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Machine Learning System for Fabric Defect Detection and Classification

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ABSTRACT

The textile sector is crucial to India's economy, and one of its most significant facets is the management of fabric quality. In computer vision, texture analysis is used for the purposes of defect detection, classification, and segmentation. In order to save manufacturing time and costs, this paper explains a fundamental method for identifying various fabric flaws in the textile industry. An essential part of quality control, automated fabric inspection systems help find textile flaws quickly and accurately while also cutting down on human labor. In this work, we assess two classifiers—the NN classifier and the SVM classifier—on a 5000 fabric image samples, TILDA dataset for the purpose of recognizing six distinct defects: holes, horizontal defects, reed markings, burls, slubs, stains, and double end marks. One of the most fundamental and significant components of modern fashion is textile. We can't fathom a world devoid of textiles. Another essential problem in the textile production sector is fabric quality monitoring. When it comes to finding various types of fabric defects, such as holes, slubs, oil stains, etc., automatic defect detection is seen to be quite interesting. Using the provided fabric samples, this study introduces a novel method for fault and defect identification. The five-step process for textile defect detection begins with collecting picture samples from the industry-standard TILDA dataset. Grayscale transformation is a preprocessing technique that is used to enhance the picture quality and eliminate undesired noise. As a last step in feature extraction, SVM takes the gray-level co-occurrence matrix (GLCM) into account. The testing phase, however, involves validating these two classifiers using the test data and calculating their sensitivity, specificity, and accuracy.

Keywords: *Neural Network (NN), Support Vector Machine (SVM), FFT (Fast Fourier Transform) and DFT (Discrete Fourier Transform).*

1. INTRODUCTION

Currently, fabric production is at an all-time high, and in the textile sector, fabric quality is the single most critical element in determining a product's retail price. Weaving high-quality fabrics is becoming increasingly important as the fashion industry responds to rising consumer demand for a wider range of garments made from a wider variety of fabrics. This diversity in texture and quality poses a significant challenge to the industry's yarn quality control systems. Efficiently classifying and detecting six distinct kinds of faults often seen in textile textiles is the primary goal of this study. Automated systems also make it possible to provide a precise way of evaluating the look and quality of yarn textiles, as well as to automatically recognize woven fabrics and wave patterns. Using digital image processing methods, the proposed work aims to identify specific defects like as oil stains, rust stains, pores, color markings, hairiness, pollutants, and breakage during waving. Additionally, it will acquire the position and forms of these defective textiles. To address the drawbacks of human visual inspection, an automated flaw detection system is suggested. Currently, human controllers depend only on their own expertise to carry out fabric inspections using a display system.

Fig (a): Human Based Inspection SystemFig (b): Machine Automated Inspection System

Fig 1: Defect Inspection System

There is a current and enormous need for high-quality textile materials and goods, and an automated system seeks to produce them as well. Despite all, it is still a tough process to accurately differentiate between pure cotton and extraneous fibers. The first step of the image acquisition method is to take high-resolution pictures using a camera. This allows for a more thorough fabric recognition procedure, which in turn uses various image processing algorithms to identify the wave pattern and establish their quality. This study detects many sorts of defects using the TILDA dataset, which consists of 5000 fabric image samples. These flaws include holes, horizontal defects, reed markings, burls, slubs, stains, and double end marks. In order to improve the quality of subsequent processing procedures, such as scaling, segmentation, RGB to grayscale conversion [3], and gray level transformation, incoming pictures must first undergo image preprocessing. This is done to decrease the embedded noise that digital image devices introduce.The next step is feature extraction, which involves selecting certain characteristics from the fabric sample photos using subimage features based on the Fast Fourier transform (FFT) and density-functional theory (DFT) methods. 1, 2 the next stage is classification, which entails comparing the input pictures' feature vectors with a database containing information such as a “Neural Network (NN) classifier” or a “Support Vector Machine (SVM)” in order to determine the kind of foreign fiber that was mixed with cotton and to categorize the samples as either normal or faulty. In addition to helping the textile sector find and extract various fabric structures and blocks automatically from textile photos, the suggested method would boost product quality, efficiency, and accuracy when it comes to textile textiles. Fabric defects, such as holes, slubs, stains, and thick yarn, are shown in Fig. 2 below, along with other characteristics of these textiles.

