International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8, Issue-1, May 2019

A Qualitative Analysis of Googlenet and Alexnet for Fabric Defect Detection

K.K. Sudha, P. Sujatha

***Abstract:** In this paper, the performance of Convolutional Neural Networks such as GoogleNet (Inception) and AlexNet are analyzed for the textile defect detection problem. The fabric images from 'Cotton Incorporated' database is used for this research work. The database images are converted to grey scale. The noises are removed from the grey scale image using Wiener filter. The noise free images are trained using GoogleNet and AlexNet to recognize new faults in the fabric. The identification of fabric fault by using GoogLeNet include image load, loading GoogLeNet network, loading pretrain network, freezing of the basic layers, and image validation. The steps in AlexNet for finding the fabric defects are image load, AlexNet network load, substitution of the final layers, training network, and image classification. According to the results of the experiment, GoogLeNet training on fabric defects is faster than that of AlexNet. The performance of GoogLeNet is the best outdoing than AlexNet on various parameter including time, accuracy, dropout, and the initial learning.*

***Index Terms:** GoogleNet, AlexNet, Convolutional Neural Network, ScaleRange, Dropout Ratio.*

I. INTRODUCTION

Every manufacturing process no matter how seamless its operation is deemed to be suffers from the possibility of defects on the finished product. Textile manufacturing is one of such areas were defects exists and is unwanted. With respect to textiles, there are two possible classifications of defects, namely major defects and minor defects. Major defects are defects that if conspicuous on the finished product could affect its salability or service ability [1]. While minor defects are defects that if present could cause a product to be rated as "second" or low quality. The primary means of textile inspection for defects is through human inspectors (Quality Control) who most times do not have sufficient training and rely on photographs of both minor and major defects in order to carry out their inspection [2]. The use of computers, diverse computer algorithms, artificial intelligence, deep learning, convolutional neural network, neural networks etc in the identification, detection and isolation of patterns, events etc, ensures that the process of defect detection in textile could be better managed and optimized. Convolutional neural network is one of the popular architectures in deep learning.

Revised Manuscript Received on 30 May 2019.

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Convolutional Neural Network refers to a special type of multilayer neural network whose design is intended to directly recognize the visual patterns in pixel images with preprocessing that is minimal. It is one of the major image recognition and image classification categories [3,4].

Object recognition and detections faces are some of the areas with a wide application of CNNs. CNN image classifications will process and classify an input image under particular categories (for example Cat, Lion, Dog, Tiger). Computers perceive an input image as entailing an array of pixels with consideration to the resolution of the image. It will see hxwxd based on the resolution of the image where h, w, and d represent height, width, and dimension respectively. For instance, a 6x6x3 image array of a matrix of RGB (where the 3 refer to the values of RGB) and a 4x4x1 image array of grayscale image matrix. Deep learning CNN models technically will train and test every input image which will go through several convolution layers with kernals (filters), pooling, and layers that are fully connected, followed by an application of the Softmax function for purposes of classifying an object with probabilistic values ranging between 0 and 1. The first layer that extracts characteristics from an image is the convolution layer [5]. It helps to preserve the relationship existing between pixels through learning images making use of small input data squares. It entails a mathematical operation which takes two inputs, a kernel or filter, and image matrix. Some of the operations that can be performed by image convolution with varying filters include edge detection, blur, and sharpen through the application of filters. Some of the popular CNN architectures include GoogLeNet, AlexNet, VGGNet, and ResNet. This paper is a comparative research between AlexNet and GoogLeNet to determine the better performing deep learning method for use in the detection of fabric defects.

II. LITERATURE REVIEW

The detection of fabric defect is an essential and necessary step when it comes to the control of quality within the textile manufacturing industry. Mei et al. [6] in their support for deep learning in the detection of fabric defects note that the traditional manual visual methods of inspecting fabric tend to be poor in precision and low in their efficiency for long-term industrial applications. They advocate for the employment of an automated learner-based approach that is unsupervised in the detection and localization of fabric defects without the need for manual intervention. The automatic approach that enables the reconstruction of image patches using a convolutional denoising autoencoder network at various levels of the Gaussian pyramid and a synthesis of the outcome of the detection from the respective resolution channels.

