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AI Driven Hybrid Descriptor and Classifier for Robust Textile Fabric Defect Detection

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Abstract

The accurate identification of defects in textile fabrics remains one of the most crucial issues in automated quality checking because identical textures, ambiguous defect patterns, and varying illumination levels in factories pose challenges. Although deep convolutional neural networks (CNNs) have proven to be good in visual recognition processes, it can be very weak in identifying fine-grained direction and micro-texture anomalies that are characteristic of woven fabrics. In order to deal with this shortcoming, this research paper introduces AI-based hybrid descriptor-classifier model that combines both manually created texture features with deep hierarchical feature learning with the goal of identifying textile defects effectively. More precisely, the multi-scale Gabor filters are used to retrieve orientation- and frequency-sensitive responses, whereas Local Binary Pattern (LBP) operators are used to acquire micro-texture variations of a localized nature. These handcrafted feature maps are combined with the middle-level CNN representations via channel-wise concatenation and maximized multi-scale feature aggregation to strengthen the discriminative ability of small and complicated defects. A balanced and augmented industrial fabric dataset is used to train the model in different lighting and texture conditions. Large experiments show that the proposed hybrid architecture has Precision of 95.4%, Recall of 93.8%, F1-score of 94.6%, mAP at 0.5 of 96.3% and IoU of 90.7% better than CNN-only and state-of-the-art object detection baselines. The system has real-time performance of 58 FPS, making it appropriate in the high-speed manufacturing systems. The investigation of ablation justifies that the combination of Gabor and LBP descriptors is much more effective in terms of the localization accuracy and robustness, especially with regard to very delicate and tiny defects. The suggested framework will create a successful collaboration between deep learning and classical descriptions of texture, which will give a high-performance and scalable solution to future generation automated textile inspection systems.

Keywords: Clothing Manufacturing Errors, Artificial Intelligence (AI), Customized Feature Descriptors, Gabor Filters, Local Binary Patterns (LBP), Convolutional Neural Networks (CNN), Deep Learning.

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1 Introduction

The textile industry is an essential part of global production, and product quality directly affects customer satisfaction, brand popularity, and economic performance. Fabric defect detection is one of the most significant steps in textile production, alongside other quality control processes. The imperfections, such as discolorations, holes, knots, frayed yarns, and mis woven areas, not only affect the appearance of the textiles but also pose huge losses to the organization from rework, rejects, and customer complaints. Hence, an automatic detection system that detects fabric defects quickly, accurately, and in time is required for quality control (Wei et al., 2021). In the past, the detection of fabric defects has always been done manually by trained inspectors. While this method may be able to detect some obvious flaws, it takes too much time, effort, and is irregular, prone to human error due to tiredness (Simson & Kinslin, 2024). Moreover, the manual method is failing to keep up with the modern demands of fast-paced textile manufacturing industries (Konstantinidis et al., 2021). Other methods of automating the process, using either traditional machine vision techniques or traditional machine learning techniques, have been attempted. However, such methods require manual design of features and are unable to adjust according to changes in fabric characteristics (Tuama, 2023; Suryarasmi et al., 2022).

Since the swift advent of Artificial Intelligence (AI), especially deep learning, automatic defect detection is now a topic under discussion (Byeon et al., 2024; Khodier et al., 2022). The CNN method performs exceptionally well in pattern recognition and image classification (Mattioli et al., 2020; Liu et al., 2020). However, a huge amount of computational power and data are needed for the use of deep learning. In other cases, deep learning fails to recognize detailed differences in texture, which can be handled effectively using traditional approaches (Zhang et al., 2023).

In order to solve these kinds of deficiencies, an AI hybrid approach has been proposed as a solution to develop an intelligent defect detector for textile fabric (Zhang et al., 2022; Fang et al., 2022). As proposed in the literature, the proposed model is the combination of both descriptors, Gabor filters, and LBP along with a classifier, i.e., CNNs (Chen et al., 2022; Kahraman & Durmuşoğlu, 2023). Gabor filters are extremely effective in describing frequency and orientation, and thus are used to describe a textured image. Similarly, LBP is highly effective for local texture description purposes. Therefore, in conjunction with the hierarchical learning capacity of the CNNs, this hybrid architecture can prove to be more effective in detection applications (Yue et al., 2022; Wang et al., 2021).

One of the main objectives of the present research is to design an effective, precise, and scalable automation solution for defect detection using artificial intelligence under various industrial conditions. It is expected that the use of this hybrid artificial intelligence approach will overcome the deficiencies in using solely the conventional approaches or machine learning algorithms, as each of them has its own strength that complements the other one (Xu et al., 2023). Lastly, the research will help enhance quality control measures, decrease dependence on humans, and boost production in modern textile industry (Zhang et al., 2022).

Key Contributions of the Research

- According to the study, it is possible to come up with an innovative model through the fusion of traditional and AI technologies for improving defect detection techniques through the use of handcrafted texture features (Gabor filter and LBP) together with deep learning techniques (CNNs).
- Unlike the former one, the proposed system enhances the accuracy of classification and also generalizes for different fabric types and defects.

- The method allows for fast and accurate fabric defect detection to be done, thus minimizing human intervention and reducing waste in the textile industry.

The structure of this paper is as follows: Chapter 2 provides a literature review of all the current techniques of detecting fabric defects both traditional image processing methods and deep learning-based techniques, discussing their disadvantages and gaps in research. Chapter 3 outlines the proposed methodology, which includes a hybrid feature extraction model combining Gabor filters, Local Binary Patterns (LBP), and Convolutional Neural Networks (CNN), as well as data preparation and model design. Chapter 4 explains the experimental environment, the performance measure, and the result comparing the proposed model. Chapter 5 presents the results, analyses them, and discusses their strengths, reliability, and implications. Finally, Chapter 6 concludes by summarizing the study's key findings and outlining potential avenues for future research and improvement.

2 Literature Review

The current research is intended to carry out a real-time inspection of defects in the textile industry. The proposed approach by them is based on an optimization of region proposals combined with CNN-based feature extraction, which results in better detection and classification of defects. Unlike traditional approaches that concentrate mainly on detection, the proposed model incorporates anomaly scoring and other post-processing elements to make the system more useful for industrial purposes. It should be noted that their study concentrates on the optimal balance between performance and defect detection rate in computations, which implies that the system is suitable for high-rate production processes (Tian et al., 2025).

Proposed a novel SDLS-YOLO, which stands for a super-light defect detector based on a robust YOLOv10n model. In order to boost detection accuracy and minimize computational costs to a significant level, which can be refined backbone architecture, feature fusion mechanism, and loss function. Primarily used in real-time inspection systems where the time constraint and limited hardware are key concerns. With reduced memory usage, SDLS-YOLO provides high precision and recall due to effective feature learning and redundant parameters. The proposed approach is extremely flexible in terms of fabric types and defect grades (Lin et al., 2024).

A deep-learning-based approach for the detection of textile defects has been designed and applied to an edge computing system with the help of YOLOv11. Which can be study the problem of identifying defects such as holes, creases, misweaving, and coloring in high-speed production lines. It should be noted that lightweight models have been proposed that provide efficient and fast defect detection. This system will reduce data transfer latency by taking advantage of edge devices. Which can be conclude that there will be improved decisions on the ground by combining object detection algorithms and edge computing systems (Chen et al., 2026).

