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HYBRID FEATURE DESCRIPTORS WITH RESNET-BASED CLASSIFIERS FOR FAST TEXTILE FABRIC DEFECT DETECTION USING NOVEL HYBRID FEATURE EXTRACTION ALGORITHM

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SUMMARY

The detection of fabric defects through automation is important for ensuring the quality of the textile material because traditional detection methods are not only very time-consuming but also subjective and cannot be applied during the process of production. The traditional models that use techniques of image processing and deep learning have various limitations with respect to the detection of minor texture alterations, structure-based defects, and real-time defect identification in industrial settings. In order to address these issues, an innovative method of fabric defect detection based on the FTEFD model and ResNet classifier is proposed. What is particularly notable about the proposed technique is that it uses not only traditional handcrafted feature descriptors but also residual deep learning approaches. After this, the feature vector is fed into the ResNet classifier using residual blocks, fully connected layers, and softmax classification to detect various defect categories like holes, spots, broken threads, misweave, and normal cloth. In terms of experiment results, it was found that the proposed system gave a model accuracy of 97.48%, precision of 96.92%, recall of 96.35%, F1-Score of 96.63%, and specificity of 97.90%, which is better than CNN, YOLOv5-based, and ResNet systems. In terms of defect-wise analysis, the proposed system also gave average accuracy of 97.66%. The comparative detection results were precision of 0.92, mAP50 of 0.85, mAP50:95 of 0.55, F1-Score of 0.84, and FPS of 129.

Key words: *fabric defect detection, hybrid feature extraction, FTEFD algorithm, residual networks, resnet classifier, texture analysis, edge detection, local pattern encoding.*

INTRODUCTION

Textile business requires a very high quality of the product in order to be competitive and satisfactory to customers [2][4]. The very fact that even small defects in fabrics can be holes, stains, slubs, misweaves, and broken yarns can considerably diminish the value of the product and the brand image. Conventionally, fabric inspection has relied on manual methods, in which trained operators under controlled lighting conditions inspect moving fabric rolls [1]. But manual inspection is subjective, inconsistent, and inefficient, especially in high-speed production environments [26]. It is these

shortcomings that have inspired the development of automated systems for fabric defect detection using image processing and machine learning methods [3].

The first automated methods mostly made use of statistical texture analysis, frequency-domain filtering and edge-based feature extraction techniques [27][5]. Though these techniques could be computationally effective, it often proved to be unable to generalize between different types of fabrics due to the variations in the weave patterns, color distribution and illumination conditions. Deep learning has shown potential for visual inspection tasks using convolutional Neural Networks (CNNs) [28][7]. Precisely, the deep residual learning approaches such as ResNet have demonstrated to be superior in image classification through not only addressing the problem of vanishing gradient but also through their deeper training of networks [8].

Deep learning models are often expensive, in terms of the scale of the annotated dataset and the amount of computer power required, making them impractical in the real-world industrial environment [9][10]. Besides, strictly deep feature representations are unable to model some fine-grained texture anomalies, which may be effectively modeled by handcrafted descriptors [11][12]. The textile fabrics are often repetitive and regular, and a combination of classical texture descriptors and deep learning models can be possible future research in terms of achieving higher detection strengths and effectiveness [13][14].

To address these challenges, this paper recommends a Hybrid Feature Extraction of Textile Fabric Defect Detection (FTEFD) model, which is a composite of a ResNet-based classifier [6][15]. The suggested technique uses manually extracted feature descriptor such as texture descriptor, edge detection, and local pattern encoding with deep residual learning [16]. The hybrid technique can be used to detect local micro-level and structural anomalies within fabric images [17][18].

The major aim of the research is to develop an efficient, effective and real time fabric defect detection algorithm that can be used across various industries. The suggested model aims to enhance classification accuracy, reduce computation cost and ensure consistent performance independent of fabric or defect type by making use of the complimentary effects of hybrid feature engineering in deep residual networks.

Key Contributions of the Research

- Uses the texture, edge and local pattern properties to ensure that small and large fabric defects are detected.
- Combines both handcrafted and deep residual learning in order to enhance the accuracy of defect classification.
- Realizes quick processing and predictable performance appropriate in the textile production set ups.

The rest of this paper is structured in the following manner: Chapter 2 includes an in-depth literature review of the available fabric defect detection tools, both traditional image processing and the ones based on deep learning. Chapter 3 explains the proposed methodology, the Hybrid Feature Extraction Algorithm (FTEFD) and how it will be combined with the ResNet classifier. Chapter 4 talks about the experimental arrangement, performance measure, and the comparison outcomes. Chapter 5 covers the discussion of the findings in depth evaluating the strengths and limitations of the suggested system. Lastly, Chapter 6 will end the paper with the probable future research and industrial enhancement.

LITERATURE REVIEW

The models for the traditional object detection, which will be applied in the domain of textile inspection, are built using the SDLS-YOLO design approach. These models have come up with solutions to the problems such as complex background images, irregular defects, and need for real-time defect detection in the production line. In the YOLO model, multi-branch extraction and dynamic up-sampling have been included as parts of the model, resulting in improved fine-grained feature representation without an increase in computation requirements. It was found that optimization in architecture design of one-stage

detectors could definitely contribute to achieving high accuracy in defect detection without sacrificing speed performance [19].

It was achieved using channel and spatial attention blocks that helped increase the selective emphasis in discriminative regions and filter out the irrelevant background textures. As a result, the experiment confirmed the hypothesis that feature refinement based on the effects of attention is fairly efficient for analyzing complicated fabrics. This work stresses the importance of finding a balance between model complexity and effectiveness to provide industrial flexibility [20].

A concept of unsupervised techniques for detecting defects in fabrics based on a small amount of annotated defective textiles. What technique is implemented, namely, an approach based on saliency detection in the spatial domain with adaptive clustering for detecting anomalous regions in the uniform fabric textures? Such approach made it possible to solve one of the most relevant problems of the defect detection industry, since there were no widely-used annotated datasets. The results demonstrated the efficiency of background filtering and defect localization without mistakes, which proved that unsupervised architectures can be an effective solution for quality control of cloth [21].

The fusion of metaheuristic optimization technique, better network parameter optimization, and robustness classification. In line with the principle of residual learning similar to that of ResNet, the model was able to extract fine texture features for diverse defects. Their experiments on different datasets made them confident that combining residual structures and intelligent optimization techniques will be very effective in improving the accuracy and generalization in a textile inspection network [22].

A better deep convolutional neural network model with safe human-robot interaction (HRI) for automatic textile inspection. This model considered not only accurate defect detection but also implementation of their model in an industrial setting. Their system is capable of detecting multiple defects in the fabrics with high accuracy, having achieved a mAP value of 97.49%. The article stresses on the significance of using advanced vision models along with the robot systems for automated and reliable fabric inspection in smart manufacturing scenarios [23].

This review has pointed out the advantages of using hybrid and multiple model architecture in increasing the robustness of fabric defect detection systems. It also explained the trade-off between computational complexity and detection accuracy and the necessity of lightweight systems in real-time industrial applications. They provided some useful information about the trends in fabric defect detection through AI-based methods [24].

In the research paper, real-time monitoring and distributed processing and smart sensing were used in order to increase the efficiency of the process. The review showed how deep learning techniques and smart manufacturing techniques can transform the future by providing high detection accuracies over 97 %. The paper has pointed out the obvious trend in fabric defect detection systems [25].