Fig 2: Sample Images of Fabrics

This work enables for automated detection of woven fabric and wave pattern and to develop an automated method in inspecting appearance and quality of the textile fabrics. In this work fabric inspection model consisting of Image preprocessing, segmentation. Feature extraction and classification operation is used so that it can detect defects with complex textures and tiny defects.Anstey, Peters, and Dawson (2005) found that human-based inspection systems fulfilled all criteria from the very beginning of the inspection process in the textile sector. The inspection process still relies on human labor, but the introduction of sophisticated weaving machines allows for larger production patterns and faster production rates. Because of the inherent limits in human physiology, human-based examination is therefore unable to meet the demands of the modern day. According to research steered by Newman and Jain (1995), human inspectors are only able to spot 60–70% of problems. This is only one of several problems with “human-based inspection systems (HIS)”. One way to characterize them is:

1. To train an inspector to be competent, the first part takes quite a while.
2. The limitations of the human body make inspections tedious and time-consuming, even when the most skilled inspectors are on hand.
3. Thirdly, production times are greater because humans perceive speed more slowly than robots.
4. Because human attention is affected by weariness and boredom, human inspectors have limited time to concentrate. Consequently, inspectors are unable to detect areas with defects.
5. According to D. Brzakovic and N. Vujovic (1996), inspectors should move at a pace of 20 m/min when checking textiles with a width of 1.6-2 meters. The detection rate in inspection systems is reduced due to the difficulty of human perception.
6. A detection rate of 100% is unattainable with human-based inspection techniques.
7. Human inspection techniques may seem to be less expensive, but they have limitations when it comes to discovering faults. Fabric profits are therefore diminished due to hidden flaws.

2. LITERATURE REVIEW

This section provides a synopsis of significant publications published in the last few years that deal with the identification of woven cloth and its patterns. Different fabric defect identification and categorization are the basis of surveys [10, 18], whereas feature extraction is the basis of surveys [12, 14, 15, and 20].

Chen et al. [4] introduce Faster GG RCNN, a novel method for detecting fabric defects. This technique uses a combination of Gabor kernels to get over the problems caused by backdrop texture. The model's remarkable accuracy is the result of its two-stage training technique, which incorporates the "Genetic Algorithm" and back-propagation. Compared to the standard Faster R-CNN, it performs much better inconditions of operation. With an average accuracy of 94.57%, our technique outperforms Faster R-CNN by a wide margin, and it has great potential for enhancing quality control and fault identification in textiles.When it comes to computer vision tasks like object recognition, segmentation, and image classification, "deep convolutional neural networks" (CNNs) really shine. In a study by Zhang et al. [5] provide a technique for automatically detecting fabric defects using one of these networks. The three main components of this method are as follows: first, segmenting the fabric image into smaller, more manageable patches and labeling them; second, using the segmented image to train a deep convolutional neural network (CNN); and third, during inspection, detecting defects by sliding the trained model over the entire image to determine the type and location of the defect. Through extensive testing on many fabric databases, the approach outperforms state-of-the-art solutions in terms of performance, resilience, and quality. This method shows promise as a means to efficiently and accurately identify fabric defects throughout the textile manufacturing process.The wavelet transform has been investigated by Ngan et al. [6] for the purpose of automated pattern recognition of defects in fabric. Defect identification in fabric made use of three separate approaches: GIS, Direct Thresholding (DT) using wavelet detailed sub-images, and WGIS, which combined the two previous techniques.

To improve the YOLOv5 object recognition algorithm and manage restricted fabric defect pictures, Jin and Niu [7] used a teacher-student architecture. While the deep teacher network reliably detects faults, the shallow student network distills information to accomplish real-time detection with no performance compromise. More than that, multitask learning is used to in order to simultaneously discover both broad and specific errors. Adding a focused loss function and central restrictions to the algorithm substantially improves the performance of the proposed method for pattern recognition. Results from tests on open-source datasets demonstrate its superiority to competing approaches, highlighting its remarkable ability to detect defects in textile photographs. The potential for this system to completely transform the textile industry's approach to fabric fault identification is immense.

To improve production-level fabric quality management, Jiang et al. [8] employed an approach based on the Dense Net, SSD algorithm. The suggested technique is an attempt to solve the problems that traditional approaches have with complicated and changing fault forms. This method ditches the old VGG16 in favor of the Dense Net network, which forms the SSD algorithm's backbone. This mitigates gradient disappearance, improves feature map transfer, and reduces network parameters. When contrasted with SSD, these updates improve both detection accuracy and performance in real time. The method's detection speed of 61FPS and accuracy of 78.6mAP during testing are rather excellent. All things considered, the results shown by this adaptive fabric defect detection system are encouraging, and it shows a lot of promise for applications related to fabric quality management.

