Identification of Defects in the Fabric using Deep Convolutional Neural Networks

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Identification of Defects in the Fabric using Deep Convolutional Neural Networks

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Abstract

The inspection of defects in the fabrics is one of the essential steps before manufacturing them in finished goods. General defects like spills or stains are often easily by the human eyes but when it comes to inspect the defects in details then it becomes difficult for the humans to detect accurately at a swift pace. This is why more efforts are drawn towards building up models, especially using Tesnorflow and Keras which are self-capable of minutely inspecting the defects with certain accuracy at a more efficient pace than humans. This project aims in developing a new pre-trained model called Dual Channel Convolutional Neural Network that uses two channels (one deep and other shallow) for classifying the defects in fabrics and comparing its performance with other pre-trained models. The research project was implemented using DAGM dataset downloaded from www.kaggle.com. Upon comparing the evaluation results of validation and training datasets, it was concluded that even though there was no significant difference between all the five models (VGG16, AlexNet, VGG19, MobileNet and DCCNN) but still the developed model out-performed three of the four models (VGG16, AlexNet and VGG19) in terms of precision, recall and F1 score values.

1 Introduction

Inspecting the quality of raw materials is considered to be one of the most crucial aspects behind any production unit. Its significance in the textile industry is even more as most of the time different fabrics are combined together to form a finished fabric and defect found in any one of the fabric can halt the entire production assembly resulting in huge financial losses for large manufacturing units (Bandara et al.; 2018). In general the valuation of the fabric gets reduced in between 40 to 60 percent depending upon the nature of the defect found in the fabric. If the fabric in the finished product is found to be defective, then apart from the financial losses the company suffers from non-monitory losses which are intangible in nature like its brand value, customer's trust and loyalty etc. Most of the defects in fabrics also known as flaws, on the surface results either from wear and tear of machines, improper stocking or other miscellaneous activities like stain spills or scratches etc. Therefore the main aim behind developing an efficient deep learning model is to maximize the machine's detection efficiency by minimizing its misclassification rate.

(Nasira et al.; 2014)

1.1 Motivation and Background

85 percent of the fabric gets rejected due to fault in the raw materials. Taking this into account identification of flaws if any, at the preprocessing stage would be considered as one of the top priorities of the manufacturing units. In earlier days these identification/ inspection of defects were carried out manually via human vision. In this method when the workers identify any defect, the whole process is paused immediately in order to fix that defect immediately. Once the defect is completely fixed, then the production is started again. Unfortunately it was a very lengthy process that involved a lot of human intervention. As human beings are prone to fatigue, hence maintaining the efficiency of the workers was a substantial challenge at that time. As the time progresses and with certain advancements in the technology the inspections were carried out using LED light sources. The fabrics were passes under the light sources to check for any possibility of defects in it. The biggest challenge over here was to maintain an environment of consistent illumination every time. Moreover the surroundings should also be of the same effect as the source. Recently, more emphasis was laid upon the improving this identification and classification of the fabric defects using deep learning with minimal human involvement. Most of such automated procedure follows a three step procedure viz. image acquisition, defect detection and post processing. In broader terms, fabrics are classified into two categories i.e. patterned and un-patterned. Amongst them the patterned fabrics are more challenging and difficult to classify because of its complex nature of design as compared to the un-patterned ones (also referred as plain fabrics). There are different methods that can be used for automating this process of defect detection including Wavelet, Fourier transforms, Markov random field, wavelet, neural network etc. (Chang et al.; 2018). This research focuses upon different techniques of Convolutional Neural Network (CNN) that can be applied for making a distinguishing classification between the defected and non-defected fabrics. With the increasing popularity of hand held gadgets like smartphones, palmtops, laptops etc. there has been a certain rise in processing information in the form of images. As per Flickr, there is an annual rise of 100 million units per year for storing the images whereas image storage for Facebook is exponentially expanding at the rate of 15 billion images per year (Cao et al.; 2019). Hence, storing, retrieving and processing such large chunk of data in the form of pixel have been a huge challenge for the industry (Zhang, Mu, Feng, Li, Yuan and Lee; 2018). In the recent times, image classification using pre trained models of Keras has drawn a lot of attention for overcoming this problem. Currently there are several techniques available for performing this task which has gradually evolved over time. These methods are broadly categorized as supervised and unsupervised methods. This paper discusses about the supervised learning models.

In the supervised methods, a unique set of features are identified form the defect free samples. On the basis of its training the model learns to distinguish the defective samples from the non-defective ones. For achieving a better test accuracy the samples should be free from any kind of distortion like translation or rotation etc. (Hamdi et al.; 2018). This paper primarily focuses upon the performance of a tailor made Convolutional Neural Network (CNN) technique called the Dual Channel Convolutional Neural Network (DCCNN) and finally making an accuracy comparison with four of the other pre-trained CNN models viz. MobileNET, AlexNET, VGG16 and VGG19 with the same set of data. Convolutional Neural Networks (CNN) is special kind of Neural Networks that are designed especially for images. Ever since its evolution from 2012, they are delivering exceptional results and are continually evolving every year. They are widely used in object segmentation, Natural Language Processing (NLP), image segmentation, image classification etc. The architecture involved behind CNN is to break down the model in several components of convolutional, sub-sampling layers and rectification of non-linearity layer (if any) (Jarrett et al.; 2009). Many a times it is observed that even after developing some sophisticated structures and enabling diversification for image classification and identification, there still exists some limitations in the model. These limitations have given birth to extended versions of CNN. One of them is the Dual Channel Convolutional Neural Network (DCCNN) which involved two convolutions running parallel to one another.

1.2 Research Question

The research question was formed by identifying the short-come of the textile industry from the existing literatures, and hence made a comparative study among different pre-trained models which also includes a newly developed model.

RQ: *"How efficient are different transfer learning methods in identifying defects using deep convolutional neural network?"*

Sub-RQ: *How much better is the new developed model i.e. Dual Channel Convolutional Neural Network in identifying defects as compared to the existing models?"*

1.3 Research Objectives and Contribution

DCCNN as a new developed model for identifying the defects in the fabric consists of two channels; deep and shallow. The shallow channel is based on transfer learning which captures more of the generic features of the dataset whereas the deeper channel dives in for capturing more specific insights and features of the image. Even though the channels were independently trained but before performing the test these were combined together to form a single channel. A pooling layer is fitted in between the two convolutional layers. These layers are broadly categorized as min, max and mean pooling. This research carried out the research process using the max pooling. Max pooling snips the maximum value as pooled value while retaining the texture of the original image.

While reviewing the existing literatures it was found that DCCNN has proven to be very successful when applied several other domains like air pollution, aviation industry etc. Hence, the bigger textile industry can be hugely benefited from this, if it delivers promising results as they need to produce the fabric in large amounts while maintaining there quality at the same time.

Contribution: The research contributes in identifying different challenges faced in textile manufacturing industry, and delivered a new solution which especially targets the requirements of Small Medium Enterprises (SME's). The model was developed with intent of increasing the efficiency of automated defect detection system in order to minimize any manual intervention in the whole process.

