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Development of Deep Learning Model for PCB Defect Detection Using PuneetNet

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Abstract—Semiconductor technology is widely used in almost every field today be it communication, satellite technology, computing, energy, automotive, healthcare, e-commerce, retail, education, administration etc. A thin size of wafer is mainly used for computation and decision making process in electronic devices and apparatus, which is made up of semiconductor material also called printed circuit board or PCB. PCB consists of millions of logic circuits designed on its surface for different purposes. The major challenge in PCB manufacturing comes at the last stage where wafer has to go through the quality analysis and inspection process. This process had been on manual mode for a long time as the advent of automation came in industries, this step became automatic too. Yet the present systems used in defect detection are less efficient and time consuming. In this paper we propose to detect wafer defects using a CNN based deep learning model which will use the image of PCB and predict if the PCB is defected or non-defected in microseconds.

Index Terms— PCB defect detection, Deep Learning, CNN, Electronic Chip Manufacturing.

I. INTRODUCTION

In printed circuit board manufacturing industry where important stages like routing, board designing are implemented manually, artificial intelligence offers tremendous opportunities for the betterment of intricate and time consuming process. Usage of AI can make the production process streamlined and efficient by offering new and alternate ways to produce. AI can assist in communication of automatic systems with each other and their operations in real time environment. It can enhance efficiency of asset management and help in reduction of scrap rate, inventory management and supply chain.

As per moore's law, the number of transistors can be placed on a specified size of chip gets doubled in every one and half year. The rate at which the size of semiconductor wafer is shrinking today AI can play vital role in boosting circuit's accuracy, speed, packing density etc. From efficient designing to packaging and testing/inspection of wafers, AI has solution for every problem. An accurate and efficient method for analyzing the sensor numerical data can be offered by machine learning algorithms which can further bring down the error rate and boost accuracy. Deep learning techniques can also be used for image analysis of wafer image in order to classify the image as faulty or good one. The introduction of computer vision in AI has opened many gates for wafer production industry to grow at a very high pace.

Defect detection and Defect classification is very important aspect of Automated Optical Inspection (AOI) in PCB manufacturing. In existing wafer inspection method, first AOI machine will send images to multi-image verification station then a human operator classifies them as defective or non-defective wafer, this method is very much prone to errors and human mistakes. To overcome this AI has produced an autonomous decision making system with accurate results. This is dependent on data patterns to learn correct algorithm behavior over the period of time. In this, data sensitivity is crucial because it can result in game changing output.

II. DEEP LEARNING

Deep Learning is part of Machine Learning which again is a part of broader term Artificial Intelligence. In Deep Learning the number of layers used in the model is very large. The neural network becomes very deep in development of deep learning model that's why it is able to extract more and refined features from the image. A lot of filters are used in convolution layer which includes horizontal and vertical filters to gain more insight in the image patterns. With the help of such convolution layers the model learns to find pattern from the similar images and completes its training. The trained model is then used to find accurate prediction about test images and define its class.

A. InceptionV3

Inceptionv3 was the third model in the inception series which was released in year 2015 by GoogleNet. This model is superior to the basic model in terms of better techniques applied for optimizing and model adaption. This model was released after many modifications which resulted in improvements to the model on multiple parameters.

Some of the improvements are as follows:

To answer the problem of vanishing gradient problem usage of auxiliary classifier is introduced. Auxiliary classifier helps in reducing the convergence problem in deep neural networks. These classifiers contributed in bringing the higher efficiency towards the end of network.

Activation dimension is expanded in network filters to

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reduce the size of grid significantly. So practically a (d*d) grid with k filters became (d/2)*(d/2) with 2k filters. Two parallel convolution blocks and pooling blocks are concatenated later to achieve this.

B. Architecture of InceptionV3 [13]

Inception v3 model consists of 42 deep layers consisting of Convolution, Pooling, padding, which provide very high accuracy to the model. Here the output size of one layer is input to another layer.

