Fabric Fault Detection using Automated Artificial Intelligence Approach

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***Abstract*—Fabric defects significantly impact the quality and aesthetics of textile products, leading to production delays and customer dissatisfaction. Traditional manual visual inspection, the primary method for fabric defect analysis, suffers from limitations like subjectivity, time consumption, and inability to keep pace with high-speed production lines. This research investigates the potential of Artificial Intelligence (AI) technologies to address these limitations and enhance fabric defect analysis. The fabric images are enhanced by pre-processing at various levels using conventional image processing techniques and they are used to train the networks. The Deep Convolutional Neural Network (DCNN) and a pre-trained network, AlexNet, are used to train and classify various fabric defects. With this accuracy, the detection and classification system based on this classifier model can aid the human to find faults in the fabric manufacturing unit.**

***Index Terms*—fabric defects, artificial intelligence, defect classifier, AlexNet, deep neural network**

I. INTRODUCTION

The textile industry thrives on delivering high-quality fabrics that meet stringent aesthetic and functional requirements. Fabric defects, however, can significantly compromise these aspects, leading to product rejections and increased production costs. Traditional manual inspection methods for detecting defects are time-consuming, prone to human error, and lack objectivity. Artificial intelligence (AI), particularly deep learning, presents a revolutionary approach to fabric defect analysis. Deep learning algorithms are adept at learning complex patterns from vast datasets of images. This capability makes them ideal for automatically identifying and classifying fabric defects with high accuracy and consistency. In the textile industry, fabrics are prone to various defects and deformities which have an obstructive effect on the quality of the product. The defects are caused by the misuse of the materials and carelessness while manufacturing. It is challenging to inspect the real fabric defects manually, due to the huge number and various categories of defects which are characterized by uncertainty. A low percentage of the defects are being detected by a manual inspection due to human fatigue, which decreases the efficiency, whereas in a real-time automatic system defect detection could be more efficient.

II. AI IN TEXTILE

In the textile industry, AI is revolutionizing the total production process and it is the need of the hour since there is an inflated demand for quality textiles. In the past decade there has been a significant leap in the number of industries using AI because both production costs and the number of faults are kept low without compromising speed and accuracy. Fabric defects deteriorate the value of textile products. The final product with a single minuscule defect can be easily rejected. Neural network (NN) with deep learning plays a vital role in inspecting and identifying defects at a much faster rate and with better accuracy. This new era of textile industry leveraged with AI brings cutting-edge revolution and has a great future a head.

III. METHODOLOGY

The Figure1 shows the block diagram of the proposed fabric defect detection system. The pre- processing techniques, like image scaling, pixel normalization and dimension reduction, are used for the training dataset. Feature extraction by the CNN model aids in characterizing and analysing the defective and non-defective texture of the fabric images. Datasets consisting of defective and non-defective fabric images are used to train the system for defect detection and classification. If the fabric image is clean, it is classified as good else it is defective. The defective images are further classified into colour, cut, hole, thread and metal contamination. Thus, image processing algorithms in DNN are used and the defects in fabrics are detected and classified.