Shalaka S Patilet. al. [10] proposed defect detection and classification in fabrics, Line scan camera is used for image acquisition , woven plain fabric are digitalized by 512*512 pixels and stored as 8 bit gray scale data in the computer and then preprocessing is carried out by RGB to gray conversion, wavelet analysis method is used for removal of noise in the signal and wavelet transformation is used for detection of different types of defects like burl, slub , knot, double end , end out and hole in fabrics and the detection of the defects is said to be accurate and has lower detection error.In order to identify foreign fibers in cotton online, **Xuehua Zhao et al. [12]** created an automatic identification method. An effective classifier based on the kernel extreme learning machine (KELM) was suggested in this study for the purpose of reliably identifying foreign fibers intermingled with cotton. We used the RGB, HSV, and gray models to extract 27 color features from the foreign fibers. The texture features were retrieved using a gray level co-occurrence matrix; in total, 41 texture features were extracted. Along with these, we obtained 7 shape features: area, euler number, form factor, eccentricity, solidity, rectangle, and sphericity. The 75-dimensional feature vector is formed from four types of features: color, texture, and shape. The suggested system is a strong contender for a new, high-performing foreign fiber identification system.**Rebhi Ali et. al. [14]** proposed defect detection and discontinuities in textured images using local homogeneity analysis and Feed Forward Neural Network (FFN), an about 89 images in which 76 defected and 13 defect free images are collected from PARTNER textile industry Tunisia for the study and FNN is used for classification of defected images, back propagation to train the neural network, mean square error to measure the performance, the overall FFN accuracy obtained in training process was about 99.05% and in testing process was 96.25%, The average classification was said to be 97.35%. A method for detecting cotton plant leaf diseases using image processing techniques was developed by Pranita P. Gulveet. al. [15]. Pictures of different leaves taken using a high-resolution digital camera are used to create the final product. Image resizing and filtering methods are used for preprocessing. Using a thresholding-based masking technique, the segmentation procedure divides a picture into subsets of pixels that are similar in terms of the pixel labeling criteria. To isolate the ROI, this mask is applied to the input picture.

Statistical texture analysis employs GLCM approach for feature extraction. An algorithm called the "Euclidean distance classifier" is used here. The method uses thresholding-based region extraction to successfully segment the sick section of the leaf sample picture. A method for automatically determining yarn mass characteristics using image processing techniques was developed by KartikBahlet. al. [17]. Additionally, it suggests a method for identifying fabric flaws in the textile sector, which might help save manufacturing time and costs, and it was created for use in automated fabric inspection. Using an 8-bit grayscale color scheme, the picture is saved in bmp format after being captured by the camera. Afterwards, an algorithm is used to remove noise from the picture.The noise-free picture is binarized by bringing it into threshold mode, which whitens the background and blackens the item or pattern of interest. The acquired picture, which is often in JPEG format, is first converted to grayscale using the RGB2 gray function in Matlab. Then, the Otsu technique is used to threshold the image. Finally, the bwlable command is used to segment the binary image. After that, we feed the segmented yarn pictures into the statistical analysis program to find out the standard deviation, area, perimeter, figure aspect, and minimum and maximum radii in each quadrant. With a range of 21 and 54, respectively, the standard deviations are rather close. In order to characterize textiles, Singh JP et al. [18] created a flexible system. A non-destructive method for measuring yarn diameter, twist angle, and hairiness has been developed in this study using computer vision methods. In order to determine the fiber's orientation on the yarn's surface, pictures of the yarn are subjected to a Fourier transformation. Following this, frequency domain filtering is suggested as a step before spatial analysis. In this investigation, an Uster tester is used, together with the Lawson Hemphill Yarn Analysis System (YAS) and Quick Quality Management (QQM). The tester is fitted with an optical sensor OM. In order to determine the twist angle, one may use spatial analysis or frequency domain analysis, both of which rely on the assumption that the surface fibers have common spatial properties like thickness and brightness. Autocorrelation, histogram equalization, thresholding, and Gaussian filtering are some of the image processing techniques that have found usage in textile characterisation.In their study on textile fabric flaw detection and identification, HalimiAbdellah et al. [19] used a vision system that included a camera with a 512*512 pixel sensor to capture pictures in JPEG format. The authors used the histogram equalization approach to improve the grayscale images. The total accuracy achieved in detecting textile defects was 96.15% after using the Otsu algorithm for thresholding and a morphological filtering approach to eliminate noise. Using image analysis technologies, Jie Zhang et al. [20] suggested a method for fabric identification. The history of weave pattern identification is quickly covered in this article. The approaches that have been described may be grouped into five types: those that rely on photoelectric analysis, those that rely on frequency domain analysis, those rely on spatial domain analysis, jointed methods, and others. One kind of optical analysis is diffraction analysis, and another is photoelectric analysis; both are used for fabric identification. Fabric diffraction images allow for the measurement of highlight size and spacing in diffraction-based research. The fabric picture was transformed into high-contrast fringes using space filters using a photoelectric analysis-based system. The Fraunhofer diffraction technique, which is comparable to the Fourier transform technology, is used in frequency domain analysis. It is possible that this method's total accuracy might exceed 80%. In order to determine the density of the woven fabric, Wavelet Transform employs a multi-scale decomposition.

3. PROPOSED METHODOLOGY

This section describes the proposed methodology used in fabric Defect detection using different image processing techniques.