Table I: Layer wise description of the architecture is as follows:

Layer	**Stride**	**i/p size**
Convolution	3*3/2	299*299*3
Convolution	3*3/1	149*149*32
Convolution padded	3*3/1	147*147*32
Pooling	3*3/2	147*147*64
Convolution	3*3/1	73*73*64
Convolution	3*3/2	71*71*80
Convolution	3*3/1	35*35*192
3*inception	Module 1	35*35*288
5*inception	Module 2	17*17*768
2*inception	Module 3	8*8*1280
Pooling	8*8	8*8*2048
Linear	Logits	1*1*2018
Softmax	Classifier	1*1*1000

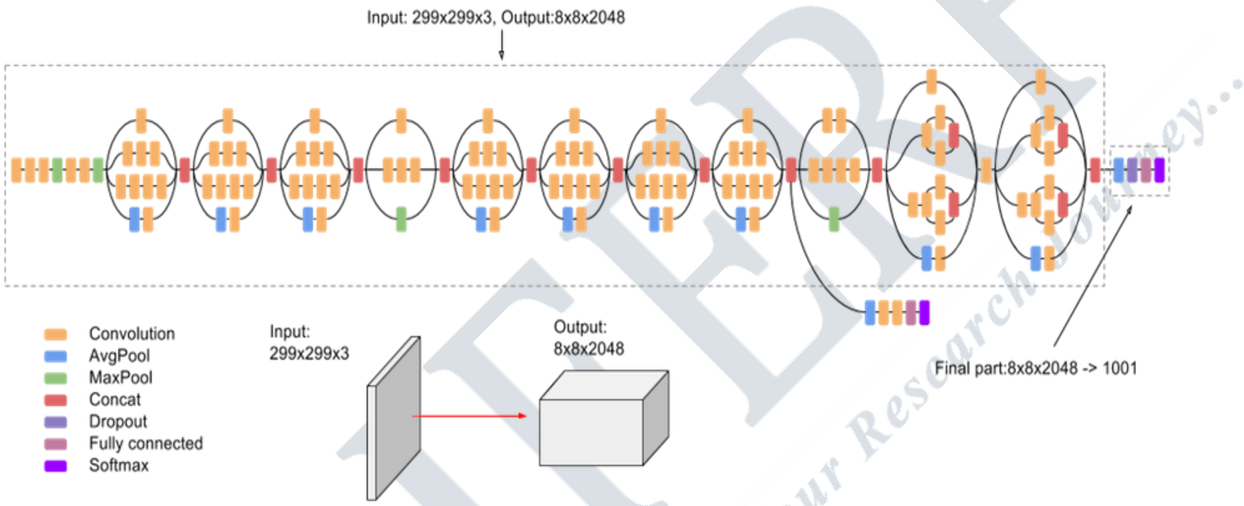


Figure 1. Model Architecture of InceptionV3

C. InceptionResNetV2 [14]

InceptionResNetv2 is a Convolutional Neural Network which is well trained on millions of images consisting of many categories such as birds, airplanes, electronic circuits and devices such as monitor, keyboard, mouse that's why this network is able to learn a lot of features for a variety of images. In this experiment we are using its learned weights to train our model for the classification of defected or Non-defected wafer. Furthermore we are comparing the results with other models.

Theimprovement in InceptionResNetV3 from its predecessor is that it uses the residual connections. Replacing the filter concatenation stage from original Inception architecture, it has provided improved Accuracy in classification tasks and reduced Losses with in the model.

III. IMPLEMENTATION

We have the image dataset of high quality PCB images straight from industry with us consisting of both defected and non-defected images. These images are divided in 3 parts as training, validation and testing set which are further sub divided into 2 parts as defected and non defected images. inceptionV3 model [13] is used as pre-trained model to train and predict while using the available images as input to the model and weights used are imagenet weights. The top layer was removed from the training process as it is different for our test case. The architecture is imported from tensorflow library from applications and used within the model.

An object is created from the inceptionv3 and inceptionresnetv3 imported algorithm in which we have fed the input size and weights, further top layer was removed from training then Flatten and Dense layers were added for further processing. Because it is a **binary classification** problem '**sigmoid'** activation function was used with the last dense layer consisting of only one neuron for class prediction.

Parameter summary: InceptionV3

Parameters	**Number**	**Size**
Total parameters	22109990	84.34MB
Trainable params	307206	1.17MB
Non-trainable	21802784	83.17 MB

