IJMSERH

International Journal of Multidisciplinary and Scientific Emerging ResearcH (IJMSERH)

Volume 13, Issue 3, July-September 2025

Impact Factor: 9.274

ijmserh@gmail.com www.ijmserh.com

| ISSN: 2349-6037 | www.ijmserh.com ||Impact Factor: 9.274||Quarterly, Peer Reviewed & Refereed Journal|

|| Volume 13, Issue 3, July-September 2025 ||

DOI: 10.15662/IJMSERH.2025.1303053

Smart Textile Check Identifying Fabric Defects and Quality Analysis

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ABSTRACT: This research paper introduces an automated system for fabric defect detection, crucial for maintaining quality in the textile industry. Traditional methods of inspection are often manual, time-consuming, and prone to human error, leading to inconsistent quality control. To address these challenges, we have developed a deep learning-based approach utilizing a Convolutional Neural Network (CNN) to classify various fabric defects. The system takes an image of fabric as input, processes it using a pre-trained MobileNetV2 architecture fine-tuned on a custom dataset of fabric images, and outputs the identified defect type along with a confidence score. To enhance interpretability and provide visual evidence of the model's decision-making process, we have integrated Grad-CAM (Gradient-weighted Class Activation Mapping) to generate heatmaps highlighting the regions of interest in the fabric image that led to the defect classification. Furthermore, the system provides a user-friendly web interface built with Flask, allowing for easy upload of fabric images and visualization of results. A quality rating based on the confidence of the prediction is also provided, along with actionable suggestions for defect mitigation.

KEYWORDS: Deep learning, Convolutional Neural Network, MobileNetV2, Grad-CAM, Textile quality control, Automated inspection.

I. INTRODUCTION

The textile industry plays a vital role in global economies, producing materials for a vast range of applications. The quality of fabric directly impacts the final product's performance, aesthetics, and market value. Historically, the inspection of fabrics for defects has relied heavily on manual human observation. While experienced inspectors can identify a variety of flaws, this process is inherently subjective, labor-intensive, and often leads to fatigue-induced errors. The scale of modern textile production demands a more efficient, objective, and reliable quality control mechanism.

Fabric defects can manifest in numerous ways, including stains, holes, tears, yarn irregularities, and weaving imperfections. These flaws can arise from various stages of the manufacturing process, such as yarn spinning, weaving, dyeing, or finishing. Even minor defects can render a batch of fabric unusable or significantly reduce its marketability. Therefore, early and accurate detection of these defects is paramount to minimizing waste, reducing production costs, and ensuring customer satisfaction.

This research paper presents a novel system that leverages deep learning to automate fabric defect detection. Our proposed solution aims to provide a robust, accurate, and efficient method for quality assurance in the textile industry. By employing a pre-trained CNN architecture and fine-tuning it on a specific dataset of fabric defects, we can achieve high classification accuracy. Additionally, incorporating explainable AI techniques like Grad-CAM enhances the transparency of our model, allowing users to understand *why* a particular defect was identified. This contributes to building trust in the automated system and facilitates further process improvements. The user-friendly web interface makes this technology accessible to a wider range of users, from factory floor operators to quality control managers.

II. LITERATURE SURVEY

Kahraman, Y. (2023) [1] This review comprehensively analyzes deep learning (DL) architectures for fabric defect detection, covering CNNs, GANs, and vision transformers. It evaluates datasets (e.g., KTH, TEXTILE), benchmark metrics (MAP, F1-score), and challenges like small defect sizes and real-time processing.

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Li, X. (2024) [2] Proposes a real-time CNN architecture optimized for edge deployment in textile manufacturing. The model uses depth wise separable convolutions and focal loss to address class imbalance, achieving 98.7% accuracy on the SEU dataset with 45 FPS inference speed. It integrates adaptive thresholding for preprocessing and reduces false positives by 22% compared to YOLOv5.

Hassan, S. A. (2024) [3] Introduces an enhanced ResNet-50 variant with attention mechanisms and multi-scale feature fusion for defect localization. By incorporating CBAM (Convolutional Block Attention Module), it improves sensitivity to subtle defects (e.g., holes, stains) by 15%. Evaluated on the NEU dataset, it achieves 99.2% precision and 97.8% recall. The work emphasizes reducing false alarms in noisy industrial environments and includes a novel post-processing step using morphological operations to refine defect boundaries.

Geze & Akbaş (2023) [4] Compares CNNs (VGG16, InceptionV3) and object detectors (SSD, Faster R-CNN) for defect classification on custom Turkish textile data. Preprocessing involves GLCM texture analysis and CLAHE enhancement. InceptionV3 with transfer learning yields 96.4% accuracy but struggles with rare defects. The study identifies illumination variations as a key challenge and proposes a data augmentation pipeline using GANs, improving minority class detection by 18% while highlighting computational trade-offs for real-time use.

