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Fabric Defect Detection with Deep Learning and False Negative Reduction

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ABSTRACT: Fabric defect inspection is essential in the textile industry to ensure product quality and customer satisfaction. Traditional manual inspection methods are time-consuming, labor-intensive, and prone to human error, making them inefficient for large-scale production. Even existing automated systems often struggle to detect small or subtle defects, leading to false negatives that can affect product reliability and brand reputation.

To overcome these challenges, this paper proposes a deep learning-based approach using CNNs, EfficientNetB4, and YOLOv8 for automated fabric defect detection and classification. The system is evaluated using benchmark datasets with a focus on reducing false negatives through data augmentation, transfer learning, and model optimization. Results show that EfficientNetB4 and YOLOv8 outperform traditional CNNs, with YOLOv8 achieving around 95% accuracy, demonstrating its effectiveness for real-time textile quality inspection.

KEYWORDS: CNN, Efficient Net B4, YOLOv8, deep learning, false negative reduction.

I. INTRODUCTION

The textile industry is one of the largest manufacturing sectors, where maintaining fabric quality is essential for ensuring customer satisfaction and sustaining brand value. Fabric defects such as holes, stains, misweaves, horizontal and vertical lines can occur during various stages of production. If these defects are not detected early, they can lead to significant financial losses and reduced product reliability. Traditionally, fabric inspection is performed manually by trained workers. However, manual inspection suffers from several limitations, including fatigue, inconsistency, and subjectivity, which reduce detection accuracy over time. Additionally, manual inspection is not suitable for high-speed production environments due to its slow processing speed.

To address these issues, automated inspection systems have been developed using image processing techniques. However, these traditional methods rely on handcrafted features and are highly sensitive to noise, lighting conditions, and variations in fabric texture. As a result, they often fail to detect subtle defects, leading to false negatives. With the advancement of deep learning, Convolutional Neural Networks (CNNs) have emerged as powerful tools for image classification and defect detection. EfficientNetB4 improves upon traditional CNNs by optimizing model scaling, achieving better performance with fewer parameters. YOLOv8, a state-of-the-art object detection model, enables real-time detection with high accuracy. Furthermore, different deep learning architectures offer unique advantages for fabric defect detection. Convolutional Neural Networks (CNNs) serve as a fundamental approach for image classification by effectively capturing spatial features such as edges, textures, and patterns in fabric images. However, traditional CNN models may have limitations in handling complex patterns and achieving high accuracy. To overcome these limitations, EfficientNetB4 is utilized, which employs a compound scaling method to optimize network depth, width, and resolution, resulting in improved feature extraction and higher accuracy with fewer parameters. In addition, YOLOv8 (You Only Look Once version 8) is incorporated for object detection, enabling the system to detect and localize defects in a single forward pass with high speed and precision. The combination of these models allows the proposed system to leverage both classification and detection capabilities, improving overall performance and significantly reducing false negatives in fabric defect inspection.

This project aims to develop an automated fabric defect detection system using deep learning models such as Convolutional Neural Networks (CNN), EfficientNetB4, and YOLOv8. The system is designed to accurately detect and classify various types of fabric defects, including holes, stains, and line defects, by analyzing image data. It is implemented in a simulated environment using publicly available fabric defect datasets, eliminating the need for physical hardware integration during development.

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II. LITERATURE REVIEW

Fabric defect detection has evolved significantly over the years, transitioning from traditional image processing techniques to advanced deep learning methods. Early approaches relied on image processing techniques such as edge detection, filtering, and thresholding. While these methods were simple to implement, they were highly sensitive to noise and variations in lighting conditions, resulting in low detection accuracy. This project addresses these limitations by combining multiple deep learning models and optimization techniques.