Each image patch's reconstruction schedule serves as an indicator for the prediction based on pixel. One can generate the final inspection outcome through a segmentation and synthesis of the residual reconstruction map at the various resolution levels. This paper outlines several benefits of using this method. The first one being that it is possible to train it using merely a few defect-free samples. This, according to them, is particularly crucial in situations where the collection of large defective sample portions of defect-free samples is hard and impractical. Second, given the multi-modal integration technique, it is relatively more accurate and robust compared to other methods of inspection. The third advantage according to the findings of their investigation, it can address different kinds of textile fabrics. They conducted an experiment to test their suggested model which yielded impressive overall performance characterized by high accuracy and acceptable recall rates.

Siegmund et al. [7] note that defect detection system is an integral component of the manufacturing process. It guarantees quality for the customers purchasing the fabrics. The three authors make a great contribution to the issue of fabric defect detection through deep learning. In their article, they explore deep neural network, a comprehensive method for the detection of two common groups of fabric defects. They observe that most of the existing detection systems require that textiles are spread out to enable the detection of errors. The technique can be applied without the need to spread out textiles or any pre-existing processing. The deep learning technique that the four authors present has its basis on transfer learning. It localizes while at the same time recognizing stain, holes, and cut defects. There is a combination of classification and localization into a single system that brings together two networks that are not identical. They point to success even in the case of voluminous shapes and the fact that the method is less intensive computationally compared to other state-of-the-art methods as some of the advantages of this approach. This article advocates for the method as an alternative to the manual methods of detecting defects including "holes and holes' or "stain/dirt' which they find to be time-consuming and prone to errors. They note that visual inspection could be a stable and reliable solution in this domain. A concern, however, is on the extent of its applicability. They opine that while visual inspection on outspread fabrics may achieve high accuracy levels, the case is different when it comes to textiles in voluminous shape. Challenges in the domain arise in the case of varying colors, uneven surface, sewing pattern, as well as the weaving of varying textile fibers such as linen, polyester, and cotton. Overcoming such challenges according to Siegmund, Prajapati, Kirchbuchner, and Kuijper (2018) requires the use of deep learning with their recommended deep learning technique being deep neural network.

Seker et al. [8] also acknowledge the essential role of deep learning in fabric defect detection in enhancing quality. Detection through human vision, according to them, has resulted in time-wasting and a declining success rate of up to 60% with the growth in market volume as well as production capacity. Due to the unique texture of fabric, it is necessary that when extracting its features, its functioning differs from that of other images. Features are critical computer vision material particularly in the classification problems. As such, the extraction of the right features is the most important phase of the error detection process. This paper explores deep learning in distinguishing multilayer architecture to achieve high image precision through the application of self-extraction to fabric defect detection. They conduct a test on stacked autoencoder, a deep learning technique, to represent input data through compression or decompression to detect defect in fabric that recorded great success. In their study, they set out to enhance the success of feature extraction through tuning up of the input value as well as the hyper-parameters auto encoder. With fining tuning of the deep model's hyper-parameters, they achieved a 96% success rate in their dataset.

Chen et al. [9] propose the combination of algorithm with convolutional neural network and Grabcut to enhance the precision of fabric texture defect detection. In their study, they begin by using a segmentation algorithm that is based on grab-cuts to locate the defects and segment them accurately in fabric image. Second, is an increase in the number of training sample through an expansion of the sample images. In the next step, they optimize the neural network to learn more efficiently the features of the fabric defects making it suitable for the recognition and classification of fabric defect. Their study provides a new fabric defect detection idea with complex texture fixtures. The author acknowledges that the achievement of accurate fabric defect detection breakthrough, as at the time of the study is still difficult. This is one of the reasons for their development of a new detection model that is based on an optimized convolutional neural network and Grabcut algorithm. The outcome of their experiment depicts that the network has higher recognition accuracy and faster recognition speed. The recognition effect is enhanced and better than that of the traditional learning method. It can detect a broad range of fabric defects texture features.

Napoletano et al. [10] also make a substantial contribution to the understanding of deep learning use in the detection of defects on fabric. Automatic detection of anomalies in nanofibrous materials and their localization help in reducing the product process cost as well as the time that visual inspection process, post-production, takes. The most effective monitoring methods are those that exploit SEM (Scanning Electron Microscope) imaging. Given the high resolution of SEM images of up to a nanometer, they can be employed in the detection and localization of fine as well as coarse-grained defects. In their article, the three authors propose a region-based method for anomaly detection and localization in SEM images that is based on CNNs (Convolutional Neural Networks) and self-similarity. The technique analyzes the extent of abnormally of each image's subregion (for the images under consideration) through the computation of a visual similarity based on CNN with respect to an anomaly-free sub-regions dictionary in a training set. In their evaluation, their proposed method is found to outperform the-state-of-the-art.