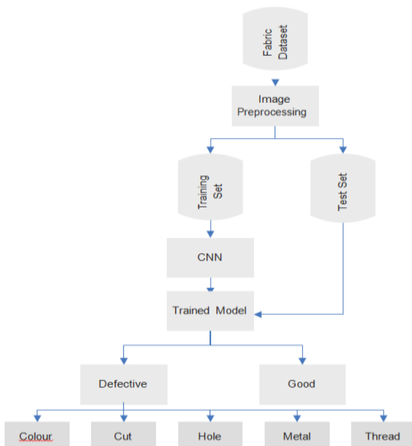


Fig.1: System architecture

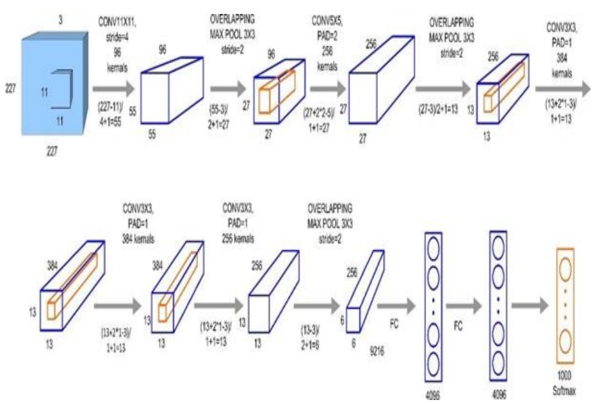
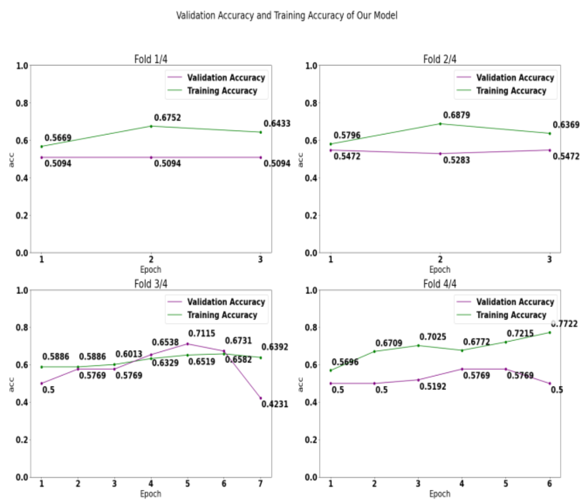


Fig.2: Network architecture

AlexNet is a pre-trained network that has the ability to classify images into 1000 object categories. The architecture of AlexNet which consists of eight layers. In the eight layers of Alexnet, the initial five layers are convolutional and the pending 3 are fully connected layers. There are 4096 neurons in each of the fully connected layers. The various convolutional filters (kernels) extract interesting features in a fabric image. Each single convolutional layer has several filters of the same size. After the five convolutional layers, the output of the remaining overlapping max-pooling layers is fed into two fully connected layers. The down sampling of the height and width of the tensors are performed by the max-pooling layers. In the proposed AlexNet architecture, there are six convolution layer operations in sequence. Except the third and fourth, all the convolution layers have 3x3 kernels, with a stride and the padding of activation function. Each max pooling operation performs zero padding with a stride of 2. It keeps the depth unchanged and down samples the height and width of the tensors.

IV. RESULTS



Plot 3: Validation accuaracy and training graph of proposed system

V. PERFORMANCE EVALUATION

AlexNet provides better performance than the other networks with an accuracy of 92.60%. The test accuracy of various architectures is given in Table.

Model	Accuracy, %
AlexNet after data augmentation	92.60
Differential evolution [7]	93.40
Co-occurrence matrix [30]	90.78
Mathematical morphology [31]	90.41
CNN with AlexNet	81.20
CNN	73.80
MLP	74.13

Table 4. Accuracy of Various Architectures

VI. ERROR MATRIX

The confusion matrix shown in Table summarizes the number of correct and incorrect predictions obtained after training with AlexNet architecture. Among the various commonly used evaluation metrics, the sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) .

Depending on the actual class and the class predicted while testing the model, the prediction is classified into one of the following [33]:

• True positive (TP) indicates the outcome, where the model correctly predicts the positive class.

• True negative (TN) indicates the outcome where the model correctly predicts the negative class.

• False positive (FP) indicates the outcome where the model incorrectly predicts the positive class when it is actually negative. It is also called a type 1 error.

• False negative (FN) indicates the outcome where the model incorrectly predicts the negative class when it is actually positive. It is also called a type 2 error.

ACTUAL CLASS

	Colour	Cut	Good	Hole	Metal	Thread
Colour	92.40	1.80	2.50	1.80	0.82	0.70
Cut	1.98	90.00	1.73	3.80	1.30	1.20
Good	2.10	4.20	90.60	1.60	0.48	1.10
Hole	1.81	2.80	3.10	91.70	0.40	0.20
Metal	0.84	0.37	1.68	0.36	95.3	1.45
Thread	0.86	0.65	0.41	0.81	2.00	95.30

PREDICTED CLASS

Table 5. Confusion matrix of the trained AlexNet

VII. CONCLUSION

The deep learning model was trained for five defect classes: cut, colour, hole, thread, metal contamination. The dataset used is a part of the public dataset, MVTec Anomaly Detection. The trained model was limited only to these five defect classes not only due to the number of images available in the open source database, but also the fact that in India these five defect classes remain as the most prevalent faults found in today's textile industry. The developed Deep Convolutional Neural Network (DCNN) classifier, which employs transfer learning using the AlexNet pretrained network yielded maximum accuracy of 92.60% after continuous testing and training. The developed DL-based classifier model could be deployed in textile production which will have a vital role in improving the overall efficiency of the fabric in quality and cost. This will not only enable accurate and rapid defect identification but also help differentiate minute differences between the defect classes. Particularly, it aids the industry in functioning without manual inspectors, which plays a crucial role concerning efficiency and net profit, especially in times like the current pandemic where remote operation is the new normal.

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