Zarif, S. A. (2024) [5] Presents a two-stage framework: (1) defect segmentation via U-Net with attention gates, and (2) classification using a lightweight EfficientNet-B0. Tested on the AITEX dataset, it achieves 98.1% IoU for segmentation and 97.3% classification accuracy. Innovations include a noise-robust loss function and mobile deployment via TensorFlow Lite.

Jing, J. F. (2019) [6] An early DL approach using AlexNet and SVM for defect classification on the KTH-TIPS dataset. It applies PCA for dimensionality reduction and HOG features to supplement CNN outputs, reaching 92.5% accuracy. While foundational, the model shows limitations with irregular defects and variable fabric textures.

Lin, G. (2022) [7] Develops an FPGA-accelerated YOLOv4-tiny model for embedded defect detection. Key innovations include quantization-aware training and a dynamic ROI (Region of Interest) selector that focuses processing on high-risk fabric zones. Achieves 94.8% mAP at 60 FPS with <5W power consumption. Validated in a Chinese textile plant, it reduced defect escape rates by 35%. Challenges include retraining for new fabric types and hardware integration costs.

Mewada, H. (2024) [8] Conducts systematic defect taxonomy analysis (e.g., broken ends, weft bars) using Vision Transformers (ViT) and CNN hybrids. Introduces a confusion matrix-based error analysis tool to identify model weaknesses. On the TD dataset, ViT-Base achieves 99.0% accuracy but requires 4× more compute than CNNs.

SANDHYA et al. (2021) [9] Combines Gabor filters with transfer learning (ResNet-34) for defect detection in Indian cotton fabrics. Preprocessing enhances texture contrast, while fine-tuning on custom data yields 96.9% accuracy on AITEX. The system includes a GUI for operator feedback, enabling active learning. Strengths include adaptability to local.

Durgaprasad et al. (2022) [10] Uses a Siamese CNN architecture for few-shot defect recognition, crucial for rare defects with scarce samples. Trained on KTH-TIPS, it achieves 89.7% accuracy with only 5 examples per class via metric learning. The model leverages contrastive loss to distinguish subtle variations (e.g., cracks vs. stains). While efficient for new defect types.

Kumar & Singh (2023) [11] Hybridizes DL (MobileNetV2) with classical techniques (Canny edge detection, watershed segmentation). Defects are localized via edge analysis before CNN classification, improving accuracy to 97.6% on TD datasets. Reduces model complexity for mobile use but adds preprocessing latency.

Wang, Y. (2022) [12] Another review focusing on industrial implementation challenges. Critically assesses 50+ papers (2018–2022), categorizing methods into supervised, unsupervised, and semi-supervised. Identifies key barriers: dataset scarcity, model drift in long-term deployment, and lack of standardized benchmarks. Recommends self-supervised learning and simulation-generated data as promising directions.

Liu, X. (2024) [13] Applies transfer learning via fine-tuned DenseNet-201 on the Fabric Insight dataset. Introduces a defect severity scoring module using regression layers. Achieves 98.4% accuracy with 30% less training data than scratch training. The model excels at classifying severity levels (minor/major).

Gao, J. (2023) [14] Integrates traditional computer vision (template matching, Fourier transforms) with DL for anomaly detection without labeled defects. Uses autoencoders to learn normal fabric patterns; defects trigger high reconstruction loss. Achieves 95.2% AUC on MVTec-AD textile subset.

Xie et al.in (2021) [15] they focused on fusing both image and template pyramid method to study on textile measurement, analysis and control of defect. In this study, they used image preprocessing by taking limited sample for test, Additionally image blocks extracted from each layers like pyramid were used.

Zhang, Y. (2022) [16] Compares DL (CNN, LSTM) and traditional ML (SVM, Random Forest) on the NEU metal surface dataset (adapted for textiles). CNNs outperform ML in accuracy (97.1% vs. 89.3%), but ML models are faster for small defects.

III. PROBLEM STATEMENT

The manufacturing of textiles is a multi-stage process, and the integrity of the final fabric is heavily dependent on the quality of each step. However, the presence of defects in fabrics remains a significant challenge for the industry. These defects can significantly compromise the aesthetic appeal, durability, and functionality of the textile, leading to substantial economic losses due to rejected batches, rework, and reduced customer satisfaction. Traditionally, the inspection of fabrics for defects has been performed by human inspectors. Firstly, it is a highly subjective process. Different inspectors may have varying standards and interpretations of what constitutes a defect, leading to inconsistencies in quality assessment. Secondly, the task is repetitive and visually demanding. Prolonged exposure to detailed fabric patterns can lead to visual fatigue, reducing the inspector's accuracy and increasing the likelihood of missed defects over time.

