Deep Learning Based Ceramic Tile Defect Recognition

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We hereby declare that this project has been done by us under the supervision of **Md. Tarek Habib, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The global market for ceramic tiles industry is highly competitive nowadays. Quality control in the production process in the ceramic tile industry has been a key factor for retaining existence in such a competitive market. Deep learning-based ceramic tile inspection systems are very useful in this respect because the manual inspection is time-consuming and not accurate enough. Hence, deep learning can help ceramic tile inspection system faster and accurate. Two difficult problems are mainly posed by deep learning-based ceramic tile inspection systems. They are defect detection and defect detection classification. Even though there has been plenty of research addressing the defect detection problem, the research aiming at solving the classification problem is scarce. Moreover, in this research, we used two models to compare with our proposed variation CNN model to find out which is the better one to identify defect detection. We have found four types of defected tiles including multi-label defected tiles. In this research, first we used VGG-16 for training and we got 54% accuracy which was not good enough. Then we tried another model for training, Inception-v3 gave us an optimistic result on training dataset which was 95%. Then we have used our proposed CNN model on the tiles dataset and we got 96% accuracy for training datasets of images. Even though Inceptionv3 has better accuracy on training datasets but for testing datasets, it gives a poor result of 33%, On the other hand with our proposed variation of CNN model we can identify defected tiles by 91%. Finally, this thesis paper focuses and proposes technical aspects of tiles defect detection in a faster and easier way by comparing our proposed variation of the CNN model with other pre-trained models.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Ceramic tiles industry has become more popular than ever before. Industries those who are manufacturing ceramic tiles, they always intend to provide the best product with short period of time and lower cost. Their production stages are technically handled; however, the manufactured products quality is to be maintained and sorted out manually. They ensure the product quality by inspecting each product manually. As their defect identification process is not automatic, so it takes a lot of time and cost also increases. As this field is highly competitive so they cannot compromise with their product quality. To ensure the product quality and solve defect detection faster some work has been done before.

One work has been done with the complication of self-regulating observation of ceramic tiles by implementing computer vision [3]. This process has applied tactics for pinhole and crack identifier for plane tiles established on a set of various line filters, Moreover, Surface tile crack identifying process is based on wigner distribution along with a novel mixed spatial frequency depiction of texture. In here, a color texture for tile defect identification algorithm is used to identify the defects by spectating the dissimilarities for both in color and structural composition of tiles. Nevertheless, various filtering tactics for different sorts of defects provides a poor quality outcome. The reason behind this is it took a high runtime and they have only worked with two types of defects .Another one was [10] by Rashmi Mishra which was to identify defects by using image processing and techniques in tiles, which requires high resolution image. The plan of action is quite similar. An automated system where the defects are to be found by investigating the images by visually inspect them, however their outcome accuracy was not determined.

Deep learning is one the most increasing areas in Computer Science. In this process first we will accumulate the images and then augment them by resizing and reshaping them. Afterwards we will divide them into separate classes including defected and non-defected images. After completion of classifying them into separate classes then we can differentiate the defected classes from the non-defected class of tiles. We can get all kinds of defected images name separately according to their classes, hence so forth our main objective of the assessment is to identify the defected images.

Classification procedure must be Capable of success, in a fair and impartial manner what's more, more than once, with proper speed and cheap. It must be able to adjust independently to adjust into materials. The procedures utilized range from Pinhole, Crack, Chipset and Iron calculations for floor and wall tiles. The introduced examination strategies have been actualized and tried on various tiles utilizing engineered and genuine imperfections. The outcomes recommended that the presentation is sufficient to give a premise to a reasonable business visual assessment framework which we will see it in the next segments. We for the most part have discovered all out eight kinds of surrenders from the current imperfection identification strategies. These sorts of imperfections are appeared in the accompanying Table 1.1.

TABLE 1.1 TYPE OF CERAMIC TILES DEFECT

Name of defect	Description
Chipped	Side of the tiles get chipped
Crack	Fracture of tiles
Pin hole	glaze surface of a tile
Iron	Discontinue of color sometimes black spot visible

The defected images are shown in following figure:

Figure 1.1.1: pinhole

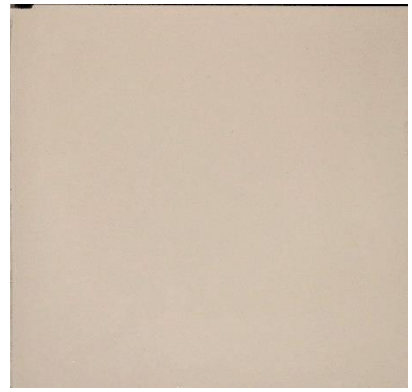


Figure 1.1.2: Chipping

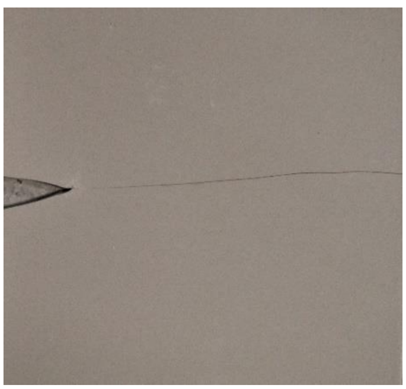


Figure 1.1.3: Crack

Figure 1.1.4: Iron

1.2 Inspiration of this study

In Ceramic Tiles Industry workers always have to work manually to find defects in tiles. Which can occur a lot of problems, they are as follows:

- As they are manually finding out defects by their own eyes there is a high possibility of error. However, machine can do this work without any error with proficiency.
- Secondly, in ceramic tiles factory there is a lot of products and checking them manually can really be tiresome, which can cause the office worker dizzy sometimes. It always happens if someone is doing same kind of work iteratively. However, a machine can do an iterative work with higher accuracy and faster as always, because machine do not get tired by doing a lot of work.
- Workers in tile industry can always make errors during the checking of product, on the other hand machines error rate is fixed.
- Finally, to detect defects of tiles in ceramic tiles industry, they need more workers and it is a matter of cost but machine can reduce the cost of it.

1.3 Fundamental principle of the study

The main principle for this thesis are as follows

- Automatic system always makes the system easy to use and also gives the most effective results from manual system. Manual system can't give the proper results and take much time. On the other side automatic system gives properly accurate result and save the time to show the results.
- Workers will lost their energy and will become tired if they work for a long period of time except machine. A machine can't be tired. They can accomplish their work at same speed from beginning to end.
- If we intend to increase our accuracy we have to use a machine to calculate. Machine will help us to amplify the prediction of the system but if we use manual

system in case of machine to calculate the accuracy then we will never get the proper results and it will decrease our accuracy of the system.

1.4 Research Questions

This paper is worried about the issue of programmed examination of artistic tiles utilizing Computer vision. It has been noticed that the location of deformities in finished tiles is a significant territory of programmed mechanical examination that has been generally neglected by the ongoing influx of research in machine vision applications. At first, we diagram the advantages to the tile producing industry. This is trailed by a categorization of run of the mill tile absconds. Next, we audit various systems as of late created to identify different sorts of imperfections in plain and finished tiles.

RQ: How to detect the defected images?

RQ2: Which model is best suited to identify the defected tiles images?