Table 1: Research objectives of different methods used for detecting the defects in fabrics using Transfer Learning

Index	Description	Metrics
Objective 1	A critical review of the existing work done in recognizing the defects in fabrics from 2012 to 2020	
Objective 2	Collecting, collating, augmenting before performing exploratory data analysis in order to extract the features that will distinguish a defective sample from a non-defective sample	
Objective 3	Implementation, Evaluation and Results using VGG16	Accuracy, Loss Precision, Recall F1 score
Objective 4	Implementation, Evaluation and Results using AlexNET	Accuracy, Loss Precision, Recall F1 score
Objective 5	Implementation, Evaluation and Results using VGG19	Accuracy, Loss Precision, Recall F1 score
Objective 6	Implementation, Evaluation and Results using MobileNet	Accuracy, Loss Precision, Recall F1 score
Objective 7	Implementation, Evaluation and Results using DCCNN	Accuracy, Loss Precision, Recall F1 score
Objective 8	Comparison of developed models with the existing models	

2 A Critical Review of Various Approaches used in Identifying Defects in the Fabric

2.1 Broad Challenges Faced while Identifying Defects in the Fabric

Inspecting the quality is considered to be very significant for textile manufacturing. The process was carried out manually by the humans which were a very subjective procedure that also led to fatigue among the workers. Image classification which is a part of image processing was deployed by the textile industries in order to overcome this problem (Mohamed and Faouzi; 2013). The aim of the research was to deploy different techniques to extract the value of the characteristics of the image from the defected fabrics and thus classify the fabrics as either defected or non-defected. Some of the techniques were thresholding, histogram equalizing and filtering. The main aim of the defect detection mechanism is to accurately detect the defected points for the smooth functioning of the entire operation (Oni et al.; 2018). More importantly it also points out that the inspection process needs to be attained at a high processing speed along with a minimal computational time in order to match the production demand. The paper aimed at reviewing and discussing different techniques and algorithms that were designed for identifying the defects in the patterned and coloured fabrics. Moreover, certain limitations that were commonly found in many papers were also highlighted; for example many of the existing Fabric Defect Detection and Classification (FDDC) techniques lacks uniformity in its datasets and as a result face challenges in high quality images. After critically examining and evaluating different computational techniques it was concluded by the researchers that more robust patterns in FDDC with a high detection accuracy with high computational time could be achieved using image fusion techniques obtained by collaborating multi spectrum information.

It is considered that a major defect or a fault in fabric can reduce its value by 45 to 65 percent. Therefore most of the textile industries are automating its manual inspection process of identifying the defects in order to maintain consistency in the inspection process which otherwise could not be achieved as manual inspection involves fatigue and qualitative uncertainties. Convolutional Neural Network (CNN) is the most commonly used deep learning technique used for the whole detection process (Ouyang et al.; 2019). The paper also discusses about a deep learning algorithm for identifying the defects in loom's fabrics along with candidate defect map generation and CNN. It is based on a hybrid approach that has used many rules of statistics as activation reference known as *Pairwise Potential Activation Layer*. The results were evaluated upon three parameters viz. precision, F1 score and recall value. The model was evaluated upon the famous TILDA dataset. It was concluded that the model successfully managed to identify different kinds of effects upon different kind of illuminating (lighting) conditions while working upon different kind of fabrics. The model managed to achieve 83, 92 and 87 percent of recall, precision and F1 score respectively. The similar objective of achieving a higher speed classification and along with precision over other the manual process was also discussed in this work which discusses about classifying the defects based upon digital image processing (Vladimir et al.; 2019). The method is based upon locating the position of the warp in the sample image. Then calculate the warp's position in order to figure out whether it could fall in the category of defected sample or not. The pattern and structure of the warp may differ from one another depending upon the kind of fabric being considered. This work is also based upon supervised learning where the model is first learns about the good sample fabric and later learns to classify the defected ones from the good samples in the same fabric design. The model has shown a promising result achieving an accuracy of 95 percent and the work claims that the computational speed of the model is 50 percent faster than the manual process.

The fabric defect detection methods can broadly be categorized in three categories: learning based, feature based and non-feature based methods. In the feature based method the HOG features are initially extracted later the feature image blocks are converted to feature matrix and consequently a feature matrix is formed using the low rank decomposition model. The HOG area is classified by low rank decomposition and feature extraction. In non-feature detection method the salient features of the fabric is captured through *Fast Fourier Transform and morphological filtering* on the fabric in order to highlight the key features of the defected area in order to obtain the global salient features of the image. Finally the learning based method includes two stages viz. training and testing. In the training stage the algorithm is fed with fabric samples for learning purpose. While in the testing phase the resultant learning is used to approximate the test sample (Zhang and Tang; 2019). Even though the research work have no statistical comparison but it managed to demonstrate though mask images that the discussed algorithm managed to perform better than the existing regional variation saliency method.

Most of the research discusses about defect identification and segmentation of patterned fabrics, but the following research was carried upon defect segmentation for plain fabrics. The methodology was based upon the principle of weighted averaging, such that the weighted average methodology was used for coloured (RGB) image into gray scale image. In order to make the defects in the background more prominent these images are further enhanced using gray level adjustment and are later refined by a lower pass filter. There were several methods been initially picked for defect segmentation but out of those finally the Robert operator was chosen for identifying and classifying the defects of the filtered images. It was accomplished by connecting the active nodes. The interested region (susceptible region of defect) was segmented from background. The experimental results had shown very high accuracy for this model as compared to the state of the art (Guan et al.; 2019).

2.2 Improvement in CNN and Other Technologies Over the Past 5 Years

With the aim of detecting the defected fabrics in real time, a method called the Fast Fourier Transform (FFT) was adopted which was based on Computer Unified Device Architecture (CUDA). The method adopts parallel implementation of FFT algorithm for detecting the defect in the fabric in Graphical Processing Unit (GPU) platform. When the results were compared with that of running the same FFT algorithm in Central Processing Unit (CPU) it was found that the discussed algorithm with GPU has significantly reduced the computational time while maintain the same level of detection accuracy. It was observed that the speed GPU based CUDA was 4.06, 4.04 and 3.92 times faster than CPU for 1024 * 1024, 2048 * 2048 and 4096 * 4096 sized images respectively. The paper achieves 2D Fast Fourier Transform for fabric defect detection as the CUDA architecture has been designed for multiple thread execution. In this while transforming the fabric image, parallel method along with high speed was deployed in order to meet the high real time characters of the actual production and fabric defect detection in FFT (Pan et al.; 2017).

Most of the fabric's defect detection algorithm carried out by artificial illumination source. A majority of them suffer from two main problems viz. the design of the pattern which is sometimes complicated in itself and illumination effect not get synchronized with the surroundings. Consequently these problems results in reduced accuracy because of misdetection and under-detection (Hamdi et al.; 2017). As a result a computer vision system which is based upon Near Infrared (NIR) imaging in order to overcome the drawbacks caused due to improper visual lighting illumination. The algorithm followed uncomplicated procedures for segmenting the defects. It was based upon standard deviation filtering which is non-extensive and minimum error thresholding in order to detect the defects. The biggest advantage of this technique was its efficiency in detecting minute sized defects even at darker lighting conditions which otherwise does not get captured in VSL images. Adding on to the advantages, the discussed NIR system was also capable in detecting the hidden oil stains that were there behind the surface of the fabric. Even though the research was based upon patterned fabrics but even the patterned fabrics appear to be plain under the infrared lighting conditions, hence it was also among the key conclusions that the proposed method could also be used for the plain texts. The results finally showed that the proposed algorithm achieved an outstanding performance of overall defect detection rate of 97 percent.