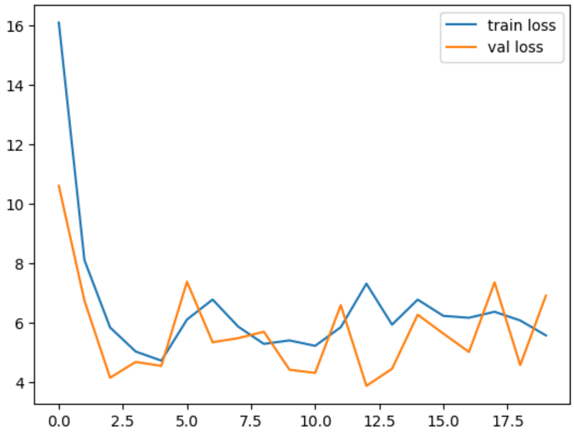
Parameter summary: InceptionResNetV2

Parameters	Number	Size
Total parameters	54567142	208.16MB
Trainable params	230406	900.02KB
Non-trainable	54336736	207.28MB

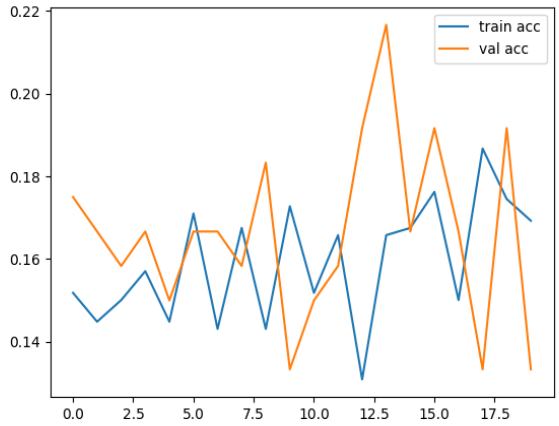
The dataset was used to train the 2 models using the above 2 Algorithms but both of these models gave very poor performance in terms of Accuracy and Losses. The results are as given below:

Loss and Accuracy Curves: InceptionV3

Loss

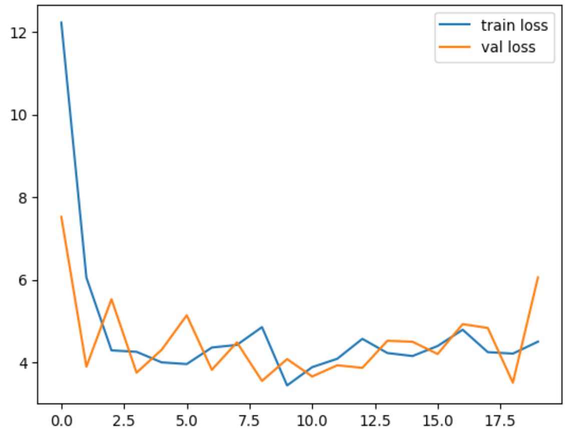


Accuracy (%)

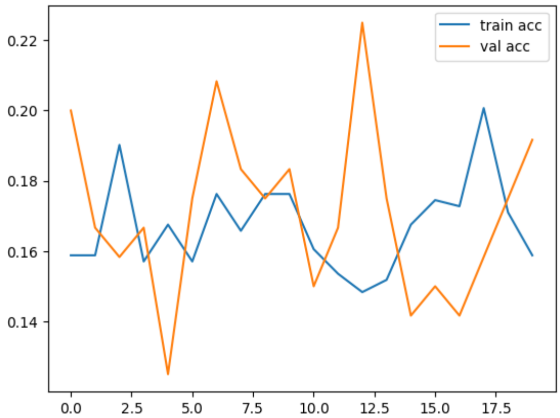


Loss and Accuracy Curves:InceptionResNetV2

Loss



Accuracy (%)



IV. PROPOSED MODEL: PUNEETNET

PuneetNet is designed to come over the shortcomings of the said above model and provide a better solution of the industry problem. It addresses each and every issue of the InceptionNet algorithm and performs as per the expectation of Electronic manufacturing industry. The different number of layers selected after number of many permutations and combinations with the layers and their other parameters like number of neurons, optimizer, loss function, performance matrices etc. after many trail runs a particular set of layers consisting of multiple trainable and non trainable parameters selected for finalizing the model which is responsible for the best possible accuracy in the said problem.