Table 1 shows the latest research work carried out on comparative analysis in the field of automated detection of defects in textile fabrics. It highlights the methodology used by various researchers using different techniques such as lightweight YOLO detectors, attention-based network, unsupervised clustering, residual learning, human-robot collaborative system, and anomaly detection systems. The table 1 also describes the database or experimental settings used in each study and highlights the practical and industrial settings where the models were tested. Besides, it identifies research gaps, including computational complexity, scalability issues, the lack of standardized tests, the inability to generalize across a variety of fabric textures, and the inability to implement in real-time industrial environments. This related study has clearly shown that a balanced hybrid model must be employed to combine efficient feature extractors and effective deep learning classifiers, achieving a balance between high accuracy and industrial feasibility.

Table 1. Comparative analysis of recent deep learning-based fabric defect detection methods

Ref No	Methodology	Dataset / Simulation Environment	Research Gap
[19]	Proposed SDLS-YOLO with multi-branch feature extraction and dynamic up sampling for lightweight real-time defect detection	Textile fabric image datasets with complex backgrounds and irregular defect patterns (industrial environment testing)	Limited generalization across diverse fabric types and need for further reduction in computational complexity
[20]	YOLOv5 backbone integrated with channel and spatial attention mechanisms for enhanced feature refinement	Fabric defect image dataset evaluated under real-time detection conditions	Performance may degrade under highly diverse fabric textures; requires further lightweight optimization
[21]	Unsupervised learning using spatial-domain saliency detection combined with adaptive clustering	Limited labeled textile defect samples; experimental textile image datasets	Reduced accuracy compared to supervised deep learning; limited classification capability
[22]	Deep residual network optimized using cuckoo search metaheuristic algorithm	Multiple fabric defect image datasets for classification evaluation	Increased training complexity due to optimization algorithm; real-time applicability not fully validated
[23]	Enhanced DCNN integrated with safe human-robot interaction (HRI) system	Industrial textile inspection setup with robotic collaboration	High computational demand; scalability to small-scale industries remains unclear
[24]	Comprehensive survey of CNN variants, transfer learning, and ensemble learning techniques	Review-based study covering multiple textile datasets and defect categories	Need for unified benchmark datasets and standardized evaluation metrics
[25]	AI-driven anomaly detection integrating CNNs, autoencoders, Vision Transformers with IoT and edge computing	Smart textile manufacturing environments with IoT-enabled sensing infrastructure	Integration complexity and deployment cost in traditional textile production units

METHODOLOGY

Overall Architecture for Proposed Methodology

Figure 1 shows the Hybrid Fabric Defect Detection System shall be introduced at the first phase where it concerns the image acquisition and preprocessing in order to get high-quality input data. High-definition industrial cameras will capture images of fabrics under proper illumination to prevent shadows or reflections. Since the fabrics are characterized by repetitive patterns and small defects, preprocessing is very important for maximizing defects. The first process is eliminating noise by employing a noise elimination technique, such as the median and Gaussian filters, in order to eliminate the noise, but retain the edges. The images are then resized and standardized to ensure that all images have the same input size for the classifier. Contrast enhancements are applied to defect regions in the fabric, while grayscale conversion is performed where necessary to simplify texture analysis. Other data augmentation methods like rotation, flipping, and scaling shall also be applied to improve the generalization capacity of the model and variety in the dataset.