Identifying the defects manually through the workforce, not just results in inconsistency in the detection but also cause increases the labor cost as manual workforce are more expensive than machines. So in order to reduce the labor cost of the extract away features of yarn dyed fabrics, a method which is based upon deep learning called YOLOV2 for detecting the defects through localization and classification. In YOLOV2 method, three of the models viz. YOLO9000, YOLO-VOC and Tiny YOLO were used for the comparison of defect detection. Among the dataset the first 276 defect images were taken for training purpose which was collected, preprocessed and finally labeled. The comparisons among the three models were done on the basis of average recall, average IOU, average precision and average predicted time. On the basis of the results gathered for the four tests, it was observed that YOLO-VOC outperformed the remaining two models with an average recall, precision, IOU and predicted time of 88.24, 86.83, 69.45 and 0.023 percent respectively. The YOLO-VOC model was again selected for improvement by optimization super parameters of convolutional neural networks (CNN). After experimenting with the trained data, the model was finally tested upon practical yarn dyed fabric images. It was finally concluded from the results that the overall YOLOV2 was turned out to be effective for detecting the yarn dyed fabrics which majorly contributed in reducing the labor cost for identifying the defects (Zhang, Zhang, Li and Gu; 2018). Another paper discusses about how Artificial Neural Network (ANN) can be used for identifying the defects in the woven fabrics in textile industry. For the execution of the discussed model, samples of 200 woven fabric samples were considered. Out of it 150 were kept for training purpose and 50 were kept for testing. Before proceeding with the application of the neural network, the images were normalize and preprocessed using image processing techniques like image augmentation. Later on they are converted into binary image while holding intensity values as threshold. The structure of the ANN that has been here comprised of (a) six neurons input layer, (b) a single hidden layer comprising of twenty neurons and (c) One neuron output layer has been used finally. The model was executed upon MATLAB 2012. The whole process began with the fabric images getting captured using camera and passed on to the computer where it gets normalized using interpolation method, filtered using median filtering methods and collecting intensity values as threshold. In ANN, the six first order values were computed from the binary image. These values are feed in the form of feature vectors to multilayer feed forward neural network. The results showed that the model has outperformed the existing state of the art both in terms of CPU's computational time as well as defect detection rate. The computational time for the existing system was 650 seconds for the mentioned dataset whereas the proposed model performed the same task in 625 seconds i.e. 25 seconds faster than the existing model. Similarly the error detection rate of the existing system was 93.4 percent whereas the proposed model managed to detect 99.1 percent of fabrics accurately with an error rate of less than one percent and outperforming the state of the art by 5.7 percent (Dr.G.M.Nasira; 2014).

Even with much technological advancement, fabric defect detection has still remained a significant problem that is still looking for a powerful industry oriented solution. Keeping that in mind this paper discussed about two powerful Fabric Defect Detection System

(FDDS) which proved to be quite effective in maintaining the quality of the fabrics while keeping the cost of the industry in check. The first one was statistical viz. Gray Level Co-occurrence Matrix (GLCM) and later on it was compared with wavelet transform. Both the approaches were made to run upon the same environment. The database taken for performing this experiment was chosen from Textile Engineering Department of Dokuz Eylul University. It was seen that the discussed method demonstrated better results for the solid patterned fabrics as compared to the other designs and the results for both the schemes were equally consistent. It was observed that both the schemes could not provide better result when there was a change in texture. Moreover, double pick, shantung effect and lattice were also undermined in this model. It was also a very challenging task to define the orientation values and distance for the two models. All the images that were fed in the models belonged to the high resolution contrast (Sadaghiyanfam; 2018).

The next paper discusses about a novel automatic visual defect detection method that localized and looked for defects in the new yarn fabrics which were not seen by the system before on the basis of the training it has undergone before without adjusting any of the tedious settings. It was a three step method viz. (a) Identifying the floating points that are of single weft and warp with full convolutional neural networks. (b) Tracking the single yarn based upon predefined rules. (c) Recognizing the defect based upon analysis. The experiment was conducted upon 1431 images upon 9 different kinds of fabrics. Out of it 89 kinds of defects were analysed. The experiment were partitioned and carried out in three different partitions viz. A, B and C where the three networks individually achieved an accuracy of 89, 95 and 97 percent respectively (Weninger et al.; 2018).

An undamaged texture generally shows a very smooth and homogeneous characteristic whereas the disrupted fabrics usually occupy small regions and has patchy ends. The experiment in this paper was based upon low rank and sparse matrix decomposition. In the experiment it was considered that the pixel of the defected images tends to be more compact. Hence a function was designed to merge this beforehand, so that the defect detection method can be carried out more efficiently. A weight merging mechanism was used in order to obtain better detection results because different fabric images have different levels of defects. The results were demonstrated as precision, F score and recall value which was further compared with two algorithms namely PG LSR and naïve Go Dec. The results showed that discussed method has easily outperformed the existing two models with a precision, recall and F score of 0.79, 0.82 and 0.80 respectively. It also showed that the discussed method was not only capable of detecting the defects accurately but was also capable of preserving the defect details as compared to the other two traditional approaches (Wang et al.; 2017).

With an intent of effectively classifying the defects in the fabrics this research discusses about an improved method which is based upon membership degree of each of the regions inside the fabric (TPA). It discusses that just by analyzing the defected regional features, the prominence of the defected region can be found using the extreme density map and features of the membership function. In order to locate the exact/ accurate region of defect in the fabric morphological processing and iterative methods were used in this paper as well. The researchers claim that the algorithm not just identifies fabric images with several patches or roughness but also provides extreme value method, coefficient for the segmentation, coefficient for the weights and a membership function. The algorithm provides much better results when compared to the existing algorithm WRA algorithm upon all the aspects of comparison. The results for defect classification of the point defects, line defects, linear defects, scattered defects and non-defected images for the discussed algorithm (TPA) were 2.7, 5.6, 12.8, 15 and 4 percent better than the existing algorithm (WRA) (Song et al.; 2020). Another paper discusses one of the conventionally and well renowned supervise machine learning method called Support Vector Machine (SVM) for identifying the defects in the fabrics. The classifier was trained by acquiring the defected samples from the dataset. The gamma variables along with the penalty cost were identified for fetching the optimal classifier by providing limited amount of samples. Hence, the SVM classifier was used in order to classify the defects. An arbitrary feature set was discussed for identifying the defects and after the proposal it was found that the provided geometric features were sufficient in classifying the defects of the fabrics. Moreover, the method was successful in identifying 90% of the defects in the fabrics Meena et al. (2018). In a similar experiment carried out with list of supervised machine learning models like SVM, Random Forest and Grid search for identifying the defects which were based upon DFT features. Like many of the recently carried out experiments, this experiment was also based upon the famous TILDA datasets containing 3200 images of jute, floral pattern, diamond print and silk designed for identifying seven types of defects viz. thread condensation, wrinkles, punches, oil spills, poor lighting conditions, blurriness from the camera and external body contact. It was found that the Random Forest method has shown the highest accuracy and kappa statistics of 37.4% and 27.4% respectively as compared over other stated models. Furthermore, it was also seen that the diamond and floral pattern fabrics have shown a similar trend in results while applying all the three methods to it. Adding on the observations, it was also found that the classification rate of ouches and oil stains have remained the same for all the classification methods and fabric types (Loonkar and Mishra; 2019).