III.PROPOSED METHODOLOGY

The GoogleNet (Inception) and AlexNet network are used for identifying the fabric faults. The projected work is divided into four steps. Step one - The fabric images are acquired from "Cotton Incorporated" fabric image database.

Step two - The images are converted to Grey scale. Step three - Noises are removed by using Wiener filter [11]. Step four - The noise-free images are used to train GoogleNet and Alexnet network. The networks identify the fabric defects and display the predicted label and prediction probability for the images in the dataset. The noise-free image dataset is splitted into 70% for Training and 30% for Validation.

A. GoogLeNet (Inception):

This architecture uses 3 different size filters (i.e., 1X1, 3X3, 5X5) for the same image and combines the features to get a robust output. It consists of 22 layers and it lessens the number of parameters from 60 million (AlexNet) to 4 million. The 1x1 convolution is introduced for dimension reduction [12]. This architecture finds the best weight during training the network and naturally select the appropriate features.

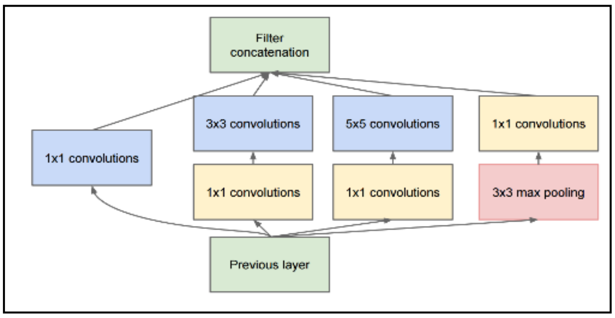


Figure 1: Inception with Dimensionality Reduction [13]

The Fig.1 illustrates the multiple convolution with 1x1filter, 3x3 filter, 5x5 filter, and max-pooling layer.

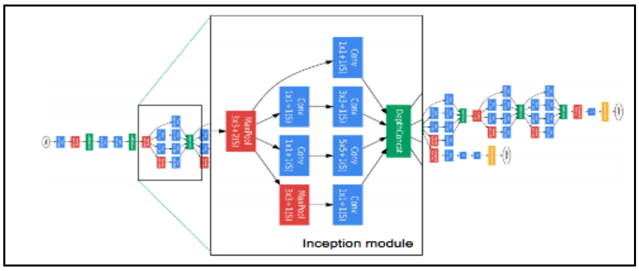


Figure 2: Inception Architecture

The Fig.2 shows the basic module in the overall network architecture. There are multiple Inception modules combined to form a deeper network by which high accuracy can be obtained.

Transfer learning provides new training for GoogLeNet and AlexNet Network to recognize new faults in the fabric. The image analysis pretrained network was trained using numerous images to categorize different fabric fault including Knots, Foreign fiber, Oil stain, and Needle line among others [14]. Images are provided to the network as input, and there is labeling of the objects in the images making up the output based on the probabilities of each of the respective object trajectory.

Steps in Classifying Fabric Fault Image using GoogLeNet:

i) Loading Images: This is the first step in the classification of fabric fault image with the help of GoogLeNet. It entails loading a small set of image data of about 200 images. The data set is divided into two categories. The first is training that makes up 70% of the images while the second one is the validation set consisting of the remaining 30% of the images.

ii) Load GoogLeNet Network: In this second set, there is an employment of the “analyzeNetwork” to help in displaying the architecture and layer information of the network. The Fig.3 displays the layers in GoogLeNet architecture and gives more information on Weights, Bias for all convolutional layers.

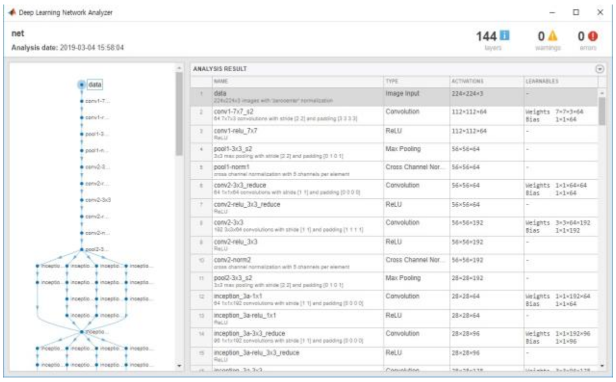


Figure 3: GoogLeNet Architecture and Layer Information.

iii) Load Pretrain Network: In this step, there is an extraction of features from the input images via convolutional layer which are then analyzed by the classification layer. The extracted features are then combined by the “loss3-classifier” and “Output” layers into loss value, predicated label, and class probabilities. Fig :4 shows that New layers replace the two layers with different data set for purposes of retraining GoogLeNet network.

