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QUALITY ANALYSIS OF FABRICS USING LABVIEW

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Abstract: Fabric defect detection is one of the major stages in the cloth manufacturing sector. Defects such as broken yarns, stains, and holes reduce the quality and value of the produced fabric. Traditionally, these defects are inspected manually, which is time-consuming and leads to operator fatigue over long periods of work. This work presents a machine learning–based fabric defect detection system implemented in LabVIEW for identifying surface defects in commonly used textile materials such as cotton and polyester with plain surfaces. The proposed approach uses extracted texture and statistical features from fabric images, which are classified using a trained machine learning model to distinguish between normal and defective regions. Compared to manual inspection methods, the proposed system provides improved accuracy, consistency, and inspection speed. While machine learning-based approaches require labelled training data and an initial training phase, they offer better robustness to variations in fabric texture and illumination. The automated inspection process reduces human effort, minimizes subjectivity, and improves consistency, making it a practical, cost-effective, and scalable solution for real-time industrial textile quality assessment.

Keywords: Fabric defect detection, support vector machine, texture analysis, industrial automation, quality control

I. INTRODUCTION

Quality inspection is an essential step in the production of high-grade fabrics. Conventionally, defect inspection has been done by hand, but this practice is vulnerable to mistakes that occur due to fatigue and the subjectivity of the operators. This shows the need to have an automated process that is more reliable, consistent, and quick in evaluating the quality of the fabric. Since the demand for quality products and increased rates of production are growing, it is vital to design an effective and accurate approach for the inspection of fabric. Machine-learning and deep-learning methods are becoming increasingly exploited in modern fabric defect inspection. By training the models based on annotated images of fabrics, the system uses large and varied datasets for training, which become strong performers and can adapt to difficult fabric patterns once trained.

This research suggests an automated system for detecting fabric defects based on machine learning. This system detects fabric images via the extraction of texture-based and statistical features, which are then used to classify the image by a trained machine-learning model to differentiate normal and defective fabric images. The offered approach will provide greater accuracy, predictability, and throughput compared to the manual one. Although the quality and diversity of the training data impact the performance of the system, the given approach is a very realistic and efficient option in terms of practical real-time inspection in textile industries.

II. METHODOLOGY

System Overview

The suggested system is based on a step-by-step approach to convert raw fabric photos into classification results. It involves image acquisition, preprocessing the image, extracting details from the image, training a machine learning model, detecting defects, and presenting the result. All the steps will enhance the quality of the data and extract valuable information that will be used to classify it correctly.

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Figure.1 The system flow diagram presents the complete pipeline of the proposed fabric defect detection and classification framework.

1. Image Acquisition

The system obtains images by loading fabric images from existing image files instead of using live camera footage for image acquisition. The fabric images are stored in a predefined directory and loaded into the processing pipeline using the image input functions available in the LabVIEW Vision Development Module. Each image represents a fabric sample to be inspected and is treated as an independent test case. The inspection process uses identical methods to acquire both reference images and test images, which ensures consistent results throughout the inspection process

2. Image Pre-Processing

Images of raw fabrics often have undesirable artifacts due to the imaging equipment, camera, or sensor, and the nature of the textile being imaged. Unless these issues are addressed in the right way, the metrics of their result detection can be inaccurate or false. The quantities of repetitive texture patterns on textile surfaces usually have slight differences in intensity. The defects like perforation, broken yarns, stains, and changes in the yarn thickness and misweave are usually not very prominent, and instead of the color difference, it is actually reflected by the slight changes in the texture. The idea behind the pre-processing phase is thus to emphasize meaningful texture variations and reduce the variations that are caused by noise or unequal lighting. In the pre-processing, corruption in the image, such as noise, uneven lighting, shadows, and limited surface contamination, is removed. In the existing system, the steps involved in pre-processing are color image to grayscale conversion, noise removal through spatial filtering, and illumination normalization. Before proceeding with any further processing, all images are checked to ensure they are readable and properly oriented. Images are used on a fixed size and height to ensure that the model takes inputs of equal size. The pixel values are scaled to a common range to reduce the difference due to light and camera configuration, and thus guarantee preserving the consistency in the dataset.