Author	Title	Summary	Major Limitations
Tomas Almedia, Filipe Moutinho, and J.P. Matos-Carvalho	Fabric Defect Detection with Deep Learning	Proposed a deep learning approach for fabric defect detection, reducing false negatives.	Very small or subtle defects may be difficult to detect, especially when they blend with the fabric texture.
Anindita Suryarasmi Wei-Jen Wang a a , Chin-Chun Chang , Deron Liang	FN-Net: A lightweight CNN-based architecture for fabric defect detection with adaptive threshold-based class determination	FN-Net is a lightweight CNN model designed for fabric defect detection that uses an adaptive thresholding method to classify defects accurately	FN-Net may struggle with highly imbalanced datasets or new, unseen defect types. Its adaptive threshold strategy might not generalize well without retraining or adjustment.
Shashi R.M	Fabric defect dataset	The Fabric Defect Dataset (by rmshashi on Kaggle) is a specialized collection of images designed for fabric defect detection	The dataset contains only a limited number of defect types, so models trained on it may not generalize well to all possible fabric defects
Z. Yu et al. (2023)	Online Fabric Defects Detection Using Convolutional Neural Network	Presents a **real-time CNN-based defect detection** system suitable for industrial production lines.	The model may struggle with real-time detection on high-resolution fabrics due to computational constraints and limited defect variety in the training data.
M. Nasim et al.	Fabric Defect Detection in Real World Manufacturing Using Deep Learning	Builds a robust detection model (YOLOv8) using a dataset collected from a real textile factory.	The model's performance may decrease on unseen fabric types or rare defects due to limited diversity in the training dataset.

III. METHODOLOGY OF PROPOSED SURVEY

Problem Statement

Manual fabric inspection is inefficient, time-consuming, and prone to human error. Existing automated systems often fail to detect small or subtle defects, resulting in false negatives. These undetected defects can lead to reduced product quality, financial losses, and decreased customer satisfaction. Therefore, there is a need for an automated, accurate, and reliable fabric defect detection system that minimizes false negatives and improves overall quality control.

The project aims to develop an automated fabric defect detection system using deep learning to enhance textile quality control. It implements and compares models like CNN, EfficientNetB4, and YOLOv8 for accurate defect detection and classification. The focus is on reducing false negatives to ensure even minor defects are identified. The system is tested using fabric image datasets in a simulated environment for performance evaluation. Overall, it seeks to achieve high accuracy, reliability, and scalability for real-time industrial applications.

Objectives

- To develop three deep learning models: **CNN, EfficientNet-B4, and YOLOv8** for defect detection.

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- To evaluate the models using standard performance metrics including accuracy, precision, recall, and F1-score, providing a comprehensive assessment of their effectiveness.
- To identify the best-performing model among CNN, EfficientNetB4, and YOLOv8 based on evaluation results and accuracy comparison.
- To design and implement a user-friendly web-based application that allows users to upload fabric images and obtain real-time defect detection results.

Architecture Diagrams for the Proposed Models

The flowchart i.e., Figure 1 illustrates an automated fabric defect detection system. Fabric images are acquired and pre-processed to enhance quality. The processed images are analyzed using a CNN-based model with false negative reduction to detect defects. A decision block determines whether a defect is present or not. If detected, the system stops for operator review and documentation; otherwise, the process continues normally.

The Block Diagram i,e., Figure 2 illustrates that the CNN system starts with the **data frame**, which contains the raw input images or dataset. These inputs undergo **preprocessing**, including resizing, normalization, and augmentation, to make them suitable for the network. The preprocessed data then passes through the **CNN layers** where features are extracted and predictions are made using convolution, activation, and pooling operations. Finally, the **output layer** interprets these features to provide the **predicted results**, such as class labels or detected objects. Histogram acts as a graphical representation of the total distribution in a digital image.

Figure3 illustrates that In CNN architecture, input images pass through convolutional layers to extract key features like edges and textures. Convolution is a mathematical operation where a small filter (kernel) slides over an image to extract important features like edges, textures, and patterns. Pooling layers then reduce the spatial size, keeping only the most important information and lowering computation. Finally, fully connected layers classify the extracted features into defect categories and provide the final prediction.