This paper presents a better deep convolutional neural network (DCNN)-based system along with the introduction of an anthropomorphic robotic inspection system that can accurately detect defects within fabrics. This model is also able to classify 13 different defect types with great accuracy. This research paper is not only concerned about developing the algorithm but, for safety and efficiency reasons, it also takes into consideration the human-robot interaction aspect as well. This system could leverage both deep learning and robot automation for continuous monitoring without having to rely upon humans in the quality control process (Machado et al., 2025).

In this study, high-level background suppression techniques were considered to improve defect detection in complicated textile patterns. These techniques are founded on the principle of isolation of defects by features, while repetitive background textures have proven to be responsible for triggering false detections in automated systems. The suggested technique proves to be significantly more reliable and accurate in the detection process by using background modeling and feature refinement in deep learning architectures. This study shows that removing texture noise helps improve model generalization. The outcome of experimental testing shows the superiority of this method over regular CNN-based detection systems (Hassan et al., 2024).

In this literature review, the focus is on analyzing existing research work on using AI technology to detect defects in manufacturing industries, particularly in the textile sector. The analysis includes an examination of the process of transition from traditional image processing approaches to modern machine learning approaches and deep learning models such as convolutional neural network, transformer, GAN, and hybrid architectures. Some of the tasks considered in this paper are classification, localization, segmentation, and anomaly detection. In addition, other concerns that need to be addressed include imbalance dataset, domain adaptation, and real-time constraints. It was found that a generalized lightweight architecture is crucial for any practical applications of these techniques (Chen et al., 2025).

Table 1: Comparative analysis of recent AI-based textile fabric defect detection methods

Author(s)	Method / Model Used	Key Contribution	Limitations / Gap
Lin et al., (2024)	Faster R-CNN with optimized region proposal (Fabric4show)	Developed a real-time industrial vision system integrating defect detection, localization, anomaly scoring, and post-processing for practical deployment.	Higher computational complexity compared to lightweight YOLO-based models.
Chen et al., (2026)	SDLS-YOLO (Improved YOLOv10n)	Proposed an ultra-lightweight model with optimized backbone, feature fusion, and loss function for real-time inspection.	May struggle with extremely small-scale or subtle texture defects.
Machado et al., (2025)	YOLOv11 with Edge Computing	Designed a real-time defect detection system deployed on edge devices for low-latency industrial applications.	Edge deployment may limit performance for highly complex defect scenarios.
Hassan et al., (2024)	Enhanced DCNN with Robotic Integration	Integrated deep learning with an anthropomorphic robot for automated inspection of 13 defect types.	System complexity and cost may limit adoption in small-scale industries.
Chen et al., (2025)	Background Suppression + Deep Learning	Improved detection accuracy by separating defect features from repetitive textile background patterns.	Performance depends heavily on accurate background modeling.
Nahar et al., (2026)	Survey of ML/DL (CNNs, GANs, Transformers)	Comprehensive review of industrial defect detection methods, highlighting trends and future challenges.	Does not propose a novel detection framework.
Ozek et al., (2025)	AI-based Review Study	Reviewed transition from manual inspection to AI-driven systems, emphasizing CNNs and sustainability aspects.	Primarily analytical; lacks experimental validation.

Here this study has a thorough examination of AI technology implementation in textile defects analysis and moving towards automation via the usage of AI. It concentrates on the use of convolutional neural networks, machine learning technology, and advanced sensors, which help to improve detection and boost production efficiency. Moreover, which can be are aware of the problem of sustainability and the importance of reducing the material cost of operation due to automation. This literature review highlights the current restrictions such as variability in data sets and computational capabilities. Hybrid and lightweight methods can be suggested as solutions to the aforementioned problem in the future. Overall, the article gives a general overview of technology development related to the present textile quality control system (Nahar et al., 2026).

Table 1 presents a comparative review of the latest advances in using AI technology for defect detection of textiles fabrics. Various deep learning-based approaches, such as the use of Faster R-CNN, lightweight networks based on the YOLO algorithm, advanced DCNN, background suppressor, as well as surveys of relevant literature are included. In the comparative analysis, the main methodology applied, the major contribution of the study and the limitations identified in it have been elaborated on. The comparative approach sheds light on current technical developments and deficiencies in the field. Despite most of the research conducted being centered around real-time detection, lightweight model design and application to industry-specific needs, there are problems related to computational complexity, detecting minor defects, diversity of datasets, and transferring knowledge across different materials. It explains the motivation behind developing a hybrid framework for the descriptor application by combining handwritten features extraction and deep learning classifier.

Research Gap

Though the field of AI-based defect detection of textiles has made progress, it is still challenging to have generalizable hybrid models capable of detecting defect patterns from varied categories of fabrics. In addition, these models fail to efficiently utilize multi-source information and detect difficult defect patterns on time. Moreover, the trade-off between accuracy and efficient computation becomes more prominent when implementing such methods for defect detection.

3 Methodology

3.1 Overall Architecture of Proposed Methodology

In figure 1 shows the end-to-end implementation of the AI-based pipeline for textile fabric defect detection. First is data collection with RGB, gray-scale, near-infrared (NIR), or line scan imagery for acquiring images of defective and non-defective textiles. Preprocessing involves noise reduction, illumination correction, contrast enhancement, intensity normalization, ROI extraction, or patch extraction. Descriptor Extraction stage combines handcrafted features like LBP, GLCM, Gabor, HOG, and other intensity-based descriptors together with CNN-based and Vision Transformers (ViT)-based learned features, producing a hybrid feature vector. Hybrid dimensionality reduction and feature selection utilize PCA, LDA, autoencoder methods, or optimization-based approaches like PSO, GA, or DE. For defect classification and recognition, a hybrid classifier with soft voting between SVM, random forest, xgboost, CNN-based, and Vision Transformers classifiers is used, assigning each image to one or more defect classes (holes, broken yarn, stains, slubs, oil spots, and others). Additionally, the system provides defect localization and visualization with tools like heatmap generation via Grad-CAM or Score-CAM visualization technique, thresholding, morphology operations, and bounding boxes. For performance evaluation, a range of metrics can be calculated, including accuracy, precision, recall, F1-score, confusion matrix, ROC-AUC, and mAP.