1.1 Color to Grayscale Conversion

The color-to-grayscale conversion is used to ensure that the color is converted to colorless (Grayscale, 2004). A greater number of fabric images are taken in color space of Red, Green, and Blue (RGB). In textiles of woven and knitted type, however, the detection of defects is mainly based on structural features as opposed to color data. Common defects can be noted based on the break in the luminance induced by the difference in yarn density, departure of surface continuity, or change in the fabric thickness. In reference to this, the conversion of color images into grayscale is the first step in pre-processing. Grayscale conversion is a method of image dimensionality reduction, used to convert an image of three color channels (red, green, and blue) into a single intensity image channel. It lessens the amount of computational effort and memory that is needed and is especially significant when the amount of computational work is required to be carried out in real-time or near-real time by inspection systems. It also removes redundant color information that is not significant in the detection of defects. The value of every pixel in grayscale images can be used to express luminance, according to the perception of humans to the contrast of small details of texture and bodies. The contrast adds value in comparison between the intact and defective regions of fabric that undergo morphology, thus making them easier to identify in the later stages. In LabVIEW Vision Development Module, instead of averaging the red, green, and blue channels, the luminance component is extracted from perceptually uniform color spaces, e.g., the Hue, Saturation, and Lightness (HSL)

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or Hue, Saturation, and Value (HSV) color space. The technique retains the variations of brightness that are relevant in the analysis of textures, yet gets rid of unnecessary details in colors.

1.2 Median Filtering

A median filter is a non-linear method that is used to minimize impulse noise in an image, also known as salt and pepper noise. On an individual basis, the filter looks into a small neighborhood and ranks the intensity values within it, and replaces the value at the center with a median. This method has the advantage of eliminating bright or dark single pixels, and it also does a better job at preserving edges compared to most linear smoothing filters.

For a discrete 2D image f(x, y), the median-filtered output g(x, y) is:

$$g(x, y) = \text{median}\{f(x + i, y + j) \mid (i, j) \in W\}$$

where,

- W- neighborhood window (for example, a 3×3 kernel) (i, j) are offsets inside that window
- Median-sort all pixel values in that window and pick the middle one

The impulse noise in fabric inspection can be due to dust on the textile surface, sensor artefact, or changes in illumination. Such artefacts usually manifest themselves in the form of single pixels that do not reflect real defects of the fabric. Median filter eliminates such noise, but at the same time, it does not remove significant structural elements like the yarn boundaries. One of the main benefits of the median filtering is that it does not blur sharp edges in terms of intensity. Numerous fabric flaws cause sudden shifts in the brightness, and median filtering preserves the edges and removes noise. Therefore, the quality of feature extraction is enhanced through this enhancement to detect defects based on machine-learning concepts.

1.3 Brightness Normalization

Lack of uniform lighting is one of the major issues with the fabric inspection system. Change in the intensity of light can be attributed to unequal distribution of light sources, shadow caused by the folds of the cloth, or even use of a curvy surface. These variations may occur, making variations in brightness that are not associated with real defects, and hence can decrease the accuracy of detection. When the differences in illumination are not corrected, the feature-extraction algorithms might react to the difference in light instead of the genuine aspect of fabrics. In its turn, it leads to the brightness normalization to make feature representations in different pictures taken under different conditions the same. The used methods are to isolate the reflectance characteristics of the fabric with light effects, with attenuation of smooth lighting gradients, and focus on local texture differences, which generates a dependable detection of defects effectively.

2. Feature Extraction

The conversion of image information to numerical feature vectors, based on descriptive terms of intensity distribution, texture, and consistency of the surface of the fabric, can be described in terms of these descriptive terms.

