flat Detection in High-Speed Railway Systems Using Fiber Bragg Gratings	Massimo Leonardo Filograno, Pedro Corredera, Miguel Rodriguez-plaza, Alvaro Andres-Alugacil, and Miguel Gonzalez-Herraez	"The Fiber Bragg Grating (FBG) sensors are used to determine the out-of-roundness in the wheels of train" in December 2013 [5].	This method does not use any type of algorithm for detection. This method is to detect the wheel defect which is based on the FBG sensor.
Condition Monitoring Approaches for The Detection of Railway Wheel Defects	Alireza Alemi, G.lodewijks, Francesco Corman	"The defects of wheels are predicted and prevented by condition monitoring system" in June 2016 [6].	The system cost is very high. It does not provide more accurate results.
A New Method in Wheel Hub Surface Defect Detection: Object Detection Algorithm Based on Deep Learning	Kai Han, Muyi Sun, Xiaoguang Zhou, Guanhongy Zhang, Hao Dang, Zhicai Liu	"The deep learning algorithm which does not require background image which is more strong and secure than traditional detection methods" in December 2017 [7].	The deep learning method requires a lot of images for training. This algorithm only provides the practical solution for inspection of wheel hub productive line.

3. IMPLEMENTATION WORK

In this paper, the wheel defects are detected by exerting the R-CNN algorithm. The R-CNN is short of "Region-based Convolutional Neural Network", which is composed of two steps. It finds the feasible number of regions in the image by selective search and secondly, it extracts the CNN features for each region independently to classify the image.

Firstly, the Data collection process is done where the X-ray images of the defective wheels are taken. Then the images of the wheels are taken for consideration and segregated as train images and test images. The train images and test images are taken in the ratio of 8:2 or 7:3 so that the result can be obtained precisely.

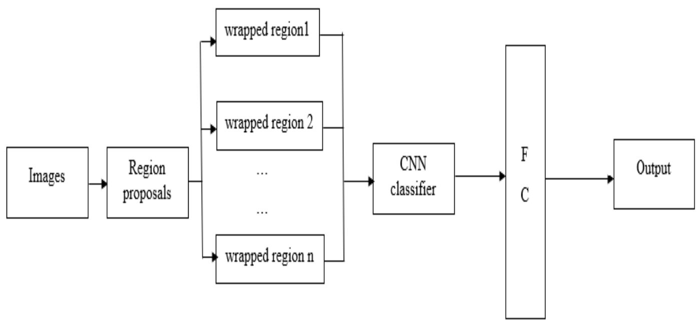

Fig -1: The architecture and working of the proposed work.

It starts with the images in which X-ray images of the wheels or defective wheels are taken and then region proposals are done based on the segmentation with the Selective Search approach. Then there occurs "n" number of regions which are termed as wrapped regions and they are given as the input to the CNN features which discerns the type of defect present in the wheel and the result is obtained by the FC (Fully Connected) layer which is one of the CNN features.

3.1 Steps involved in Defect Detection

The train images are trained by aiding the object detection models and followed by the below procedure which gives more accuracy to obtain the result.

Step 1: Data collection.

Step 2: Labeling data.

Step 3: Generating TFReords for training.

Step 4: Configuring training.

Step 5: Training model.

Step 6: Testing the object detector.

The outset is to collect the data which is to be trained and tested and saved in the training and testing directory respectively and they are labeled by *LabelImg* where each image is opened by *Open Dir*. To devise the bounding box, the *Create RectBox* is utilized and after annotating the image, "Save" button is clicked. This process is replicated for all the images of the training and testing directory.

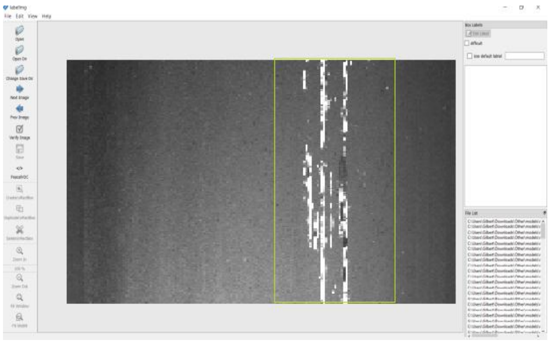

Fig -2: Labeling the image

The TFRecords are concocted by two scripts known as *xml_to_csv.py* and *generate_tfrecords.py* files. The first script creates two files in the image directory, which is *test_labels.csv* and another is *train_labels.csv*. The second is used to give the labeling for the labeled image with their defect name.