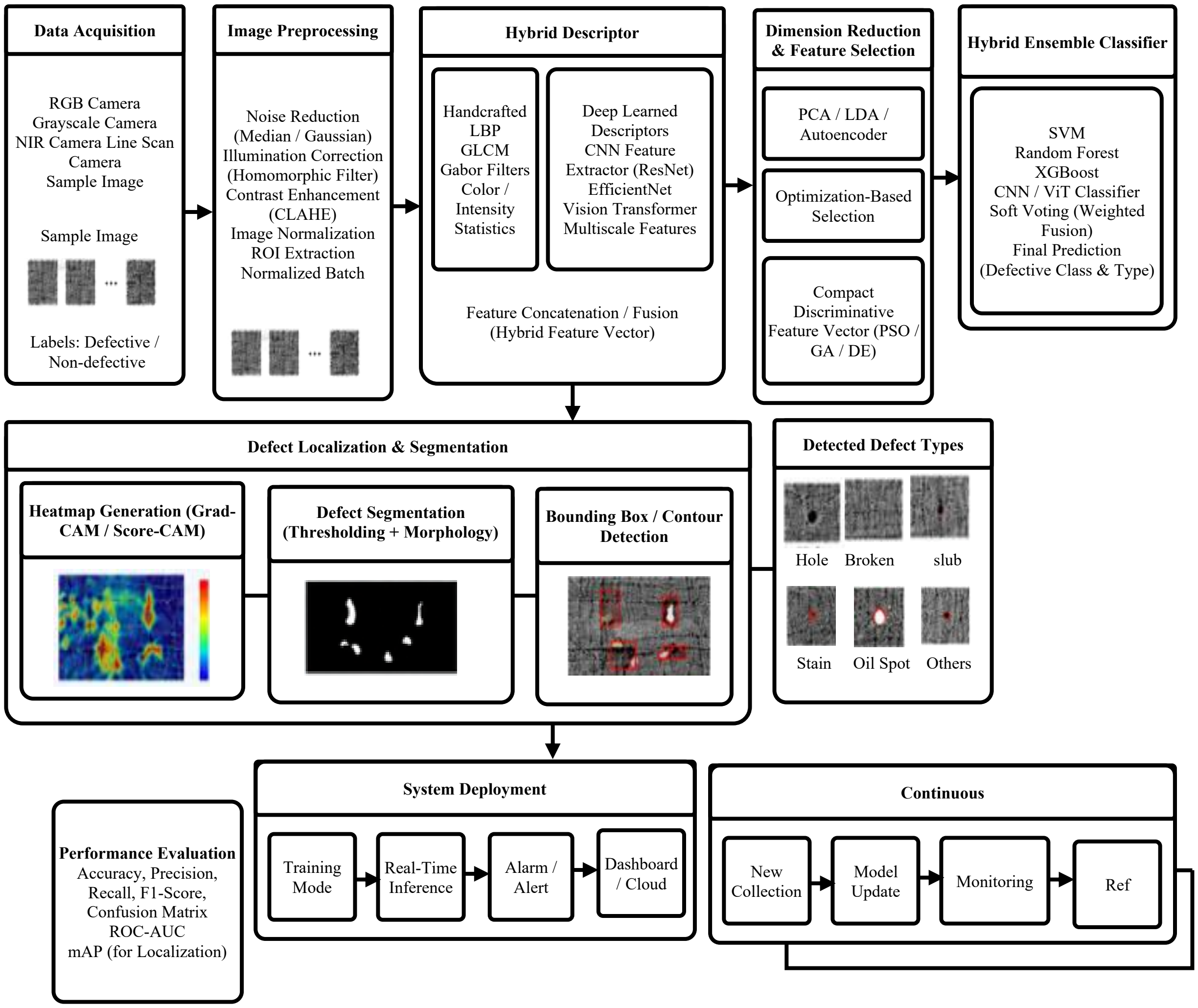

Figure 1: Overall architecture of proposed methodology

3.2 Working Principle of CNN in Textile Fabric Defect Detection

CNN is a special multilayer feedforward neural network designed to deal with image data. It has the characteristics of sparse interaction and parameter sharing. Inspired by biological visual neural networks, the sparse interaction means that each hidden neuron only connects a small piece of adjacent area of the input image; the parameter sharing allows the convolution filter to share the same weight matrix and bias in the process of convolving the input image, ensuring the translation invariance of the image and reducing the number of weight parameters. The CNN is mainly composed of convolutional layers, pooling layers and fully connected layers in figure 2.

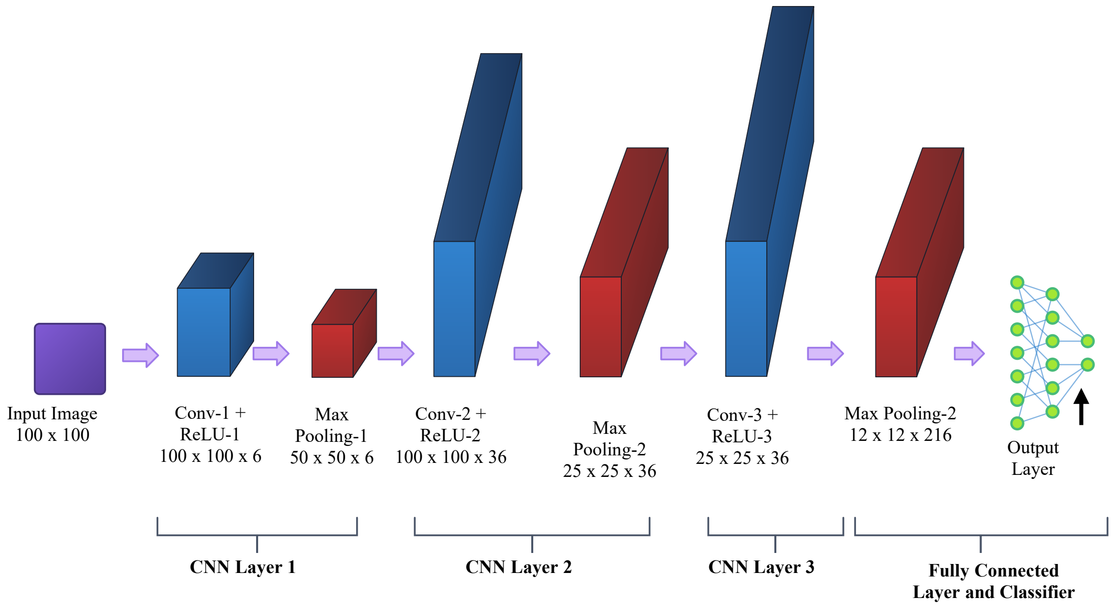

Figure 2: Working principle of CNN in textile fabric defect detection

The convolutional layers of the CNN are also called the feature extraction layers, which have a number of convolution filters to extract different features of the input image. In the convolutional layer, the convolution filter of the current layer performs a convolution operation on the input images, and then obtains new feature maps through the activation function. The new feature map can be calculated by equation (1).

$$x_j^{l+1} = \beta_f^l . p\left(x_j^i\right) \qquad (1)$$

From the above equation (1) describes the x_j^l describes the jth feature map in the lth layer of the network. K_j^l represents the jth convolution filter. M_j defined the set of feature maps convoluting with K_j^l in the lth layer. b_j^l represents the bias in the jth feature map in the lth layer. $*$ is the 2D convolution operation and $f(.)$ defined the activation functions.

$$y_t = signmoid(\sum_{h=1}^{q} w_h . z_h + b \qquad (2)$$

From the above equation (2) describes the $sigmoid(.)$ Represents the limited value as $(0,1)$. y_i defined the actual output defined the probability with the ith sample combined with positive category; q is the number of neurons and z_h defined the output value of the n neuron in the previous. w_h represents the weight between the output neuron and z_h and b defined as bias.

For a multi-class representation,

$$Y_t = [Y_{11}, y_{12}, \ldots \ldots Y_{1l}]^T = softmax(W.Z), \sum\nolimits_{j=1}^{l} y_{lj} = 1 \qquad (3)$$

From the above equation (3) describes $softmax(.)$ defined as the normalization function, which is such that each map should contain the element of vector W.Z with the interval of (0,1). IN this sum of elements is equal to 1. Y_i defined as the actual vector of the network output on the ith sample.W is the weight matrix between the output layer and z is the output vector of the neurons. The largest element of Y_i and y_{ij}. The input sample class represented by $class$ j.