1.5 Expected Output

- Deep learning approach that successfully recognize defect at a higher rate.
- Can detect various types of defects effectively
- A large data set of images of defective ceramic tiles can provide a better outcome to recognize the defected tiles.

1.6 Layout of Report

Our thesis report is organized as follows:

- Chapter One includes introduction to our project, motivation, research questions, and expected outcome.
- Chapter Two includes “Background”, related works, research summary, and challenges.
- Chapter Three includes Research Methodology.
- Chapter Four includes Experimental Results and Discussion.
- Chapter five includes Summary and Conclusion.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

To gain some perspective on the research field and its main challenges, a literature survey is performed on image defect detection based on image classification. This process can be seedless and effective. Moreover, detecting defect have become a new industrial utilization of computing technologies.

2.2 Related Works

Programmed assessment and imperfection discovery utilizing picture handling is a territory of machine vision that is as a rule generally embraced in numerous ventures. It is utilized for high throughput quality control underway frameworks, for example, the identification of imperfections on produced surfaces.

There are some related work in this field such as color correction, surface defect detection etc.

There are several works have done comparing with our research. Ehsan Golkar (2011) [6] , in journal of American science, identify border defect detection using automated visual inspection system.N.Sameer Ahamad and J.Bhaskara Rao(2016) proposed a morphological operation using computer vision for tiles image defect detection. In June 2012 [18], Masci has solved steel defect with classification method.

2.3 Challenges

There are many challenges we faced during this process. The main challenge for our thesis was not only a huge number of data collection but also to make sure that the data is in its purest form. It was challenging to collect data because no company would like to give their dataset for work, due to security issue. However, we get to connect with the Great Wall Ceramic Industry and collected our desired data. After collecting the dataset labelling those datasets was another challenge. Then after labelling the images we needed to find an optimum model to identify the images. We had to go through in various techniques and apply different algorithms to get the best outcome which is quite challenging enough.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

In this section, we will discuss the research subject and instrumentation, data collection procedure,data processing, proposed methodology, statistical analysis, and implementation requirements. Firstly, in the research subject and instrumentation, we will discuss our topic. In the data collection procedure, we have discussed how we collected our data. Next, in the data processing part, we have discussed how we pre-processed it for our model. Then in the proposed methodology, we briefly addressed the algorithms and methodology that were used for this classification. Consequently, in the statistical analysis, we highlighted a few statistical methods and flow charts of the project. Finally, the chapter is closed by a clear concept about what we used for the project.

3.2 Research Subject and Instrumentation

This undertaking expects to make a visual framework that is fit for identifying the floor and wall tiles. In this process, we used inceptionv3 model [17] by Christian Szegedy to identify the defected images. In this case as the testing results were lowers so then we used VGG16 model [16] by Karen Simonyan to identify the defected images. However, in VGG16 model the accuracy was too low. So we modified a new Convolutional neural network model to identify defected images and which gives us a magnificent output. Procedures of applying these model are demonstrated in the following flowchart:

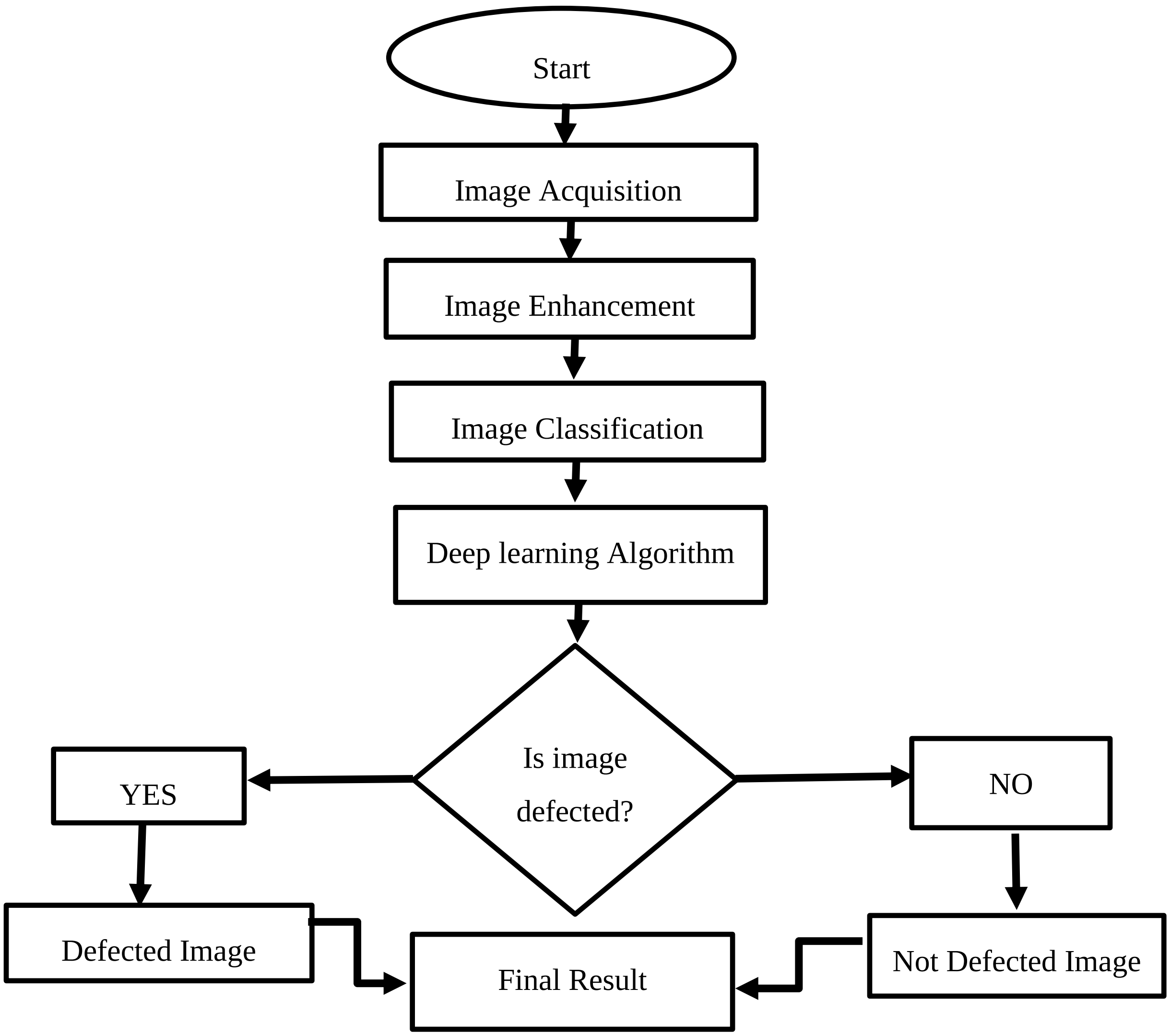


Figure 3.2.1: Strategy of Work

3.3 Data Collection Procedure

Image collection is the way toward acquiring a digitalized picture from a true source. In the collection procedure each step may present irregular alteration into the estimations of pixels in the picture which is alluded to as commotion. We went to Ceramic Tile Factories for collecting images. A picture of ceramic tiles is caught and we have saved it for further handling.