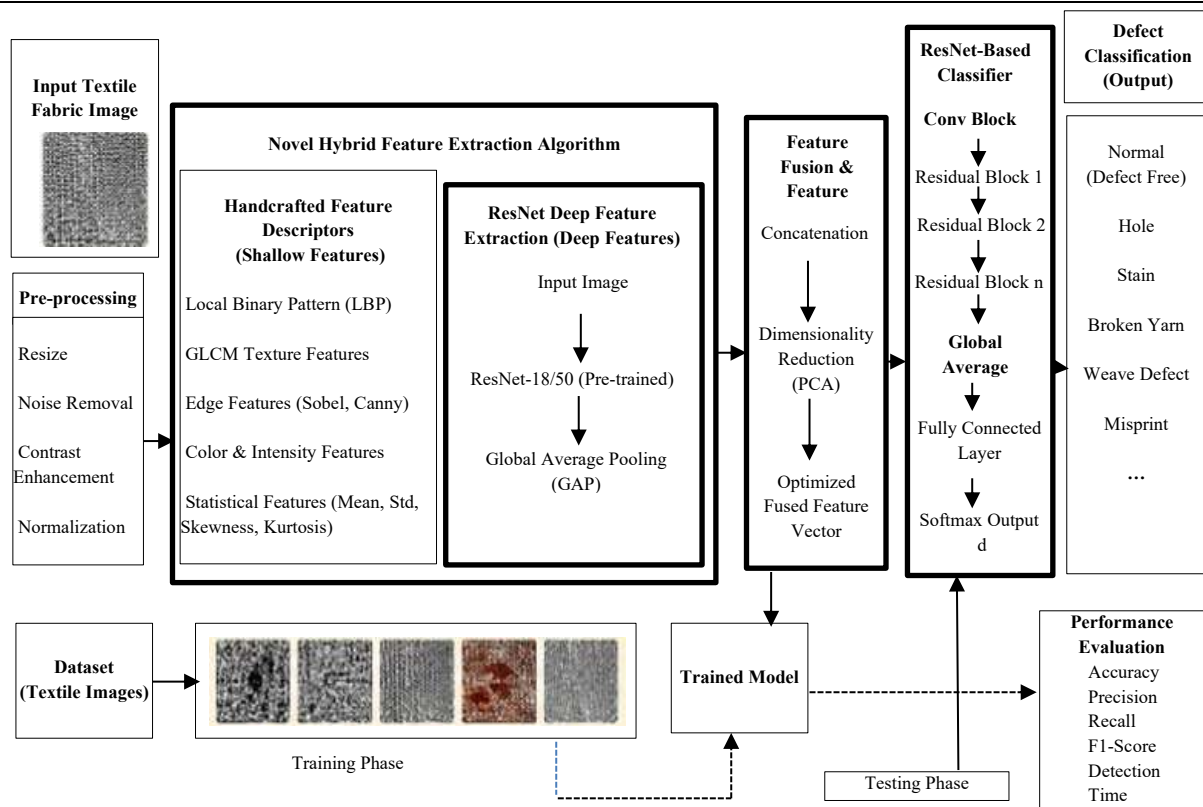


Figure 1. Overall architecture for proposed methodology

Hybrid Feature Extraction Algorithm for Fast Textile Fabric Defect Detection

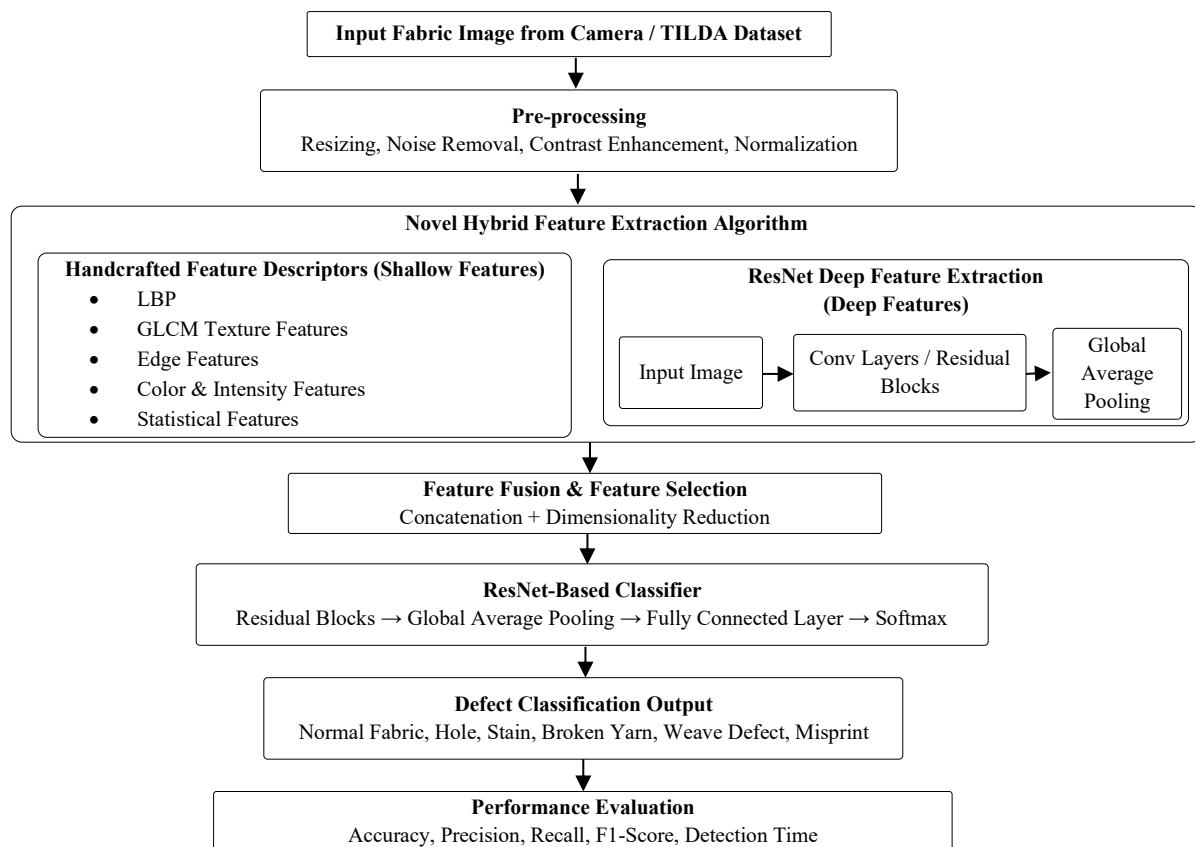


Figure 2. Hybrid feature extraction algorithm for fast textile fabric defect detection

Figure 2 depicts the proposed hybrid defect detection approach, which is a combination of hand-crafted texture features along with the features of deep ResNet for accurate and efficient classification. First of all, the fabric is acquired either from the camera or from the TILDA dataset. Subsequently, the image is pre-processed through various methods like resizing, denoising, and normalization of contrast. Further, the proposed algorithm operates on two levels in parallel. On the one hand, shallow descriptors, such as local binary patterns, grey-level co-occurrence matrix texture descriptors, edge descriptors, color and intensity features, and statistical descriptors, are employed to extract patterns of visible defects. On the other hand, ResNet extracts deep features via convolutional layers, residual blocks, and global average pooling. In order to avoid redundancies, the two sets of extracted features are combined, and feature selection takes place, reducing the number of features and optimizing the process. Afterwards, the selected features are provided to the ResNet-based classifier, consisting of residual block layers, fully-connected layers, and softmax for the classification of fabric into classes such as normal, hole, stain, broken yarn, weave defect, and misprint.

In the task of detecting fabric defects, complex models often use extra computation when handling simple tasks, which can slow down the detection process. To address this, we use a lightweight ResNet-18 as the base for our network. We also add WTConv to the original residual blocks to create a WTConv-Block module. This helps improve the network's ability to extract features and increases the area it can look at, all while using less computation and memory. This makes the model better suited for use on edge devices.

WTConv breaks down the input using a wavelet transform, splitting it into low-frequency and high-frequency parts. This allows separate handling of different frequency details. The input is filtered and reduced in size through the wavelet process to capture features at various frequency levels. Then, a small deep convolution is used on each part to better understand local details. Lastly, the processed features are put back together using the Inverse Wavelet Transform.

$$Y = IWT \left(\text{Conv}(W, WT(X)) \right) \quad (1)$$

From the above equation (1) describes the X denotes the input sensor, W represents the convolution kernel weights. Conv , WT and IWT should represent the convolution operations, wavelet transform, and inverse functions.

Optimization of Loss Functions

RT-DETR model employs GIoU loss function to enhance the accuracy of predicting bounding box coordinates to solve the problem of IoU loss that may create problems in cases where there is no intersection between objects. However, in cases where there are few simple samples and plenty of complex ones, the model faces difficulties in detecting objects precisely, thus failing in its position prediction ability. To solve this problem and enhance the detection of dense and small defects, the two losses of Focaler-IoU and MPDIoU are used. Focaler-IoU uses adjustable parameters for handling imbalanced number of textile samples. It works by focusing on aligning the shape of the predicted box with the real box by reducing the distance between them, which helps in getting more accurate object locations and making the model learn faster. This makes the model better at finding small or hard-to-see defects in textiles, while still keeping high accuracy when identifying objects on complex textured backgrounds. The formula is as follows.

$$\text{MPDIoU} = \frac{A \cap B}{A \cup B} - \frac{d_1^2}{w^2 + h^2} - \frac{d_2^2}{w^2 + h^2} \quad (2)$$

$$L_{\text{MPDIoU}} = 1 - \text{MPDIoU} = 1 + \frac{d_1^2}{d^2} + \frac{d_2^2}{d^2} \quad (3)$$

From the above equation (2), (3), A should defined as real box, B represents the predicted box, w and h represents the width and height, d_1^2 represents the square distance among the upper left corner of B to A and d_2^2 represents the squared distance from the bottom right corner B to A.

$$\text{IoU}^{\text{focaler}} = \begin{cases} 0 & \text{IoU} < d \\ \frac{\text{IoU} - d}{u - d} & d \ll \text{IoU} \ll u \\ 1 & \text{IoU} > u \end{cases} \quad (4)$$

Equation (4) above describes how to adjust the parameter d and u , Focaler-IoU focused on the variety of regression samples, loss function formula,

$$L_{\text{Focaler-IoU}} = 1 - \text{IoU}^{\text{focaler}} \quad (5)$$

Equation (5) above describes the effort to improve the accuracy and combine with IoU and MPDIoU for a more accurate focus on the different samples. Loss function defined in equation (6).

$$L_{\text{focaler-MPDIoU}} = L_{\text{MPDIoU}} + \text{IoU} - \text{IoU}^{\text{Focaler}} \quad (6)$$