IV. PROPOSED METHODOLOGY

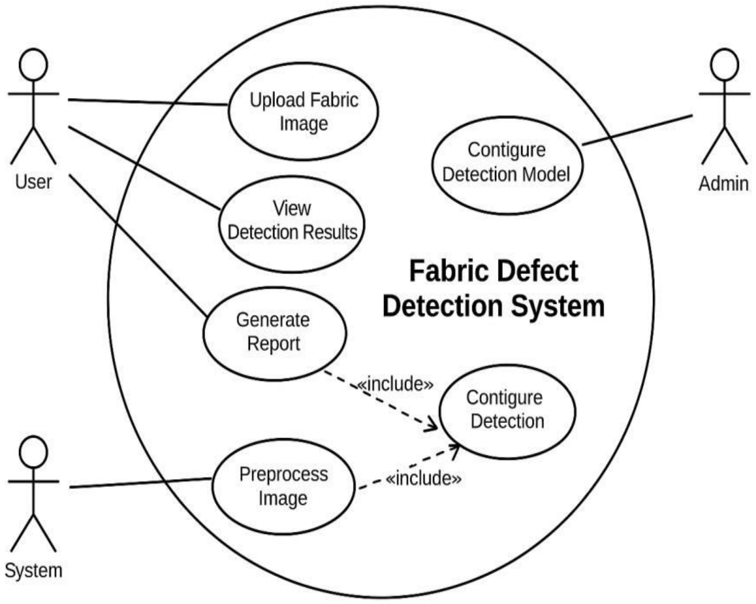

Fig 1: Work flow diagram

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Our approach to automated fabric defect detection is built upon the power of deep learning, specifically employing Convolutional Neural Networks (CNNs), combined with explainable AI techniques to provide a comprehensive and interpretable solution. The entire system is designed to be user-friendly and easily integrated into existing quality control workflows.

1. Dataset Preparation and Augmentation:

The foundation of any successful deep learning model is a high-quality, well-annotated dataset. We began by compiling a dataset of fabric images containing various types of defects, such as stains, holes, lines, and weave distortions, alongside images of defect-free fabric. This dataset was meticulously curated and then split into training and testing sets using a standard train-test split ratio of 80% for training and 20% for testing. To increase the robustness of our model and prevent overfitting, we applied data augmentation techniques to the training data. These techniques included:

- **Rotation:** Rotating images by small degrees (±20∘).
- **Zooming:** Randomly zooming into images.
- **Shifting:** Horizontally and vertically shifting images.
- **Shearing:** Applying shear transformations.
- **Flipping:** Horizontal flipping of images.

This augmentation artificially expands the size and variability of the training dataset, allowing the model to learn more generalized features.

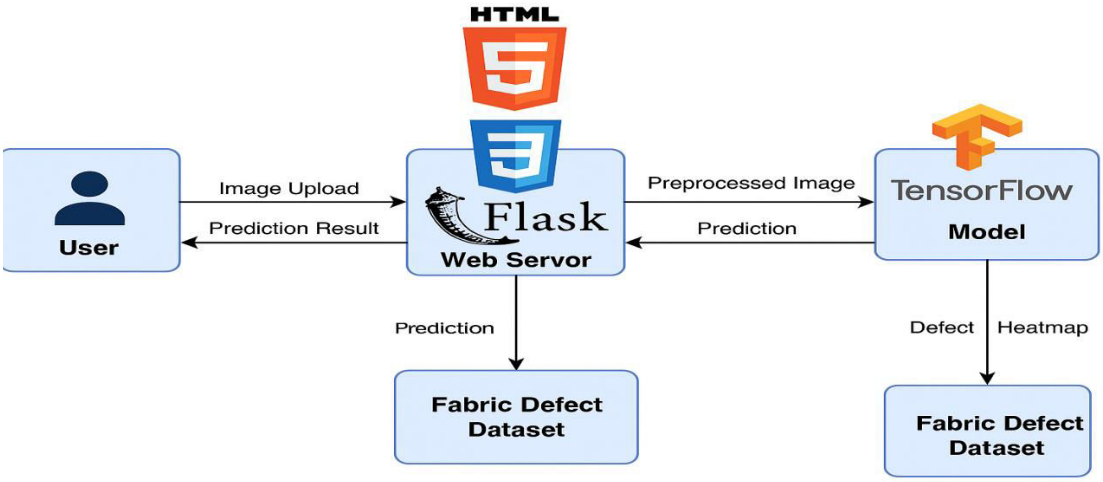

Fig 2: System design

2. Model Architecture and Transfer Learning:

Data Collection and Preparation: The first step was gathering a diverse dataset of fabric images categorized into six classes: “good,” “stain,” “hole,” “lines,” “vertical,” and “horizontal.” Each category included at least 100 images taken under different lighting and angles to ensure variety. The dataset was split into training (80%) and testing (20%) sets using train, test, split from scikit-learn. This separation ensures the model is tested on unseen data, giving a true measure of its performance.