In this manner, we get new pictures that contain the wall tiles and floor tiles imperfection just to make simpler for the distinguishing procedure.

3.4 Data Preprocessing

The ceramic tiles data have been collected through camera. The datasets that we have were incompetent to use in algorithm. For this first we have to edit those images by using Adobe Photoshop. Then to resize it and make it fit to our algorithm we used Image data generator to augment those images. The augmentation procedure are as follows for each algorithm:

1. Proposed Variation of CNN: We used shape of 256 height, 256 width and 3 channels to get the best outcome for this algorithm.

2. VGG16 Network: In this process we used similar shape of our previous model with .2 extra zooming.

3. Inception v3: Finally in inception v3 we used 299 height and 299 width for best outcome.

3.5 Proposed Methodology

3.6 Methodology

Predicting defected images of tiles can be done in many different ways. For our thesis, we choose two pre-trained models Vgg16 and InceptionV3 and hence, we used our own proposed variation of CNN model to predict the images. In this process, first we preprocess the dataset of defected tiles. After that, we split our dataset into two-part, training and testing part. For training and testing, we have used all of three algorithms step by step. Following figure 6 explain about our methodology used in our research.

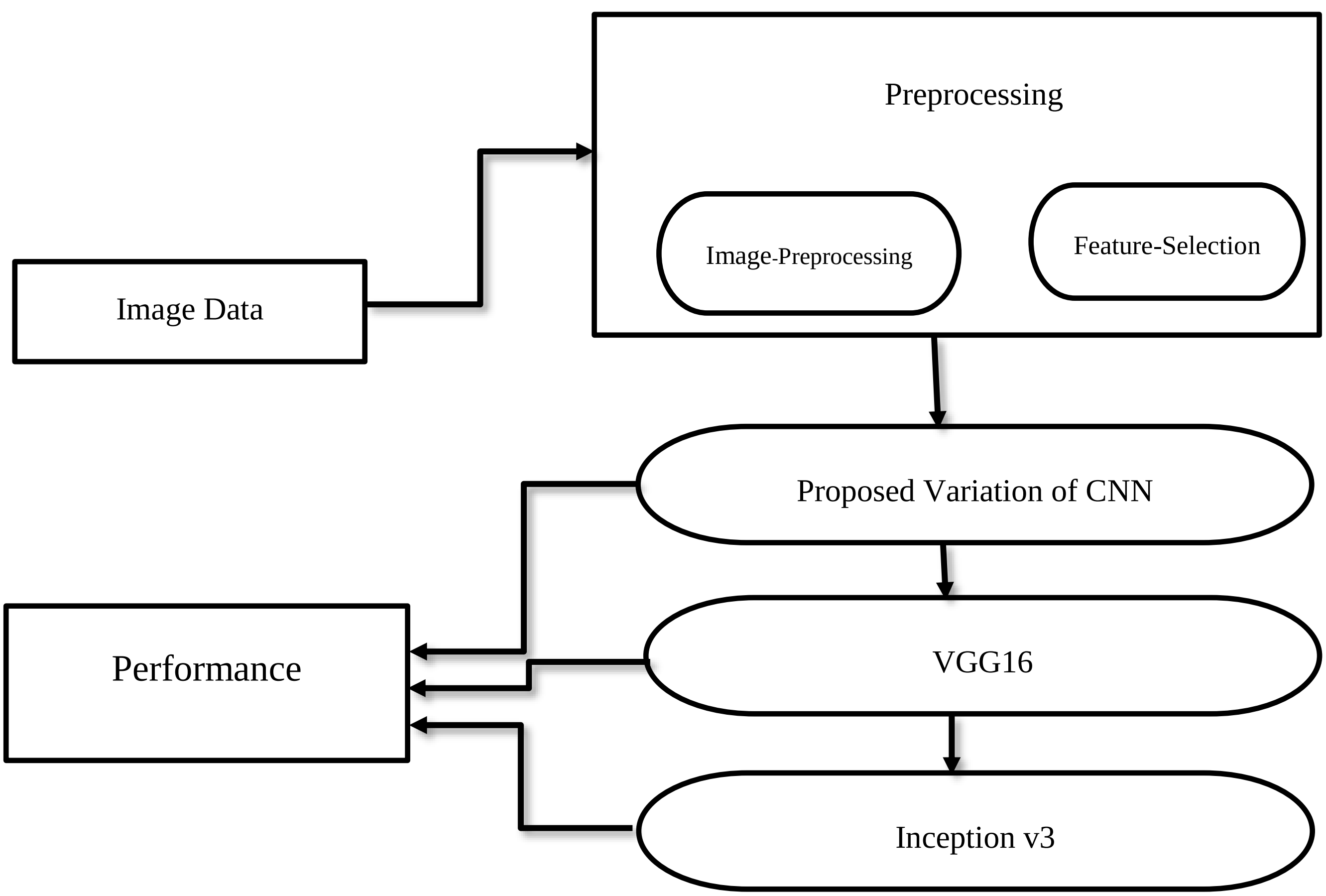
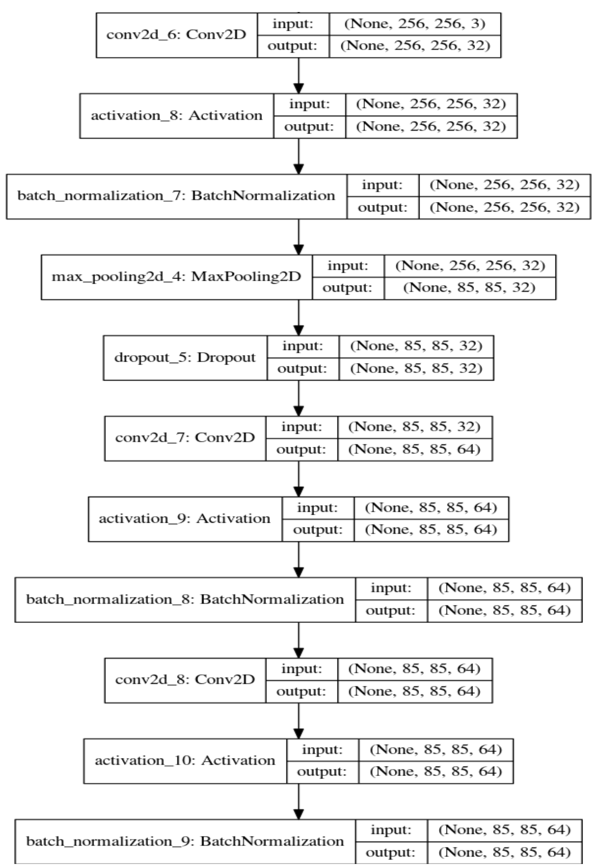


Figure 3.6.1: Methodology of Research

3.7 Deep learning Algorithms

Proposed Variation of Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm where it takes images as input from which it can comprehend its weights and biases for different aspects in the image and capable of differentiating them from one another. In ConvNet the data pre-processing is lesser and easier than other classification methods. In contrast, ConvNet has the ability to learn the images of characteristics and differentiate one from the other. As our images defects of pinhole which are similar to a dot, so we used lower strides so that our neurons can detect it and differentiate this image from the other. And as for chipped defects we have used padding so that the edges can be identified easily. Our proposed variation of CNN neural network layers and parameters are given below:



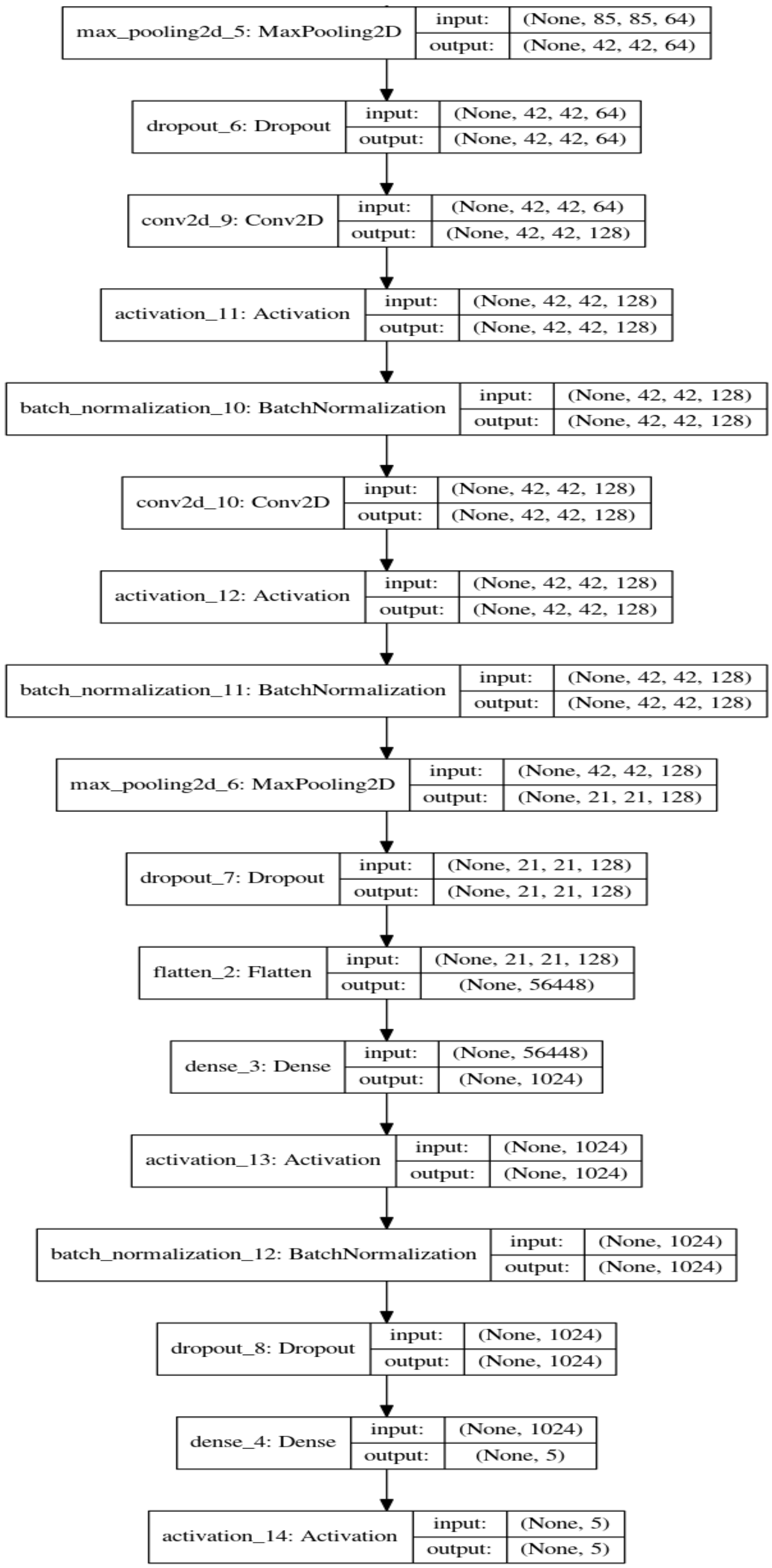


Figure 3.7.1: Output Parameters of CNN Model

VGG16 Model

The VGG-16 Model was trained on the ImageNet database. As this model was trained extensively, it can provide magnificent accuracy even if the image data sets are small. This model has 16 convolution layers and it uses kernel size of 3*3 .The model has three fully connected layers. For final layer activation function SoftMax is used. And Rectifier Linear Unit known as ReLu activation function is used to all hidden layers.

VGG-16 model has lots of hidden layers and parameters. For extensive layers and parameters the model is fit for many classification method but in our case it gives a poor accuracy.

The schematic of the VGG-16 is illustrated below:

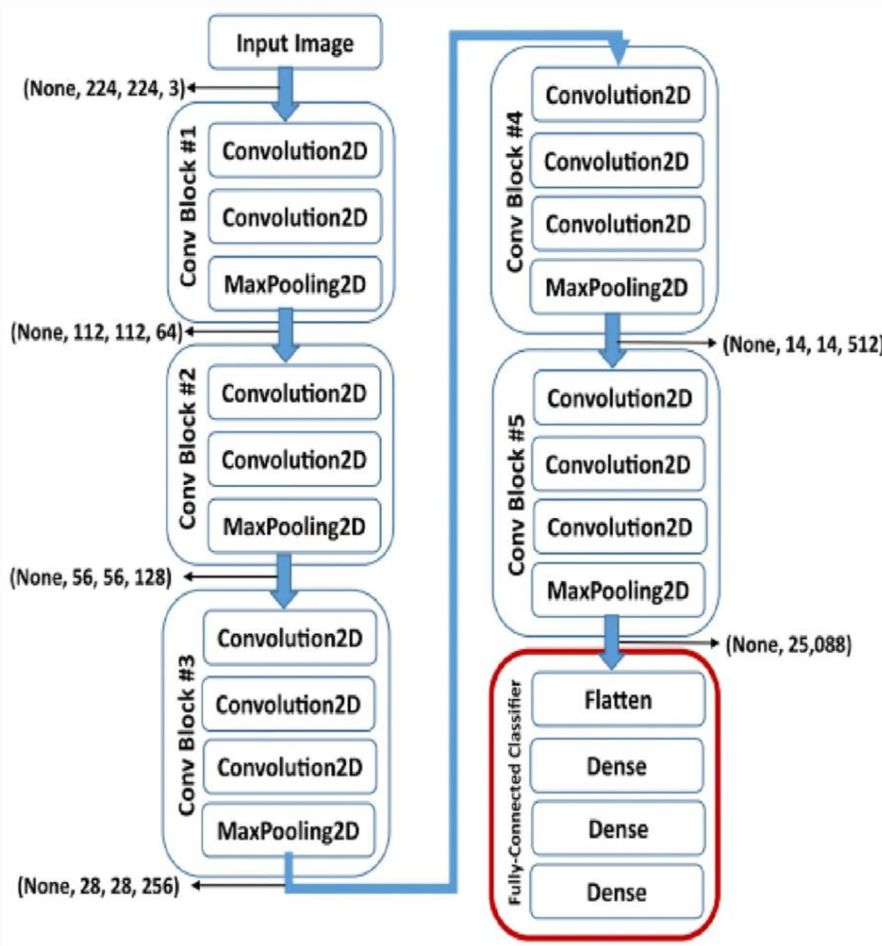


Figure 3.7.2: Vgg16 model

Inceptionv3

Inceptionv3 is a Convolutional neural network for assisting in image analysis and object detection and got its start as a module for Google net. It can give best performance with image shape of 299,299. So, we changed our image shape into height of 299 and width of 299. This model has a lot of neural networks. In here in each neural network activation function rectifier linear unit is used which is known as Relu activation function. And for output we used Softmax.