3.3 Dataset Preparation and Preprocessing

Proposed methodologies entail systematic organization and preprocessing of datasets to ensure that a high-quality input to the deep learning network Zheng et al., (2020) is provided. Capturing of images of fabrics is done in the actual production line in the industrial textile manufacturing process at varying degrees of lighting, types of fabrics, and production speeds to simulate realistic manufacturing conditions (Xiao et al., 2021). Data consist of diverse defects of holes, stains, misweaves, wrinkles, and color differences, which provide varied classifications that reflect the diversity of the real world. Images will be manually annotated using bounding boxes to identify defect areas to train the object detector network in a supervised manner. Various pre-processing techniques include image resizing to standard resolution, normalization, and reduction of noise to reduce distortion by sensors. Furthermore, additional data augmentation strategies like horizontal and vertical flips, random rotations, scaling, brightness, and contrast improvements are performed in order to increase the size of the dataset and overcome class imbalance. Moreover, the background texture improvement/elimination technique is employed to avoid repetitive pattern interference because it normally causes false alarms in textile inspection systems. Then, the entire dataset is split into training, validation, and testing sets in an optimal ratio to prevent overfitting and obtain a performance assessment in an objective manner. Through this well-organized approach, one can make sure that the deep learning network is provided with a diverse set of high-quality labeled images, thereby increasing its detection accuracy and feasibility.

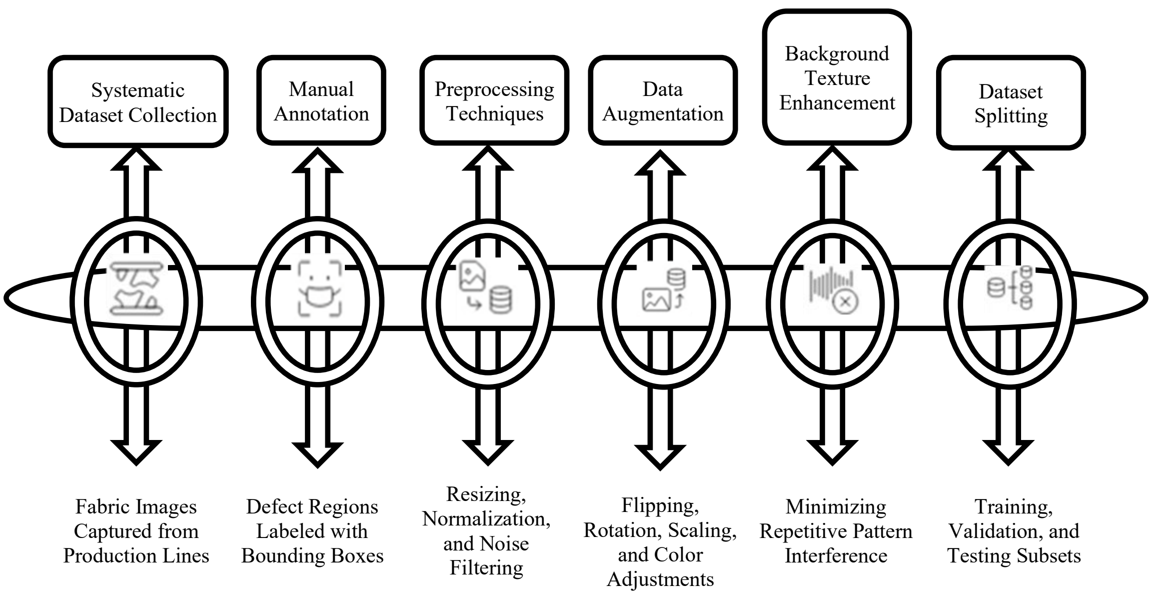

Figure 3: Data collection and preprocessing workflow for fabric defect detection

In figure 3 demonstrates the whole workflow of the data processing pipeline for fabric defects detection. First, systematic dataset collection is conducted, meaning that fabric defect pictures are taken directly from manufacturing lines in order to simulate real industrial environment. Next, it is followed by the step of manual annotation, where defective areas are outlined using bounding boxes as ground truth labels for supervised models. Preprocessing is carried out to ensure uniformity and quality of data, through the processes of image resizing, normalization, and filtering out any background noise, ensuring optimal training of the algorithm. Data augmentation is implemented, including flips, rotations, scaling, and coloring operations, to improve the variety and generalizability of the training data. Background texture improvement was included as a technique aimed at minimizing pattern interference typical for fabrics. Lastly, splitting of the data into train, validation, and test datasets was carried out in order to properly evaluate the model.

3.4 Model Architecture and System Design

In this section, the focus will be on the design and implementation of the proposed deep learning-based defect detection framework. The framework architecture has been built employing a lightweight object detector backbone that works in real-time conditions and is specifically tailored for industrial purposes. Semantic features are extracted from the backbone of the network and combined with manually engineered Gabor and LBP texture maps channel-wise. Multi-scale feature integration has been incorporated into the framework to improve the detection capabilities of the model at all three scales. In addition, the neck part combines the properties of different resolutions making the process more contextualized and reduces false detections. All the tasks, including bounding boxes regression, object classification, and prediction of confidence scores, are performed in the head part of the network. Depthwise separable convolutions and reduction in the number of parameters have been introduced to decrease the computational costs related to memory consumption and latency. A loss function was selected to find a balance between classification and localization errors. Furthermore, NMS (Non-Maximum Suppression) technique is applied after this stage in order to get rid of overlapping predictions which are unnecessary and to improve the output of object detection process. The entire framework is run through an advanced deep learning algorithm running on the platform that supports extremely fast computation speed. This framework has been ideally designed to maintain equilibrium between object detection and computation speed in real time scenarios, particularly for high-speed textile manufacturing environments. The efficacy of combining manual Gabor & LBP features along with CNN features is tested experimentally.

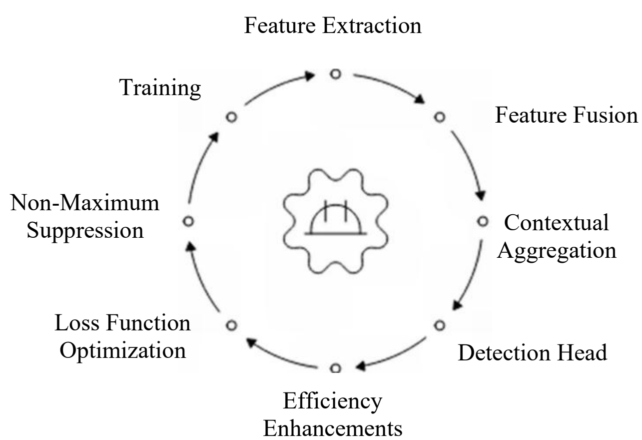

Figure 4: Proposed detection framework and optimization cycle

In figure 4 shows the architecture of the developed fabric defect detection model with an optimization workflow. This involves feature extraction, in which deep convolution layers are optimized to extract meaningful features of input fabric images. The features obtained from this process are then fed into feature fusion and contextual aggregation, in which multi-scale features and small-scale defects are fused and aggregated to obtain context-aware features. The bounding box and classification output are generated using detector heads. The process provides efficiency for computing purposes and reduces the complexity of the model. Loss function optimization is the process involved in ensuring that learning is done appropriately through reduction of the errors that can be made during the learning processes such as localization and classification errors. Non-Maximum Suppression (NMS) is used for eliminating overlapping bounding boxes as Which can be are redundant, resulting in improved detection performance. Training in this case involves a circular sequence, as indicated by the shape of the circular diagram.