Figure 1: Flowchart for Fabric Detection

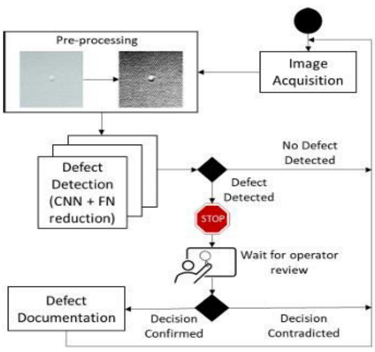


Figure 2: Block Diagram of CNN Model

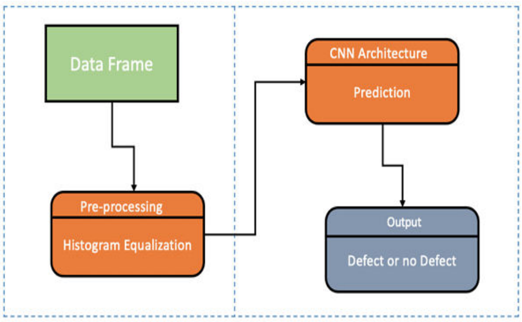
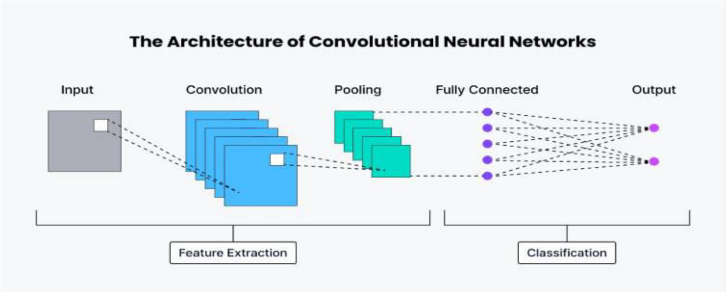


Figure 3: Architecture of CNN



EfficientNetB4 is an advanced CNN architecture that achieves high accuracy with optimal efficiency using compound scaling of depth, width, and resolution. It starts with a stem layer that processes the input image through a convolutional layer to extract basic features. The network consists of multiple blocks (Block 1 to Block 7) that progressively learn low-level to high-level features. Each block contains modules that perform convolution, feature extraction, and dimensionality reduction. Shortcut connections (Add layers) help preserve important features and prevent vanishing gradient problems.

Some blocks are repeated multiple times to enhance learning and detect complex patterns in images. Overall, EfficientNetB4 provides efficient feature extraction and high performance, making it ideal for fabric defect detection.

YOLOv8 is an efficient object detection model that processes fabric images in a single forward pass to identify defects. It uses a backbone for feature extraction (edges, textures, defects), a neck for feature fusion, and a detection head to predict defect locations, bounding boxes, and confidence scores. This one-step process enables fast and accurate real-time detection. Additionally, an optional transformer module can enhance feature representation, making YOLOv8 a reliable solution for fabric defect detection.

Figure 4: Architecture of Efficient Net B4 Model

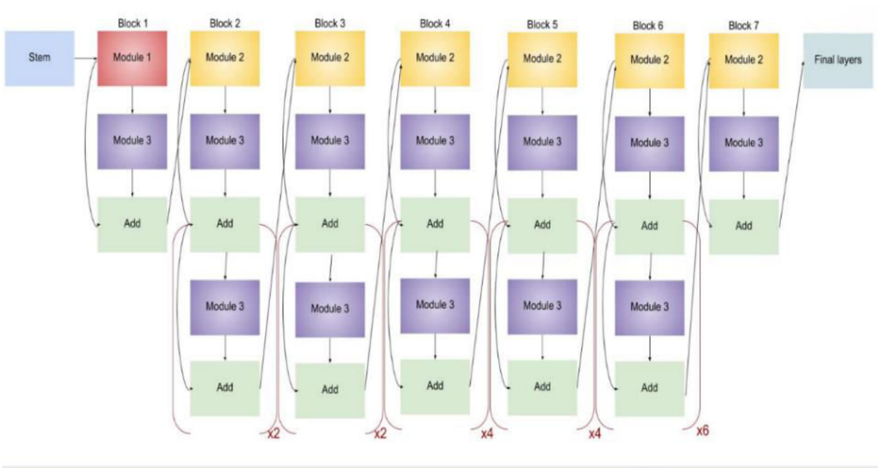
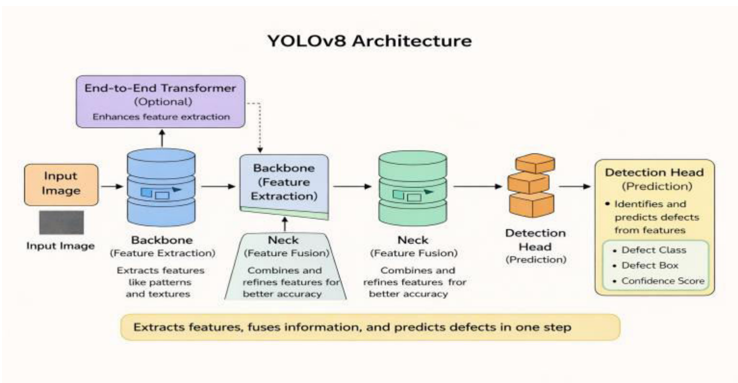