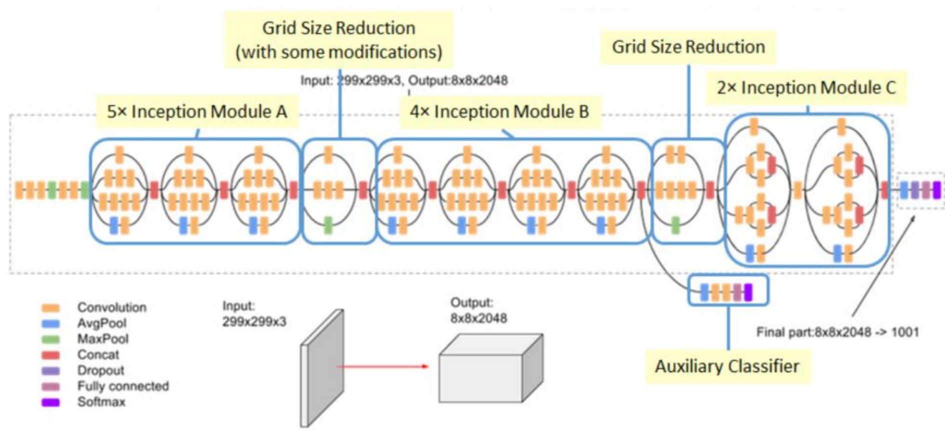


Figure 3.7.3: Inception-v3 Architecture

In this process, First, The preprocessed images should be put into the neural networks for image analysis. After learning the images into the neural networks it can classify the images from defected images from the non-defected images.

3.8 Testing procedure

The testing procedure for tiles defect detection is to use activation function in this model. The activation function will give out the optimistic result of finding the defected tiles from non-defected tiles. The flowchart of testing strategies for defected tiles framework is illustrated below:

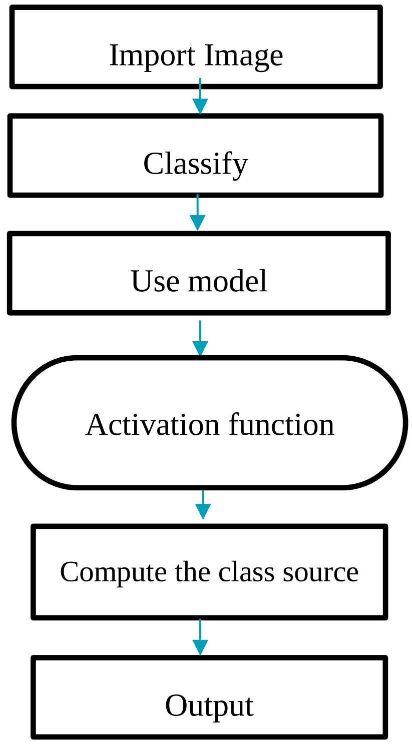


Figure 3.8.1: Testing Strategy

3.9 Data Visualization Plot

Inceptionv3

By using inception v3 model the accuracy for identifying images from each class was certainly high which was 95%. However, to test this defected data from test dataset it gives us a poor accuracy of 33% which explains that among 3 images it can identify one which was extremely poor.

