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Computer Vision based Automated Fabric Classification for Textile Industries

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***Abstract*— Manual inspection remains a major bottleneck in textile industries due to its subjectivity, inconsistency, and high labor dependency. Manual inspection is expensive, time consuming and lacks scalability and productivity. This research presents a deep learning–based automated stain and defect classification system using five convolutional neural network (CNN) architectures: MobileNetV2, ResNet50, GoogLeNet (Inception-v1), EfficientNetB0, and a custom CNN. A balanced dataset of 136 textile images was preprocessed and augmented to enhance feature variability. Experimental evaluation demonstrates that GoogLeNet achieves the highest validation accuracy of 96%, while MobileNetV2 provides a strong efficiency–accuracy balance suitable for real-time deployment. Training curves for accuracy and loss across all models, along with a comparative study, are presented. While maintaining performance on par with advanced existing models, the proposed approach significantly improves prediction speed, supporting its application in real-time fabric inspection. The system shows promising potential for integration into industrial inspection pipelines to reduce human error and improve fabric quality control.**

***Index Terms*— Fabric defect detection, deep learning, computer vision, MobileNetV2, GoogLeNet, EfficientNet, textile inspection, transfer learning.**

I. Introduction

The textile and apparel industry plays a vital role in the global and Indian economies. Globally, the sector contributes approximately 1.6–2 % of the world's GDP, reflecting its significance in manufacturing and consumer markets. In India, the textile and apparel industry accounts for nearly 2.3 % of the national GDP, around 13 % of industrial production, and approximately 12 % of total exports, making it one of the country's most important industrial sectors. Owing to its large economic impact and labor-intensive nature, ensuring fabric quality through efficient and automated inspection systems has become increasingly important. Textile quality inspection traditionally relies on manual visual assessment, which is slow, error-prone, and non-scalable. With the advancement of deep learning with its automated feature extraction methods, automated inspection systems can now perform consistent, accurate, and high-speed detection of stains, surface irregularities, and structural defects in fabric. This research evaluates five CNN-based models—MobileNetV2, ResNet50, GoogLeNet, EfficientNetB0, and a custom CNN—through transfer learning and fine-tuning. The primary objective is to determine which architecture is most suitable for real-time industrial deployment considering accuracy, loss behavior, computational efficiency, and robustness.

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II. Literature Review

Automated fabric defect detection has become an important research area in computer vision due to the high demand for quality control in textile industries. Traditional inspection methods rely heavily on human inspection, which is slow, inconsistent, and prone to errors. The adoption of deep learning and computer vision techniques has enabled faster, more reliable, and scalable solutions. Mohammed et al. (2025) proposed a fully convolutional neural network for fabric defect detection. Their approach utilized deep convolutional layers to automatically learn features from fabric images, eliminating the need for handcrafted features. The model achieved high accuracy on benchmark datasets, demonstrating the effectiveness of end-to-end CNN architectures for defect identification. Revathy and Kalaivani (2024) developed an improved Mask R-CNN model for fabric defect detection. By leveraging instance segmentation, the model was able to detect multiple defects simultaneously and localize them accurately. The study highlighted the advantages of combining object detection and segmentation techniques for industrial inspection.

Liu et al. (2022) presented a deep learning-based method for fabric defect detection, which incorporated pre-trained networks for feature extraction. Transfer learning significantly reduced training time while maintaining high accuracy, particularly for datasets with limited samples. Karegowda et al. (2024) investigated stain defect detection in textile fabrics using state-of-the-art transfer learning models such as VGG16, ResNet, and Inception. Their results showed that multi-branch architectures like Inception achieved higher accuracy by capturing features at multiple scales, which is critical for identifying defects of varying sizes. Beljadid et al. (2022) applied deep learning for automatic fabric defect detection, focusing on efficient model design and deployment in industrial settings. Their approach emphasized the balance between accuracy and computational cost, an important consideration for real-time inspection systems. Jing et al. (2020) proposed Mobile-UNet, a lightweight convolutional network tailored for fabric defect segmentation. By combining depthwise separable convolutions with UNet's encoder-decoder structure, the model achieved fast inference times suitable for embedded systems.