Figure 5: Architecture of YOLOv8 Model



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IV. IMPLEMENTATION OF THE SYSTEMS

The proposed fabric defect detection system is implemented using Python programming language and executed in the Google Colab environment, which provides efficient computational resources and GPU support for training deep learning models. The implementation is designed in a modular manner to ensure flexibility, scalability, and ease of integration.

Software Tools

The system utilizes several software tools and frameworks for development and execution. Python is used as the primary programming language due to its simplicity and extensive support for machine learning libraries. TensorFlow and Keras are employed for building and training deep learning models, including CNN and EfficientNetB4. OpenCV is used for image processing tasks such as resizing, normalization, and enhancement of fabric images. The YOLOv8 framework is used for object detection, enabling fast and accurate identification of defects within images.

System Modules

The system is divided into multiple functional modules, each responsible for a specific task in the defect detection pipeline:

- **Data Preprocessing Module:**

This module prepares the input dataset by performing operations such as image resizing, normalization, and noise removal. These steps improve image quality and ensure consistency in the data, which is essential for effective model training.

- **Data Augmentation Module:**

To increase dataset diversity and improve model generalization, data augmentation techniques such as rotation, flipping, scaling, and cropping are applied. This helps the model learn from varied data and reduces overfitting.

- **Model Training Module:**

In this module, three deep learning models—CNN, EfficientNetB4, and YOLOv8—are trained using labeled fabric defect datasets. CNN serves as a baseline model, EfficientNetB4 uses transfer learning for enhanced feature extraction, and YOLOv8 is trained for object detection and localization of defects.

- **Defect Detection Module:**

This module uses the trained models to analyze input images and detect the presence of defects. YOLOv8, in particular, provides bounding boxes along with defect classification and confidence scores.

- **Evaluation Module:**

The performance of the models is evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics help in comparing the models and selecting the best-performing one.

- **Evaluation Metrics:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad \text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad \text{Recall} = \frac{TP}{TP + FN} \qquad \text{Precision} = \frac{TP}{TP + FP}$$

The performance of the proposed models is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model's predictions, while precision indicates the proportion of correctly predicted defect samples among all predicted defects. Recall measures the ability of the model to correctly identify actual defect cases, which is particularly important for reducing false negatives. The F1-score provides a balanced measure by combining both precision and recall. These metrics collectively ensure a comprehensive evaluation of the model's performance in fabric defect detection.

Web Application

To make the system user-friendly, a web-based application is developed and integrated with the best-performing model. The application allows users to upload fabric images and receive instant predictions regarding defect type and location. The results are displayed with confidence scores, making it easy for users to interpret the output. This web interface demonstrates the practical applicability of the system and provides a foundation for future real-time industrial deployment.