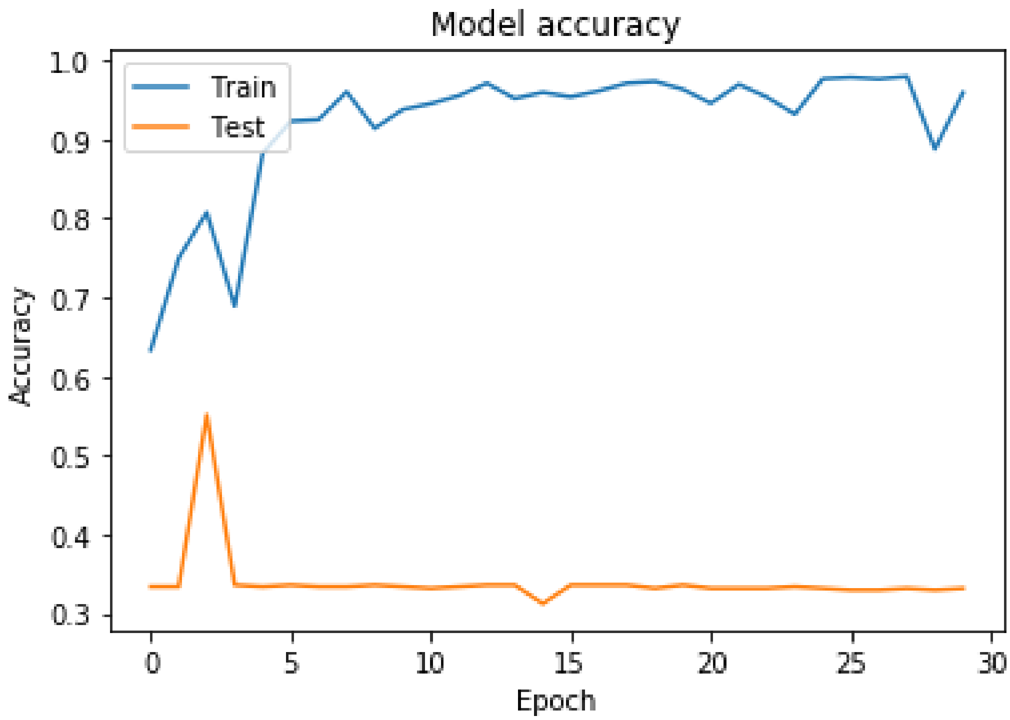


Figure 3.9.1: Model accuracy of Inceptionv3

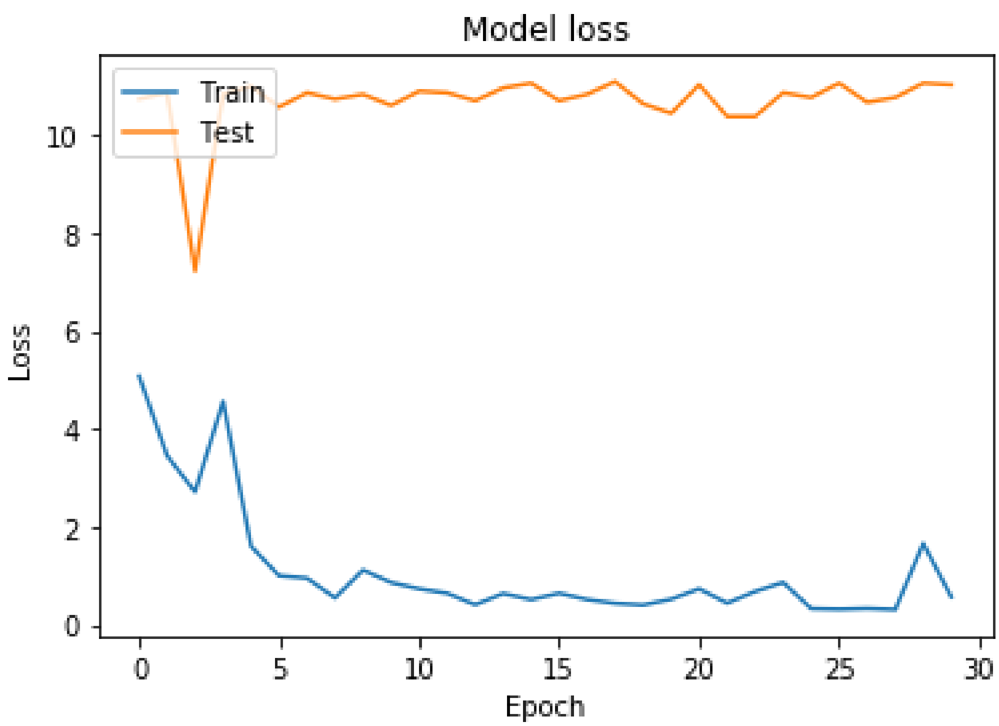


Figure 3.9.2: Model loss of Inceptionv3

Vgg16 Network

Vgg16 model is well known for classifying images. But in our case, it gives us a poor accuracy of 55% as for test data it gives us accuracy around 33%. As the accuracy was low so the loss was higher too.

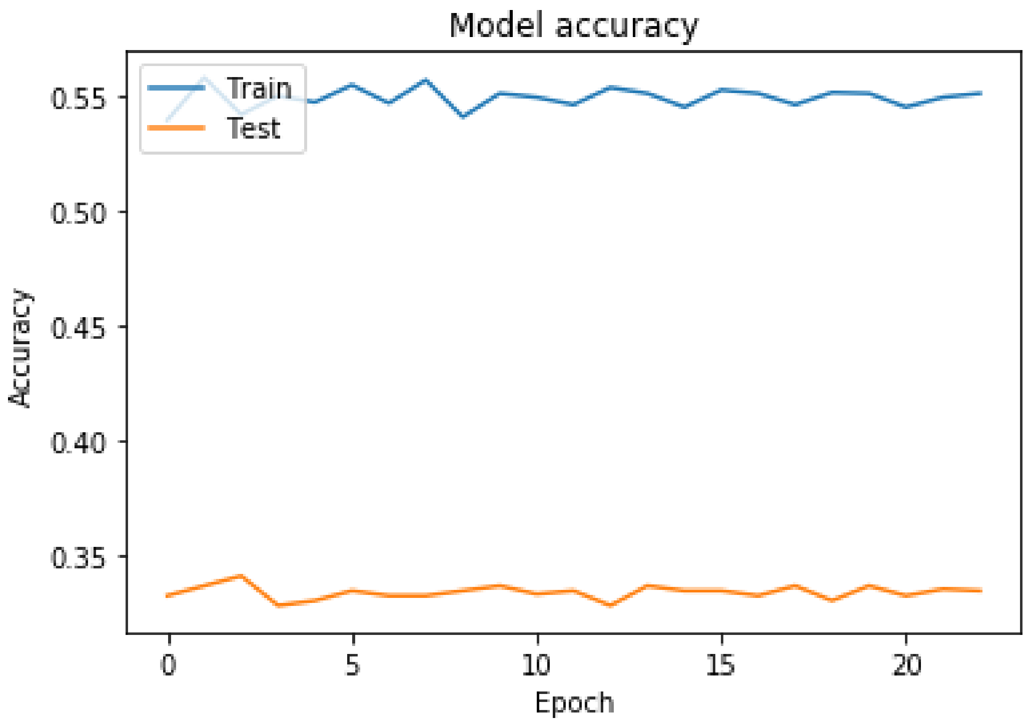


Figure 3.9.3: Model accuracy of Vgg16 Network

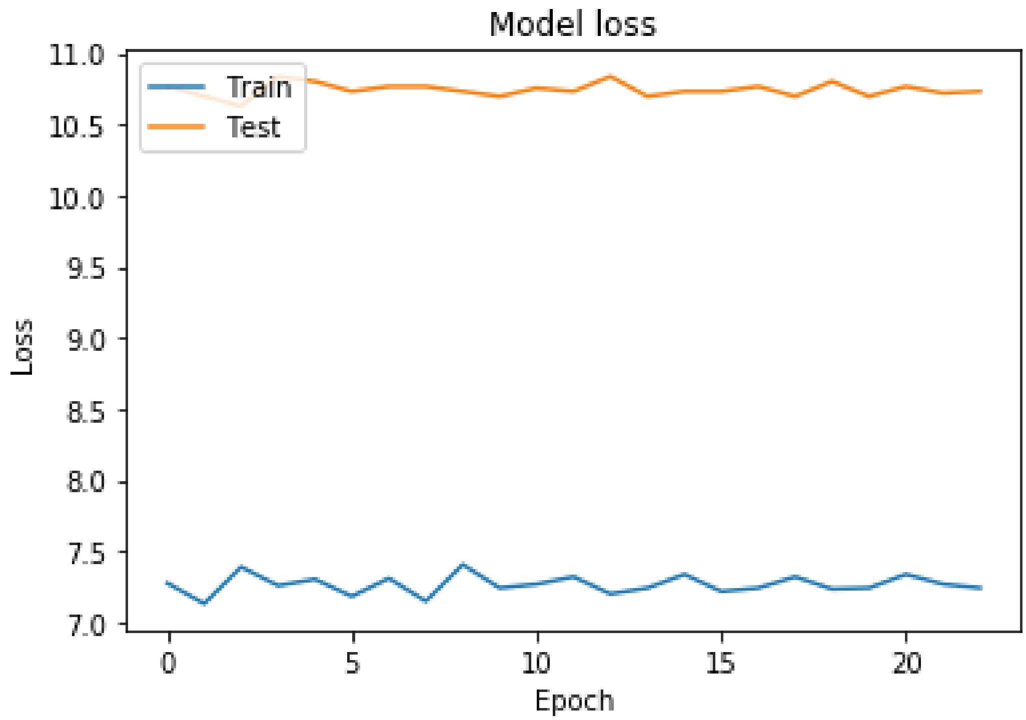


Figure 3.9.4: Model loss of Vgg16 Network

Proposed Variation of CNN

In this model we used lower strides of pixels in each convolutional neural network which helps the neural network to comprehend the image data better. We got accuracy of 96% for training dataset and as for testing data we got accuracy of 91% Instead of categorical cross entropy we have used binary cross entropy for loss as we are having multi class image data which helped us to decrease the loss and increase the accuracy for both training and testing dataset.