Hu et al. (2020) explored unsupervised fabric defect detection using generative adversarial networks (GANs). This method does not require labeled defect data, making it suitable for scenarios where defect samples are scarce. The GAN-based approach was able to learn normal fabric patterns and identify anomalies effectively. Andalib et al. (2012) applied artificial neural networks with K-fold validation for fabric fault detection. Their work highlighted the importance of cross-validation techniques in small datasets to improve model generalization and reduce overfitting. Mak and Yiu (2009) utilized a pre-trained Gabor Wavelet Network to extract texture features for segmenting defective regions in fabric images . Their work demonstrated the effectiveness of wavelet-based representations for capturing fabric texture variations. However, a major limitation in fabric defect detection remains the limited diversity of defective sample images available for training robust models. To address these challenge, Zhang et al. (2021) proposed Defect-GAN, a generative adversarial network designed to synthesize high-fidelity normal and defective fabric samples with substantial diversity.

III. Proposed Methodology

The methodology employed in this work is carefully designed to meet the requirements of automated fabric defect inspection. Owing to the complex texture characteristics of fabric materials and the scarcity of annotated defect samples, the study adopts a hybrid framework that integrates feature extraction with deep learning techniques. Texture-aware feature representations facilitate effective modeling of fabric patterns, while the learning-based component enables the detection of intricate defect variations that are challenging to capture using conventional rule-based approaches. In addition, the proposed methodology prioritizes computational efficiency, which is essential for deployment in real-time industrial inspection environments. The approach is validated using benchmark fabric defect datasets and is systematically compared with existing state-of-the-art methods based on standard evaluation metrics. This ensures both methodological soundness and practical applicability. Consequently, the adopted research strategy effectively addresses key challenges related to detection accuracy, model generalization, and real-world deployment.

The workflow as shown in Fig. 1consists of:

- ➢ Dataset acquisition
- ➢ Preprocessing and augmentation
- ➢ Model training through transfer learning
- ➢ Performance evaluation
- ➢ Saving and deploying the trained model

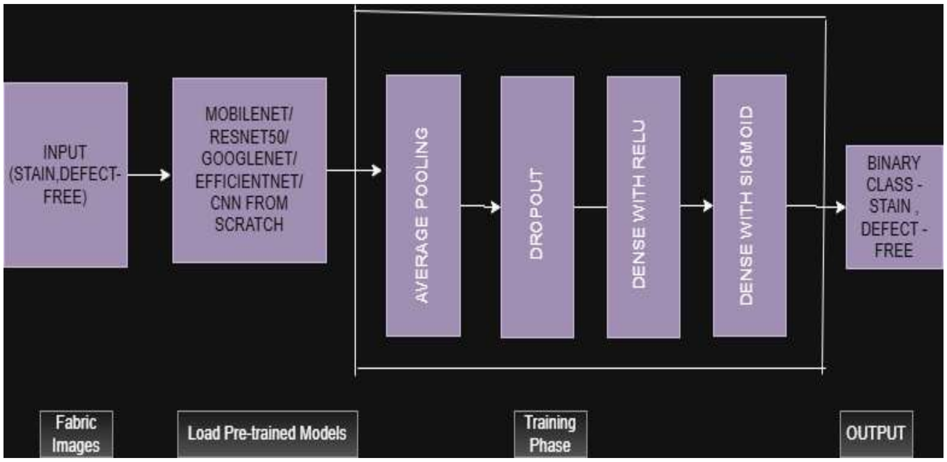

Fig. 1: Overall workflow of the proposed textile inspection system.