Table 1.
Extracted Feature and IMAQ functions used for various extraction steps

Feature Category	Extraction Method	Extracted Features	Purpose
Intensity Statistics	IMAQ Quantify	Mean, Standard Deviation	Global brightness & contrast
Histogram Features	IMAQ Histogram	Mean, Standard Deviation	Pixel distribution analysis
Texture Features	IMAQ Extract Texture Feature	Texture descriptors	Surface regularity
Edge Features	IMAQ Canny Edge Detection	Mean, Standard Deviation of edge image	Structural irregularities
Gradient Features	IMAQ Extract HOG Feature Vector	Gradient orientation values	Shape and edge structure
Row-wise Features	Row average calculation	Row intensity profile	Spatial consistency

As flaws in woven fabrics can be seen as local abnormalities amid an otherwise uniform pattern of texture, characteristics are extracted from processed grayscale images to represent healthy and corrupted areas. To obtain the statistical intensity parameters, mean, and standard deviation in this work, the statistical parameters of the whole brightness and contrast variations are calculated with the help of the histogram analysis and Image Acquisition (IMAQ) Quantity. The average values of intensity in rows are also obtained in order to depict the patterns in the spatial distribution of the image Further texture and structure data are obtained through Histogram of Oriented Gradients (HOG) feature vectors. Canny

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edge detection is also used to emphasize structural irregularities, and statistical values of the resultant edge map are included to measure a change in edge density. All the extracted features are packed into a fixed-length feature, which gives a succinct but descriptive representation of the fabric surface, thus assisting proper defect classification.

3. Machine Learning Models Training

The fabric defect detection system was tested based on the proposed fabric feature vectors, which were computed based on greyscale fabric images, and run with the support vector machine (SVM). The training set had 2,000 images, and it was classified into four categories, which are good, hole, oil spot, and thread error. Normality of features was ensured so that all the descriptors contributed equally to the training process. The findings reveal that a combination of various handcrafted feature extraction techniques can be used to give a strong representation of the surface properties in fabrics, thus detecting defects.

Table 2.
Number of images used for training SVM model

Class	**Description**	**Number of Images**	**Role**
Good	Defect-free fabric samples	500	Normal class
Hole	Missing material or puncture defects	500	Defect class
Oil Spot	Stain or contamination defects	500	Defect class
Thread Error	Misalignment / broken thread patterns	500	Defect class
Total	—	**2000**	—

For a linear SVM, the decision boundary is:

$$w^T x + b = 0$$

Where:

- w = weight vector (normal to the hyperplane)
- x = input feature vector
- b = bias

Before training, there is feature normalization on the features so that they are all put on the same scale. This inhibits attributes with a broader range of numbers from dominating the learning process. The data will be split into a training and a validation set to measure the performance of the model and minimize overfitting. The classification assignment involves four categories of the good fabric, hole defects, oil-spot defects, and thread-error defects. The balanced dataset is used (the dataset has 500 images in each class) so that a total of 2,000 images are going to be used during training and evaluation.

4. Visualization and Results Display

The visualization module was implemented using the LabVIEW Front Panel interface, enabling real-time monitoring of inspection results. The visualization component plays a critical role in industrial deployment, as operators require immediate and interpretable feedback rather than raw numerical outputs.

During inspection, the system performs the following visual operations:

- The acquired fabric image is displayed in real time.
- The final classification result (Good, Hole, Oil Spot, Thread Error) is displayed prominently.
- A status indicator (green/red LED style) provides instant quality decision feedback.

The interface was designed to be simple, operator-friendly, and compatible with continuous inspection systems operating on production lines.

III. RESULTS AND DISCUSSIONS

The fabric defect detection system was tested based on the proposed fabric feature vectors, which were computed based on grayscale fabric images, and run with the support vector machine (SVM). The training set had 2,000 images, and it was classified into four categories, which are good, hole, oil spot, and thread error. Normality of features was ensured so that all the descriptors contributed equally to the training process. The findings reveal that a combination of various

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handcrafted feature extraction techniques can be used to give a strong representation of the surface properties in fabrics, thus detecting defects.