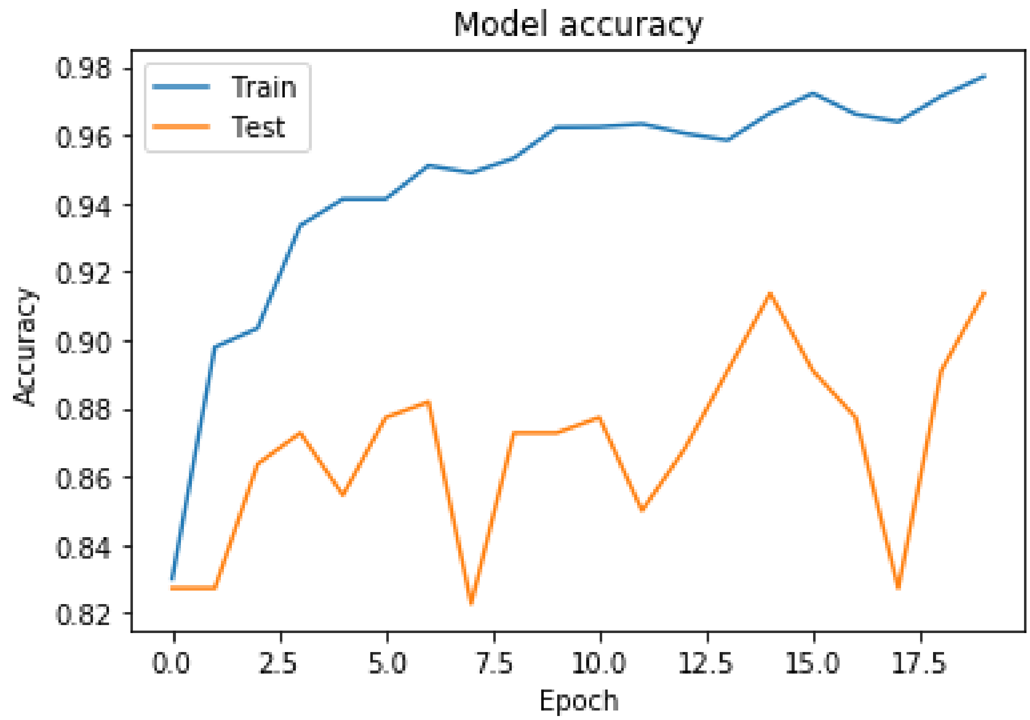


Figure 3.9.5: Model accuracy of proposed variation of CNN

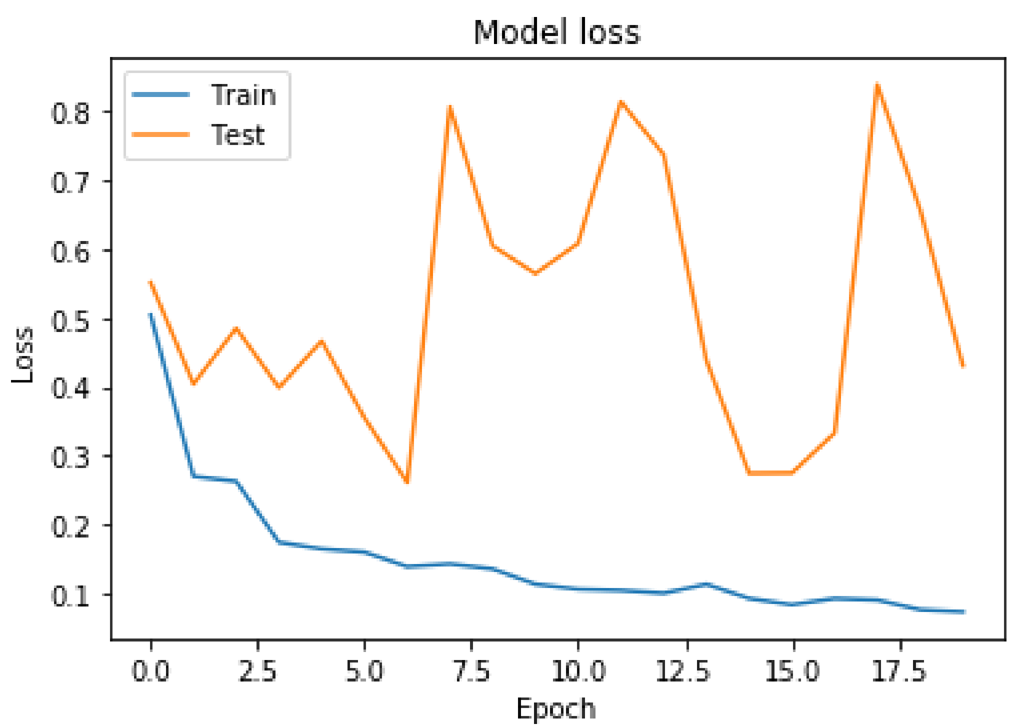


Figure 3.9.6: Model loss of proposed variation of CNN

3.10 Implementation Requirements

The ceramic tiles have been caught through the online camera hung hanging in the balance generation at the industry. So as to improve the proficiency of the activity, a progression of coordinated picture handling will be led ahead of time to encourage the learning of the deep learning model. There are three models been used in tiles datasets to detect the defects of tiles. Among them two of the models were pre-trained models which were vgg16 with and another was raw modified convolutional neural network.

After reviewing all the necessary statistical or theoretical concepts and methods, we created a list of Hardware, Software and developing tools we need for predicting defects of tiles. The probable necessary things are:

Hardware/Software Requirements

- Operating System (Windows 7 or above)
- Ram (more than 8 GB)
- Web Browser (preferably chrome)
- GPU Nvidiagtx1050ti

Developing Tools

- Python 3.7
- Anaconda
- Jupyter notebook
- Tensorflow
- Keras
- Pandas
- Sklearn

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Introduction

This part will delineate the processes that has been created and a portion of the outcomes discovered during test runs. Among three of the models, our model was best suited for image defect detection as it gives better understanding in image identification for both training and testing results. Most choices depended on straightforward visual examination of results as it was difficult to utilize any scientific exhibition number.

The final model has been created by the image type. As the size of the defects were small so we had to train our model to identify them from each pixels. We were successive to do this by increasing the layers of neurons and lowering the strides per pixels.

4.2 Experimental Results

Proposed Variation of Convolutional Neural Network To measure the effectiveness and accuracy of the algorithms we run the proposed variation of neural network model consisting of maximum height of 256, width of 256 and channel of 3 with batch size of 10. Then we divide the dataset into training (70%), and test (30%) subsets.
We got the following result after 20 epochs.

Loss: 0.1043

Accuracy: 0.9689

Validation loss: 0.4306

Validation accuracy: 0.9136

VGG16 Network To measure the effectiveness and accuracy of the algorithms we run the Neural Network model consisting of maximum height of 256, width of 256 and channel of 3 with batch size of 10. We divide the dataset into training (70%), and test (30%) subsets. We got the following result after 20 epochs,

Loss: 7.3122

Accuracy: 0.5463

Validation loss: 10.3640

Validation accuracy: 0.3570

Inceptionv3 To measure the effectiveness and accuracy of the algorithms we run the Neural Network model consisting of maximum height of 299, width of 299 and channel of 3 with batch size of 10. We divide the dataset into training (70%), and test (30%) subsets. We got the following result after 20 epochs,

Loss: 0.7283

Accuracy: 0.9594

Validation loss: 11.0284

Validation accuracy: 0.3319

TABLE 4.1 LOSS AND ACCURACY TABLE

model	Loss	Accuracy	Validation loss	Validation Accuracy
Proposed variation of CNN	0.1043	96%	0.4306	91%
VGG16	0.73122	54%	10.3640	35%
Inception_v3	0.7283	95%	11.0284	33%

4.3 Descriptive Analysis

The examples of Non-defected images and defected images are the preparation datasets for CNN.