2.3 Algorithms using Pre-Trained Models

In this paper, identification of the defects was broadly classified into three steps. The first step comprised of image pre-processing Butterworth Low pass filter. Once the pre-processing is done, in the second stage the Haralick defined attributes are extracted from the pre-processed data obtained from the first phase using Gray Level Co-occurrence Matrix (GLCM). The extracted images were later used for training upon the neural networks classifier for detecting the defects in fabrics using Back Propagation. Finally when the model is established, it is implemented and compared using different learning rates of the learning algorithms. It was observed that GLCM feature energy provides better accuracy with a learning rate of 0.07 (Gnanaprakash et al.; 2019).

Apart from the conventional pre-trained deep learning approaches that have been seen in the previous research papers, there were also some studies carried out with slight modifications upon the existing ones. In this study slight changes have been made upon the existing structure of DenseNet in order to be more effective than the conventional study. Along with it an optimized version of the cross entropy is adopted as the loss function. Finally during the implementation phase six of the expansion schemes were used for enhancing the dataset in accordance to the type and nature of different kind of defects in the fabrics. In order to make the sample distribution even, equal chunks of all the defect types were used for determining the final enhancement. At the end, the defects system is built for testing the performance of the model based upon edge device in the real world scenarios (Zhu et al.; 2020).

In one of the recent researches carried out this year, the deep convolutional neural networks were used for carrying out identification of the defects. It has used 3 of the famous pre-trained models viz. DetectNet, GoogleNet and VGGNet. There were three parameters (Precision, Recall and F1 score) taken into consideration for evaluating the performance of each models. It was observed that the performance of DetectNet model turned out to be the best among all the three models for all the three parameters followed by VGGNet and GoogleNet. It was finally concluded that even though DetectNet outperformed VGGNet but there was not much of a difference between the two models. The precision, recall and f1 score of DetectNet was 1, 0.98 and 0.96 respectively. On the other hand the performance of VGGNet was 0.89, 1 and 0.95 for the same set of parameters (Beljadid et al.; 2020).

3 Methodology used and Project Design Specifications

At first, this chapter illustrates about each step of the methodology that is being used for identifying the defects in the fabric. Then design of the project based on which the implementation steps are carried out are discussed. Finally a brief statistical analysis of the dataset is being discussed before carrying out any cleaning or pre-processing in it.

3.1 Fabric Defect Methodology

As the volume of data has been increased by leaps and folds over the past few years for most of the industries including the textile industry, hence it is very much crucial for the business to deploy a data mining and implementation process which is sufficient in itself in terms of project reliability, repetitiveness and adaptability to those employees who have with very less or no knowledge about that industry. The most commonly used methodologies for data mining and implementation are CRISP-DM (Cross-industry standard process for data mining), KDD (Knowledge Discovery in Databases) and SEMMA (Sample, Explore, Modify, Model, and Assess). This project is designed upon the underlining principles of KDD but with modifications.

A detailed process of the steps followed for identifying the defects have been illustrated below in figure 1.

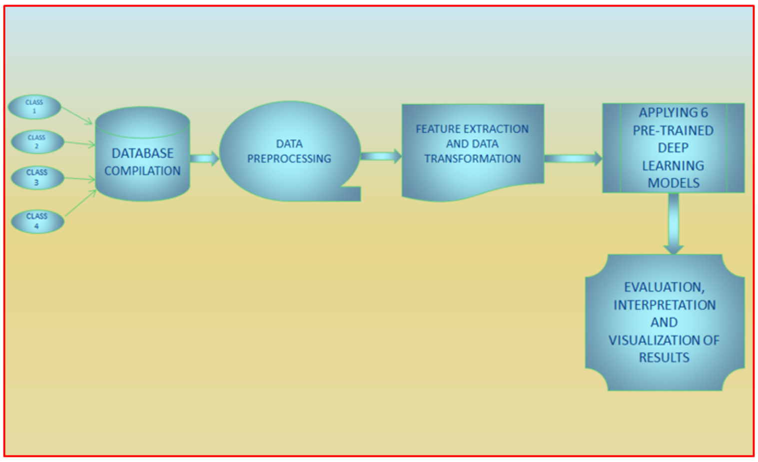

Figure 1: Methodology used for fabric defect detection

• **Data Compilation** This is the first step not just in this project but for most of the projects that are related to data processing and extraction. The models in the projects were trained using the DAGM *(Deutsche Arbeitsgemeinschaft für Mustererkennung e.V., the German chapter of the International Association for Pattern Recognition)* dataset which initially comprised of around 38,000 images in 10 different classes. But only 4 out of 10 classes of the dataset have been chosen for executing this project which comprised of 7608 images: 2523 images for validation and 4995 images for training purpose.

• **Data cleaning and preprocessing** Following activities were done for cleaning and preprocessing:

(1) **Same label names across different classes** It was observed that the labels of the defected and non-defected images across all the classes were the same and it would be impossible to train the models having the same name. The images were renamed using a third party software called the 'flexible renamer'.

(2) **Size of the image** Most of the models in this research were taking an image size of 224 * 224 into account. But sizes of the images in the dataset were of the size 512 * 512. So before putting these images into training for the models they were rescaled in testing and validation datagen.

• **Data transformation** Most of the models in this project have used image augmentation for extracting more characteristics from the image in order to train the model better. This is done by extracting more features from a single image by analyzing the image from different angles. For example: flipping it, zooming in and out, increasing the brightness and contrast of the image etc. Apart from augmentation, the images were also resized to fit into the respective models.

• **Data mining** In this stage, 5 different pre-trained deep learning methods viz. VGG16, VGG19, MobileNet, Dual Channel Convolutional Neural Network (DCCNN) and AlexNet were being used. Among these the first five models were trained upon by running tensorflow at the back end and keras at the front end, whereas the last model (AlexNet) was trained only with keras without keeping tensorflow at the back end.

• **Evaluation, interpretation and visualization** After applying the models, they were finally compared, evaluated, interpreted on different parameters like validation accuracy, loss function, precision, recall, F1 score etc.

(1) The accuracy of the model is number of correct predictions made over total number of outcomes

(2) Precision is defined as total number of correct prediction over the sum of correct prediction and false predicted results which were not true but predicted to be true. Precision = True Positive / (True Positive + False Positive)

(3) Recall is total number of correct prediction divided by the sum of correct prediction and the prediction which was falsely predicted. Recall = True Positive / (True Positive + False Negative)

(4) F1 score is the measure of the accuracy of the overall model computed in terms of Harmonic mean. The reason for deploying harmonic mean is that it minimizes the impact of the extreme values (outliers)

Finally these values are visualized in the form of graphs.