ResNet Classifiers for Fast Textile Fabric Defect Detection

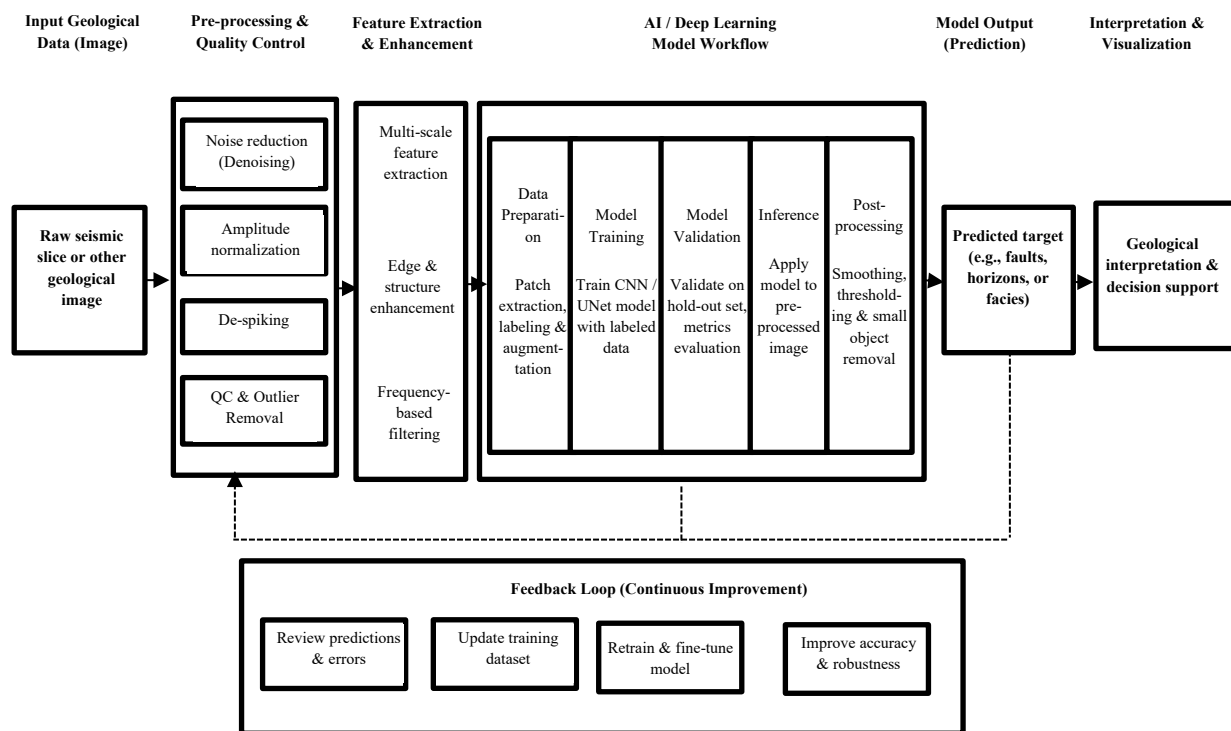


Figure 3. ResNet classifier for fast textile fabric defect detection

Figure 3 represents the ResNet-based defect detection system in fabric that helps detect defects in textiles faster and accurately. The process starts by providing an input fabric image, where the initial image is first processed by a pre-processing step, which includes resizing, noise filtering, enhancing contrast, and normalizing the image. After pre-processing, the input image is passed through the ResNet-based feature extraction step, where convolutional layers and ResNet blocks extract features from the fabric image through convolution operations. The obtained feature maps are pooled by applying global average pooling, thus creating compact features out of them. Then, the obtained features undergo the feature fusion and selection, retaining only the most discriminative features to be used for defect classification. After this step, the selected features are provided as an input to the ResNet-based classifier, which will

pass through fully connected layers and will be classified based on a softmax function as one of six different categories, including normal fabric, hole, stain, broken yarn, weave defect, or misprint.

It is known that breaks in textured images usually show important features like edges. The main challenge is figuring out how to find these breaks. One way to solve this is by using homogeneity (H). Let P defined as the squared window, mask of $(2N + 1)$ width centered on the pixel. Window P defined as the difference vectors $CP_i = (x_i - X_c, y_i - y_c)$ where (x_i, y_i) defined the neighbour of the center (X_c, Y_c) defined as,

$$c - N \leq x_i \leq c + N, \quad c - N \leq y_i \leq c + N \quad (5)$$

From the above equation (5) describes the (x_i, y_i) defined the coordinate of the pixel P_i , c coordinate with the center pixel P_c and N is the integer number defined the mask size.

Image Acquisition and Preprocessing

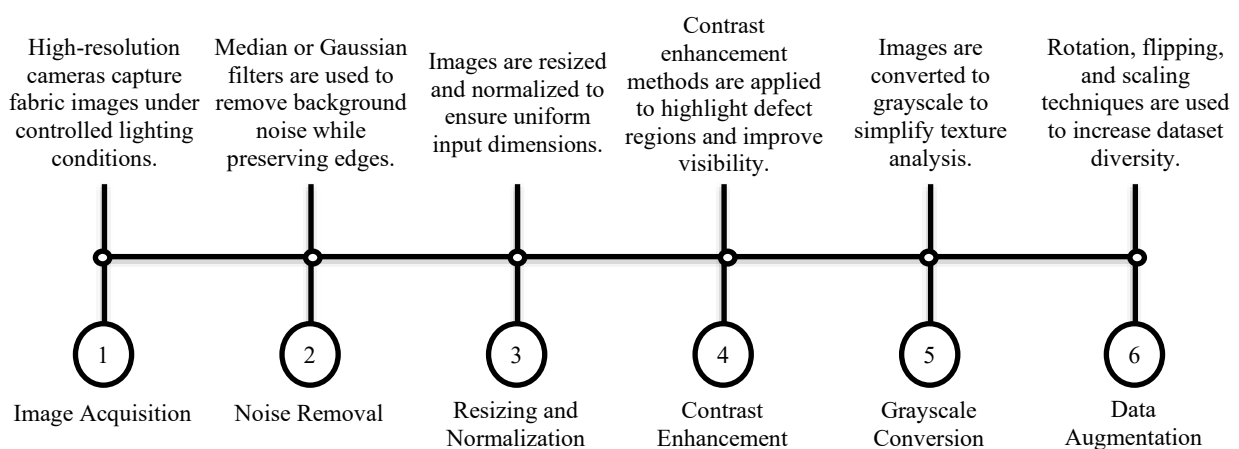


Figure 4. Fabric defect detection image preprocessing workflow

This figure 4 shows the major processes in the image preparation of fabrics in the detection of defects. It starts with the capture of the images with high-resolution cameras and controlled lighting in order to have clear and consistent captures. The photos are then filtered to remove noise that is undesired and capture desired details as the background noise is removed. This is followed by resizing and normalization to standardize input dimensions to enable standard processing. The enhancement of contrast is carried out to reveal the defect areas and show the imperfections more easily. The pictures are then turned into grayscale so that analyzing the texture can be simplified and less computers can be used. Lastly, data augmentation methods like rotation, flipping, and scaling are employed to enhance the variety in the set of data to enhance the resilience and precision of the defect detection model.

Hybrid Feature Extraction Algorithm (FTEFD)

The suggested Hybrid Feature Extraction for Textile Fabric Defect Detection (FTEFD) algorithm combines several feature descriptors that are complementary in nature in order to define both local and global features of a fabric defect. The features of the textile fabrics are complex; hence, using one method of extracting features will not be adequate in capturing the defects patterns. The FTEFD system functions as a combination of texture and frequency-based descriptors methods (to analyze texture), edge detection techniques to detect structural anomalies, and local pattern encoding techniques to encode micro-level variation. The repetition of weave patterns is modeled with the help of the texture descriptors and the discontinuities, like cracks, holes, or broken yarns, are emphasized by edge-based features. Local pattern encoding is useful in recording minor distortions of the surface. These aspects are combined into a single feature representation which offers a rich and discriminative depiction of cloths. The algorithm can be used to create a robust foundation to the correct classification by merging handcrafted descriptors and it is robust to changes in fabric type, lighting conditions and defect morphology.