Salient Features of PuneetNet:

- High Efficiency
- Excellent performance
- Very less bulky
- Easy to train
- Computations are easy
- Regularization is achieved through auxiliary classifiers
- Not so deep in neural network
- Speed is better
- Factorization into small convolutions
- Converting spatial factorization to asymmetrical convolution
- Reduction in grid size

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Architecture of PuneetNet:

```
Layer (type)                Output Shape              Param #
=================================================================
conv2d (Conv2D)             (None, 224, 224, 32)      2432

batch_normalization (Batch  (None, 224, 224, 32)      128
Normalization)

conv2d_1 (Conv2D)           (None, 224, 224, 64)      51264

dropout (Dropout)           (None, 224, 224, 64)      0

conv2d_2 (Conv2D)           (None, 224, 224, 96)      55392

batch_normalization_1 (Bat  (None, 224, 224, 96)      384
chNormalization)

flatten (Flatten)           (None, 4816896)           0

dense (Dense)               (None, 80)                385351760

dropout_1 (Dropout)         (None, 80)                0

dense_1 (Dense)             (None, 96)                7776

dense_2 (Dense)             (None, 2)                 194
```

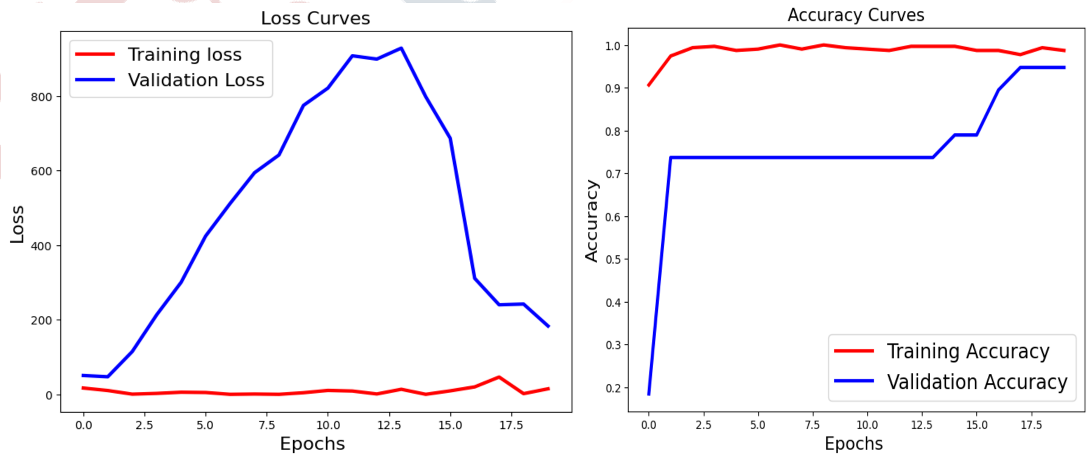
Parameter summary: PuneetNet

Parameters	Number	Size
Total parameters	385469330	1.44GB
Trainable params	385469074	1.44GB
Non-trainable	256	1KB

A. DropOut

Dropout Layers are used in between the convolution and dense layers to bring down the number of nonperforming or less performing neurons so only the most efficient neurons get to participate in the computation process. This step gives a boost to the processing speed in order to improve the overall efficiency of the model.

Loss and Accuracy Curves: PuneetNet



Comparison Table

Algorithm	Loss	Accuracy(%)
InceptionV3	6.9	13.33
InceptionResNetv2	6.0	19.17
PuneetNet	**1.7**	**94.74**

B. Data preprocessing

In the available dataset the size of images was different from each other so size of each image was brought to the same pixel so as to process smoothly. All the images were converted into same size to introduce uniformity into the process.

C. Data Augmentation

The more number of training images we have the better will be the training of model. So our model will be able to predict the class accurately. So in order to increase the training images we have implemented image data augmentation technique where we have made more images from existing images by applying angle rotation, zooming in, zooming out, horizontal and vertical flip etc. by applying these operation we have created many images from single images.

D. Image Data Generator

Image data generator was used in this model to rescale all the images from different sizes into similar size in order to get the best normalization of data. Dividing all the images by 255 brings the pixel size in between 0 and 1. This helps in bringing down the volume of computation and makes the calculation super fast.

Compilation

Optimizer	Adam (learning rate = 0.001)
Metrics	Binary accuracy
Loss function	Binary crossentropy

V. CONCLUSION

As shown in the results we have achieved 94.74% Accuracy from the proposed model. Further, loss is also minimum which is 1.7. PuneetNet has been the best model for accurate classification and prediction of defective and non-defective PCB images. This model can be installed in the production facility where quality control and inspection work is carried out. A high quality camera can be installed at the facility which can be connected to the system. The image taken by the camera will be fed into the model and compared with the trained images further based on the image patterns it will show if the particular PCB is defected or not. The developed model is very accurate as shown by testing image data and is very helpful in accurately make right prediction therefore bringing more transparency and less testing time for wafer inspection.

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