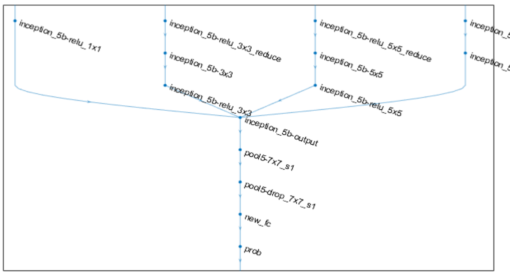


Figure 4: New Layer Graph

iv) Freezing the Basic Layers: In this step, GoogLeNet is ready to conduct retraining of the new data set. Set the initial layers to zero. Significant freezing of the layers increases the network’s training speed.

v) Network Training: The input images for a network that is to be trained have to be 223x223x3 in size. However, the images in the data set vary in terms of size. Image size is restored through the use of augmented image datastore. Augmentation of data when it comes to the training of the network restricts overfitting while at the same time keeping a memory of the characteristics of the training images. In Fig: 5 the graph shows the training accuracy – 100%, loss – 0%, elapsed time – 33 sec, maximum iterations in training progress – 204, validation frequency – 3 iterations, learning rate – 0.0003.

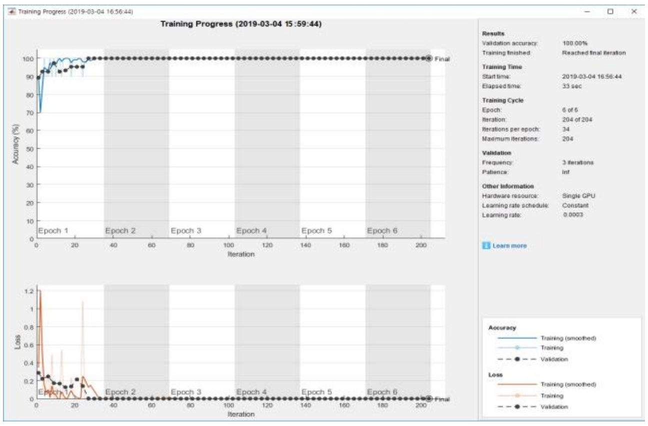


Figure 5. Training Progress

vi) Image Validation: This is the final step involving classifying the authorized images using predicted labels and forecasting the probabilities of the images that hold those labels. The Fig: 6 displays the fabric fault with the accuracy percentage. The fabric fault accuracy for 'Wrong End' is 99.8%, 'Slought-off' is 100%, 'Stain' is 100% and 'Missing-Picks' is 100%

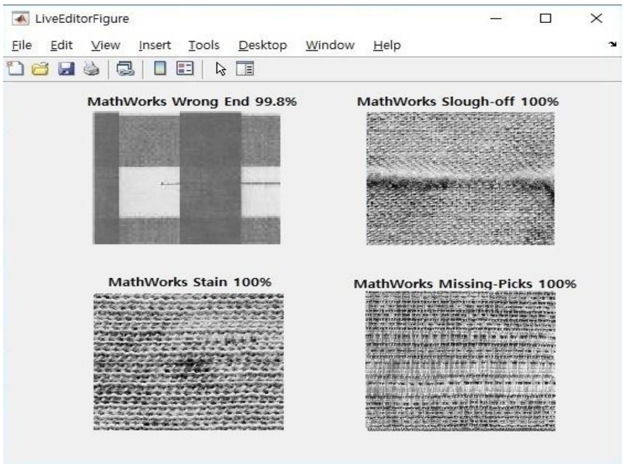


Figure 6: Fabric Fault Detection with Predicted Label and Forecasting Percentage

B.AlexNet:

AlexNet was proposed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. AlexNet is extremely large than LeNet. This architecture comprises of eight layers: Five convolutional layers and three fully connected layers. Two new concepts i) Maxpooling and ii) ReLU activation is introduced in this architecture [15]. The input RGB images for AlexNet is of the size 227 X 227 X 3. The convolutional layers use 11 X 11 filters with a stride of 4 and the maxpooling uses 3 X 3 filters with a stride of 2.