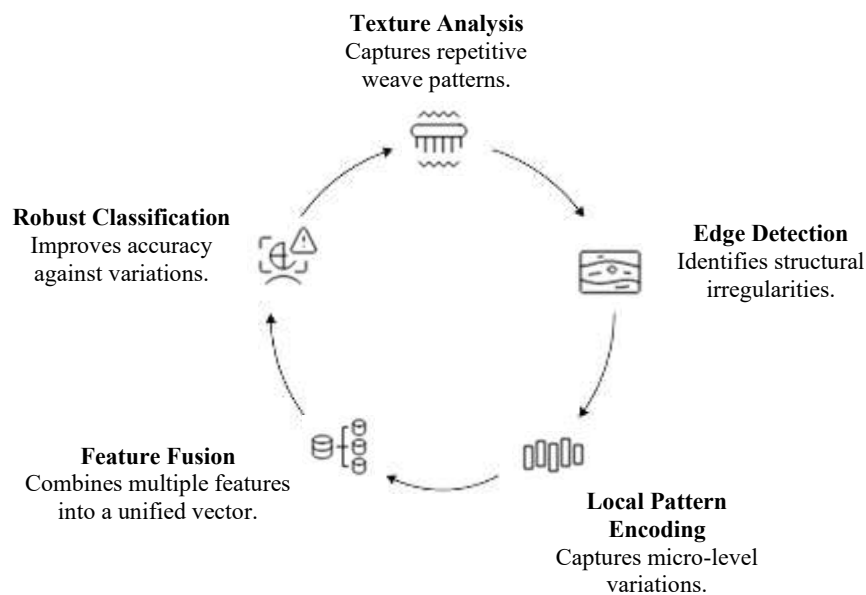


Figure 5. Cyclical framework for fabric defect feature extraction and classification

This figure 5 gives a cyclical model of detecting fabric defects which combines various feature extraction and learning steps. The first step is to do the analysis of texture to obtain repeatable weave patterns in fabric structures. Structural irregularities which could be the indication of defects are then detected by edge detection. Local pattern encoding captures micro-level, small-scale details, allowing finer details of small imperfections to be captured. These characteristics are grouped together by feature fusion in a single feature that builds on the overall representation. Lastly, strong classification uses the combined features to enhance the accuracy of the detection and to deal with the changes in lighting, texture, and the types of materials. The cyclic structure is focused on the constant improvement, as every step will add more credible and accurate detection of defects.

ResNet-Based Classification Framework

In the final stage, the extracted hybrid features are integrated with a deep residual learning-based classification model, specifically ResNet. Residual learning enables the training of deeper neural networks by addressing the vanishing gradient problem through shortcut connections. The fused hybrid feature vectors are fed into the ResNet-based classifier, which learns high-level discriminative representations for defect classification. The residual architecture is more effective in propagating features and increasing the stability of convergence and enables the model to distinguish normal and defective fabric samples. Some of the hyperparameters that are being optimized are learning rate, batch size, and number of epochs to get a balance of accuracy versus efficiency. The output from the classification is the prediction of the type of defect and the scores in terms of confidence. It is the combination of the handcrafted features along with deep residual learning that makes it accurate in the detection and generalization.

This figure 6 demonstrates a hybrid solution to detecting defects of fabrics, combining handcrafted features and deep learning features to enhance the classification. It starts with feature extraction, where the traditional texture-based features are fused with deep features to create hybrid representations. This combination of feature vectors is then fed into a ResNet model that learns discriminative, high-level representations necessary to accurately detect defects. The most important parameters of the model like learning rate, batch size and epochs are fine-tuned during training to improve performance. Lastly, the learned ResNet produces defect-class predictions and confidence scores, enabling efficient and robust fabric defect detection.

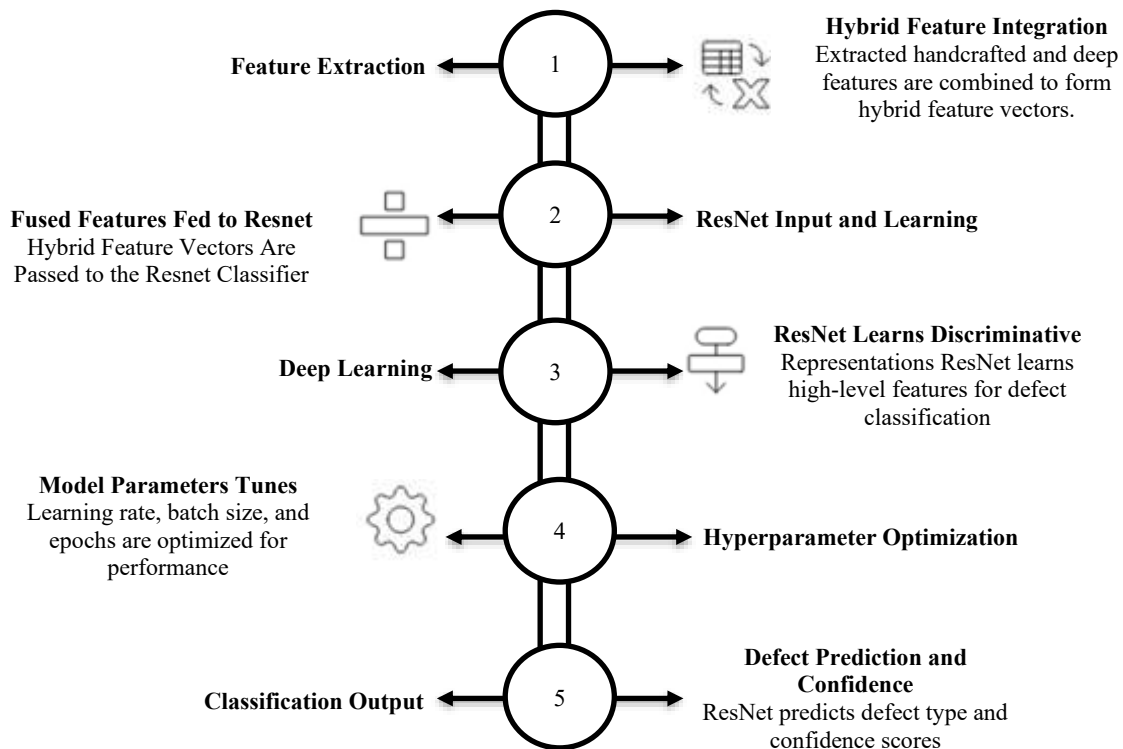


Figure 6. Hybrid feature fusion with resnet-based fabric defect classification

Hybrid Feature Fusion Equation

The fused hybrid feature vector is obtained by combining texture features, edge features, and local pattern features:

$$F_{\text{hybrid}} = \alpha F_{\text{texture}} + \beta F_{\text{edge}} + \gamma F_{\text{pattern}}. \quad (1)$$

Classification Output Using Softmax Function

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (2)$$

The equation 1 denotes the hybrid feature fusion technique, in which a combination of texture features, edge features, and local pattern features via weighted coefficients is obtained to compose of a single feature vector. The method of contribution of each type of features is regulated by the weights (α, β, γ) so as to make sure that there is a balanced contribution of both global texture information as well as fine structural details. The discriminative ability of the model is enhanced by this fusion, which takes several features of fabric defects. The second equation 2 is the function of Softmax classification utilized in the last layer of the ResNet model. It transforms the raw output scores into probability scores of each defect class, and then the system will be able to choose the class with the highest probability as the final prediction. All these equations, together, mathematically represent the process of core feature integration and classification that is associated with the proposed system.