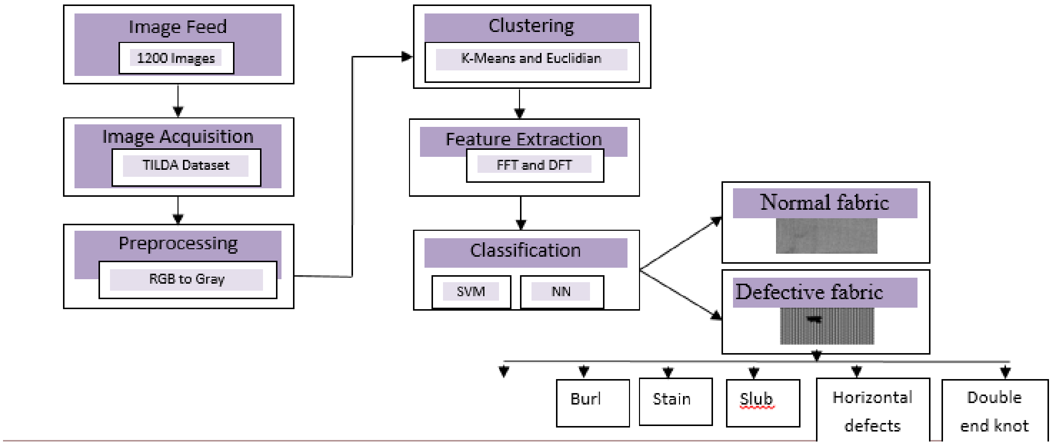


Fig 3: Block Diagram of the Proposed Framework

Figure 3 depicts the proposed work's architecture for detecting various fabric image flaws. In this work, the images are acquired from the standard TILDA dataset using an image acquisition technique that involves feeding the feed into the system and capturing the image with a digital camera. To improve the image quality before further processing, a preprocessing technique is employed, which includes converting the image from RGB to grayscale and resizing the image. In order to find objects and borders in photos, segmentation divides a digital image into many segments. When a picture is segmented, what comes out is either a collection of contours or segments that together cover the whole image. The frequency content, phase, and other signal parameters may be retrieved using feature extraction using fast Fourier transforms (FFTs) and density-functional theory (DFTs). Next, SVM and NN classifiers are used to categorize the photos, allowing for the detection of both normal and faulty fabric images.

3.1 Different Image Processing Techniques

1. **Dataset:** This project proposes to use the standard TILDA dataset and examine around 5000 fabric image samples. Fabric samples, both good and bad, are included in the dataset.
2. **Image Acquisition**: Digital cameras produce images with higher resolution and quality. Building an image database is obviously application-specific. For consistency's sake, we've saved all the photos in JPEG format.
3. **Image Pre-processing**: The preprocessing of the input images is required to enhance the image quality for further processing. This module includes various preprocessing methods such as color conversion, resizing, segmentation etc. The image is resized to 256*256 and then image enhancement and median filters are used to improve the quality of input images for further processing like edge detection and also to reduce the noise.
4. **Clustering:** Clustering is the process of measuring similarity where different clustering techniques such as K-means clustering and Euclidean distance classifier are used for defect detection.Segmentation is also used for assigning particular labels to every pixel in the image **[15]** it also involves partitioning images into different groups of pixel.The segmentation involves counter segmentationfor segmentingdifferent types of defects based on shape and size of the defected area.
5. **Feature Extraction**: The feature extraction involves FFT (Fast Fourier Transform) and DFT (Discrete Fourier Transform), where FFT is mathematical operation that decomposes a signal into sum of sinusoidal signals. In digital image processing the input signal is represented in the spatial domain[x,y] where N represents the width and M represents the height of the texture and f(x,y) represents the gray level intensity of the pixel at the position (x,y) the Fourier transform of the image is given by eq(1) for frequency variables u=0…N-1 and v=0..M-1 The FT takes the gray level image as input and translates the values from the spatial domain to the frequency domain and from FT of the image we extract the magnitude spectrum that represents the quality of each frequency.

$$\mathbf{F(u,v)} = \sum_{x=0}^{N=1} \sum_{y=0}^{M=1} f(x,y) e^{-j2\pi(\frac{ux}{N}+\frac{uy}{M})} \quad \mathbf{(1)}$$

6. **Classification**: The intended class is determined by comparing the input photos' feature vectors with those in the database using a neural network classifier. Two different classifiers are compared in this work one is SVM and the other is NN for classification of different types of defects **[5]**.

   a. **Support Vector Machine (SVM):** The support vector machine classifier's primary goal is to derive the function f(x) that defines the hyperplane's decision boundary. Figure 4 shows that two pieces of input data are separated by the hyper plane. Using the margin M, we can get the distance between the hyper plane and the nearest point in both sets of data.