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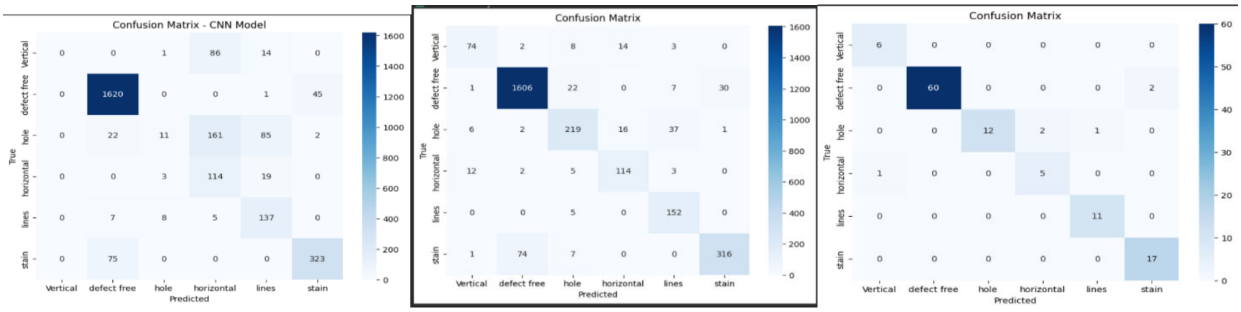
Example images for testing the YOLOv8 Model on webpage

To further validate the performance of the proposed models, additional example fabric images were used for testing. The models were tested on these unseen images to analyze their ability to generalize and accurately detect defects in real-world scenarios. The results obtained from this testing confirm the effectiveness of the models in identifying different types of fabric defects and maintaining good accuracy.

V. ANALYSIS OF SYSTEMS

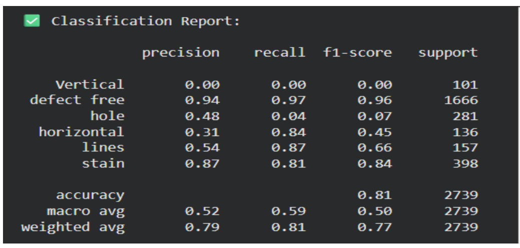
Analysis of three models based on confusion matrixes after testing

Figure 6: Confusion Matrix for CNN, EfficientNetB4, YOLOv8



Classification Reports and Metrics for the three models:

Figure 7: Classification Report for CNN Model and Training and Validation Metrics


Classification Report:

	precision	recall	f1-score	support
Vertical	0.00	0.00	0.00	101
defect free	0.94	0.97	0.96	1666
hole	0.48	0.04	0.07	281
horizontal	0.31	0.84	0.45	136
lines	0.54	0.87	0.66	157
stain	0.87	0.81	0.84	398
accuracy			0.81	2739
macro avg	0.52	0.59	0.50	2739
weighted avg	0.79	0.81	0.77	2739

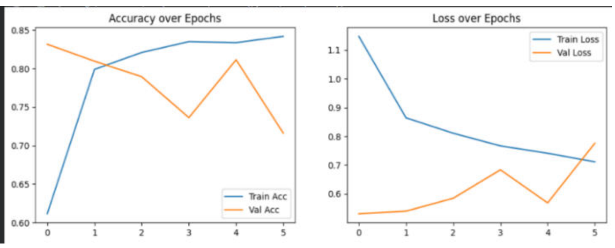
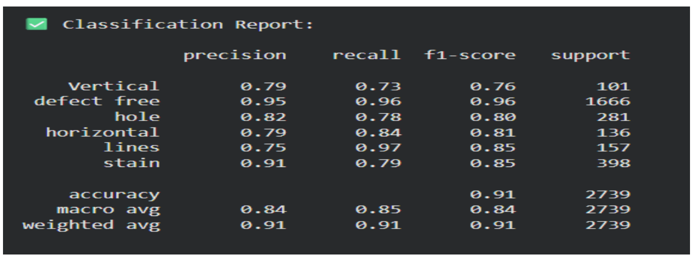


Figure 8: Classification Model for EfficientNetB4 Model and Training and Validation Metrics


Classification Report:

	precision	recall	f1-score	support
Vertical	0.79	0.73	0.76	101
defect free	0.95	0.96	0.96	1666
hole	0.82	0.78	0.80	281
horizontal	0.79	0.84	0.81	136
lines	0.75	0.97	0.85	157
stain	0.91	0.79	0.85	398
accuracy			0.91	2739
macro avg	0.84	0.85	0.84	2739
weighted avg	0.91	0.91	0.91	2739