Configuring training is compassed before training and it is cleaved into two steps like *Creating a label map* and *Creating training configuration.* The Training model is used to commence the training where the R-CNN algorithm is used to conjecture the type of defect and location of it.

The last step is to test the object detector and to detect the defected regions of the input images of the wheel. The wheel can have either one defect or more than one defect and the type of defect is stipulated by the colors.

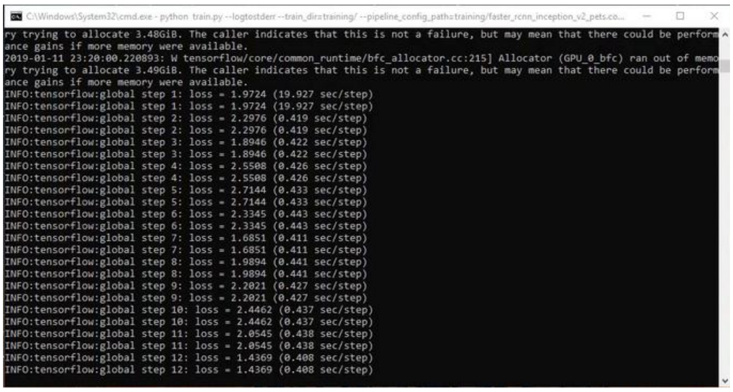

Fig -3: Training

3.2 R-CNN

The R-CNN is short for "Region-based Convolutional Neural Network" that utilizes the Selective Search algorithm which splits up the image into several regions. These segregated regions are applied to the CNN features and the output contains the extracted features of the given input image. This detection describes the test time usage of the image of the defective wheel.

The input image is given as the image pixel values with the following dimensions: [[width × height × depth]. The Selective Search is a region proposal algorithm used for detecting the defect of the wheel and is based on enumerating the similar regions of an image on the basis of texture, size and shape compatibility. The below figure describes how the image becomes after region proposal is being done.

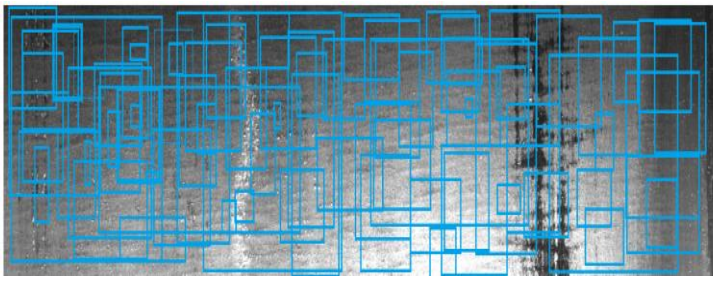

Fig -4: Region Proposal

Step 1: Initially create regions for the X-ray image of the wheel.

Step 2: Use a greedy algorithm to iteratively group regions together:

- ✓ The similarities between all the adjacent regions are computed.
- ✓ The two most similar regions are grouped together, and new similarities are calculated between the resulting region and its neighbors.

Step 3: Step 2 is repeated until they form as a single image.

ALGORITHM FOR COMAPRING TWO REGIONS

Input: X-ray images

Output: Set of object location L.

Obtain initial regions $R = \{r_1, \ldots, r_n\}$. Initialize similarity set $S = \emptyset$;

foreach *Neighboring region pair* (r_i, r_j) **do**

Calculate similarity $s\,(r_i, r_j)$;

$S = S \cup s\,(r_i, r_j)$;

while $S = \emptyset$ **do**

Get highest similarity $s\,(r_i, r_j) = \max(S)$;

Merge corresponding regions $r_t = r_i \cup r_j$;

Remove similarities regarding $r_i : S = S \setminus s\,(r_i, r_*)$;

Remove similarities regarding $r_j : S = S \setminus s\,(r_*, r_j)$;

Calculate similarity set S_t between r_t and its n neighbors;

$S = S \cup S_t$;

$R = R \cup r_t$;

Extract object location L from all regions in R;

3.3 Similarity Metrics

The defects are detected by R-CNN algorithm in which the images of the wheel are cleaved into a greater number of regions with some procedures and the similarities are computed by some of the parameters for like checking the color similarity between two regions, size similarity, etc. Since we use X-ray images, color similarity is Zero. It uses multiple grouping criteria and leads to a balanced hierarchy of small to large objects [8] [9].