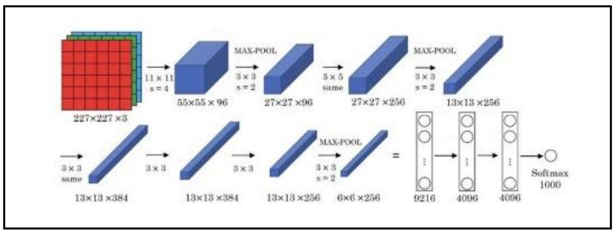


Figure 7: AlexNet Architecture [16]

Steps in the Classification of Fabric Fault Image using AlexNet

i) Image Loading: Unzip 204 images and load as a new set of data. The MATLAB function "splitEachLabel' divides 70% of the images for training and remaining 30% for validate [17].

ii) Loading AlexNet: In this second step, load the AlexNet pretrained network. It will display the information of the network layer. Fig.8 display work flow of AlexNet and exhibit weight, bias, stride and padding used in convolutional, ReLU, max pooling layers.

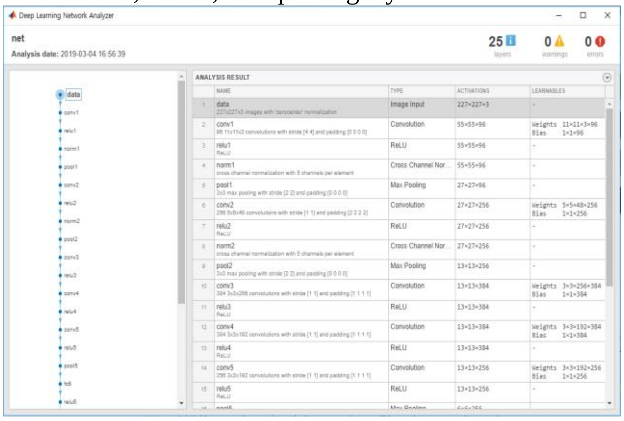


Figure 8: AlexNetNetwork Architecture and Layer Information

iii) Substitution of the Final Layers: The third step involves the substitution of the three layers with fully connected layers that include Classification output layer and softmax layer.

iv) Training Network: The MATLAB function 'trainNetwork(imds,layers,options)' is used for image classification. The imds - accumulate the input images, layers - specify network architecture, options - "InitialLearnRate, MiniBatchsize, InitialLearnRate, MaxEpochs, ValidationData, ValidationFrequency, Plots, Training-progress" are applied to identify the fabric defect. Fig.9 shows the accuracy plot for AlexNet with options value.

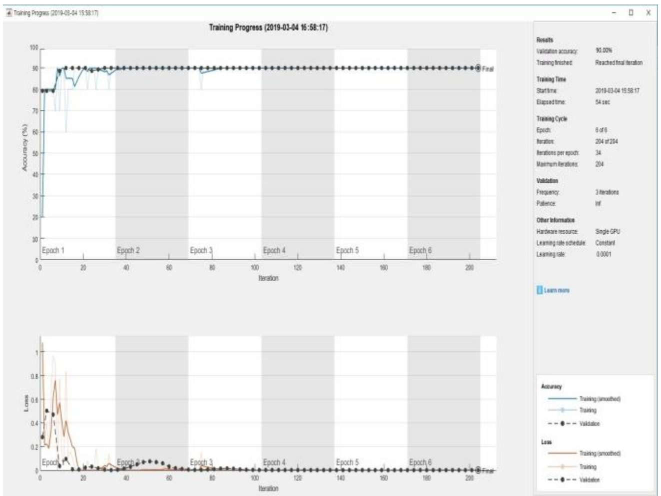


Figure 9: AlexNet Training Progress

v) Image Classification: In this step, the classification is done by using validation images and accuracy is also calculated. Fig.10 shows validation images along with predicted labels and prediction probability.

