International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 06 | June 2020 www.irjet.net p-ISSN: 2395-0072

Detecting Defects in Power Connector using Machine Learning via Convolution Neural Networks

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Abstract – *Detecting bad quality components in hardware manufacturing is an error-prone & time consuming manual process and results in detecting a bad one as a good one. If a faulty component is detected at the end of the production line there is a loss in upstream labor, consumables, factory capacity as well as revenue. On the opposite hand, if an undetected bad part gets into the ultimate product there will be customer impact also as market reaction. This could potentially cause irreparable damage to the reputation of the organization. We adopted a mixture of pure computer vision approach to extract the region of interest (ROI) from the image and a pure deep learning approach to detect defects in the ROI. With deep learning-based computer vision, we achieved human-level accuracy and better with both of our approaches computer vision and machine learning we substantially reduced the human review rate. We can automate component inspection with machine learning & reduce the human review rate.*

Key Words: Convolution neural network, Deep learning, VGG16, VGG19, ResNet50, MobileNetV2, Inception V3, Mobile Net, Good Class, Damaged, Convolution layer, Max pooling, Fully connected

1. INTRODUCTION

In this paper, we have deployed the concept of deep learning known as convolution neural networks (CNN) as we can realize nowadays deep learning is growing in each and every field Deep learning is executed in each platform and its outcome is impressive. Increased level of automation in manufacturing also demands automation of production outcome is impressive. Increased level of automation in manufacturing also demands automation of production quality inspection with little human intervention. The trend is to succeed in human-level accuracy or more in quality inspection with automation. To stay competitive, modern Industrial firms strive to realize both quantity and quality with automation without compromising one over the opposite. A variety of approaches for automated visual inspection of printed circuits are reported over the past 20 years. This posting takes the user through a use case of deep learning and showcases the need for optimizing the full stack (algorithms, inference framework, and hardware accelerators) to get the optimal performance. Quality inspectors in manufacturing firms inspect product quality usually after the merchandise is manufactured, it's a time consuming manual effort and a rejected product leads to wasted upstream factory capacity, consumables labor, and cost. With the fashionable trend of AI, industrial firms are looking to use deep learning-based computer vision technology during the assembly cycle itself to automate component quality inspection. The goal is to minimize human intervention at the same time to reach human-level accuracy or more as well as optimize factory capacity, labor cost, etc. The usage of deep learning is varied, from object detection in self-driving cars to disease detection with medical imaging deep learning has proven to realize human-level accuracy & better.

2. PURPOSE

As we know Power connector is the most important and crucial part of each and every electronic product and nowadays electronic products are used in each and every product in our day to day life [7]. Hence, our life is reliant on electronics. Any defect or malfunction in Power Connector may lead to catastrophic condition to the human beings so the industries who manufacture the Power connector need to be sure that the defective or damaged Power Connector should be detected and restrict it from going into hand to hand use. There are many image subtraction techniques that have been implemented in Electronics industries [8,9] in the past but as we know deep learning has been a booming concept. Nowadays in detecting and classifying objects with any appreciable accuracy [10,11].Detecting and classifying the good Power Connector and defective Power Connector would avoid many accidents and save the time of human beings.

3. REGION OF INTEREST (ROI) EXTRACTION WITH COMPUTER VISION

Inspecting the Connection area for defects rather than other areas in the Connector. ML accuracy increases when neural networks focus only on the area of interest rather than the whole area processes Involves Gray scaling, transformations curve out the ROI from the image.

4. CONVOLUTION NEURAL NETWORK

Convolution neural network (ConvNets or CNNs) is one of the main categories to do images classifications. CNN image classifications takes an input image, processes it and classifies it under certain categories CNN looks for patterns in an image. Computers sees an input image as array of pixels and it depends on the image resolution Based on the image resolution, it will see h x w x d .there are five main operations in the CNN input layer, convolutional layer, Relu layer, pooling layer, and fully connected layer. In addition to it in Figure 1, the structure of CNN is displayed with different layers.

4.1 Input Layer

The raw pixel values of the image will be held by input. During this case, a picture of width 32, height 32, and with three color channels red, green, blue (R, G, B) is shown in the input of Figure 1.