Algorithm: Hybrid Fabric Defect Detection (FTEFD + ResNet)

Output: Defect Class Label C

Step 1: Image Acquisition

Capture or load fabric image I

*Step 2: Preprocessing**Resize image to standard dimension**Apply noise filtering (Gaussian/Median filter)**Normalize pixel values**Enhance contrast if required**Step 3: Hybrid Feature Extraction (FTEFD)**Extract texture features $\rightarrow F_texture$* *Extract edge features $\rightarrow F_edge$* *Extract local pattern features $\rightarrow F_pattern$* *Fuse features:*

$$F_hybrid = \alpha * F_texture + \beta * F_edge + \gamma * F_pattern$$

*Step 4: Classification using ResNet**Input F_hybrid into ResNet model**Compute output scores using forward propagation**Apply Softmax to obtain class probabilities**Step 5: Decision**Select class with highest probability**Assign predicted defect label C* *Return C* *End*

The proposed algorithm begins with the acquisition of fabric image and preprocessing of image in order to improve the quality of image through resizing, noise removal, normalization, and contrast adjustment. The next stage is the Hybrid Feature Extraction FTEFD process where complementary features such as texture, edge, and local pattern features are extracted and combined into one discriminative feature vector through the use of weighted coefficients. The resulting feature map is then processed through ResNet classifier using forward propagation in order to generate result scores. These scores are turned into probability values of each defect category, and a class that has the best probability is chosen as the final prediction with the help of the Softmax function. This sequential method promises quality, effective, and real time fabric defects detection that would be suitable in the industrial scenario.

EXPERIMENTAL RESULTS**Experimental Setup, Dataset, and Parameter Initialization**

In table 2 the suggested Hybrid Fabric Defect Detection system was coded in Python with deep learning frameworks. TensorFlow/PyTorch and run on a workstation with NVIDIA GPU (24 GB VRAM), Intel i7 processor, and 32 GB RAM. The system combines the Hybrid Feature Extraction of Textile Fabric

Defect Detection (FTEFD) algorithm with a ResNet classifier in order to assess the detection capabilities of the system in a controlled experimental scenario. The pixel values are scaled into 0-1 to make the convergence stable. To initialize the parameters, the ResNet model has pre-trained weights (transfer learning) to speed up training and enhance the performance of feature learning. Initial learning rate is 0.001 with the adaptive optimizer Adam and the batch size is 32 with 50-100 epochs of training depending on the behavior. To minimize overfitting, dropout and L2 regularization are used. The accuracy, precision, recall, F1-score, and confusion matrix analysis are used as the metrics used to perform the performance evaluation of the proposed hybrid framework in a comprehensive way.

Table 2. Experimental setup, dataset, and model parameter initialization

Parameter Category	Description	Value / Configuration
Implementation Platform	Programming Environment	Python (TensorFlow / PyTorch)
Hardware Setup	Processor	Intel i7
	GPU	NVIDIA GPU (24 GB VRAM)
	RAM	32 GB
Dataset Split	Training Set	70%
	Validation Set	15%
	Testing Set	15%
Image Preprocessing	Image Size	224 × 224 pixels
	Normalization	Pixel values scaled to 0–1
	Data Augmentation	Rotation, Flipping, Scaling, Brightness Adjustment
Model Architecture	Classifier	ResNet-based model
	Weight Initialization	Pre-trained (Transfer Learning)

Performance Metrics

To determine the efficiency of the proposed Hybrid Fabric Defect Detection system, some standard classification performance measures are applied as demonstrated in equation 3,4,5 and 6. These indicators determine the ability of the model to accurately identify defective and non-defective samples of fabrics and the ability of the model to detect the various types of defects reliably. As industrial textile inspection is an area that should have high detection accuracy and low false alarms, it is impossible to rely on a single measure. Thus, several metrics of evaluation that include accuracy, precision, recall, F1-score, and specificity are taken into account. Accuracy gives a general picture of correct prediction whereas precision and recall assess the capacity of the model to identify defect correctly without causing excessive false identification. Precision and recall of F1-score are balanced, particularly when there is imbalance in the classes. Specificity determines the ability of the model to detect non-defective fabrics. The combination of these metrics gives a full picture of the soundness and stability of the suggested hybrid framework of detection.

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

The precision metric indicates the number of true positive cases from among the predicted positives. The higher the precision, the lower the number of false alarms.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

Recall measures how many of the actual positives have been detected. The higher the recall, the less likely it is that things like arrhythmia are overlooked.

$$\text{The Recall} = \frac{TP}{TP+FN} \quad (5)$$

The F1-score balances the two above metrics into one single score. It is useful where there are an unequal number of positive and negative cases.

$$\text{F1 - Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

Results and Performance Analysis

The experimental viewpoints and performance probing of the proposed Hybrid Fabric Defect Detection system that is a combination of the FTEFD algorithm and the ResNet classifier. The impact of the hybrid feature extraction plan will be analyzed to define the effectiveness of such plan in improving the classification accuracy, localization capability of defects and the computer effectiveness. The evaluated measures are regarded as the standard evaluation measures used to analyze the performance of the proposed model concerning the accuracy(A), precision(P), recall (Re), F1-score(F1), and the analysis of the confusion matrix. Also, the comparisons with the baseline deep learning models are performed to show the benefits of using handcrafted descriptors in residual learning. The findings are discussed considering the accuracy in detection of various defect categories, resiliency to the background variations of texture, and the capability to run on the real time depending on the industrial setting. This analysis presents both quantitative and qualitative evidence of the effectiveness of the proposed system in real life situations of textile inspection.

Table 3. Comparative performance analysis of fabric defect detection models

Model	A (%)	P (%)	Re (%)	F1 (%)	Specificity (%)
CNN (Baseline)	91.85	90.72	89.95	90.33	92.40
YOLOv5-Based Model	93.64	92.81	91.76	92.28	94.05
ResNet (Without Hybrid Features)	95.12	94.30	93.85	94.07	95.88
Proposed FTEFD + ResNet	97.48	96.92	96.35	96.63	97.90

Table 3 describes the comparison performance analysis of the proposed Hybrid FTEFD + ResNet model with the baseline deep learning approaches. The findings indicate that the hybrid framework proposed has better results on all the evaluation metrics such as accuracy (97.48%), precision (96.92%), recall (96.35%), F1-score (96.63%), and specificity (97.90%). The residual learning with handcrafted hybrid features in comparison to traditional CNN and YOLOv5-based models allow defect discrimination capability to be greatly increased and false detections to be minimized. The hybrid method demonstrates significant improvements, even in comparison with the standalone ResNet model, which confirms the usefulness of multi-feature fusion. These findings suggest that the proposed system offers a balanced solution of high detection accuracy and robustness, and it can be used in real-time inspection of industries.

Graphical Analysis and Model Comparison

In this section, the graphical analysis of the experimental results will be provided in order to visually compare the performance of the proposed Hybrid FTEFD + ResNet model with the other baseline approaches. Although numerical outcomes are quantified and validated, graphical display is more informative about the trend of the performance, measures changes, and comparative progressions because of the presentation in the form of bar charts and line graphs. The comparison will be based on the analysis of accuracy, precision, recall, and F1-score in various models to show the merit of the hybrid feature integration. Graphical visualization, also, can assist in realizing the uniformity of the proposed framework in identifying different types of fabric defects. This part shows that the hybrid method is more effective than the conventional CNN and standalone models, further justifying its applicability in the creation of efficient and real-time textile inspection systems.