- **Texture similarity**

The texture features can be obtained by extracting the gaussian derivative of the image in 8 directions. Secondly, construct a 10-bin histogram for each channel which results in a 240-dimensional descriptor.

$$S_{texture}\left(r_i, r_j\right) = \sum_{k=1}^{n} \min\left(t_i^{\,k}, t_j^{\,k}\right)$$

where t_i^k is the histogram value for k^{th} bin in texture descriptor.

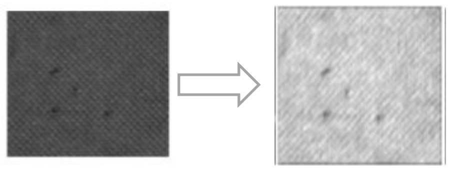

Fig-5: Example for texture similarity.

- **Size similarity**

The size similarity can be used to merge the smaller regions in a quicker manner. This parameter ensures that the regions are formed from the parts of the image and not beyond the image.

$$s_{size}\left(r_i, r_j\right) = 1 - \frac{size\left(r_i\right) - size\left(r_j\right)}{size\left(im\right)}$$

where $size(im)$ is the size of image in pixel.

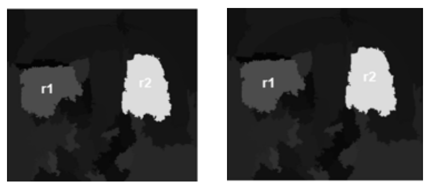

Fig-6: Example for size similarity metric.

- **Shape Compatibility**

The shape compatibility measures how two regions fit into each other. If r_i fits into r_j, then the two regions can be merged in order to fill gaps.

$$s_{shape}(r_i, r_j) = 1 - \frac{size(BB_{ij}) - size(r_i) - size(r_j)}{size(im)}$$

where *size* (BB_{ij}) is a bounding box around r_i and r_j.

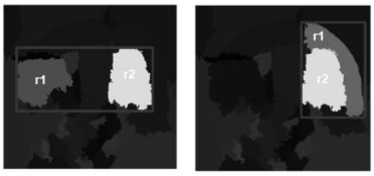

Fig-7: Example for shape similarity.

- **Final Similarity**

The final similarity between two regions is defined as a linear combination of a mentioned 3 similarities.

$$s(r_i, r_j) = a_1 s_{texture}(r_i, r_j) + a_2 s_{size}(r_i, r_j) + a_3 s_{shape}(r_i, r_j)$$

Where r_i and r_j are two regions or segments in the image and a_i € 0, 1 denotes if the similarity measure is used or not.

In the next step, we take each region proposal and computes each region with CNN features. The convo layer is the place where the CNN learns and it has many parameters such as filters, strides and so on and sometimes it is also known as feature extractor layer because the features of the images are extracted in convo layer itself. The parameters can be calculated as,

$$(((m*n)+1)*k)$$

where,

m – shape of width of filter.

n – shape of height of filter.

k – number of filters.

The Convo layer acquires the volume of size of $W_1 \times H_1 \times D_1$ and it requires the parameters like number of Filters *"K"*, their spatial extend *"F"*, the strides *"S"*, and the amount of zero padding *"P"*. After the processing gets over, this layer generates a volume of size of $W_2 \times H_2 \times D_2$ where

$$W_2 = \frac{(W_1 - F + 2P)}{S} + 1$$

$$H_2 = \frac{(H_1 - F + 2P)}{S} + 1$$

$$D_2 = K$$

The activation function is a type of node that is placed in between the neural networks and it is one of the non-linear transformations and the transformed output is fed to the layers of neurons as the input to it.

The main purpose of the pooling layer is to mitigate the spatial volume of the defected image of the wheel after it is been given to the convo layer and also to speed up the computation process. This type of layer also accepts the volume of size as $W_1 \times H_1 \times D_1$ which is similar to that of convo layer. It has few parameters like spatial extent *"F"* and strides *"S"*. It produces the volume of size as follows,

$$W_2 = \frac{(W_1 - F)}{S} + 1$$

$$H_2 = \frac{(H_1 - F)}{S} + 1$$

$$D_2 = D_1$$

The Fully Connected layer (FC) connects every neuron in one layer to every neuron in another layer and the neurons have the connection to all the activation and it is computed with the help of matrix multiplication. The number of parameters in this layer is

*((current layer n * previous layer n) + 1*

The main purpose of this layer is to categorize the images between several category by training [10].