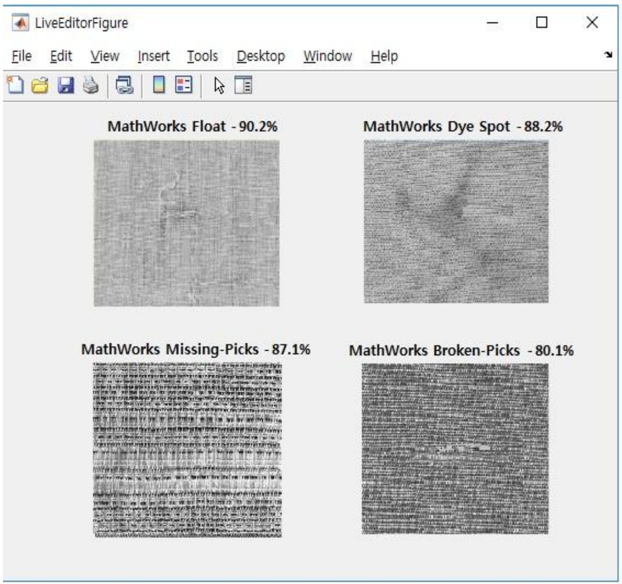


Figure 10: Fault Identification using AlexNet

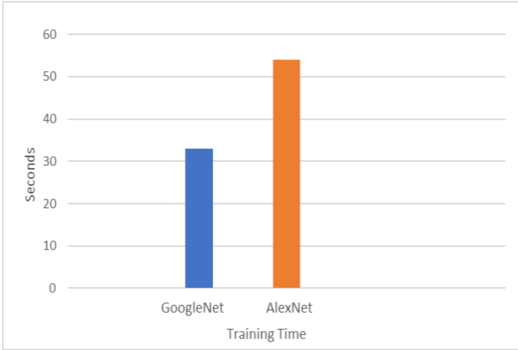
IV. EXPERIMENTAL RESULTS AND DISCUSSION

GoogleNet and AlexNet network are trained using MATLAB R2018b with a GPU system with the following specifications. Processor: Intel ® Core™ i7-8700 CPU @3.2GHZ and Graphics Card: NVIDIA GeForce GTX 1060 6GB.Various parameters are considered to compare the performance of GoogleNet and AlexNet. Table 1: presents the mathematical values to compare both the networks.

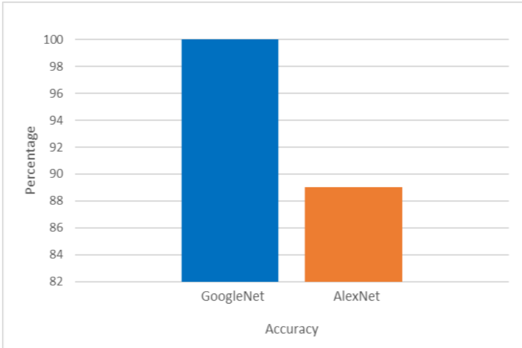
Table 1: Comparative Analysis on GoogleNet and AlexNet architecture for Fabric Defect Detection

Network Type	Parameters					
	Time	Accuracy	Layers	Dropout	Initial Learning Rate	Scale Range
GoogleNet	33 Sec	100%	22	0.4	0.03	10%
AlexNet	54 Sec	90%	8	0.5	0.01	NIL

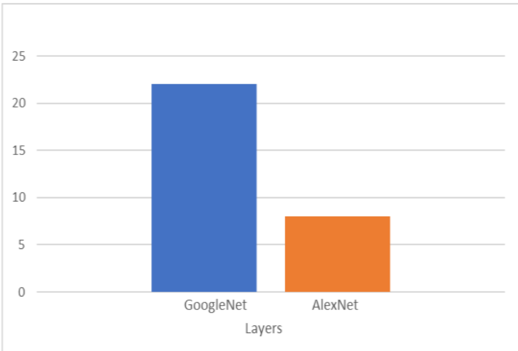
GoogleNet identifies the fabric defect in 33 seconds with 100% accuracy for 204 images, whereas AlexNet takes 54 seconds with less accuracy of 90% for the same number of images. The dropout value for AlexNet is 0.5 which increases the training time of the network. If the Initial Learning Rate factor is greater than 0.01 then the network needs lesser time to train the images. The Initial Learning Rate for AlexNet is 0.01 and so it takes longer time to train the network when compared to GoogleNet. GoogleNet has 22 layers which increases the accuracy but it can increase the overfitting problem. The overfitting problem can be overwhelmed by data augmentation. The data augmentation includes ScaleRange which flips the images vertically and randomly transform it to 30 pixels and it scale them likely to 10% both horizontally and vertically. The parameters 'Dropout' and 'Initial Learning Rate' increases the training time and likewise 'Number of layers' and 'ScaleRange' increases the accuracy of the GoogleNet.