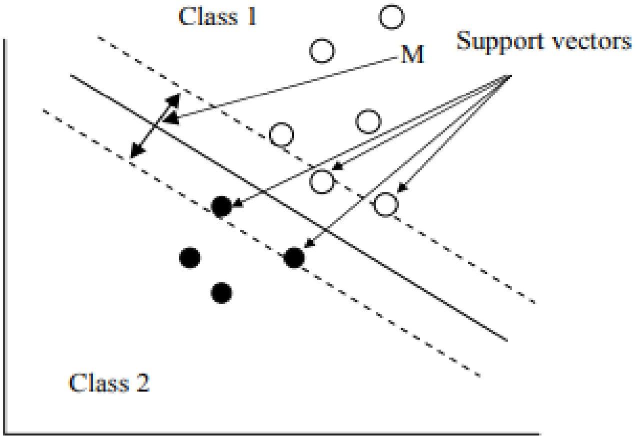


Fig 4: SVM Optimal Separation Hyperplane

To obtain the optimal hyper plane f(x) is given by

$$\mathbf{f(x)} = \sum_{n=1}^{t} y_{na_n} \, (x_n . x) + b \qquad \textbf{(2)}$$

Where $x_n$is the input data point, a_n is the Lagrange multiplier and it must be $a_n \geq 0$, n is the number of input data, b is a scalar threshold. **[20]**

b. Neural Network (NN): There are basically 3 layers in this proposed work of Neural network classifier (a)Input layer (b) Hidden layer (c) Output layer as shown in fig 5.

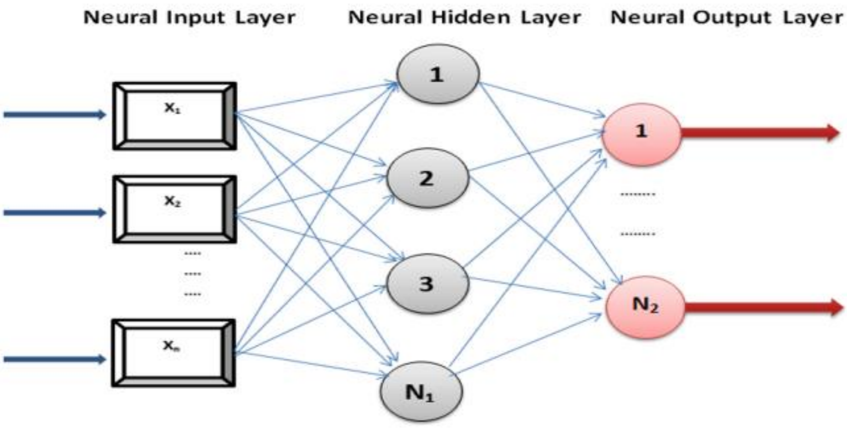


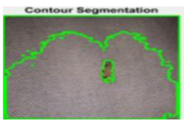
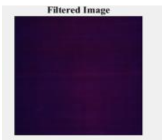
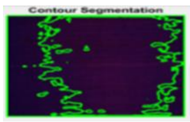
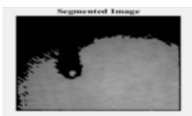
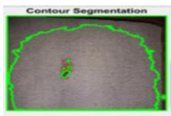
Fig 5: Workflow of NN

The process flow of a Neural Network classifier for defect classification is illustrated in Fig. 5. The input images are passed through a hidden layer, which does not provide feedback to the previous layer. The output is then classified as either defective or normal fabric images. The images that were extracted during feature extraction are used to train the classifier for defect classification. Finally, the images are passed through a fully connected layer, which retrieves enhanced quality in order to obtain a more precise output [11].

4. EXPERIMENTAL RESULTS AND DISCUSSION

Gathering textile fabric photos from the standard TILDA dataset, this suggested study considers about 5000 fabric image samples for experimentation. This project's modules are built in Matlab 2019(b).

Table 1:Types of Defects Detection and Segmentation

Sl.no	Type of Defect	Fabric Image Samples	Filtered Image	Segmented Image	Counter Segmentation
1	Hole				
2	Horizontal defect				
3	Burl				

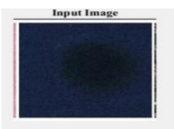
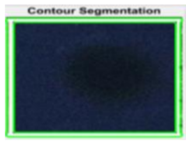
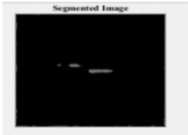
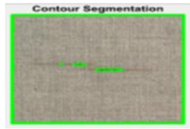
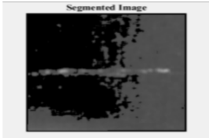
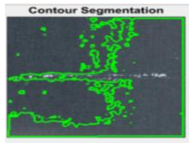
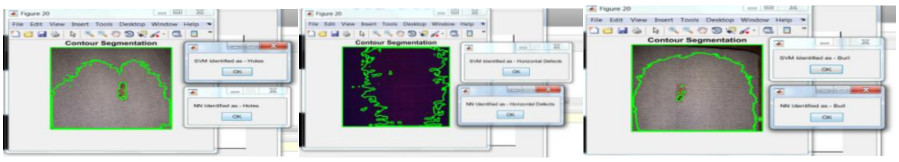
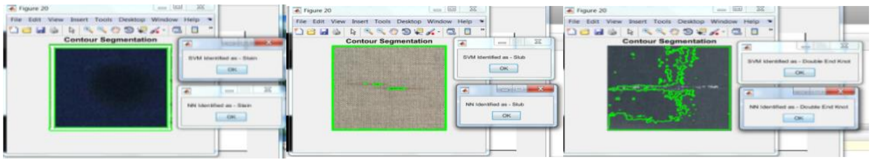
4	Stain				
5	Slub				
6	Double end knot				

Table1 describes different types of defects detected like hole, horizontal defect, burl, slub, stains, double end knot and segmentation of the images using SVM and NN classifiers.