4. Performance metrics

In this paper, the accuracy and defect count are compared with the existing system and the proposed system. The existing system is done by using CNN and this project uses R-CNN algorithm to find the defect. The accuracy rate gets increased when compared to the existing system. The count of the defects of each type is not specified in the existing system but it is computed in the proposed work.

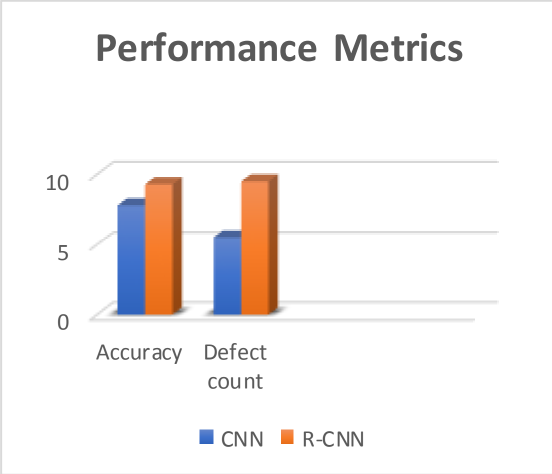

Fig-8: Comparison between CNN and R-CNN

4.1 Accuracy

The accuracy is calculated by True positive and False Negative values. The Intersection over Union (IoU), IoU computes intersection over the union of the two bounding boxes; the bounding box for the ground truth and the predicted bounding box. The threshold value should be set for IoU so that, it can be detected if it is valid or not. The accuracy is calculated by the below equation.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

- If IoU ≥ threshold value, classify the object detection as True Positive (TP).
- If IoU < threshold value, then it is a wrong detection and classify it as False Positive (FP).
- When a ground truth is present in the image and model failed to detect the object, classify it as False Negative (FN).
- True Negative (TN**):** TN is every part of the image where we did not predict an object. This metrics is not useful for object detection, hence we ignore TN.

5. Simulation of results

The results show the defected wheel of the given input wheel. This shows that the training will stop until it gets a satisfying loss. This process always gives the type of defect and the location of the particular defect.

The defects are indicated by a separate color. Each color indicates the different types of defects. The blue color indicates the type 1 defect. The yellow color indicates the type 2 defect. The violet color indicates the type 3 defect. The red color indicates the type 4 defect. This is also specifying the different types of defect which is present in one single wheel.

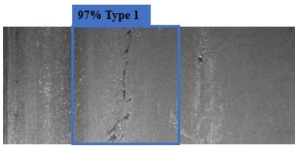

Fig-9(a): Type 1defect

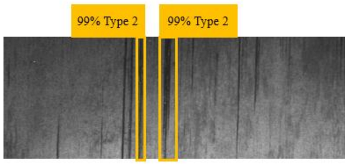

Fig-9(b): Type 2 defect

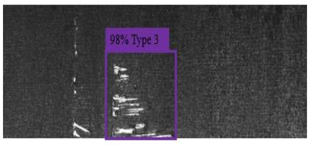

Fig-9(c): Type 3 defect

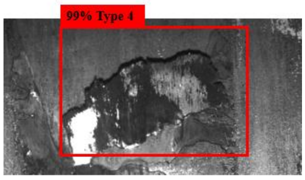

Fig-9(d): Type 4 defect

Table-2: Description of Type of Defects

DEFECT TYPES	DESCRIPTION	RESOLVING TECHNIQUE
Type 1 (Blue)	It is one of the types of service defect known as Thermal cracking defect. Thermal cracks are the outcome of alternate heating as well as cooling of the tread and rim parts of the wheel, and originate from metallurgical changes. Thermal cracks are the most severe form of wheel defect [11].	The thermal cracks can be removed by machining but extra care must be used to ensure that the crack has been completely eliminated in the operation.
Type 2 (Yellow)	This defect is Inherent defect where these defects are encountered during steel-making, shaping and machining operations which are associated with faults in the making of steel and manufacturing into wheels.	The action required to solve this type of defect is to cast the wheel of the freight train during the manufacturing of wheel.
Type 3 (Violet)	Rolling contact fatigue (RCF) cracks is caused by repeated	RCF can be completely eliminated if