3.2 Project Design Specifications

This section aims to diagrammatically illustrate the different steps that are followed in sequence starting from importing the dataset into python till visualization of the results for detecting the defects in the fabrics belonging to 4 different classes. The design of the model is built upon 2-tier architecture. The reason for choosing 2-tier architecture over 3-tier was the source of data being collected. The data is large enough to perform exploratory analysis on its own and neither did it require creation of new primary dataset nor did it require any sort of merger with other datasets to form a heterogeneous database. The first layer is the presentation layer which consists of the visualized form of the results that were interpreted during individual comparison. In business logic layer, the data after being imported is pre-processed and later transformed which also included image augmentation. Once the data is transformed, then the features are extracted in a pickle file. On the basis of the extracted features they are trained again in python with image data generator using training and validation datasets. The features are trained using 5 pre-trained models. Out of these 5 are conventional pre-trained models viz. AlexNet, VGG16, VGG19 and MobileNet and the fifth one i.e. DCCNN is tailor made model which is made by combining VGG16 along with 3 convolutional layers running parallel to one another to form a dual channel of convolutional network. Once all the models are trained, the results of each of them are compared to check which of the six performs outperforms the remaining ones. The architecture of the design is explained below in figure 2.

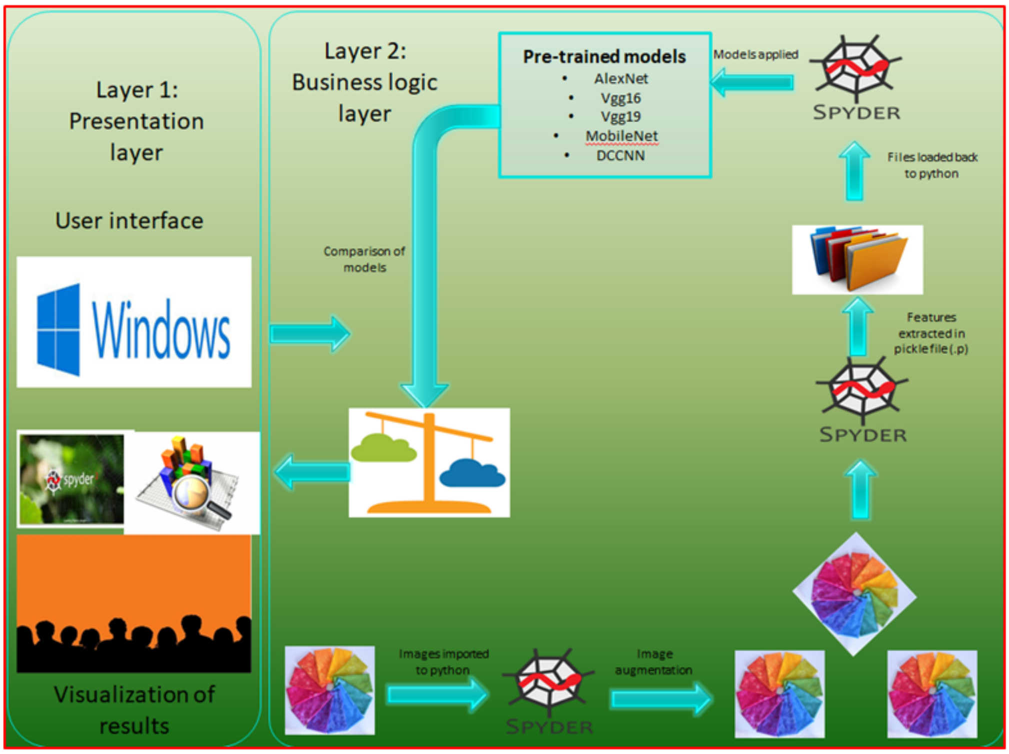

Figure 2: Layout of the design architecture

3.3 Exploratory Data Analysis

The main aim of carrying out exploratory data analysis upon the image datasets is to perform an initial investigation to check if there exists any kind of heterogeneity or anomaly, finding out different patterns that separates the classes from one another and trace distinguishing characteristics if any in terms of image size, image format of any exceptional image. The name of the dataset for carrying out this research is DAGM (Deutsche Arbeitsgemeinschaft für Mustererkennung e.V., the German chapter of the International Association for Pattern Recognition). There following points were identified while carrying out the initial exploratory analysis upon the dataset:

• Pattern of the defect: During the initial observation it was observed that three out of four classes were having same kind of defect i.e. a line striking through it and the fourth class has a knitting defect in it.

• Images looked grayscale but were colored: The images of the dataset initially looked as if they were grayscale. But upon investigating it was found that they held an RGB (red, green and blue) value and are having colored pixels. So there wasn't any need of converting the image from grayscale to color using cv2 at the time of implementation.

• Uneven sets of classes: It was observed that the sizes of the classes were not same and that might have resulted in more training of one class than the other. In order to avoid this situation, same proportion of datasets were being taken with every class size equal to the size of minimum class.

• Tracking the status of the models: Carrying out 5 pre-trained models upon such large sized dataset takes hours of training and it becomes difficult to analyze the progress of the models. So in order to overcome this difficulty, tqdm has been applied to check the progress of each model. Tqdm is derived from an Arabic word 'taqaddum', which means progress.

3.4 Conclusion

It can be concluded that the project was carried out using the overall methodology guidelines of KDD but with slight modifications as the step of image augmentation was also carried out in the third step of feature extraction for data transformation. Each of the steps was rigorously followed in each of the six models applied in order to maintain the uniformity in the process. The data was collected from one of the largest database repository i.e. www.kaggle.com. The software used in this project are spyder (for python), flexible renamer.

4 Implementation, Evaluation and Results for Fabric Defect Detection Models

4.1 Introduction

In this section firstly, a brief overview of slight modifications which are done in the architecture of the first four pre-trained models (VGG16, AlexNet, VGG19 and MobileNet) were discussed. Then the whole architecture of the developed model was discussed. All five models are based upon transfer learning where the weights and the number of layers in the models are adjusted and finally the features are extracted on the basis of network established. After proposing the model architecture, each of the model is implemented using fitgenerator() with ten epochs. After the implementation phase, the findings are evaluated in terms of training, validation accuracy and loss. Finally, the developed models are loaded to check how efficiently they were predicting the validation results. This was done by finding out the precision and recall value from confusion matrix and finally generating F1 score from it for each of the model.

4.2 VGG16 Model

4.2.1 Implementation

VGG16 is of the size (224,224,3) where 3 represents colored images. The reason for which the model is named VGG16 is because the model consists of 16 weighted layers segregated in 5 convolutional blocks. The first two block consists of two convolutional layers each of the filter size (3*3) followed by ReLU and max pooling layer of stride (2,2). The third block consists of 3 convolutional layers along with ReLU and pooling layer of the same stride. The fourth and fifth block consists of 3 convolutions each followed by ReLU and max pooling. After passing through the combination of max pooling and convolutions, a feature map of the size (7,7,512) is obtained. This is further flattened to form the size (1, 25088) feature vector. After this the final feature vector is passed through 3 fully connected layers, where the third layer provides an output of 2 classes (Defected and Non-defected fabrics). Then the output of the 3 fully connected layers is passed through the activation layer called sigmoid. Here the five convolutional layers are freezed so that it gets unaffected while the model is being trained. The model is trained upon the dataset of 4995 images, out of which 2523 images are for testing and 5085 images are for training.

4.2.2 Evaluation and Results

The images were for 10 epochs on a batch size of 100. The model was run in spyder environment which is quite efficient in handling large chunks of data. The performance of the model was first checked in terms of accuracy and loss. Later on the precision, recall and F1 score of the model was evaluated from the confusion matrix on the basis of predictions of the model. The model achieved a training accuracy of 65.24%. Initially when the model started from the first epoch, the accuracy was 60.08%, but gradually as the epochs increased the accuracy also improved to 65.24%. On the other hand, the validation accuracy of the model remained quite stable right through the first epoch till the tenth one. It started from 68.75% in the first epoch and managed to achieve 68.68% in the final epoch. Similarly, the validation loss increased to 68.12% in the tenth epoch and did not showed much signs of improvement since the beginning of the training. However, the training loss drastically fell from 2.08 to 0.65 showing great signs of improvement. Figure 3 illustrates the comparison between the validation and training losses and accuracies.