3.1 Confusion Matrix Analysis

The confusion matrix was being developed to evaluate the performance of the proposed Support Vector Machine (SVM) classifier using the predicted class labels and the ground-truth labels of the test data set. It gives a tabular display of the results of the classification through comparison of both real fabric classes and those proposed in the model. In the case of a multi-class problem with four classes, which are Good, Hole, Oil Spot, and Thread Error, the confusion matrix takes the form of a 4 x 4. The true classes are represented in each row, and the predicted classes are represented in each column. The entries in the main diagonal indicate the correctly classified samples, and the off-diagonal elements reward the misclassifications. Based on the confusion matrix, the following four basic evaluation measures are calculated on each of the classes based on a one-versus-rest strategy: -

- True Positive (TP) is the quantity of samples that are accurately deemed as a part of a specific group.
- False Positive (FP) is the number of samples that are wrongly identified as being in that category.
- False Negative (FN) is the number of samples that are members of the class, but are incorrectly classified as belonging to another category.
- True Negative (TN) is the observed cases that were correctly predicted to be not in that class.

As far as the defect type is Hole, the true positives will be images of hole defects that will be recognized correctly. False negatives include holes that are categorized as Good, Oil Spot or Thread Error. False positives refer to (non-hole) images that have been incorrectly labelled as a hole, whereas true negatives are samples that were correctly rejected as not holes. These values are obtained directly from the confusion table following training of the SVM model on validation data. The classifier produces approximated labels per test image, and it then compares these results with the ground-truth labels; a confusion matrix is then formed, which sums up correctly labelled and wrongly labelled predictions. After calculating TP, FP, FN, and TN of each class, the usual measures of evaluation, Accuracy, Precision, Recall, and the F1-Score, are calculated. Precision measures the accuracy of positive predictions, recall measures how well the system is able to identify real defects, and F1-Score gives the harmonic analysis of precision and Recall, therefore, presenting a balanced performance measure. The confusion matrix not only assesses the overall performance but also can explain inter-class confusion patterns. An example of such a situation is that the differences in texture between a thread defect and an oil-spot defect are similar, so the overlap of errors results in overlapping patterns. These insights will be important in improving the model and future improvement of features.

Table 3.1: The conclusion matrix of the SVM Classifier illustrates the comparison between the actual fabric defect class and predicted class, evaluation of classification performance across good, hole, thread error, and oil spots

	Predicted				
Actual		Good	Holes	Oil Spot	Thread error
	Good	97	2	0	1
	Holes	3	94	1	2
	Oil Spot	4	33	85	8
	Thread Error	2	1	13	84

Table 3.1 explains The classification matrix shows that a classifier is performing well at identifying Good and Holes defects with high accuracy but moderately for Oil Spot and Thread Error. Oil Spot and Hole defects appear to be particularly confused by the classifier and this seems to indicate that they have similar characteristics. Overall, the classifier has an overall accuracy of 83.72%, which indicates that it performs reasonably well, however, there is room for improvement in identifying defect types that are similar in nature to each other.

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Table 3.2 Calculation for the classification performance of various image classes

Class	True Positive (TP)	False Positive (FP)	False Negative (FN)S	Precision = TP/(TP+FP)	Recall = TP/(TP+FN)	F1 = 2TP/(2TP+FP +FN)
Good	*97	9*	3*	96%*	***97%**	96%*
Hole	*94	36*	6*	95%*	94%*	94%*
Oil Spot	*85	**4	45	88%*	85%*	*86%
Thread Error	*84	*11	* 16	**87%***	84%*	***85%**

Table 3.3 explains. the performance of the proposed fabric defect classification system was evaluated using Precision, Recall and F1-score metrics, shown in Table X. Overall, the model had the highest performance for the Good class followed by Hole defects; however, the lower performance for Oil Spot and Thread Error was due to higher levels of false positive/negative classification, respectively. In conclusion, the proposed classification model demonstrates consistent/accurate defect classification across multiple types of fabrics

.