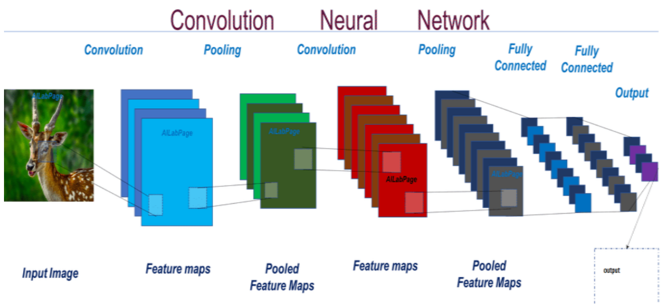

Fig. 1. Structure of convolution neural network

4.2 Convolution Layer

The layer of convolution is the core building block of a convolutional network. Let's first discuss what the convolution layer computes. The convolution layer's parameters consist of a set of learn-able filters. Every filter is small spatially (along width and height), but extends through the full depth of the input volume. For example, a typical filter on the first layer of a convolutional networks (ConvNet) might have size 5x5x3 (i.e. 5 pixels' width and height, and three because images have depth 3, the color channels)(more precisely, convolve) each filter across the width and height of the input volume and compute dot products between the entries of the filter and the input at any position. As we slide the filter over the width and height of the input volume we'll produce a 2-dimensional activation map that provides the responses of that filter at every spatial position. Intuitively, the network will learn filters that activate once they see some sort of visual features such as an edge of some orientation or a blotch of some color on the primary layer, or eventually entire honeycomb Now, we will have an entire set of filters in each convolution layer and will produce a separate 2-dimensional activation map. we will stack these activation maps along the depth dimension and produce the output volume.

- An image matrix (volume) of dimension **(h x w x d)**
- A filter **(f_h x f_w x d)**
- Outputs a volume dimension **(h - f_h + 1) x (w - f_w + 1) x 1**

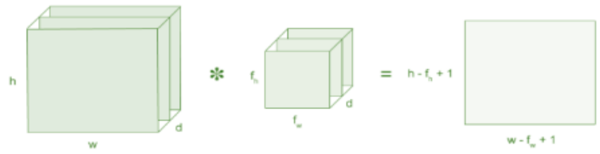

Fig. 2. Working of 2 Dimensional convolutions [13]

An example of 2-dimensional convolutions is shown in Figure 2. In this case, we restrict where the filter or kernel lies entirely within the image. Draw boxes with arrows to show how the upper-left element of the output is created by applying the filter to the corresponding upper-left region of the input. If we use a two dimensional image i as our input, we probably also want to use a two-dimensional filter (i.e., k) and we can also write as follows.

$$S(i,j)=(k*i)(i,j)= \sum_m \sum_n I(I - m, j - n)k(m,n)$$

4.3 ReLU Layer

An additional operation called ReLU has been used after every convolution operation in Figure 3. ReLU stands for rectified linear measure and may be a non-linear operation. ReLU layer will apply an element wise activation function, such as the max (0, x) thresh holding at zero. ReLU is an element-wise operation (applied per pixel) and replaces all negative pixel values within the feature map by zero. The purpose of ReLU is to introduce non-linearity in our ConvNet since most of the real-world data we might want our ConvNet to learn for non-linear (Convolution is a linear operation element wise matrix multiplication and addition, so we account for non-linearity by introducing a nonlinear function like ReLU). This leaves the size of the volume unchanged.

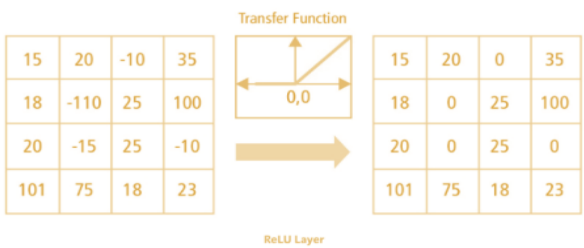

Fig. 3. Graphical representation of ReLU

4.4 Pooling Layer

The pooling or down sampling layer is liable for reducing the special size of the activation maps. In general, they are used after multiple stages of other layers (i.e. convolutional and non-linearity layers) so as to scale back the computational requirements progressively through the network as well as minimizing the likelihood of over-fitting. Spatial pooling (also called sub-sampling or down sampling) reduces the dimensionality of every feature map but retains the most important information. Spatial pooling can be of different types: Max, Average, Sum etc. In case of max pooling, we define a spatial neighborhood (for example, a 2×2 window) and take the largest element from the rectified feature map within that window. Rather than taking the most important element we could also take the average (average pooling) or a sum of all elements in that window. In practice, Max Pooling has been shown to work better We Fig. 4. Pooling layer down-samples the quantity spatially, independently in each depth slice of the input volume we slide our 2×2 window by 2 cells (also called 'stride') and take the utmost value in each region.

As shown in the function of pooling is to progressively reduce the spatial size of the input representation. Especially pooling, it makes the input representations (feature dimension) smaller and more manageable. The function of pooling is to progressively reduce the spatial size of the input representation. Especially pooling, it makes the input representations (feature dimension) smaller and more manageable.

Since we take the maximum/average value during a local neighborhood. It helps us reach an almost scale-invariant representation of our image. this is often very powerful since we can detect objects in a picture regardless of where they're located.