	contact stress during the rolling motion. These cracks are generally developed on the tread surface and are not perpendicular to the running direction and this type of defect can lead to spalling [13].	stresses and tractions can be reduced sufficiently and/ or steel strength raised sufficiently. The reduction of RCF can also be done through the control of wheel wear shape [12].
Type 4 (Red)	The Shattered Rim defect arises at the sub-surface of tread part of the wheel which results in fatigue initiation that further progresses circumferentially and when the fatigue crack gets connected with tread part, a chunk of metal is dislodged from tread.	A method for preventing shattered-rim comprises the steps of measuring the maximum defect size within the rim, and determining whether the maximum defect size is less than a predetermined maximum permissible defect size.

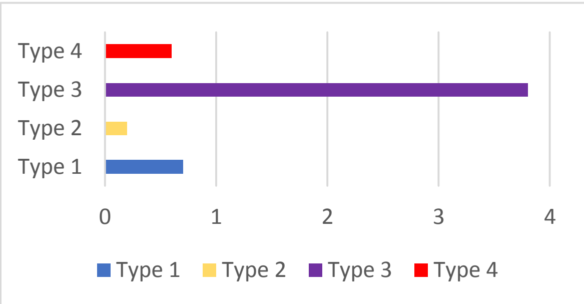

Fig-10(a): Defect count of one type

The above graph specifies the rate of defects which are present in the training session. This graph is generated in between the training period and it makes sure that, it is easy to calculate the amount of variety of defect which is placed in the wheel. The number of each type of defect is calculated by the below equation.

$$Frequency = \frac{count\ of\ defect}{Sum\ of\ count\ of\ defect} \times 100$$

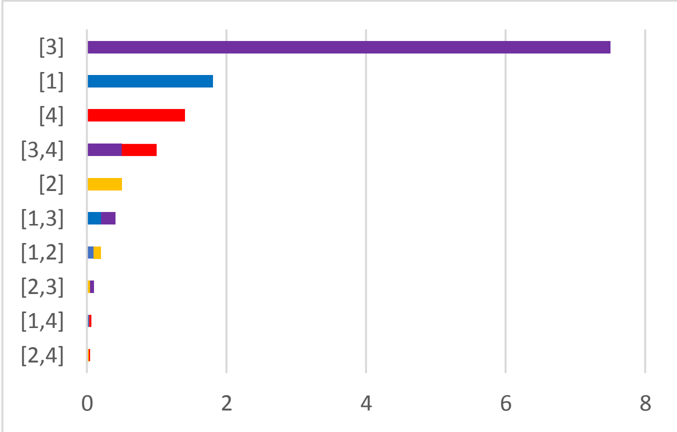

Fig-10(b): Defect count of different types

The above graph shows the different types of defect which is present in the single wheel. Suppose the wheel having two types of defects which are indicated by [2,3] which specifies the wheel having type 2 and type 3 defects which followed by the color orange and violet. In this way, this graph is generated during the training session. The above graph also specifies the single type of defect as well as more than one type of defect which are all present in the defected wheel. The total number of the possible combination of defect is calculated by using the below equation.

$$Frequency\ of\ possible\ combination = \frac{permuation\ of\ count\ of\ defect}{Sum\ of\ permutation\ of\ count\ of\ defects} \times 100$$

6. Conclusion and future work

We have presented the machine learning methods to detect the defect which is present in the railway wheel. The algorithm or method used for detecting the wheel flaws is R-CNN (Region- based Convolutional Neural Network) algorithm. To evaluate our method, we collect datasets from different sources as train and test images. Generally, sensors are used to check whether the wheel has a defect or not and then the type of defect is categorized by the CNN algorithm. Since sensors are kept on the slab of the railway track for checking whether the defect, so the utilization of the machine learning technique is much less and mainly concentrates on the working of the sensor. Hence, our paper uses the R-CNN algorithm for prediction of wheel defects and this algorithm is mainly used in the concept of machine learning method where it demonstrates the improved performance and effective utilization of this technique.

Further, future work can be done in such a way that the defect can be predicted even during the running time of the train. So, some of the external features can be integrated into the machine learning methods which tries to detect the defects in runtime too. Predicting the defects during the running time can make much easier to identify and also to resolve the defects and the operations done during maintenance time can be reduced. It can be done in real-time by giving a Neural Schema to the Robot which does the detection work and can also be done with the help of 3-D representation.

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