3.5 Training Strategy and Performance Evaluation

The methodology will entail training of the models, optimization, and thorough analysis of performance. The training is performed on a supervised learning method with mini-batches of annotated fabric images being presented to the network. An update to the weights of the model with each loss value calculated is made with a stochastic gradient descent (SGD) or an adaptive optimization algorithm such as Adam. In training, scheduling techniques of learning are applied to provide a stable convergence and minimize oscillations. In addition, monitoring of validation and early stopping methods will also help avoid overfitting and improve generalization capability. Various performance measures have been employed in assessing the effectiveness of the algorithm. Which can be include precision, recall, F1 score, mAP, and time for inference per image. Confusion matrices are utilized in interpreting the misclassification patterns of defects. For assessing the practical application of the model in an industrial environment, different test scenarios are employed. It includes various illumination levels, fabric textures, and defect sizes. Moreover, computational performance metrics such as model size, number of parameters, and frames per second (FPS) are also measured to prove its capability to be deployed on hardware devices (edge or embedded). Comparison is made with the current existing state-of-the-art models to establish the improvements made in accuracy, efficiency, and scalability. Through this approach, one will be assured that the model being designed not only detects defects effectively but also meets the requirement of the industry in terms of real-time, accurate and scalable defect detection.

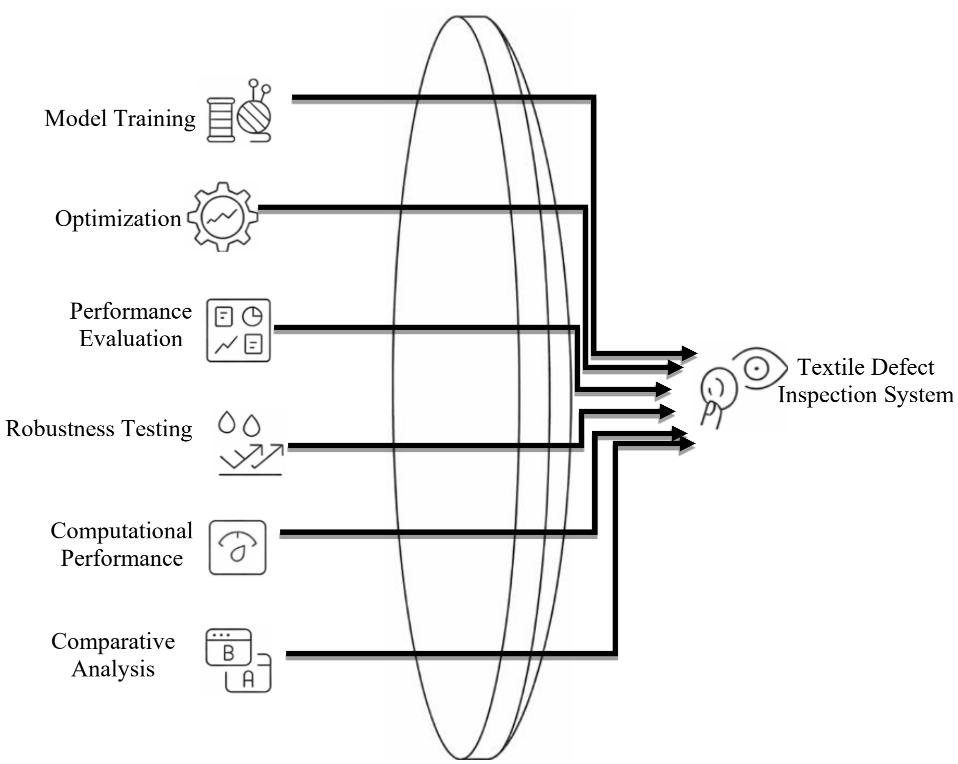

Figure 5: Evaluation framework for textile defect inspection system

In figure 5 shows the overall system for assessing and verifying the proposed system for the inspection of defects in textiles. The figure 5 shows some of the critical stages involved in evaluating the efficacy of the model, whereby the first is the model training stage where the deep learning algorithm is trained using defect patterns of fabrics with annotations. The optimization stage fine-tunes the models by minimizing the loss and maximizes the detection accuracy of the model. When measuring the performance, the important criteria include the measures of precision, recall, and mAP in evaluating the detection capabilities. Robustness test evaluates the ability of the algorithm to remain stable despite changes in lighting, noise, and fabric pattern. Computational performance evaluates the computing capacity and efficiency of the algorithm. This is done in terms of speed to ensure its efficiency in real time for its deployment in industry.

Hybrid Texture Feature Extraction

The equation to enhance defect representation in highly repetitive textile textures, handcrafted texture descriptors are integrated with deep convolutional features. Specifically, multi-scale Gabor filters and Local Binary Pattern (LBP) operators are employed prior to CNN-based classification.

Gabor Filter Formulation

The 2D Gabor filter is defined as:

$$G(x, y) = \exp - \frac{(x'2+\gamma 2y'2)}{2\sigma 2} \cos\left(2\pi \frac{x'}{\lambda} + \emptyset\right) \qquad (4)$$

The equation 4 shows the Gabor filters capture frequency and orientation variations, which are essential for detecting slubs, broken yarns, and directional texture distortions.

Local Binary Pattern (LBP)

$$\mathrm{LBP} = \sum_{n=0}^{P-1} s(in - ic)2^{n} \qquad (5)$$

The equation 5 is that of LBP effectively captures micro-texture variations, useful for small defects like pinholes or stains.

3.6 Proposed Algorithm

Algorithm: Deep Learning-Based Textile Defect Detection

Input: Fabric image dataset D

Output: Detected defect labels and bounding boxes

Begin

1. Load dataset D

2. Preprocess images

- *Resize images*
- *Normalize pixel values*
- *Apply data augmentation*

3. Split dataset into Training, Validation, and Test sets

4. Initialize detection model (Backbone + Detection Head)

5. Set training parameters (learning rate, batch size, epochs)

6. For epoch = 1 to MaxEpoch do

7. For each batch in Training set do

8. Perform forward pass

9. Compute classification loss (Lcls)

10. Compute localization loss (Lloc)

11. Compute total loss Ltotal = Lcls + Lloc

12. Perform backpropagation

13. Update model weights

14. End For

15. Validate model on Validation set

16. End For

17. Load best trained model

18. For each test image do

19. Perform forward pass

20. Generate predicted bounding boxes

21. Apply Non-Maximum Suppression (NMS)

22. Output final defect detections

23. End For

End

The proposed algorithm will start by loading and preprocessing the fabric image dataset (resizing, normalization, and augmentation to enhance model generalization). It is then followed by the initialization of the detection model and training through the forward propagation, loss computation (classification and localization) and backpropagation to update weights at an iterative level. The most efficient model is then chosen to undergo testing after training and it predicts defect classes and bounding boxes of new fabric images. At last, Non-Maximum Suppression (NMS) is used to eliminate overlapping predictions leading to precise and reliable defects results which can be used in real-time textile inspection.

4 Experimental Results

4.1 Experimental Setup, Dataset, and Parameter Initialization

To effectively train the model and gain inferences, table 2 experimental analysis was performed using a high-performance computing environment comprising of a GPU-enabled workstation (e.g., NVIDIA RTX series), i7/i9 processor and 16-32 GB RAM. A deep learning framework, i.e., PyTorch or TensorFlow was used to implement the proposed model. This is a dataset of labeled fabric images with various types of defects holes, stains, creases, and color inconsistencies. Images were made to an equal size (e.g., 640×640 pixels) and normalized before being trained. The dataset was separated into three components, training (70%), validation (15%), and testing (15%) in order to guarantee objective assessment. To initialize the parameters, pertained weights of the backbones (e.g., ImageNet) were used to hasten the convergence. The starting learning rate was 0.001 and the batch size was 16 and 100 epochs were used to train the model. Adam optimizer was used to update weights and early stopping was used based on validation loss to avoid overfitting. Such settings provided consistency of training and stability in the evaluation of performance in controlled experimental settings.