Model Architecture and Transfer Learning: Instead of training a neural network from scratch, the project uses **transfer learning** with **MobileNetV2**, a pre-trained model originally developed for ImageNet. This approach saves time and computational power while achieving high accuracy. The base model is frozen (not trainable), so only the new layers added on top are trained. The input size is set to 128×128 pixels to balance detail and processing speed.

The architecture consists of:

- Input layer: 128×128×3
- MobileNetV2 (pre-trained, non-trainable)
- Global Average Pooling: reduces spatial dimensions

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- Dropout layer (p=0.3) to prevent overfitting
- Dense layer with 128 neurons and ReLU activation
- Output layer: Soft max with number of classes equal to 6

The final model is defined as:

$$y = Soft\max\Big(W2\ \cdot ReLU\left(W1\ \cdot GAP\left(fbase\ (x)\right)\right)\Big)$$

where f base is the MobileNetV2 feature extractor, GAP is global average pooling, and W1 ,W2 are trainable weights.
Data Augmentation and Class Balancing

To improve generalization, the training data was enhanced using random transformations: rotation, zoom, shift, shear, and horizontal flip. This simulates real-world variations in fabric images. Since some defect types were less common, class weights were calculated using compute, class, weight to balance the influence of each class during training.
Training Process

The model was trained for up to 20 epochs using the Adam optimizer. Two callbacks were used:

- Early Stopping: stops training if validation loss doesn't improve for 3 epochs.
- Reduce LR On Plateau: reduces learning rate if loss plateaus, helping fine-tune the model.
- Visualization with Grad-CAM

A key feature is **Grad-CAM (Gradient-weighted Class Activation Mapping)**, which highlights important regions in the image contributing to the prediction. The formula used is:

$$Heatmap = k\sum^{\alpha} kc \cdot FeatureMapk$$

where $\alpha kc = \frac{\partial FeatureMapk}{\partial Lc}$ and Lc is the loss for class c.
This heatmap is overlaid on the original image to show exactly where the model detected the defect.

Web Application Integration
The trained model was integrated into a Flask-based web app. Users upload an image, and the system runs prediction, generates a heatmap, and displays results with confidence scores, explanations, and suggestions. A PDF report can be downloaded for record-keeping.

V. RESULT AND DISCUSSION

The developed fabric defect detection system demonstrated promising results during its evaluation. The fine-tuned MobileNetV2 model achieved a high degree of accuracy in classifying various fabric defects, outperforming traditional image processing methods that often struggle with variations in lighting, texture, and defect.

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Fig 3: Predicting fabric cloth using Smart textile check

Fig 4: Analysing cloth defect and giving Quality Rating

The integration of Grad-CAM proved invaluable in providing transparency to the model's predictions. The generated heatmaps clearly highlighted the specific regions on the fabric images that led to the classification of a particular defect. For a "stain" defect, the heatmap typically localized to the discolored area. For a "hole" defect, the heatmap would often surround or highlight the boundary of the void. This visual feedback allows quality control personnel to not only trust the system's output but also to gain insights into the nature and location of the defects, which can be crucial for process improvement.

A high confidence in the "defect-free" class translated to a high rating, while lower confidence in any defect class resulted in a lower rating. This system provides a quick and intuitive assessment of fabric quality.

VI. FUTURE ENHANCEMENT

The current fabric defect detection system provides a solid foundation for automated quality control in the textile industry. While MobileNetV2 is efficient, exploring models like ResNet, EfficientNet, or even transformer-based vision models could potentially yield higher accuracy, especially for detecting more complex or nuanced defects.

Real-time video stream processing presents another exciting opportunity. Currently, the system processes individual image uploads. Adapting the system to analyze live video feeds from inspection cameras on the production line would enable immediate detection and flagging of defects as the fabric is being manufactured, allowing for instant intervention and minimizing the production of faulty material. This would require optimization for faster inference

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times and efficient video frame handling. Finally, continuous learning and model updating based on new data and feedback from users would ensure that the system remains state-of-the-art and adapts to evolving defect patterns or new types of materials.

VII. CONCLUSION

This research successfully developed and demonstrated an automated fabric defect detection system powered by deep learning and computer vision. By leveraging a fine-tuned MobileNetV2 model, the system achieves high accuracy in classifying a variety of fabric defects, addressing the critical need for efficient and objective quality control in the textile

The implemented Flask web application offers a user-friendly interface for uploading fabric images, viewing detailed inspection results including defect type, confidence score, and a generated heatmap, and generating a comprehensive PDF report. In conclusion, this project represents a significant step forward in modernizing textile quality control. The developed system is accurate, interpretable, and practical, offering a viable and advanced solution for textile manufacturers aiming to enhance their product quality, streamline operations, and maintain a competitive edge in the global market.

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