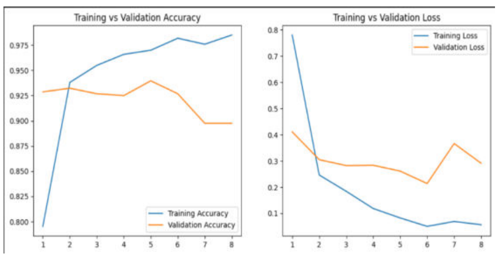


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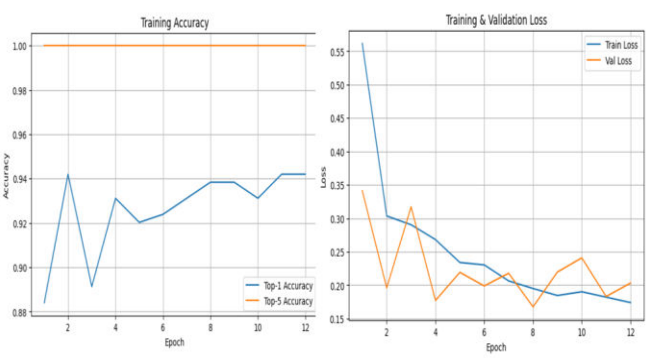
Figure 9: Classification Report for YOLOv8 Model and Training and Validation Metrics

Classification Report:

	precision	recall	f1-score	support
Vertical	0.86	1.00	0.92	6
defect free	1.00	0.97	0.98	62
hole	1.00	0.80	0.89	15
horizontal	0.71	0.83	0.77	6
lines	0.92	1.00	0.96	11
stain	0.89	1.00	0.94	17
accuracy			0.95	117
macro avg	0.90	0.93	0.91	117
weighted avg	0.95	0.95	0.95	117



VI. RESULTS AND DISCUSSION:

The performance of the proposed fabric defect detection system was evaluated using three deep learning models: CNN, EfficientNetB4, and YOLOv8. The evaluation was carried out using standard performance metrics, with accuracy being the primary metric for comparison.

The CNN model achieved an accuracy of **81%**, serving as a baseline for the study. While the model was able to identify common defects, its performance was limited in detecting subtle and complex defect patterns, resulting in relatively higher false negatives. EfficientNetB4 showed a significant improvement in performance, achieving an accuracy of **91%**. The use of transfer learning and advanced feature extraction enabled the model to better capture intricate patterns in fabric images. This resulted in improved classification accuracy and reduced misclassification compared to the CNN model. Among all the models, YOLOv8 demonstrated the best performance with an accuracy of **95%**. The model effectively detected and localized defects within images, showing strong performance across all defect classes. It also significantly reduced false negatives, making it highly suitable for fabric defect detection tasks.

Overall, the results indicate that advanced deep learning models such as EfficientNetB4 and YOLOv8 outperform traditional CNN models. YOLOv8, in particular, proved to be the most efficient and accurate model, making it ideal for real-time defect detection applications.

A web-based application was developed using the YOLOv8 model for practical implementation. Users can upload fabric images and receive instant defect predictions. The model detects defects and provides bounding boxes along with confidence scores. It accurately identifies defects such as holes, stains, and line patterns. This demonstrates the system's real-time capability and suitability for automated fabric inspection.

This web page gives the instant results for the image. It takes the input image and gives the instant prediction od the defect present in the given image.

Figure 10: Web Application based on YOLOv8 Model

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VII. CONCLUSION

This project presents a deep learning-based approach for automated fabric defect detection using CNN, EfficientNetB4, and YOLOv8 models. The system is designed to improve fabric quality inspection by accurately detecting and classifying various types of defects from image data. Among the implemented models, CNN served as a baseline, while EfficientNetB4 improved feature extraction using transfer learning. YOLOv8 demonstrated the best performance with the highest accuracy of 95%, effectively detecting and localizing defects with reduced false negatives.

The use of data augmentation and model optimization techniques further enhanced the robustness and generalization of the system. The implementation of a web-based application using YOLOv8 showcases the practical applicability of the proposed approach, allowing users to upload images and receive real-time predictions.Overall, the system provides a reliable, accurate, and scalable solution for automated fabric defect detection. Although developed in a simulated environment, it has strong potential for real-time deployment in textile industries, contributing to improved quality control and reduced manual effort.

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