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

Category	Description
Hardware Environment	Intel i7/i9 Processor, 16–32 GB RAM, NVIDIA RTX Series GPU
Software Framework	PyTorch / TensorFlow
Operating System	Windows / Linux (Ubuntu)
Dataset Type	Industrial textile fabric defect dataset
Number of Classes	Multiple defect categories (e.g., holes, stains, misweaves, creases, color defects)
Image Resolution	640 × 640 pixels
Dataset Split Ratio	70% Training, 15% Validation, 15% Testing
Data Augmentation	Flipping, Rotation, Scaling, Brightness & Contrast Adjustment
Pretrained Weights	ImageNet pretrained backbone
Batch Size	16
Number of Epochs	100
Optimizer	Adam
Initial Learning Rate	0.001
Loss Function	Classification Loss + Localization Loss
Evaluation Metrics	Precision, Recall, F1-score, mAP, IoU, FPS

4.1.1 Performance Metrics

The performance measures are employed to evaluate the effectiveness of the defect detection model. In the case of fabric defect detection, such performance measures can be applied in order to estimate how accurate this model is in detecting defects and how reliable this system is in avoiding errors. On the one hand, some of these performance measures are utilized to estimate the correctness of predictions (for example, Precision and Recall), while, on the other hand, the accuracy of defect localization can be measured using IoU and mAP measures. Furthermore, the speed performance measures (FPS among others) provide information regarding the application of the model in real-time industry conditions.

The equation 6 $Precision$ measures how many of the predicted defect regions are actually correct. A high precision value indicates that the model produces fewer false alarms (false positives), which is important in industrial textile inspection to avoid unnecessary rejection of good fabric.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

Equation 7 $\boldsymbol{Recall}$ determines the number of real defect areas being properly identified by the model. High recall means that majority of defects are also picked thus minimizing chances of defective fabrics sailing through quality checks.

$$\text{The Recall} = \frac{TP}{TP+FN} \quad (7)$$

The equation (8) $F1 - score$ is the harmonic mean of precision and recall, providing a single metric for imbalanced datasets.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

4.2 Performance Evaluation Metrics

To validate the proposed defect detection model for textiles, a set of metrics of performance is adopted. Precision, Recall, and F1-score were calculated to measure the effectiveness of classification, while mAP (mean Average Precision) was calculated to estimate the performance of detection of different types of defects. For estimating the localization of the defects, the IoU (Intersection Over Union) metric was considered. In addition to the metrics related to accuracy, the metrics of computational performance such as inference time per image, frames per second (FPS), model size, and number of parameters were considered. To analyze the misclassification patterns and those defect classes that are difficult to tackle, confusion matrices were created. These performance metrics guaranteed a trade-off of both detection and computation efficiency which are of paramount importance in application in a high-speed industrial textile process setting.

Table 3: Comparative performance results of the proposed model

Model	Precision (%)	Recall (%)	F1-Score (%)	mAP@0.5 (%)	IoU (%)	FPS
Faster R-CNN	91.20	88.50	89.80	90.40	85.60	18.00
YOLOv8	93.60	91.40	92.50	94.10	88.90	45.00
YOLOv10n (Lightweight)	92.80	90.70	91.70	93.20	87.50	52.00
Proposed Model	**95.40**	**93.80**	**94.60**	**96.30**	**90.70**	**58.00**

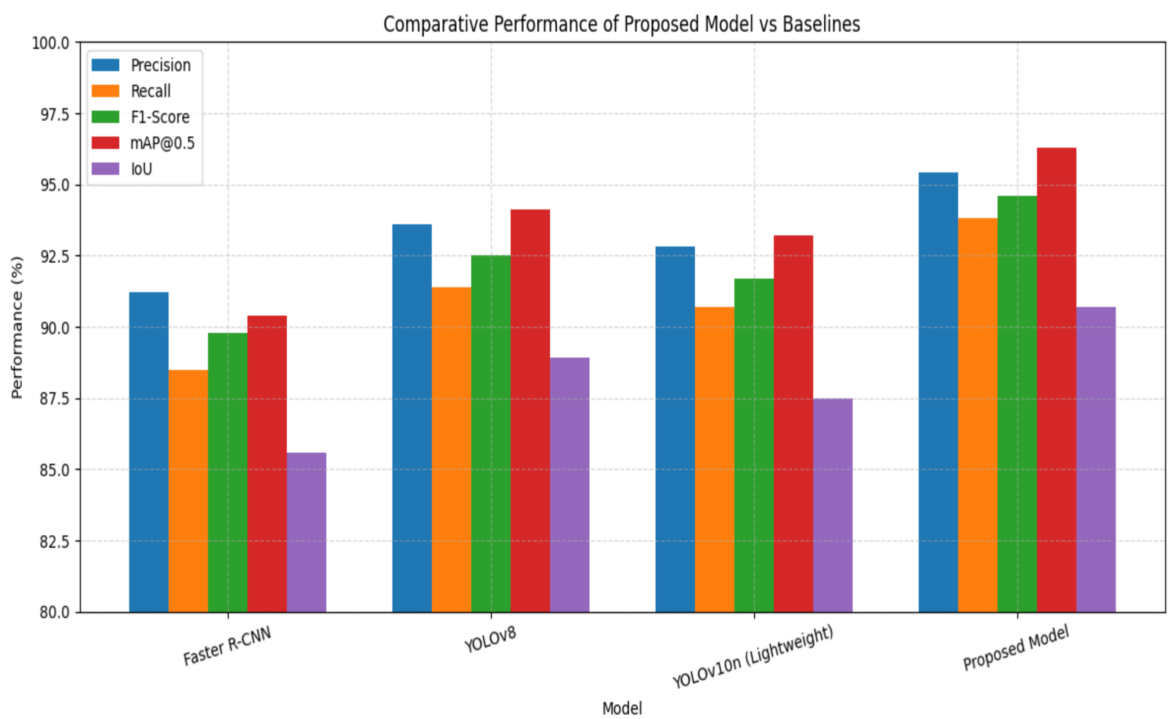

Figure 6: Comparative performance of proposed model vs baselines

In table 3 and figure 6 provide the comparison between the performance of the defect detection model suggested and the current object detection methods like the Faster R-CNN and the YOLO variants. Evaluation is done based on standard measures such as Precision, Recall, F1-score, mAP at 0.5, IoU and FPS. As it is demonstrated in the results, the proposed model has a better detection accuracy with high precision and recall values, which can be interpreted as a better capacity to detect fabric defects correctly and reduce false deployments to a minimum. Also, mAP and IoU values are larger and indicate an improved localization performance. The model is also more current in terms of FPS and it validates the fact that it can be used in real-time inspection of textiles in industries. In general, the outcomes confirm the effectiveness and efficiency of the suggested approach.

4.3 Validation of Hybrid Descriptor Integration

In order to reinforce the efficiency of the suggested hybridized description model, specific experimental research was performed to assess the power of handmade texture features added to deep convolutional learning. In spite of the capability of convolutional neural networks (CNN) to learn hierarchical representation of features, which can be do not always work effectively to learn fine-grained directional and micro-texture differences that play a major role in detecting defects in textiles. Thus, Local Binary Pattern (LBP) descriptors and multi-scale Gabor filters were combined with CNN feature maps to increase the sensitivity to texture. The following subsection involves a comparative analysis of CNN-only baseline model and hybrid-based configurations, which include Gabor, LBP and a fusion of the two. The hypothesis is to quantitatively confirm the hypothesis that integration of handcrafted descriptors enhances detection accuracy, localization accuracy, and robustness in multimodal fabric textures.