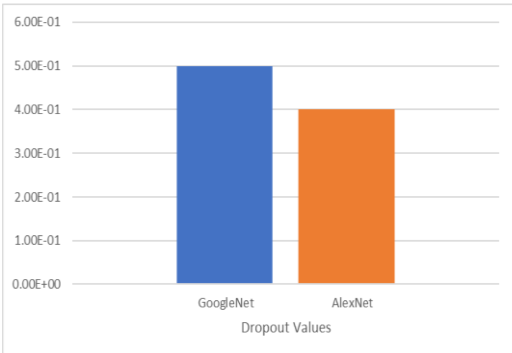
[a]



[b]



[c]



[d]

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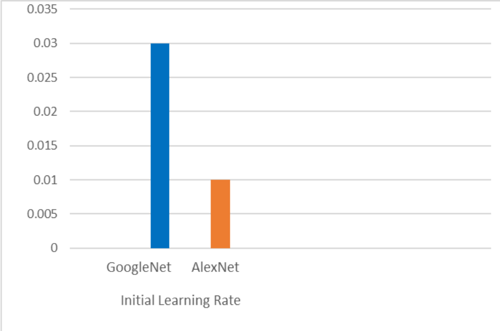
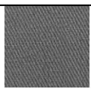
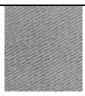
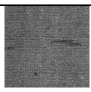
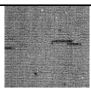
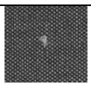
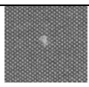
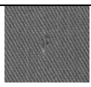
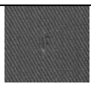
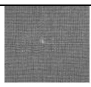
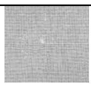
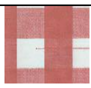
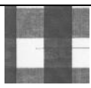
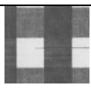
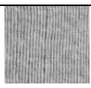
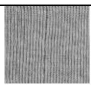
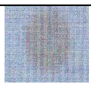


[e]

Figure 11: Comparative Plots for GoogleNet VS AlexNet - [a] Training Time, [b] Validation Accuracy, [c] Number of Layers, [d] Dropout Values, [e] Initial Learning rate.

Table 2: Fabric Defect Detection Using GoolgeNet, AlexNet and Predicition Probability

S. No	Image Name	Original Image	GoogLeNet	AlexNet	GoogleNet Prediction Probability	AlexNet Prediction Probability
1.	Coarsepick				98%	87%
2	Creasesueded				100%	90%
3	Filling				100%	91%
4	Gknot				100%	90%
5	Burl				98%	86%
6	Burlmark				99%	89%
7	Jerkin				100%	100%
8	Needleline				100%	90%
9	Compactcreases				98%	87%
10	Oilstain				99%	87%

The above Table 2 implies GoogLeNet is better than AlexNet in terms of performance. An inception module forms the network's basic building block. The implication of this is that the inception module can do multiple convolutions with varying filter sizes while at the same time pooling in a single layer. As such, after training, the network automatically determines the type of layer to employ at any given time for achieving the best outcome instead one having to choose. In the case of AlexNet, the decision concerning the convolutions for each layer are made purely experimentally as there is no fixed pattern.

GoogLeNet employs combinations of inception models with each involving some pooling, convolutions at varying scales, and concatenation operations. Its 1x1 feature convolutions also function like feature selectors. AlexNet lacks standard when it comes to the number of convolutions before max-pooling, as well as the size of the filters used. The inception module used by GoogLeNet has smaller convolutions that enable a reduction in the number of parameters to four million only. GoogLeNet architecture covers greater death in parallel paths with various sizes of receptive fields while having a low rate of error. GoogLeNet is made up of 22 layers in deep. This results in a substantial reduction in the number of parameters that drop from 60 million (associated with AlexNet) to four million. GoogLeNet uses a simple global average pooling in place of the layers that are fully-connected layers at the end, which serves to average out the values of the channel across the 2D feature map following the last convolution layer. This also contributes to the drop in the number of parameters. The employment of a large network width and depth enables GoogLeNet to rid itself of the FC layers without compromising the accuracy. It achieves a top-5 accuracy and is faster than AlexNet or even VGG. The AlexNet is less efficient since 90% of its FC layers consist of parameters.