(a)Hole (b) Horizontal defect (c) Burl



(d) Stain (e) Slub (f) Double end knot

Fig 6: Test Results of Defect Detection

The **Fig 6** shows screenshot of different types of defects like hole, horizontal defect, burl, stain, slub and double end knot identified by SVM and NN classifiers.

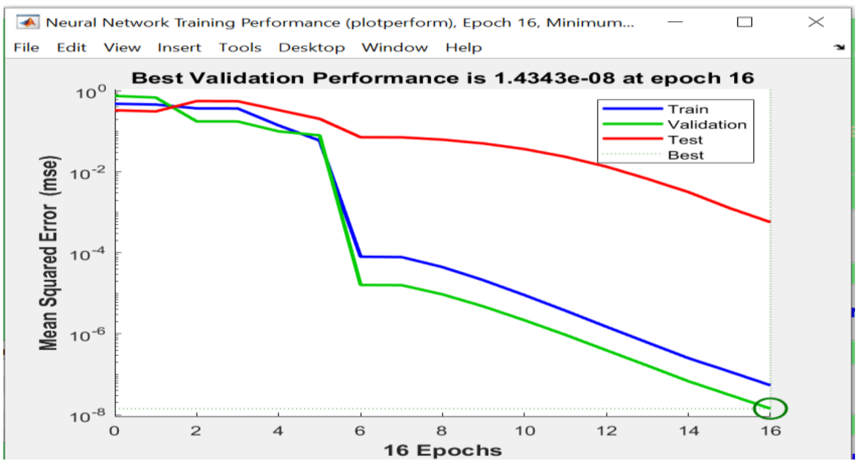


Fig 7: Validation of Performance

The performance curve can be shown in Fig. 7, which includes training, testing, and validation of the performance. At epoch 16, the best validation is indicated to be 1.4343e, compared to the mean square error. The cumulative squared error between the compressed and original images is represented by the mean squared error, which is used to compare the quality of image compression.

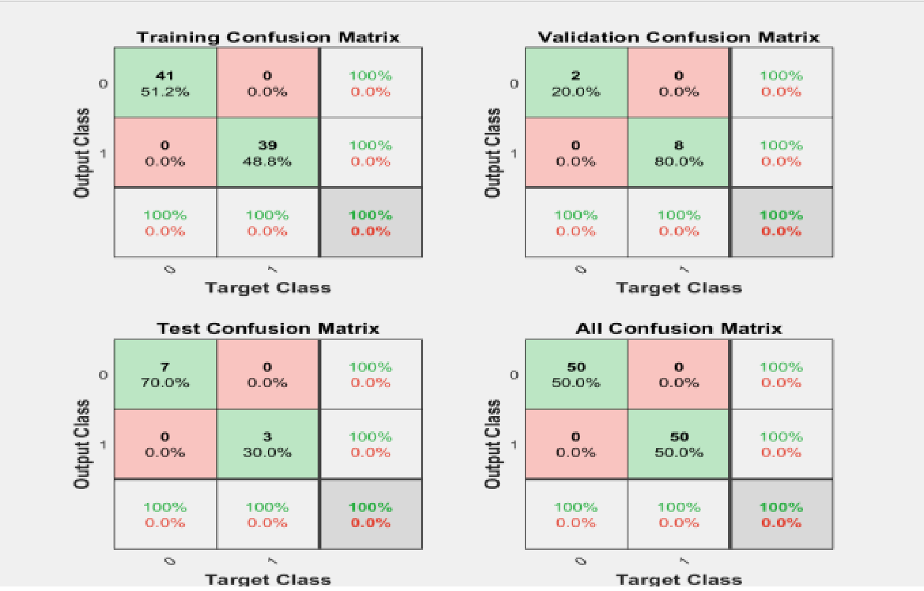


Fig 8: Confusion Matrix Obtained for Training, Testing and Validation of the Classifiers.

Here the confusion matrix is used for characterizing image classification accuracy where the above **Fig 8** describes the training, testing and validation of results for target class and output class. This study makes use of the whole TILDA dataset of 5000 fabric image samples.