Meaning of the keywords: Accuracy, Precision, Recall and F1 score has been discussed in the Methodology section.

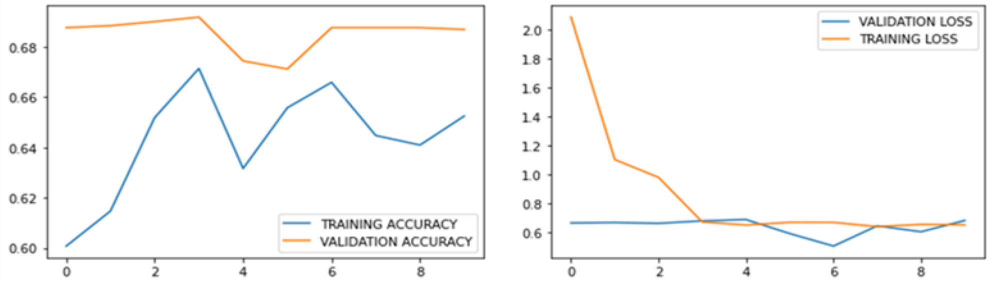

Fig 3(a) Accuracy comparison Fig 3 (b) Loss comparison

Figure 3: Performance of VGG16 during training and validation

Interpretation

A confusion matrix is plotted show to how well the model is able to predict the validation dataset. The confusion matrix shows that the model is successfully able to detect 1466 and 599 non-defected and defected fabrics successfully. On the basis of true positive, true negative, false positive and false negative values obtained, the precision and recall values are computed as 0.89 and 0.76 respectively. It means that 89% of the fabrics that were identified by model as non-defected were actually non-defected, whereas 76% of the non-defected fabrics were correctly identified. So the F1 score is computed to be 0.81 from table 2.

Table 2: Confusion matrix for VGG16

	Non defective (Actual)	Defective (Actual)
Non defective (Predicted)	1466	173
Defective (Predicted)	445	599

4.3 AlexNet Model

4.3.1 Implementation

The architecture of AlexNet is such that it consists of 5 convolutional and 3 fully connected layers. After the first two convolutions there is an overlapping max pooling layer. Then the third, fourth and fifth convolutional layers are attached directly after the max pooling layer. Thereafter, the fifth convolutional layer another overlapping max pooling layer is attached and then the final output goes to the 2 fully connected layers. From there the connected layers feed the final into sigmoid binary classifier of 2 classes i.e. defected and non-defected. Here again the weights of the first 5 convolutions are freezed while training with the dataset and remaining 3 fully connected layers are allowed to change the weights while training.

4.3.2 Evaluation and Results

The dataset was trained upon 12 instead of 10 epochs because the training and validation accuracy showed sharp decrease in the performance at the end of tenth epoch and from the eleventh epoch it started to rise again and becoming more stable than before. The model recorded a training and validation accuracy of 66.45% and 69.77% respectively.

The training accuracy showed a very marginal improvement from the first epoch whereas the validation accuracy remained almost the same (figure 4).

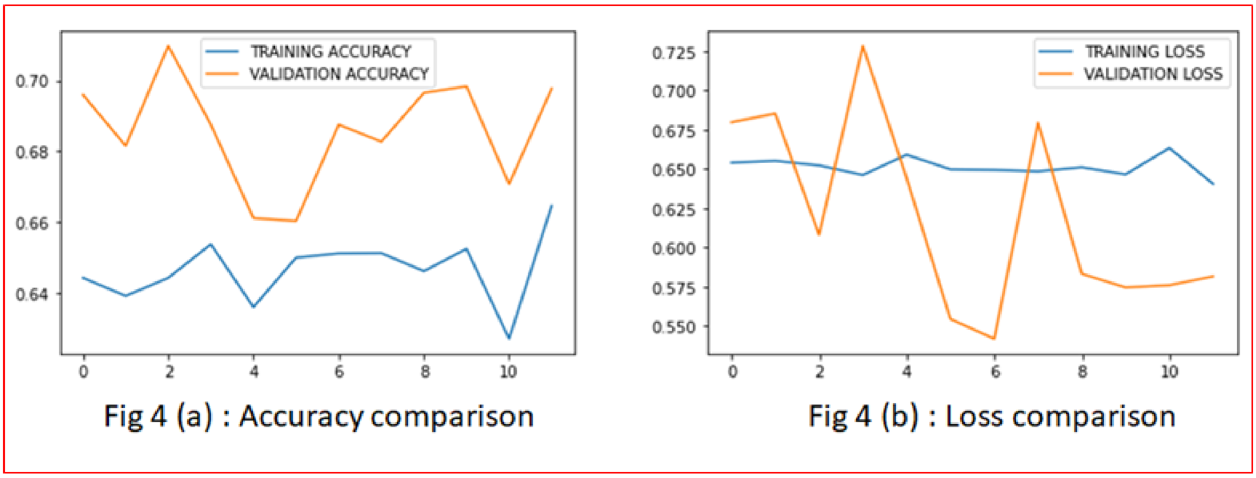

Figure 4: Performance of AlexNet during training and validation

Interpretation The confusion matrix is drawn finally to check the prediction accuracy upon the validation set (table 3). The matrix shows that out of 2683 fabrics, the model is successfully able to predict the 1502 non-defective fabrics as non-defective and 644 defective fabrics as defective. Hence the precision and recall of the model is turned out to be 0.87 and 0.82 respectively. It means that 87% of the fabrics that were identified by model as non-defected were actually non-defected; whereas 82% of the non-defected fabrics were correctly identified On the basis of precision and recall the F1 score is computed to be 0.85.

Table 3: Confusion matrix for AlexNet

	Non defective (Actual)	Defective (Actual)
Non defective (Predicted)	1502	216
Defective (Predicted)	321	644

4.4 VGG19 Model

4.4.1 Implementation

The architecture of VGG19 is similar to that of VGG16. The only difference being that instead of 16 convolutional layers it has 19 layers in it, with one additional layer in fourth and fifth convolutions each. The model is trained upon Imagenet dataset having more than one million images. VGG19 also has ReLU as activation layer and max pooling in between the two convolutional blocks. Finally it is connected to three fully connected layers of the size 4096, 4096 and 2 (output classes – defected and non-defected).

4.4.2 Evaluation and Results

This model was trained upon for 10 epochs and the validation accuracy and loss was observed to be slightly better than VGG16. It recorded a training accuracy of 65.54%

whereas the validation accuracy was observed to be 70.19%. The loss function also showed great signs of improvement as it got reduced from 2.13 to 0.63 from first epoch to the tenth epoch (figure 5). There were 49 steps in each of the epoch. It was obtained by dividing the training set of 4995 by the batch size i.e. 100.