V.CONCLUSION AND FUTURE ENHANCEMENT

Evidently GoogLeNet performs better than AlexNet as a deep learning method for the detection of defects in fabric. Various authors have contributed to the subject of deep learning in detecting fabric faults as evidenced by the review of the existing body of literature. A primary basis for the support of CNN is that the traditional manual visual methods of inspecting fabric tend to be poor in precision and low on their efficiency in long-term industrial applications. GoogLeNet and AlexNet are some of the top deep learning methods employed in the defect detection process. While both do a great job in enabling this process, GoogLeNet's performance outweighs that of AlexNet with respect to different parameters. The results of the experiments indicate that the former is better than the latter in terms of speed, accuracy, dropout, and the initial learning rate. As such, preference should be one GoogLeNet over AlexNet when faced with the choice of the best fabric defect detection deep learning method. In future, a hybrid convolutional neural network will be developed to identify the fabric fault in less amount time.

REFERENCES

1. Tian Wang, Yang Chen Meina, QiaoHichem Snoussi. (February 2018). “A fast and robust convolutional neural network-based defect detection model in product quality control”, The International Journal of Advanced Manufacturing Technology, vol 94, issue 9, pp 3465–3471.
2. Sri Winiarti, Adhi Prahara, Murinto, Dewi Pramudi Ismi. (2018). A. P, “Pre-Trained Convolutional Neural Network forClassification of Tanning Leather Image”, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 9, pp. 212-217.
3. Jing Junfeng, Fan Xiaoting, Li Pengfoi, Hong Liang. (2017). “Yarn-dyed fabric defect detection based on deep-convolutional neural network”, Journal of Textile Research, vol 38, issue 2, pp 68-74.
4. Tong, L. Wong, W. Kwong, C. (2017). “Fabric Defect Detection for Apparel Industry: A Nonlocal Sparse Representation Approach”. IEEE Access, vol 5, pp 5947–5964.
5. Shuang Mei, Yudan Wang, and Guojun Wen. (2 Apr 2018). “Automatic Fabric Defect Detection with a Multi-Scale Convolutional Denoising Autoencoder Network Model”, Sensors, pp 1-18.
6. Siegmund, D., Prajapati, A., Kirchbuchner, F., & Kuijper, A. (2018, September). “An Integrated Deep Neural Network for Defect Detection in Dynamic Textile Textures.”, International Workshop on Artificial Intelligence and Pattern Recognition, pp: 77-84.
7. Abdulkadir Seker, Ahmet Gürkan YUKSEK. (April 2017). “Stacked Autoencoder Method for Fabric Defect Detection”, Cumhuriyet University Faculty of Science Science Journal (CSJ), Vol. 38, pp. 342 - 353.
8. Yujun Chen, Liming Wu, Xin Li and Yanan Zhao. (2017).” A High-Precision Fusion Algorithm for Fabric Quality Inspection”, 2nd International Conference on Computer Engineering, Information Science and Internet Technology (CII 2017), pp 575-582.
9. Napoletano, P., Piccoli, F., & Schettini, R. (12 Jan 2018). “Anomaly detection in nanofibrous materials by cnn-based self-similarity”. Sensors, Vol 18, Issue 1.
10. Abdulkadir Şeker, Kadir Aşkın Peker, Ahmet Gürkan Yüksek, Emre Delibaş. (2016).” Fabric defect detection using deep learning, Publication” 24th Signal Processing and Communication Application Conference (SIU), IEEE, pp:1437- 1440.
11. P.Sujatha and K.K.Sudha. (July 2015).” Performance Analysis of Different Edge Detection Techniques for Image Segmentation”, Indian Journal of Science and Technology, vol. 8, issue 14, pp.1 - 6, July 2015.
12. Zhu, Z. Wang, X. Bai, S. Yao, C. Bai, X. (2016). “Deep learning representation using autoencoder for 3D shape retrieval”, Neurocomputing, vol 204, pp 41–50.
13. http://web.cse.ohiostate.edu/~panda.2/5194/slides/2.c.GoogLeNet.pdf (accessed on 3rd April 2019)
14. Bell S, Zitnick C L, Bala K,et. (2016). “Inside-outside net: Detecting objects in context with skip pooling and recurrent neural networks”, Computer Vision and Pattern Recognition, pp 1-11.
15. DanielYapi, MaroueneMejri, Mohand SaïdAllili, NadiaBaaziz. (2015). “A Learning-Based Approach for Automatic Defect Detection in Textile Images”, IFAC-PapersOnLine, vol 48, issue 3, 2015, pp 2423-2428.
16. https://indoml.com/2018/03/07/student-notes-convolutional-neural-networks-cnn-introduction/ (accessed on 3rd April 2019).
17. MATLAB Available online https://www.mathworks.com/help/matlab/ref/matlab.io.datastore.imagedatastore.spliteachlabel.html (accessed on 10th March 2019).

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