IV. Dataset and Preprocessing

The dataset taken from Kaggle includes:

- 68 non-defective fabric samples and a sample is shown in Fig. 2.
- 68 stained fabric samples and a sample is shown in Fig. 3.

Total: 136 images (balanced binary classification). Preprocessing includes:

- Resizing to model input dimensions
- Normalization
- Augmentation: rotation, zoom, brightness variation, shift, flipping
- Preprocessing improves feature diversity and prevents overfitting.

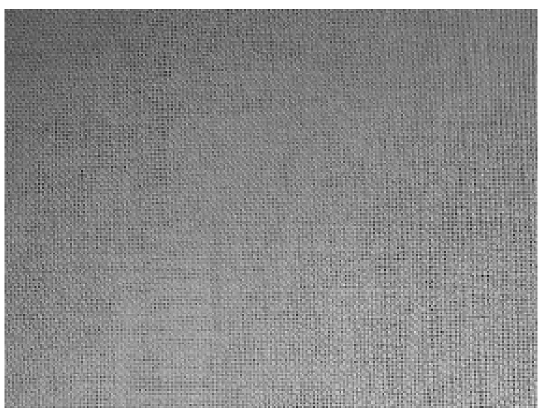

Fig. 2 Defect-free Fabric

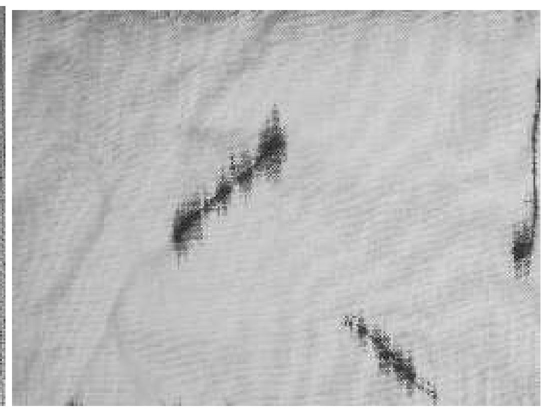

Fig. 3. Fabric with Stain

V. Experimentation and Results

MobileNetV2 employs depthwise separable convolutions, inverted residuals, and linear bottlenecks, enabling lightweight and efficient learning—ideal for edge devices. Its performance in terms of accuracy is shown on Fig. 4. ResNet50 features skip connections that solve the vanishing gradient problem:

$$H(x) = F(x) + x$$

The Inception module extracts multi-scale features through parallel 1×1, 3×3, and 5×5 convolutions. EfficientNet scales depth, width, and resolution uniformly using compound scaling. It includes convolution, ReLU activation, max-pooling, dropout, and sigmoid output. The performance if ResNet50, GoogLeNet, EfficientNetB0 and CustomNet are depicted in graphs shown in Fig. 4, Fig. 5, Fig. 6, and Fig. 7.