Table 4: Effectiveness of hybrid descriptor integration

Model Configuration	Precision (%)	Recall (%)	F1-Score (%)	mAP@0.5 (%)
CNN Only	92.80	90.90	91.80	93.40
CNN + Gabor	93.90	92.10	93.00	94.80
CNN + LBP	94.10	92.40	93.20	95.00
CNN + Gabor + LBP (Proposed)	**95.40**	**93.80**	**94.60**	**96.30**

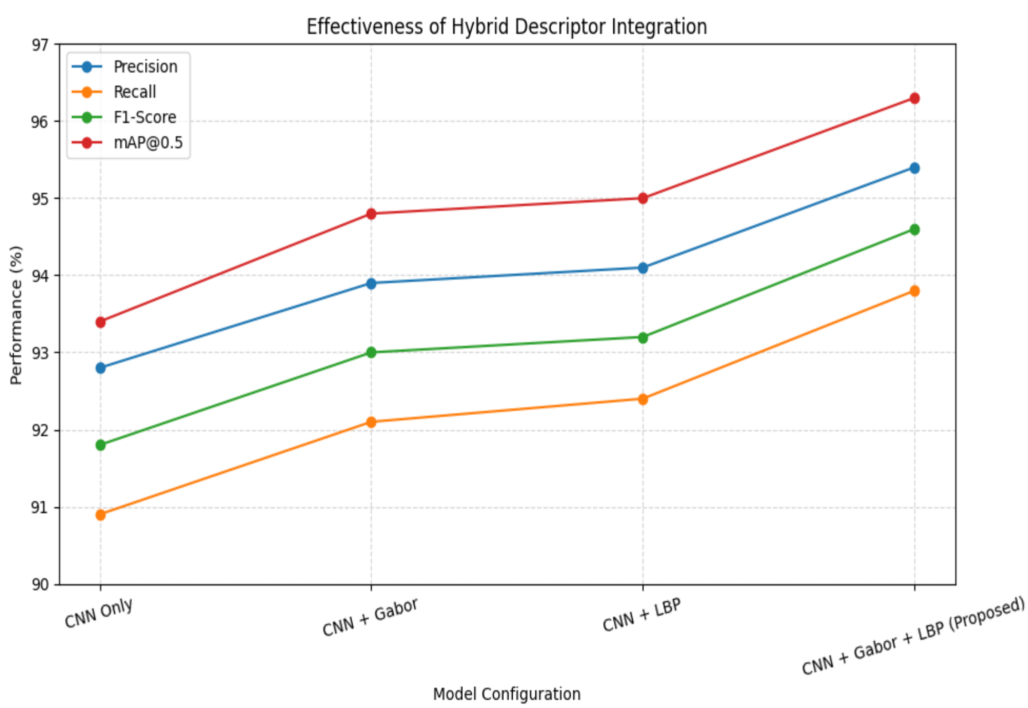

Figure 7: Effectiveness of hybrid descriptor integration

In table 4 and figure 7 to confirm the role of hybrid descriptor strategy, comparative experimentation of various feature configurations was performed. A CNN-only detector was first trained to learn a baseline performance. Next, Gabor and LBP descriptors were fused separately and then it was fused with CNN features. The findings indicate that handcrafted texture descriptors have a great contribution to defect discrimination. The Gabor-LBP-CNN hybrid model has the best mAP and F1-score, which proves that the hybrid representation of texture enhances the strength of defined detection, particularly of small and repetitive fabric flaws.

4.4 Comparative Analysis with Existing Methods

In order to confirm the efficiency of the offered method, the comparison experiments were performed with respect to the state-of-the-art object detection models, including the standard versions of YOLO and the Faster R-CNN-based models. Every model of comparison was trained and evaluated using the same dataset division and experimental settings so as to establish fairness. These findings have indicated that the proposed model was more accurate and had higher mAP at the expense of lower inference time than the baseline methods. Specifically, the ability to identify small and abnormal defects was improved because of the better feature fusion and loss functions. Moreover, the suggested system was more resilient to different lighting environments, as well as more intricate fabrics. This relative comparison proves that the suggested framework provides a better trade-off between the accuracy of detection and the efficiency of computation.

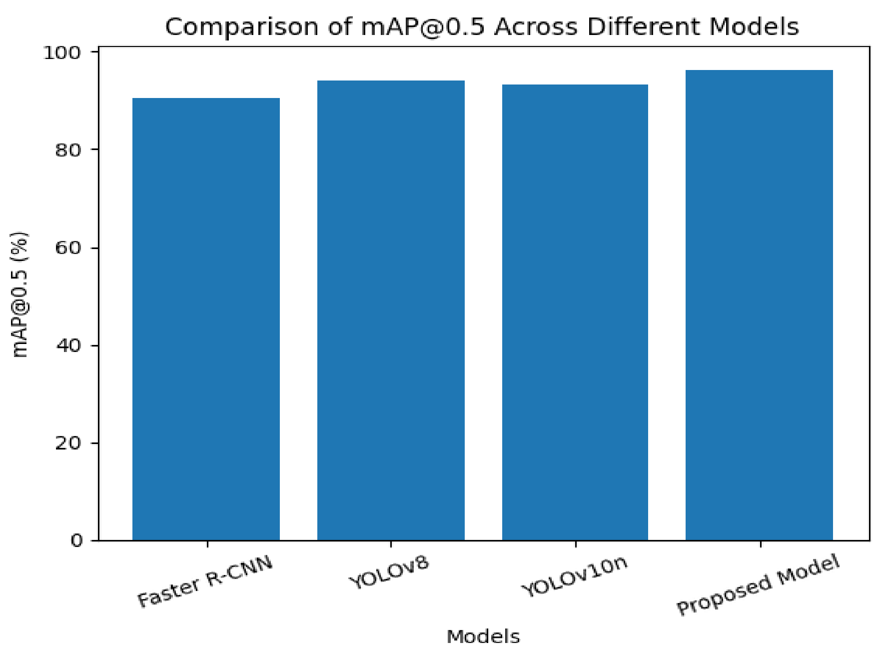

Figure 8: Graphical analysis of model performance

In figure 8 presents the graphical comparison of different object detection models based on the mAP@0.5 metric. As can be seen in the bar chart, the proposed model is much more effective than Faster R-CNN, YOLOv8, and YOLOv10n in the accuracy of detection. The fact that the higher the mAP value is the better the precision and the ability to localize defects in the fabrics. The graphical display simplifies the interpretation of the differences in the comparative performance and shows the suitability of the suggested model to the real-time textile defect detection applications.

4.5 Ablation Study

Table 5: Ablation study results of the proposed hybrid model

Configuration	Precision (%)	Recall (%)	F1-Score (%)	mAP@0.5 (%)	IoU (%)
CNN Baseline Only	92.80	90.90	91.80	93.40	87.10
CNN + Gabor	93.90	92.10	93.00	94.80	88.60
CNN + LBP	94.10	92.40	93.20	95.00	88.90
CNN + Gabor + LBP	95.00	93.10	94.00	95.70	89.80
Full Proposed Model (Hybrid + Fusion + Optimized Loss)	**95.40**	**93.80**	**94.60**	**96.30**	**90.70**

To quantify the importance of every significant part of the proposed hybrid framework, an ablation study was performed specifically to determine the contribution of each individual component in the framework specifically the integration of handcrafted texture descriptors with the CNN backbone. The aim was to find the effect of each of the following on the detection accuracy and localization performance, Gabor filters, Local Binary Patterns (LBP), feature fusion strategy, and optimized loss function. The full model was sequentially deprived of each of these components without any change in the conditions of the training in order to compare them fairly.