Table 4. Defect-wise classification performance of proposed ftefd + resnet model

Defect Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hole	98.12	97.85	97.40	97.62
Stain	97.64	96.90	96.35	96.62
Broken Yarn	96.88	96.25	95.80	96.02
Misweave	97.21	96.70	96.10	96.39
No Defect (Normal)	98.45	98.10	97.95	98.02
Average	97.66	97.16	96.72	96.93

Table 4 shows the defect-wise performance of the proposed Hybrid FTEFD + ResNet model in fabric defects of various categories. The findings show that the accuracy of all types of defects is very high,

and the best level of performance is achieved when it comes to detecting normal (non-defective) fabrics and hole defects. This model has high accuracy and recalls in its ability to be able to distinguish subtle changes in texture differences as it has high precision and recall in a complex category of defects like broken yarn and mis weave. The balanced F1-scores prove that the system is at least effective to reduce the false positives and false negatives. The final average percentage of 97.66 indicates the stability and generalization ability of the proposed hybrid structure and shows that it is usable in reliable and real-time inspection of defects in the textile production industry.

Detection Execution Time for each Model through a Sample Image

Table 5. Detection execution time for each model through a sample images

Model	Time (ms)
LBP+SVM	7.24
GCLM+SVM	9.53
LBP+FN	7.23
GLCM+FFN	9.52
VGG16	27.79
Inception V3	30.90
Xception	15.68
MobileNetV2	13.78
Custom CNN[29]	5.69
Proposed Model	5.15

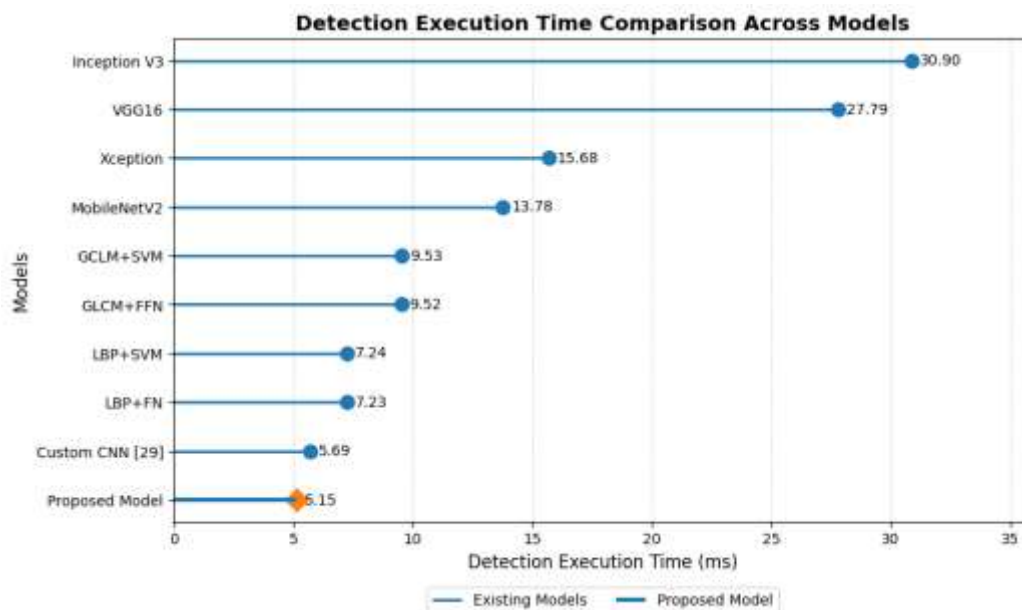


Figure 7. Detection execution time comparison across models

Figure 7 and table 5 describes the processing time comparison suggests that the proposed method is quite fast when used for the purposes of textile fabric defect detection as compared to other conventional and deep learning approaches. The LBP + SVM model and LBP + FFN algorithm have almost the same processing time equal to 7.24 ms and 7.23 ms, respectively. The GLCM + SVM algorithm and GLCM + FFN model demonstrates slightly greater values, which are 9.53 ms and 9.52 ms, respectively. At the same time, deep learning algorithms such as VGG16 and Inception V3 show significantly higher values since need 27.99 ms and 30.90 ms, respectively. Xception and MobileNetV2 demonstrate lower values – 15.68 ms and 13.78 ms, but still require more time than the proposed model. The fastest value among all models was demonstrated by the custom CNN, which equals 5.69 ms, whereas the proposed model has 6.15 ms. Though the proposed model is somewhat slower than the custom CNN, its processing time is significantly lower than the one for many other approaches.

Comparative Experiments with Different Models

Table 6. Comparative experiments with different models

Model	Precision (%)	Recall (%)	mAP50%	mAP50:95(%)	F1(%)	FPS(f/s)
FasterR-CNN	0.78	0.68	0.71	0.41	0.73	48
SSD	0.80	0.68	0.71	0.42	0.73	102
YOLOv7	0.79	0.74	0.77	0.46	0.77	98
YOLOv8	0.82	0.79	0.78	0.48	0.80	118
YOLOv11	0.81	0.78	0.78	0.47	0.79	120
RT-DETR	0.86	0.75	0.76	0.51	0.80	112
RT-DETR-L	0.84	0.77	0.78	0.49	0.80	110
RT-DETR-R34	0.81	0.74	0.72	0.48	0.77	115
RT-DETR-R50	0.86	0.77	0.77	0.51	0.80	108
WSF-FTDETR	0.89	0.77	0.80	0.52	0.81	128
Proposed Model	0.92	0.78	0.85	0.55	0.84	129