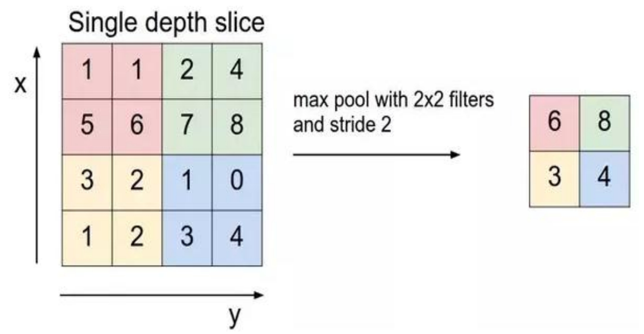

Fig. 4. Pooling layer down samples the volume spatially, independently in each depth slice of the input volume

4.5 Fully Connected Layer

Neurons during a fully connected layer have full connections to all activation within the previous layer, as seen in regular neural networks. Their activation can hence be computed with a matrix operation followed by a bias offset. The output from the convolutional layers represents high-level features within the data. While that output might be flattened and connected to the output layer, adding a fully-connected layer is a cheap way of learning nonlinear combinations of those features.

4.6 Output

After connecting all the previous layers with the assistance of a fully connected layer, it's time for classifying the output. I would explain the way to predict the output with a little example. Allow us to consider we've trained a group of images which has 2 classes X and O after the training such 2 classes. We provide the input i.e to classify whether it's X or O. As in Figure 5, we will see that the weights represent that there is a 92% probability that the given input is assessed as X and 51% is O.

In CNN for two classes, we use binary cross-entropy and the function referred to as sigmoid during the appliance of this function. Our results are going to be displayed in 0 or 1. As we can see in Table I, X is represented as 1, and O is represented as 0. It also displays that there's a 92% probability of X as an input and 51% probability of O. The table also represents 57% of the entire error displaying V-E Day for X and 49% for O.

Depending on these trained weights, the CNN detects and classifies the pictures on the ratio of probability.

Table -1: CALCULATION OF ERROR

	Right answer	Actual answer	Error
X	1	0.92	0.08
O	0	0.51	0.49

5. METHODOLOGY OF EXPERIMENT

Recently, after going through the production and quality inspection line in the industry, we realized that a lot of skilled manpower and time is dedicated in quality inspection of the product to deliver a product that is 100% perfect. But this whole process can also be done with the help of CNN (convolution neural network), which would eventually reduce a lot of time, man power and increase the accuracy. To implement this method, Images of power Connector has been extracted for a preliminary study. Almost 3000 images have been used in this experiment which is divided into 2 classes good and damaged.

This preliminary study has been initiated using 2 the classification process using the Inception model Total No of images used 2000,framework used is TensorFlow, Loss used is Cross entropy, Batch size is 12, total No of epochs: 15, the damaged images are addressed to the single class and good images to another class. 2000 sets of images are being used for training in which 1000 to good class and 1000 damaged, 400 sets of images are used for the test in which 200 damaged and 200 belong to good. Apart from these images, another CNN approach using transfer learning in which the idea is to use existing models VGG16, VGG19, ResNet50, MobileNetV2, Inception V3 Mobile Net and only adjust it to our data.

After training, we have tested it with a data-set, in Tables 2 and 3, we have displayed the result of the 1st approach and 2nd approach which displays accuracy

6. RESULTS

Size of the target data set plays a crucial role. To know at what data set size transfer learning would be still beneficial what layer is the model still able to generalize to a small data set size. It is of both academic and practical interest to research at what target data set size transfer learning can still provide any additional value.

Table -2: 1ST APPROACH TRAINING, VALIDATION AND TESTING

Model	Training	Validation	Testing
Inception	92.12%	82.12%	72.10%

For any kind of machine learning application, a large data-set and the algorithm play a vital role as we can see the result of classifying. The good power connector was better than classifying defective one due to having a data-set of good power connectors more than the defective ones.

Table -3: 2nd APPROACH, TRAINING, VALIDATION AND TESTING

Model type	20%	30%	70%	100%
VGG16	91.4%	94.7%	95.2 %	95.2%
VGG19	94.5%	96.1%	96.1%	99.2%
ResNetV2	82.2%	86.8%	91.6%	93.8%
MobileNetV2	90.5%	92.3%	94.5%	97.2%
Inception v3	92.1%	95.1%	94..2%	98.2%

7. CONCLUSIONS

This paper introduces that defects in the power connectors can be detected and classify using CNN with appreciable accuracy. We have achieved an overall accuracy of 87% in classifying the defects in the power connector. As future work, there is a higher accuracy of detection and classification for more data to learn.

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