Formulas to find: -

1. Precision = TP / (TP + FP)
2. Recall = TP / (TP + FN)
3. F1 score= 2TP / (2TP + FP + FN) Or F1 = 2 × (Precision × Recall) / (Precision + Recall)

Derivation

*TP= 97
*FP = (97+3+4+2 − 97) =9
*FN = (2+0+1) =3
*Precision= 97/ (97+9) =97/106=0.915 ~96%
*Recall= 97/ (97+3) =97/100= 97%
*F1=×97/(194+9+3)=194/206=0.942≈96%

Table 3.3
Final values and observations for the classification performance of various image classes

Class	Precision (%)	Recall (%)	F1-Score (%)	Observations
Good	96%	97%	96%	Stable texture and intensity distribution enable clear classification
Hole	95%	94%	94%	Strong structural discontinuities captured by edge and HOG features
Oil Spot	88%	85%	86%	Gradual intensity variations sometimes overlap with thread defects
Thread Error	87%	84%	85%	Texture irregularities are occasionally similar to oil spot patterns
Overall Model (Macro Avg)	92%	90%	91%	Multi-feature combination improves robustness

Table 3.3 explains that with 92% precision, 90% recall, and 91% F1-score, the overall performance of the model was impressive. The good and hole class achieved very high accuracies, due to the clear texture and structural differences, but oil spot and thread errors scored slightly lower in performance because of their similar textures. Overall, the use of a multi-featured approach guarantees accurate and balanced classification of fabric defect types.

The classifier was also accurate with regard to discriminating between bad samples and perfect materials. Statistically significant intensity values and stable texture patterns were obtained, and gave dense clusters of feature distributions in an image of good fabric. This homogeneity enabled the SVM to draw clear boundaries of decision between normal and

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defective classes. Also, the intensity average of rows and the histogram statistics that were used aided in the capture of global structural uniformity, a significant characteristic of material free of defects. The most reliably identified defects were found to be hole defects since they provide sharp structural discontinuities, which edge-based features and the Histogram of Oriented Gradients (HOG) features are conditioned to pick up. The Canny edge statistics generated high differences that were compared with natural cloths, allowing them to be recognized. The isotropic features of texture also emphasized the sharp variations in the weaving design, and this increased the separation among classes. The challenges of classification were greater because oil spot and thread errors were superficially close. The oil spots produce light intensity, gradual variations as opposed to sharp interruptions, whereas thread errors add limited, almost invisible texture variations. The overlaps lead to misclassifications that occur in some instances. However, these two aspects are alleviated by the combination of statistical and gradient-based features, and the variety of features is necessary to depict global intensity and local structural changes. The results have shown that when disparate feature extraction techniques are used complementary, they bring about a higher model robustness compared to the application of a given type of descriptors. Information on statistical intensity is provided globally, information on pattern consistency is provided by means of the use of texture, structural anomalies at the edges are detected using edge statistics, and shape and orientations are described using HOG descriptors. All these features allow the system to generalize to different types of defects and be computationally efficient and interpretable, which is preferable in an industrial inspection setting that requires real-time processing and a reasonable description. To conclude, the experimental results prove the assumption that a classical machine-vision system using hand-designed features and an SVM predictor would provide a robust performance in fabric defect detection. Even though the deep-learning methods might be superior in the circumstances with very changing conditions, the given approach provides benefits in terms of predictability, minimum requirements in the quantity of calculations, and less testing, which qualifies it to be used in the controlled manufacturing process.

Resultant Images for Cotton showing various Defect Detection

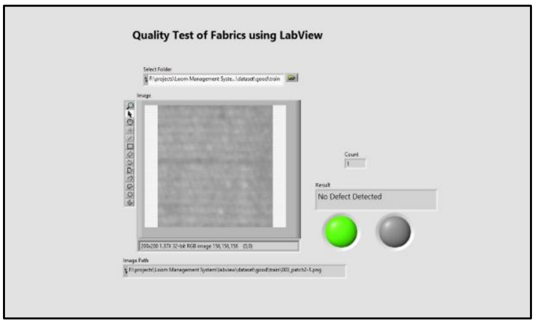

Fig. 2 (A)

Figure 2(A) shows the classification result for a defect-free cotton fabric sample. The system correctly identifies the sample as “Good,” demonstrating reliable performance across different fabric materials and confirming the model’s generalization capability.