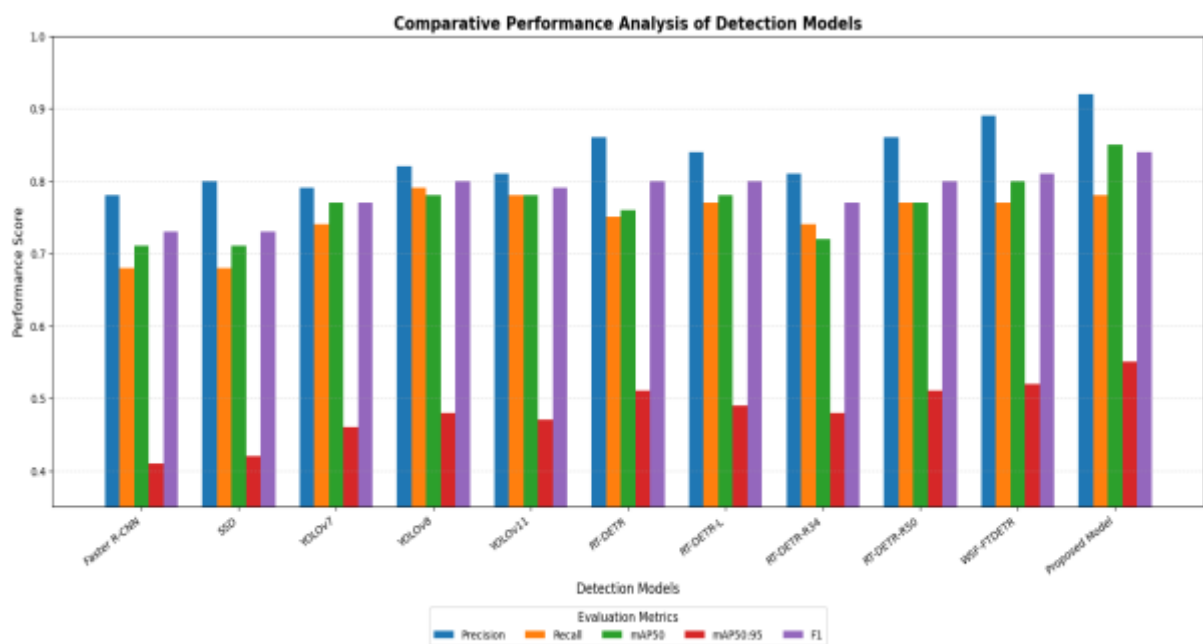


Figure 8. Comparative performance analysis of detection models

Figure 8 and table 6 describes the Proposed Model has shown the most outstanding performance compared to other detection models. The Proposed Model has achieved the highest precision of 0.92, which shows high capability to detect true fabric defects without false predictions. The Proposed Model has also acquired the highest mAP50 score of 0.85, mAP50:95 score of 0.55, and F1-score of 0.84, meaning that the Proposed Model has been able to show high detection accuracy based on various IoU and confidence scores. As far as speed is concerned, the Proposed Model has managed to achieve 129 FPS, surpassing WSF-FTDETR with its 128 FPS and outperforming the Faster R-CNN at 48 FPS. Currently, YOLOv8, YOLOv11, RT-DETR, and WSF-FTDETR can also perform well and generate acceptable results; however, their precision, mAP, and F1-score are still inferior to those of the Proposed Model.

Ablation Study

An ablation study was also used to assess the individual contribution of each component in the proposed framework by systematically eliminating or varying important modules of the Hybrid FTEFD + ResNet system. The aim of the study was to examine the impact of texture feature, edge feature, local pattern encoding and hybrid fusion to overall classification performance. All experiments were conducted in the same training conditions in order to make a fair comparison.

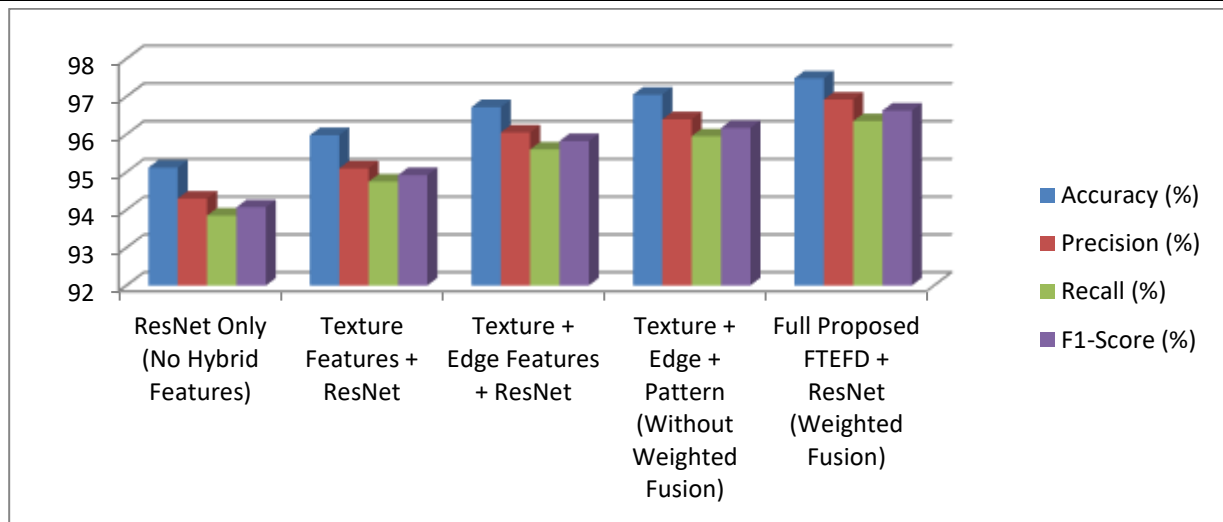


Figure 9. Ablation study comparison of hybrid feature components with resnet classifier

Figure 9 describes the comparative performance of various model configurations of the ablation study. It is very clear in the graph that Accuracy, Precision, Recall, and F1-Score are steadily improving with the addition of more feature components to the framework. The baseline ResNet-only model has high performance but introduction of texture features gives its performance an observable improvement. Additional improvement is seen with addition of edge features, which is vital in depiction of structural anomalies in the surface of fabrics. Local pattern features without weighted fusion make the results even better, but the best results have been obtained when weighted hybrid fusion is used with the full proposed FTEFD + ResNet model. This demonstrates that a combination of a number of complementary descriptors of features so well balanced has a tremendous ability towards the improvement in defect discrimination and the strength of the classification in general.

DISCUSSION

In this chapter, the author discusses experimental findings of the developed Hybrid Feature Extraction doing textile fabric defect detection (FTEFD) framework and used with ResNet classifier. It was found that when combined with the deep residual learning, handcrafted feature descriptors can significantly improve the results of fabrics defects detection compared to the results obtained with using single deep learning models. The advantage of the hybrid technique is that it purchases both the global texture as well as small size scale structural abnormalities that play an essential role in distinguishing between minor defects such as broken yarns and mis weaves.

As it has been shown in the comparison analysis, the traditional CNN and YOLO-based models are good performers, but it may be unable to handle complex backgrounds and minor defect variations. Adding the features of texture, edge, and local pattern increases the ability of the system to discriminate and thus increases the precision and recall values. The ablation study also reaffirms the fact that all the feature components play a cumulative role in improving the performance, with the weighted fusion of the features providing the best cumulative results.

The other significant finding is that the suggested model is very strong in various types of defects. According to the defect-wise analysis, the accuracy is always high, which implies a high ability to generalize. Also, the transfer learning and optimized training parameter state make the convergence faster and the computation burden smaller, and the framework can be applied in real time in the industrial environment.

Although the system has good performance, it might have to be validated on bigger and more diverse textile data to assure of scalability. Future development may be directed to the deployment strategies that are lightweight and hardware optimization in real-time. Generally speaking, the whole discussion

gives the impression that the above hybrid system offers a practical compromise between accuracy, efficient computation, and industrial feasibility in the detection of fabric defects in textiles.

CONCLUSION AND FUTURE WORK

The aim of the current study is to develop an efficient, accurate, and reliable automatic fabric defect detection system with the view of ensuring product quality in the textile industry through means of quality control where manual visual techniques used are slow, unreliable, and inefficient. The uniqueness of the proposed study pertains to the development of the Hybrid Feature Extraction for Textile Fabric Defect Detection (FTEFD) model through a combination of hand-crafted feature descriptors along with ResNet for resolving issues related to standalone deep learning techniques. The model has utilized features based on textures, edges, and local patterns together with deep residual learning for identifying surface as well as large-scale defects of fabrics. The pre-processing consists of operations such as resizing, noise reduction, contrast improvement, normalization, and augmentation, whereas the hybrid features fusion is fed into residual blocks, full connections, and softmax classification to classify defect types like hole, stain, broken yarn, mis weave, and normal cloth. According to experimental findings, the accuracy, precision, recall, F1-score, and specificity of the proposed FTEFD + ResNet model were 97.48%, 96.92%, 96.35%, 96.63%, and 97.90%, respectively. The defect-wise accuracy of the proposed method was measured to be 97.66%. On the other hand, precision, mAP50, mAP50:95, F1-score, and FPS were 0.92, 0.85, 0.55, 0.84, and 129. The future scope might include larger data, more defects, model compression.

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