4.1 Analysis of Results

The findings from the defect analysis may be categorized as either true positive (TP), false positive (FP), true negative (TN), or false negative (FN) [5, 9]. Both the top half of the rectangle, which represents actual defects like TP and FN, and the bottom half, which represents non-defects like FP and TN, are shown. Figure 9 shows that TP and FP are determined by the identified faults, which are represented by the inner rectangle [10].

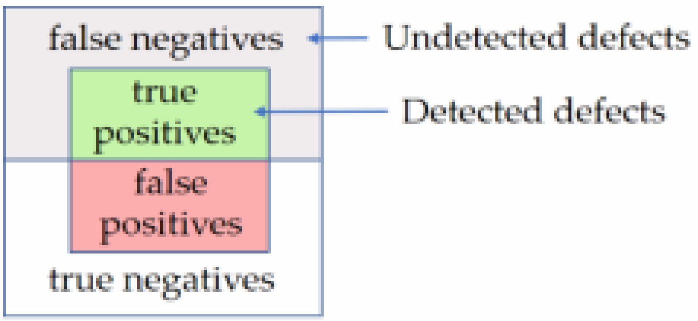


Figure 9: "The Definition of True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) of Detected Defects and True Defects."

The following are the performance measures used for analysis of the algorithm developed.

(TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative)

1. **Accuracy (Acc):** Accuracy is out of all classes what the percentage of correct prediction.

$$\text{Acc} = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \quad \textbf{(3)}$$

2. **Sensitivity:** It is measure of Performance; it measures how sensitive a signal is to an added disturbance. (True positive

rate)

$$\textbf{Sensitivity} = \frac{\textbf{TP}}{\textbf{TP+FN}} \quad (4)$$

3. **Specificity:** It is measure of performance, ability to correctly identify those without errors (True negative rate)

$$\textbf{Specificity} = \frac{\textbf{TN}}{\textbf{TN+FP}} \quad (5)$$

Table 3: Overall Performance Measure of SVM and NN Classifier.

Model	**Accuracy**	**Sensitivity**	**Specificity**
SVM	98	98	100
NN	99	99	100

Table 3 describes the overall performance comparison of SVM and NN classifier in terms of accuracy, sensitivity and specificity and the overall performance of the NN classifier is better when compared to SVM classifier in terms of accuracy (99%) and sensitivity (99%).

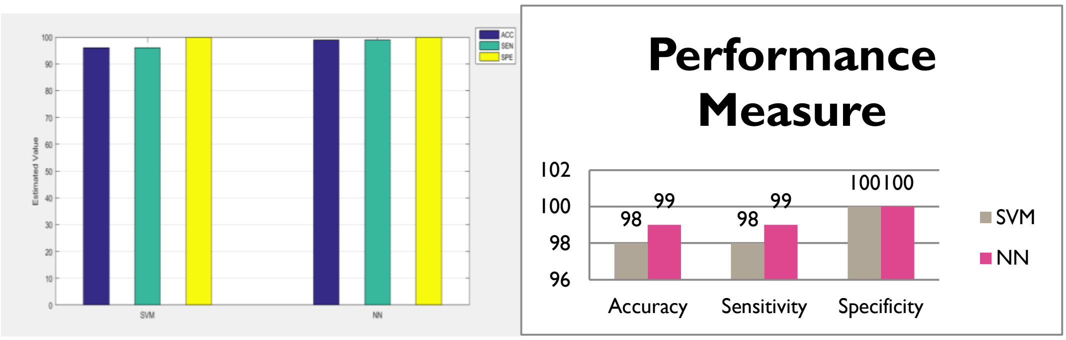


Fig 10:Graphical Representation of Overall Performance Measure Using SVM and NN Classifiers.

5. CONCLUSION

Using support vector machines (SVMs) and natural neural networks (NNs), this research presents a new approach to fabric defect detection that uses DFTs and FFTs for feature extraction, classifies samples as either normal or defective, and uses less computational time and hardware resources overall. The suggested approach is straightforward, easy to grasp, and a breeze to put into action. With a NN classifier accuracy of 99% and an SVM classifier accuracy of 98%, it also intends to provide improved performance outcomes. Based on this, the NN classifier outperforms the SVM classifier when it comes to defect classification.

REFERENCES

[1] Chao Li, Jun Li, Yafei Li, Lingmin He, XiaokangFu,andJingjing Chen, “Fabric Defect Detection in Textile Manufacturing: A Survey of the State of the Art”, Hindawi Security and Communication Networks, Volume 2021, 10 May 2021, pg. 1-13.

[2] TamasCzimmermann, GastoneCiuti, Mario Milazzo, Marcello Chiurazzi, Stefano Roccella, Calogero Maria Oddo and Paolo Dario, “Visual-Based Defect Detection and Classification Approaches for Industrial Applications - A SURVEY”, MDPI journal, March 2020, pg. 1-25.

[3] AnumKhowaja, Dinar Nadir, “Automatic Fabric Fault Detection Using Image Processing”, 2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), 05 March 2020, pg. 1-5.