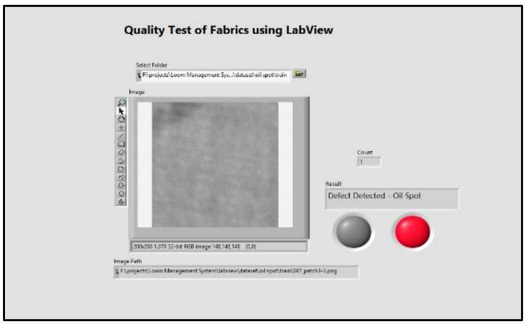

Fig 2 (B)

Figure 2(B) illustrates the detection of an oil spot defect. The model successfully identifies gradual intensity variations and classifies the defect accurately.

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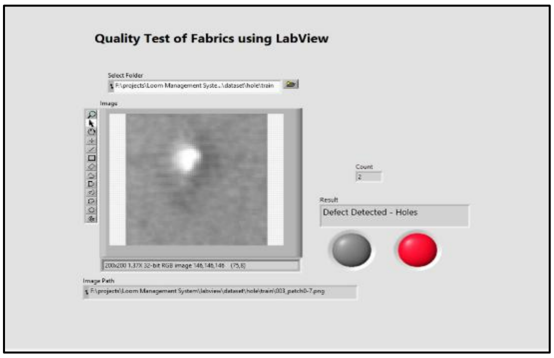

Fig 2 (C)

Figure 2 (C) presents the result for a thread error defect. The system detects irregular texture disruptions and classifies them appropriately, despite similarities with oil spot patterns.

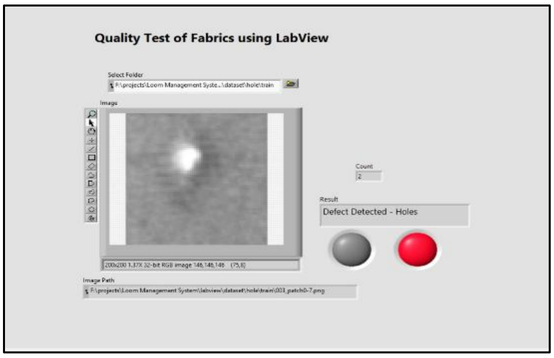

Fig 2 (D)

Figure 2(D) displays the detection of a hole defect. The model accurately captures strong structural discontinuities using edge and HOG features, resulting in correct classification

Resultant Images for Polyester showing various Defect Detection

Fig 3 (A)

Fig 3 (A) free polyester fabric sample. The system correctly identifies the sample as “Good,” demonstrating reliable performance across different fabric materials and confirming the model’s generalization capability.

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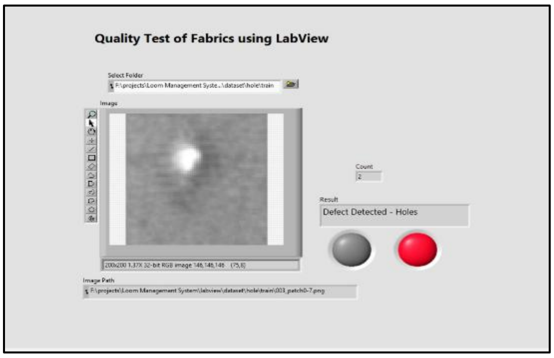
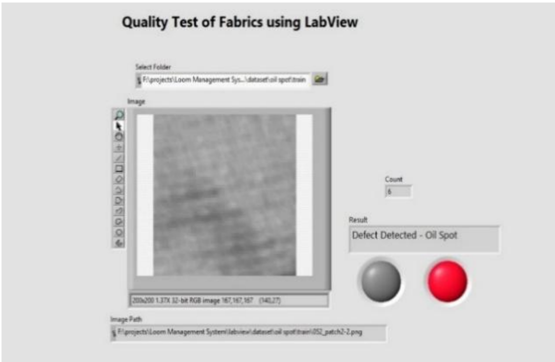


Fig 3 (B)

Figure 3(B) displays the detection of a hole defect in polyester fabric. The strong edge discontinuities and localized intensity variations are effectively captured, leading to accurate classification.