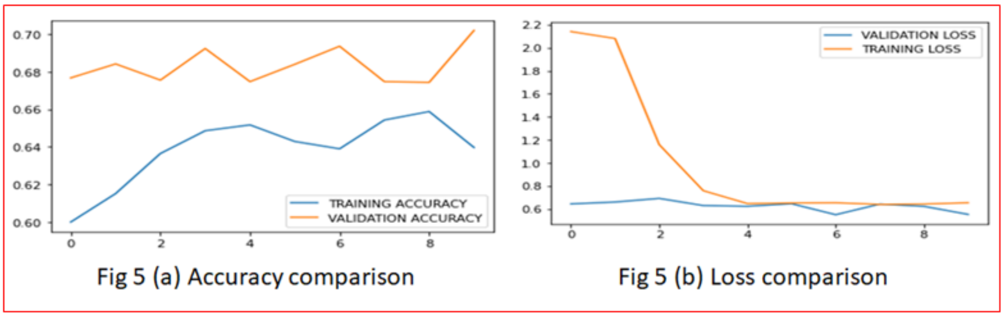

Figure 5: Performance of VGG19 during training and validation

Interpretation

Finally it can be interpreted from the confusion matrix that the model is able to predict 81% of the validation dataset properly. The precision and recall of the model is 0.89 and 0.79 respectively (obtained from table 4). Therefore the F1 score is 0.83. Hence, 89% of the fabrics that were identified by model as non-defected were actually non-defected, whereas 79% of the non-defected fabrics were correctly identified.

Table 4: Confusion matrix for VGG19

	Non defective (Actual)	Defective (Actual)
Non defective (Predicted)	1311	173
Defective (Predicted)	337	862

4.5 MobileNet

4.5.1 Implementation

It has a streamlined architecture that depth wise separates its convolutions to establish a lightweight neural network to provide an efficient model for mobile phones and similar embedded devices. Separate depth wise convolution filters are comprised of depth wise convolutional filters and point convolutions. The filter evaluates each of the convolutions on each input channel and point convolution filter combines output of depth convolution in a linear manner with 1 * 1 convolutions. Shown in the figure 6.

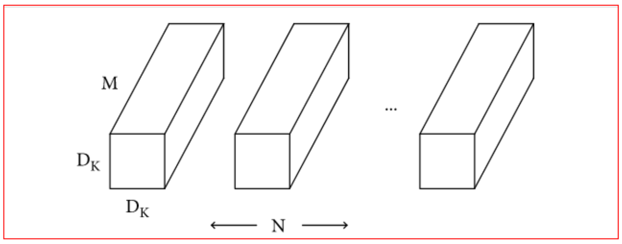

Figure 6: Convoluions of MobileNet

The connection mode of MobileNet is also different from other traditional architecture as each layer is connected to the precious network layer in such a manner that the outputs in feature maps of all the existing layers becomes the input of the next feature.

4.5.2 Evaluation and Results

The model was trained upon 10 epochs. Even though the training accuracy continuously increased at a slow pace (started from 0.6456 and ended at 0.7648) but the validation accuracy first dropped drastically in the first three epochs and then from the fourth epoch it started showing signs of improvement and ultimately reached up to 0.7541. Moreover, the loss function showed similar trend for training and validation, with validation graph falling more steeply from 0.8271 to 0.6546 in the last three epochs as shown in figure 7.

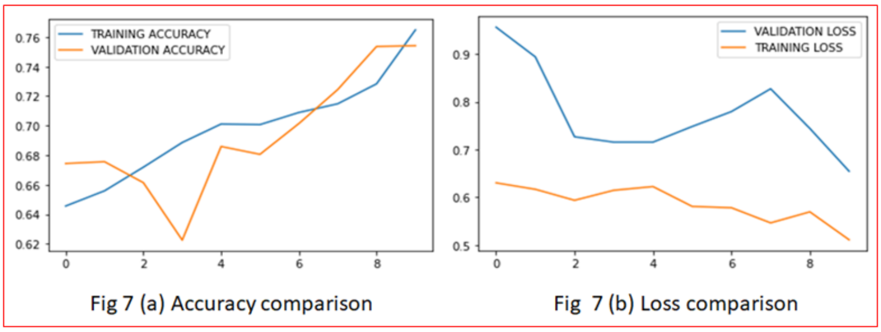

Figure 7: Performance of MobileNet during training and validation

Interpretation

Finally the confusion matrix of 2683 images was plotted and the result shows model managed to predict 87% of the test dataset correctly i.e. True Positive + True Negative = 87%. The model is not able to accurately predict 187 + 55 fabrics correctly. Hence the precision and recall value of the model comes out to be 0.96 and 0.89 respectively. It means that 96% of the fabrics that were identified by model as non-defected were actually non-defected; whereas 89% of the non-defected fabrics were correctly identified On the basis of precision and recall the F1 score is computed to be 0.93 on the basis of table 5.

Table 5: Confusion matrix for MobileNet

	Non defective (Actual)	Defective (Actual)
Non defective (Predicted)	1562	55
Defective (Predicted)	187	879

4.6 DCCNN

4.6.1 Implementation

Dual Channel Convolutional Neural Network consists of two channels (deep and shallow). The first channel comprises of VGG16 which is based upon transfer learning which captures the overall understanding of the generalized features of the images and the second channel captures much deeper features and minute details than the first channel. Both channels are clubbed together to form a new model which is capable of providing better classification accuracy. During the training phase the channels are trained independently while during the testing both the channels are merged together for exerting combined effort in classifying the fabric images. It uses max pooling for pooling the model. The functionality of the fully connected layer is to combine multiple image maps as the model passes through different layers of pooling and convolutions in order to extract semantic features of image with proper classification. The structure of Dual Channel Convolutional Neural Network is depicted below in figure 8.

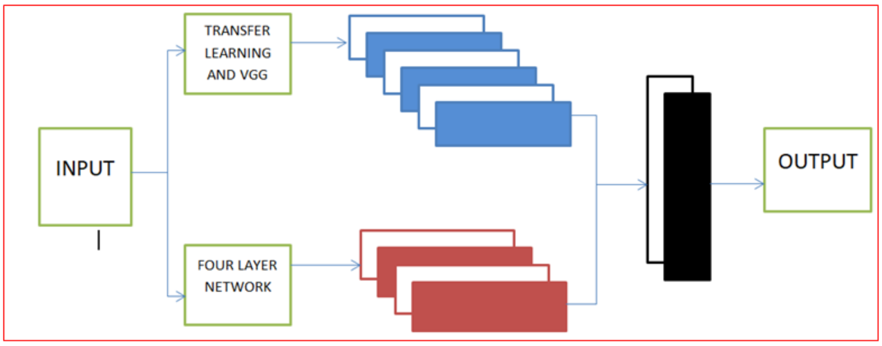

Figure 8: Architecture of DCCNN

4.6.2 Evaluation and results

The model was trained upon 10 epochs and that after the third epoch when the model got a bit stable, the validation and training accuracy followed the same trend and remained almost the same at the end of tenth epoch. They were recorded as 73.41 and 72.56 percent for training and validation respectively (from figure 9). Whereas in terms of loss, training loss showed a promising signs till the sixth epoch by getting dropped till 0.6022, but unfortunately after that it got spiked up and ended up at 0.6404 along with validation loss of 0.6518.