[4] Young-Joo Han, Ha-Jin Yu, “Fabric Defect Detection System Using Stacked Convolutional Denoising Auto-Encoders Trained with Synthetic Defect Data” MDPI Journal, April 2020, pg. 1-10.

[5] Subrata Das, Amitabh Wahi, Sundaramurthy S, Thulasiram N, Keerthika S, “Classification of knitted fabric defect detection using Artificial Neural Networks”, 2019 international conference on advances in computing and communication engineering (ICACCE), 30 April 2020, pg. 1-5.

[6] Shilpa, T, & Bai A, “A Review on Cardiovascular Disease Detection using Machine Learning Algorithms. Solid State Technology”, Volume 63(5), 2020, pg. 8754-8768.

[7] Aqsa Rasheed, Bushra Zafar, Amina Rasheed, Nouman Ali , Muhammad Sajid, SaadatHanif Dar, Usman Habib , TehminaShehryar and Muhammad Tariq Mahmood , “Fabric Defect Detection Using Computer Vision Techniques: A Comprehensive Review”,Hindawi Mathematical Problems in Engineering, Volume 2020, November 2020, pg. 1-24.

[8] Shuxuan Zhao , Li Yin , Jie Zhang , Junliang Wang , Ray Zhong, “Real-time fabric defect detection based on multi-scale convolutional neural network”, The Institution of engineering and technology (IET) journal, Volume 2, Issue 4, December 2020, pg.189-196.

[9] PeiranPeng , Ying Wang, Can Hao, Zhizhong Zhu, Tong Liu and Weihu Zhou, “Automatic Fabric Defect Detection Method Using PRAN-Net”, MDPI journal, Volume 10, Issue 23, November 2020, pg. 1-13.

[10] Shalaka S Patil, Dr V T Gaikwad, Defect Detection and Classification in Fabric using Image Processing Technique, “International Journal for Innovative Research in Science & Technology”, Volume 5, Issue 11, April 2019, pg. 40-45.

[11] PrasannaBandara, ThilanBandara, TharakaRanatunga, VibodhaVimarshana, SulochanaSooriyaarachchi and Chathura De Silva “Automated Fabric Defect Detection”, 2018 International Conference on Advances in ICT for Emerging Regions (ICTer), September 2018, pg. 119-125.

[12] Xuehuazhao, Daoliang Li, Bo Yang,ShuangyinLiu,Zhifang Pan and Huiling Chen “An Efficient and Effective Automatic Recognition System for Online Recognition of Foreign Fibers in Cotton", IEEE Volume 4, June 2016, pg. 1-5.

[13] Zhang Xiaowei, Fan Xiujuan “Fabric Defect Detection based on GLCM Approach” 6th International Conference on Information Engineering for Mechanics and Materials (ICIMM 2016), Volume 97, November 2016, Pg 673-677

[14] Rebhi Ali, S. Abid, FarhatFnaiech, “Fabric Defect Detection Using Local Homogeneity Analysis and Neural Network”, Hindawi Publishing Corporation Journal of Photonics, Volume 2015, Oct 2015, pg. 1-9.

[15] Pranita P. Gulve , Sharayu S. Tambe, MadhuA.Pandey, S.S.Kanse, “Leaf Disease Detection of Cotton Plant Using Image Processing Techniques”, IOSR Journal of Electronics and Communication Engineering (IOSR-JECE), 2015, pg. 50-54.

[16] H Ibrahim Celik a, L CananDulger , Mehmet Topalbekiroglu, “Fabric defect detection using linear filtering and morphological operations”, Indian Journal of Fibre& Textile Research, Volume 39, September 2014, pg. 254-259.

[17] KartikBahl, Jagdev Singh Kainth, “Evaluation of Yarn Quality in Fabric using Image Processing Techniques”, International Journal of Science and Research (IJSR), Volume 3 Issue 3, March 2014, pg. 558-561.

[18] Singh JP, Anuhbav G, Aprajita A, Himanshi S and Vandana J, “Digital Image Processing Techniques A Versatile System for Textile Characterization”, J Textile SciEng, Volume 4 ,Issue 3, 2014, pg. 1-5.

[19] HalimiAbdellah, Roukhe Ahmed, OuhmadSlimanem, “Defect detection and identification in textile fabric by SVM method”, IOSR Journal of Engineering (IOSRJEN), Volume 04(12), 2014, pg. 69 -77.

[20] JieZhang, BinjieXin,Xiangji Wu, “A Review of fabric identification based on image analysis technology”, Textiles and light industrial science and technology (TLIST), Volume 2 Issue 3, July 2013, pg. 120-130.

[21] Y Ben salem, S.Nasri, “Woven fabric defect detection based on texture classification algorithm”, 8th international multi-conference on systems, signals & devices, Volume 43, Issue 24, March 2011, pg.1-5.