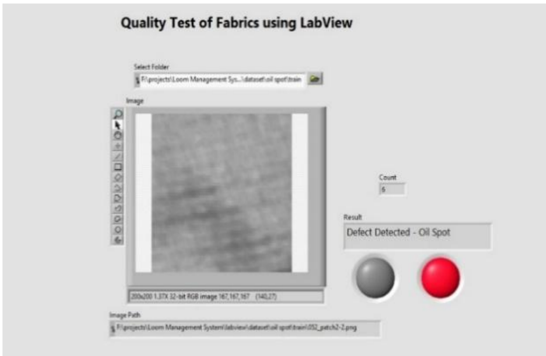


Fig 3 (C)

Figure 3(C) illustrates the detection of an oil spot defect in polyester fabric. The model successfully captures gradual intensity variations and accurately classifies the defect, indicating robustness in handling subtle texture changes.

Fig 3 (D)

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Figure 3(D) presents the classification result for a thread error defect in polyester fabric. Despite structural similarities with oil spot patterns, the system correctly identifies the irregular texture distribution and assigns the appropriate defect class.

IV. CONCLUSION

The proposed system aims to detect fabric defects using handcrafted feature extraction combined with a Support Vector Machine (SVM) classifier. A comprehensive set of descriptive features is extracted from pre-processed grayscale images, including statistical intensity measures, histogram distributions, texture descriptors, edge features, and Histogram of Oriented Gradients (HOG) features. These features collectively capture both global and local image information, providing a structured numerical representation of normal fabric patterns as well as defective regions. By integrating brightness statistics with structural and gradient-based features, the model learns to distinguish variations in texture and morphology associated with defects such as holes, oil stains, and thread irregularities. Defect-free fabrics are generally easier to classify due to their uniform texture and consistent intensity distribution. In contrast, structural defects introduce noticeable disruptions in edge continuity and gradient orientation, making them detectable through edge-based and orientation-based descriptors. The main advantages of this approach is its computational efficiency and practical applicability. Compared to deep learning models, which typically require large datasets and high-performance computing resources, the feature-based SVM framework can be effectively trained on smaller datasets with modest hardware requirements. Moreover, handcrafted features are explicit and interpretable, making the system easier to analyse, debug, and optimize. This makes the method particularly suitable for industrial environments where imaging conditions are controlled, and real-time processing is essential

.

V. FUTURE WORK

Although the existing feature-based Support Vector Machine (SVM) model works well when imaging is under controlled conditions, a number of enhancements can be sought in future studies. it is recommended that deep learning methods, including Convolutional neural networks (CNNs) are explored. CNNs do not rely on handcrafted features as hierarchical patterns are automatically learned by the CNNs using the raw images. This is able to enhance resilience with respect to luminance variations and multifaceted cloth textiles. Lightweight architecture transfer learning can be employed to ensure efficient computations. The existing system carries out image-level classification. Further research that can be done in the future is defect localization and segmentation, which will help to locate the exact position of defects. More accurate defect edges and automatic rejection systems in industry production lines can be offered using region-based or pixel-level detection methods. The model must be tried on a selection of a broader range of fabrics, both with patterns and knit dresses, and pictures taken in various environmental conditions. It is also possible to use data augmentation methods to minimize overfitting and enhance generalization. Also, statistical texture characteristics can be used along with deep-learning-based descriptors, which can enhance the distinction between similar visual defects, i.e., oil stains and thread errors. One can also look into ensemble classification techniques in order to achieve an overall better performance.

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