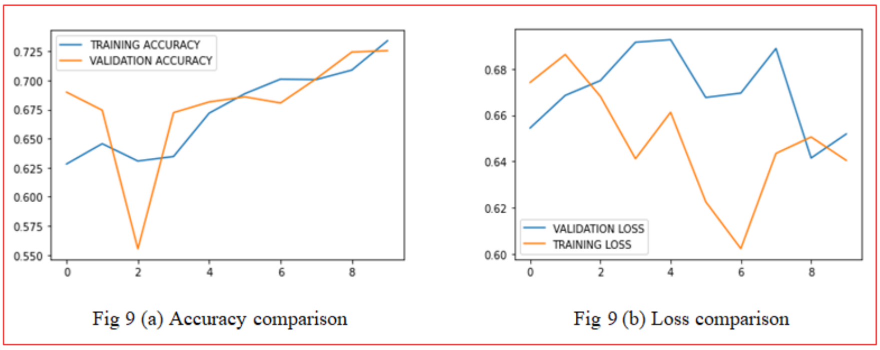

Figure 9: Architecture of DCCNN

Interpretation

From the confusion matrix of 2683 images, the model successfully predicted at least 83 percent of the images correctly, whereas a maximum of 17 percent of images were identified either defected as non-defected or non-defected as defected. Hence the precision and recall value of the model comes out to be 0.93 and 0.83 respectively. It means that

93% of the fabrics that were identified by model as non-defected were actually non-defected; whereas 83% of the non-defected fabrics were correctly identified On the basis of precision and recall the F1 score is computed to be 0.87.

Table 6: Confusion matrix for DCCNN

	Non defective (Actual)	Defective (Actual)
Non defective (Predicted)	1473	108
Defective (Predicted)	308	794

5 Discussion and Comparison of Results

In this section, a detailed comparison among all the five pre-trained models viz. VGG16, AlexNet, VGG19, MobileNet and DCCNN have been made to check which of them exceeds in which all sections of evaluation and which one lags behind (figure 10). The models were first evaluated on the basis of their validation accuracy and the loss they incur during ten or twelve epochs. Later, on the basis of confusion matrix precision and recall values were evaluated to ultimately check the F1 score of each model.

It was observed that even though there was not much significant difference among three parameters (precision, recall and F1 score) of all the five models, but still our developed model (DCCNN) minutely managed to out-perform 3 out of 4 existing pre-trained models viz. VGG16, AlexNet and VGG19. But because of the complexity in the architecture using 13 depth wise convolutions, each containing a depth wise convolution, batch normalizations, ReLU, conventional convolution batch normalization (again) and ReLU, it would be advantageous for MobileNet to better classify the defects and finally resulting in better performance than the developed model.

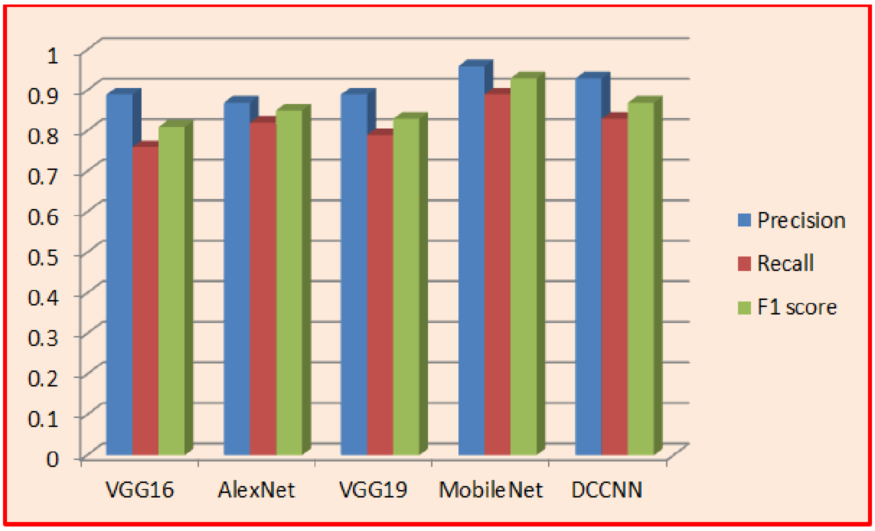

Figure 10: Precision, recall and F1 score of the models

Similarly, on comparing the validation accuracy while training the model, similar performance trend was being observed among the five models, with MobilNet having the best training and validation accuracy, closely followed by our developed model having an accuacy of 73.41 and 72.56 percent respectively for training and validation set (figure 11).

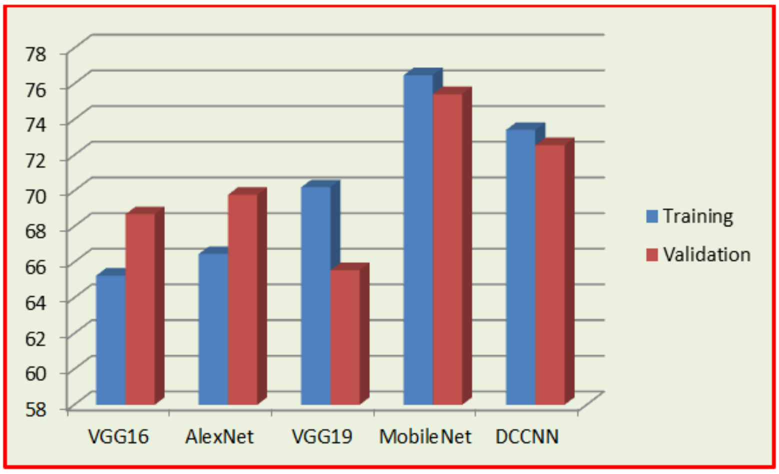

Figure 11: Training and validation accuracy of the models

6 Conclusion and future work

Keeping a check upon the quality is one of the prime concerns for any manufacturing company. Hence, this research was carried out with intent of increasing the efficiency of automated fabric defect detecting system which in future can completely replace manual inspection procedure which incurs more cost and is less reliable than the machine driven process. The research was carried out using five pre-trained models. Out of five models, four of them were pre-established models viz. VGG16, AlexNet, VGG19 and MobileNet, and the last model i.e. DCCNN was developed for this research by merging a transfer learning based shallow layer (used as VGG16) along with deep convolutional layer having three convolutions inside. The images were rigorously normalized, augmented and fine-tuned in order to solve the problem for overfitting, before training them for 10 or 12 epochs. It was observed that even though the training and validation performance of all the five models were quite competitive but still the developed model managed to out-perform three of the four models (VGG16, AlexNet and VGG19). Only MobileNet was able to perform well that too buy a very small margin. There was a difference of only 3 and 6 percent in precision and recall values between MobileNet and DCCNN with MobileNet exceeding with both. However, the F1 score of MobileNet was 0.93 whereas for DCCNN it was 0.87. It is because of the complexity in the architecture and large number of convolution layer, MobileNet performed slightly better than DCCNN. Hence it can be concluded that if a company has a large scale manufacturing process and is looking for a more complex model that can afford to install and run larger model with more complexity in the convolutions, than they can install MobileNet. But for most of the Small Medium Enterprise (SME's) where the cost of the automation process would be a big concern, there DCCNN can turn out to be an ideal solution as it provides accuracy very similar to that of MobileNet with much simpler convolutional design.

Future work
If the developed model proves to be successful for SME's then in future the shallow layer can be experimented to be trained with heavier and more complex pre-trained models like DenseNet and Xception instead of training it with VGG16 which is less complex in architecture than those models.

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