We have pre-processed and augmented the dataset so that our CNN function can work admirably. For each categories we have added different parameters and took necessary steps so that our model could easily differentiate the defected tiles from non-defected ones. Kernel size and padding and all setups for neural network creates a clear perception of dataset for machine to learn and classify the images.

4.4 Summary

In enterprises, gathering preparing dataset is normally expensive and related techniques are exceptionally dataset-subordinate. So most organizations can't give Big-information to be broke down or registered. For this reason, the acknowledgment precision can be clearly enhanced as expanding information growth. It implies, it will be a decent answer for tackle the issue of little dataset later on. To summarize, the improvement of an AI based keen imperfection location framework will add to mechanical advancement, industry, national advancement and different applications

CHAPTER 5

SUMMARY AND CONCLUSION

5.1 Summary of the Study

Ceramic Tile Industry is developing to become one of the key bits of the entire society as we probably are aware of it. It is used in buildings, shops and to build many other things. In this paper, we have proposed a model established on deep learning and artificial intelligence, so that we can identify and differentiate the defected tiles from non-defected tiles.

This methodology starts with recovering pictures from the tried castings. By using convolutional neural network we can identify the defected images. We assessed our methodology as far as inclusion of the proposed division strategy and exactness of the categorization of the areas. The outcome appeared that, though our accuracy in categorization is extremely high, the inclusion of the framework ought to be improved.

As in industry level, workers are currently using their own eyes to identify the defects, with this model even with a normal camera can identify the defects which is low cost and faster.

5.2 Conclusion

Our main goal was to build a model that helps identify the defected images by comparing the models. We choose our proposed variation of convolutional neural network as deep learning approach to predict the images. In this research, we achieved an accuracy of 96% for our testing datasets, which means almost all the images which are in validation can be detected properly. Our results suggest that our model with has an effective marking solution and deserves further exploration.

5.3 Recommendation

There are some recommendations for this image identification such are:

- Try to clean the dataset and augment them properly.
- Bigger datasets can provide higher accuracy.

5.4 Implication for Further Study

Few Implications that are possible in further study using this tiles images are:

1. We can use Generative Adversarial Network in this datasets of images which can help use to build fake images. By doing so, we can make newer designs of tiles by combining some tiles images.
2. By Using R-cnn or convolutional Rnn can be a new approach for detecting tiles defect detection.

APPENDICES

Appendix A: Research Reflections

To our work, many work has been done previously for defect detection on ceramic tile. However, no work has been done to identify the defects of ceramic tile using deep learning. Our very kind supervisor help us to work through this problem and help us to go through every possible problem. Throughout our research, we have achieved a lot of knowledge. Our research was not only about applying algorithms and method we also needed to learn and analyze data and modifying algorithms according to datasets perspective.

Appendix B: Related Issues

In the beginning of our research, we didn’t have any datasets and no hands on experience with image defect identification on deep learning. We took time to learn Keras and Tensorflow for this. First, we have practiced on various datasets. Then we started working with the main dataset to see our expected outcomes.

What we have learned so far from this research, that for each work, first, we need to ready our dataset and analyze it. After analyzing, we need to try out various algorithms according to previous work that has been done to similar types of datasets. Finally, we can go with the best procedure and do modification for best output.

REFERENCES

[1] Vincent LEBRUN, “Quality Control of Ceramic Tiles by Machine Vision”, Flaw Master 3000, Surface Inspection Ltd. 2001.

[2] Richard Bridge, “Computer Image Processing”. Tessellate Support Services PLC, Oxon, England, Issue V1.R2.M0, June, 2003.

[3] C. Boukouvalas, J. Kittler, R. Mari, M. Mir Mehdi and M. Petrous, “Ceramic Tile Inspection for Color and Structural Defects”. I.E.E.E. Transactions on Pattern Analysis and Machine Intelligence, 14(1), March 1998.

[4] Song K Y, Petrous M, and Kittler J, “Texture crack detection”, Machine Vision Applications, to appear , Publisher: IEEE , January 1995.

[5] S. Faghih-Roohi, S. Hajizadeh, A. Núñez, R. Babuska and B. De Schutter, "Deep convolutional neural 282 networks for detection of rail surface defects," 2016 International Joint Conference on Neural Networks 283 (IJCNN), Vancouver, BC, 2016.

[6] C. Huang, D. Chen and X. Tang, "Implementation of Work piece Recognition and Location Based on 301 Opencv," 2015 8th International Symposium on Computational Intelligence and Design (ISCID), 302 Hangzhou, 2015.

[7] Dhananjay Theckedath and RR Sedhamkar, “Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks” 1 ,Article number: 79 ,2020.

[8] S. Kotsiantis, “Supervised Machine Learning: A Review of Classification Techniques,” in Proceeding of the 2007 conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Applications in health, HCI, Information Retrieval and Pervasive Technologies, 2007.

[9] Y. Singh, A. Kaur, and R. Malhotra, “Comparative analysis of regression and machine learning methods for predicting fault proneness models,” International Journal of Computer Applications in Technology, June 2009.

[10] Atul N. Shire ; M.M. Khanapurkar ; Rajashri S. Mundewadikar, “Plain Ceramic Tiles Surface Defect Detection Using Image Processing”, In IEEE Fourth International Conference on Emerging Trends in Engineering & Technology,2011.

[11] Deng J, et al. Imagenet: a large-scale hierarchical image database. In: IEEE conference on computer vision and pattern recognition, 2009. CVPR 2009. IEEE; 2009.

[12] Pal S. Transfer learning and fine tuning for cross domain image classification with Keras. GitHub: transfer learning and fine tuning for cross domain image classification with Keras; 2016.

[13] Gopalakrishnan K, et al.” Deep convolutional Neural Networks with transfer learning for computer vision-based data-driven pavement distress detection”. Constr Build Mater. (2017)

[14] Karim and Zaccone, “Deep Learning with TensorFlow”, Packt Publishing”. pp. Chapter 4,March 2018.

[15] C. Boukouvalas, J. Kittler, R. Marik, M. Mirmehdiand, M. Petrou, “Ceramic Tile Inspection for Color and Structural Defects”, under BRITE-EURAM, project no. BE5638, pp 6, University of Surrey, 2006.

[16] Karen Simonyan, Andrew Zisserman,”Very Deep Convolutional Networks for Large-Scale Image Recognition”, Computer Vision and Pattern Recognition, 10 April, 2015

[17] Christian Szegedy , Vincent Vanhoucke ,Sergey Ioffe , Jon Shlens , Zbigniew Wojna “Rethinking the Inception Architecture for Computer Vision by Christian Szegedy”. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Publisher; IEEE, (12 December 2016.

[18] Masci, J., Meier, U., Ciresan, D., Schmidhuber, J., Fricout, G.: Steel defect classification with max-pooling convolutional neural networks. In: Proc. of International Joint Conference on Neural Networks (IJCNN), pp. 1–6 June 2012.

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