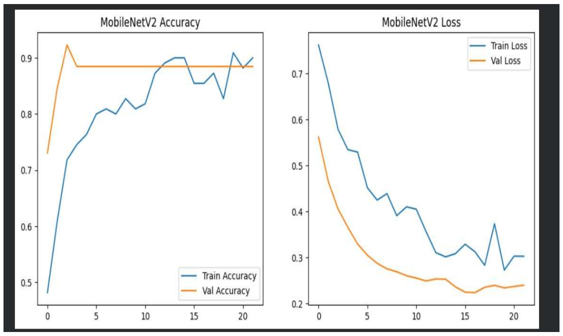

Fig. 4. Performance of MobileNetV2

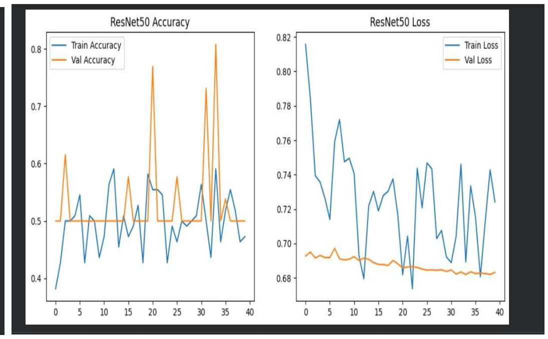

Fig. 5. Performance of ResNet50

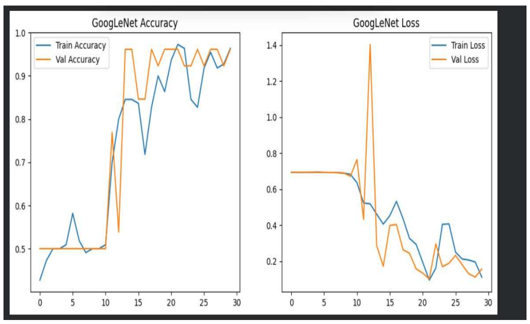

Fig. 6. Performance of GoogLeNet

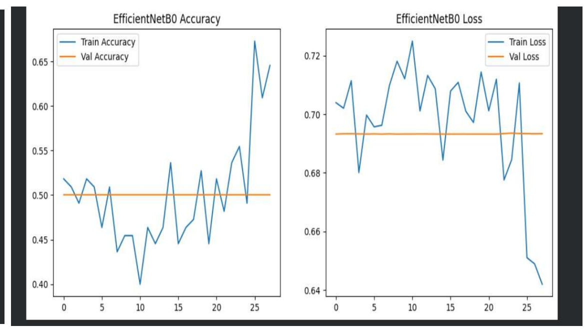

Fig. 7. EfficientNetB0 – Performance

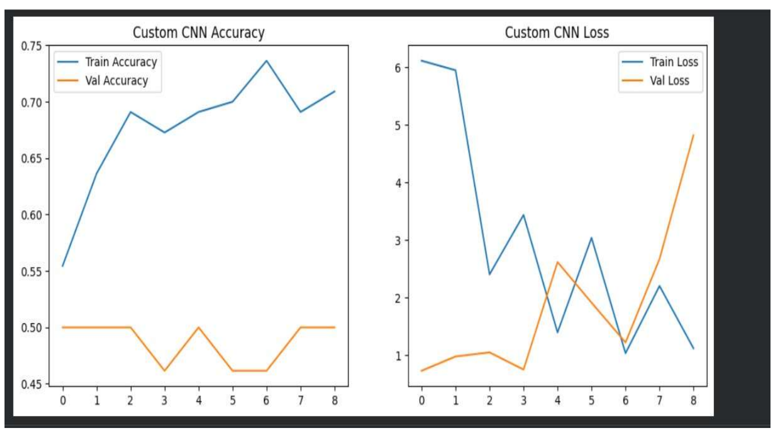

Fig. 8. Performance of Custom CNN

VI. RESULTS

The performance analysis of the five CNN models that were experimented are provided in Table 1. GoogLeNet demonstrates the best performance, followed by MobileNetV2. ResNet50 and EfficientNetB0 struggled due to dataset size limitations.

TABLE I. PERFORMANCE ANALYSIS

Model	Train Acc	Train Loss	Val Acc	Val Loss
MobileNetV2	0.86	0.36	0.88	0.23
ResNet50	0.49	0.71	0.50	0.68
GoogLeNet	0.97	0.10	0.96	0.15
EfficientNetB0	0.66	0.62	0.50	0.63
Custom CNN	0.73	0.12	0.50	0.48

VII. Conclusion and Future Work

This work demonstrates that deep learning, particularly GoogLeNet and MobileNetV2, can significantly improve textile surface and stain inspection accuracy. GoogLeNet achieved a validation accuracy of 96%, while MobileNetV2 offers a lightweight and deployment-friendly alternative.

Future work may include:

- Multi-class defect identification
- Localization of stains using object detection models
- Large-scale dataset collection
- Deployment on edge devices and FPGA

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