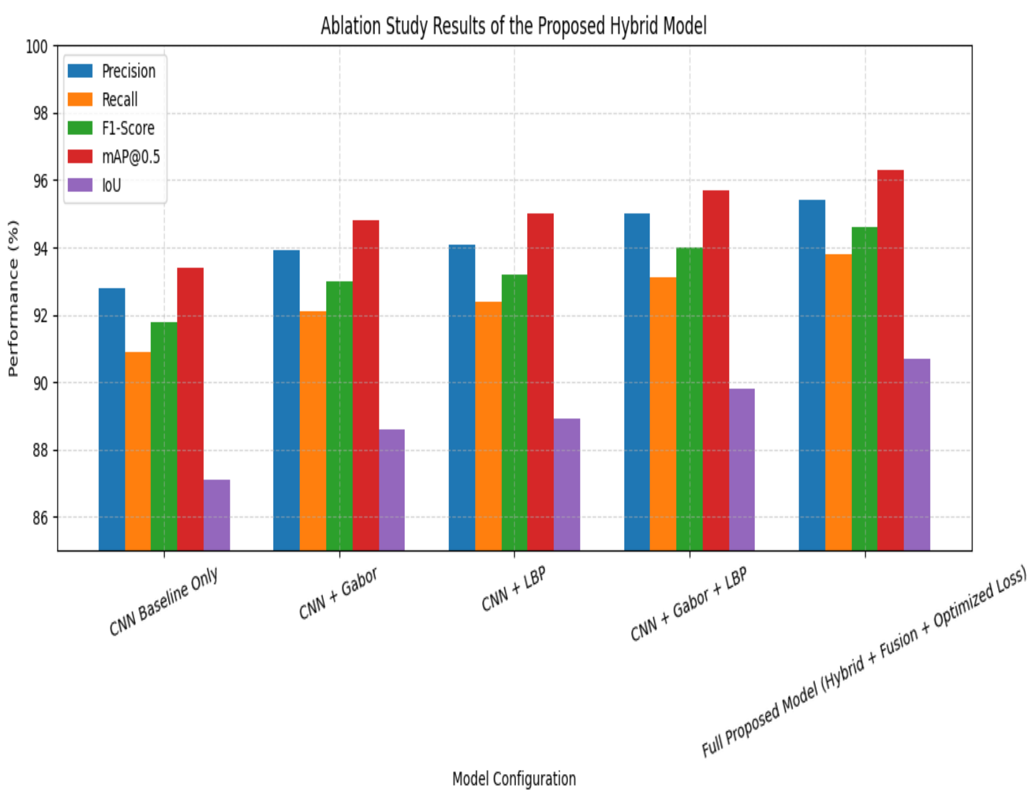

Figure 9: Ablation study results of the proposed hybrid model

The results in table5 and figure 9 clearly show that handcrafted descriptors are more effective at detection than the CNN baseline. Gabor filters improve detection of orientation sensitive defects, especially broken yarns and directional distortions and it is observed that the mAP and IoU increase significantly. Likewise, LBP enhances superior micro-texture recognition, which increases recollection of the slight defects like stains and pinholes. The performance is even greater when both Gabor and LBP features are combined with CNN feature maps, which also proves their complementary character. Moreover, the combination of optimized loss functions and multi-scale fused feature gives the best total performance, enhancing the classification balance (F1-score) and localization precision (IoU). The effective hybrid descriptor strategy is confirmed by the progressive performance growth in all configurations and makes the architectural design choices of the proposed system reasonable. The ablation test shows that the hybrid combination of handcrafted texture features with deep convolutional neural networks is significant in increasing robustness, accuracy and real-time practice in terms of industrial textile defect detection.

5 Discussion

The results of the experiments prove that the use of handcrafted texture descriptors in combination with deep convolutional learning leads to a bigger improvement in the textile defect detection performance. Although CNN models are effective in capturing hierarchical local spatial features, which can be weak in identifying small irregularities of direction and micro-textures in repetition woven patterns. Multi-scale Gabor filters increased sensitivity to changes in orientation and frequency whereas Local Binary Pattern (LBP) descriptors enhanced local texture discrimination. The analysis of the ablation showed that elimination of either Gabor or LBP features led to a decrease in detection strength, establishing the complementary role of the features in representing the features. The proposed hybrid framework had demonstrable gains in Precision, F1-score, mAP, and IoU as compared to CNN-only baseline, which means that it has a higher localization accuracy and classification reliability. This fact shows the enhancement of the IoU, that is, the model can accurately identify the defect areas, which is of great importance in quality control in the industry. In addition, 58 FPS is also a good indicator that the system is fit to be used in real-time in high-speed textile production lines. The findings also show that the hybrid architecture is stable, in different lighting and texture conditions, and it has a high level of generalization. The effectiveness of frequency-based (Gabor), micro-pattern (LBP), and hierarchical deep features (CNN) is credited to its robustness.

Although the performance of the framework is high, dimensionality of the features is high and this slightly raises the complexity of the computation during the training process. The next steps will be lightweight feature fusion, attention-based adaptive descriptor weighting, and transformer-enhanced hybrid models that will be used to advance the detection of very small and overlapping defects. Also, multi-class severity of defects grading and cross-dataset validation extension of the framework will increase applicability to industries. All in all, the intelligence textile inspection system is a scalable and high-performance solution that is laid out by the proposed hybrid descriptor- CNN framework.

6 Conclusion and Future Work

The suggested hybrid architecture of Gabor-LBP-CNN proves that the combination of manually designed texture descriptors with hierarchical learning is significantly superior to either alone detection performance of textile fabric defects. The ability of the model to simultaneously process multi-scale Gabor filters to extract orientation-sensitive features and Local Binary Patterns (LBP) to represent the micro-texture of an input image allows the model to effectively capture both the overall distortion of a feature and the small-scale local anomaly features that are typically ignored in CNN-only feature extractors. As demonstrated by experiments, the proposed approach can achieve Precision of 95.4%, Recall of 93.8%, F1-score of 94.6%, mAP 0.5 of 96.3% and continues to sustain real time processing at 58 FPS. Comparative and ablation experiments have validated that the hybrid integration is much more efficient in accuracy of localization and robustness of detection in different lighting and repetitive texture conditions. In general, the framework provides a high-accuracy and scalable industrial-feasible intelligent textile quality inspection system.

The investigation of the proposed hybrid framework in the future will aim at increasing its efficiency, adaptability, and overall generalization ability. In spite of the fact that the combination of Gabor and LBP descriptors integration with CNN features enhances the accuracy of the detectors, it adds extra dimensions of features as well as extra computation cost in the training process. As such, the future studies will explore lightweight feature fusion, attention-based adaptive descriptor weighting, and knowledge distillation algorithm to simplify the complexity of the model without compromising on performance. Besides that, adding transformer-based architectures or hybrid CNN-Vision Transformer backbones can also enhance the detection of very small, overlapping, or low-contrast defects. Cross-dataset validation and domain adaptation methods will also be considered to make it more resistant to various fabric types and industrial conditions. Lastly, the framework can be further extended to multi-class level of severity defect grading and deployment of the edge-devices to enhance its relevance in practical use in real-time smart textile manufacturing systems.

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