Computer Vision and Deep Learning based Automated Fabric Inspection System

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***Abstract*— Manual inspection is subjective, inconsistent, and heavily dependent on labour, it continues to be a major bottleneck in the textile industry. In addition to being expensive and time-consuming, manual examination is not productive or scalable. Using three convolutional neural network (CNN) architectures MobileNetV2, ResNet50, Google Net (Inception-v1) this study offers an automated surface and defect classification system based on deep learning. To improve feature variability, a balanced dataset of 136 textile images was pre-processed and enhanced. The proposed method greatly increases prediction speed while retaining performance on par with sophisticated current models, facilitating its use in real-time fabric inspection. In order to lower human error and enhance fabric quality control, the technology exhibits encouraging potential for incorporation into industrial inspection pipelines. Additionally, transfer learning models are used to classify fabric surface types (front and back) and fabric defect kinds (holes, knots, netting numerous, thick bar, thin bar, broken end) in order to determine the type of surface, detect the defect type, and determine whether the fabric has stains. It is observed that GoogLeNet exhibits higher accuracy of 92% for fabric surface type classification and 90% for fabric defect classification, compared to the other models.**

***Index Terms*— Fabric defect detection, Fabric Surface Type, Defect types, deep learning, computer vision, MobileNetV2, Google Net, Efficient Net, textile inspection, transfer learning.**

I. INTRODUCTION

The world and Indian economies depend heavily on the textile and clothing sector. The industry's 1.8–2.4% global GDP contribution reflects its importance in consumer and manufacturing markets. One of India's most significant industrial sectors, the textile and clothing industry contributes about 2.8% of the country's GDP, 15% of industrial production, and 15% of all exports. Ensuring fabric quality through effective and automated inspection systems has grown more crucial because to its significant economic impact and labour-intensive nature. Traditionally, textile quality inspection has relied on sluggish, error-prone, and non-scalable manual visual examination. Stains, surface abnormalities, and structural flaws in fabric may now be consistently, accurately, and quickly detected by automated inspection systems thanks to the development of deep learning and its automated feature extraction techniques. Through transfer learning and fine-tuning, this study assesses three CNN-based models: MobileNetV2, ResNet50, GoogLeNet, N. Finding the best architecture for real-time industrial deployment while taking accuracy, loss behavior, computational economy, and robustness into account is the main goal. This study explores the application of deep learning techniques for automated classification of fabric surface types and detection of fabric defects. Transfer learning-based TensorFlow models, including GoogLeNet, ResNet, were employed to leverage pre-trained feature extraction capabilities. The proposed approach aims to improve accuracy and efficiency compared to traditional manual inspection methods in the textile industry. By training and evaluating multiple convolutional neural network architectures, the study provides a comparative analysis of their performance on fabric datasets. The results demonstrate the potential of advanced deep learning models in enhancing quality control and reducing human error in fabric inspection processes

II. LITERATURE REVIEW

A deep learning-based technique for fabric defect identification that used pre-trained networks for feature extraction was introduced by Liu et al. (2022).

Particularly for datasets with small sample sizes, transfer learning greatly shortened training times without sacrificing accuracy. Kare Gowda et al. (2024) used cutting-edge transfer learning models including VGG16, ResNet, and Inception to study stain defect detection in textile materials. According to their findings, multi-branch architectures like Inception were able to identify flaws of different sizes with greater accuracy by capturing features at several scales.

The strong demand for quality control in the textile industries has made automated fabric flaw identification a significant field of computer vision research. Conventional inspection techniques mostly rely on human examination, which is laborious, erratic, and error-prone. Faster, more dependable, and scalable solutions have been made possible by the use of deep learning and computer vision techniques. A fully convolutional neural network was proposed by Mohammed et al. (2025) for the detection of fabric defects. Their method eliminated the requirement for manually created features by automatically learning features from fabric photos using deep convolutional layers. The model demonstrated the efficacy of end-to-end CNN architectures for defect identification by achieving high accuracy on benchmark datasets. An enhanced Mask R-CNN model for fabric flaw identification was created by Revathy and Kalaivani (2024). The model was able to precisely locate and identify several problems at once by utilizing instance segmentation. The study emphasized the benefits of integrating segmentation and object identification methods for industrial inspection.

Hu et al. (2020) investigated the use of generative adversarial networks (GANs) for unsupervised fabric flaw identification. This approach can be used in situations when there are few defect samples because it does not require labelled defect data. The GAN-based method successfully recognized abnormalities and learned typical fabric patterns. In order to detect fabric faults, Andalib et al. (2012) used artificial neural networks with K-fold validation. Their research shown how crucial cross-validation methods are for enhancing model generalization and lowering overfitting in limited datasets.

With an emphasis on effective model design and implementation in industrial settings, Beljadid et al. (2022) used deep learning for autonomous fabric flaw identification. Their method focused on striking a compromise between computing cost and accuracy, which is crucial for real-time inspection systems. Mobile-UNet, a lightweight convolutional network designed for fabric defect segmentation, was proposed by Jing et al. (2020). The model achieved quick inference times appropriate for embedded systems by fusing UNet's encoder-decoder structure with depth wise separable convolutions.

Mak and Yiu (2009) extracted texture information for fabric picture segmentation using a pre-trained Gabor Wavelet Network. Their research showed how well wavelet-based representations capture differences in fabric texture. Nonetheless, the little variety of faulty sample photos available for training reliable models continues to be a significant barrier to fabric defect identification. Defect-GAN, a generative adversarial network created to create high-fidelity normal and defective fabric samples with significant variability, was proposed by Zhang et al. (2021) as a solution to these problems.

Huang et al. [11] present several deep learning approaches for detecting different types of fabric defects in 2021. Their work consists of two main components: segmentation and detection. For segmentation, the model requires only about 50 defective samples and is capable of detecting defects in real time at 25 frames per second (FPS).

A two-step solution is presented by Voronin et al. [12] in 2021. The first step uses block-based alpha rooting along with a domain-based image enhancement technique. The second stage employs a neural network-based architecture.

Compared to traditional machine learning and deep learning techniques, this system achieves more precise defect detection. Rong-qiang et al. [13] proposed an enhanced convolutional neural network called CU-Net in 2021 for fabric defect detection. This method improves the traditional U-Net by incorporating an attention mechanism and size compression training.The proposed approach achieves accuracy scores of 98.3% and 92.7%, showing improvements of 4.8% and 2.3% over existing methods.

Xiang Jun et al. [14] proposed a learning-based technique for automatic fabric defect detection in 2021, followed by an improved histogram comparison method.A LeNet-5 model is used as a voting classifier to identify defect types, while a VI-model predicts local defects. The trained classification model achieves an accuracy of 96%.

Wu et al. [15] developed convolutional neural networks (CNNs) in 2021 to classify defects in fabric images collected from textile environments. Their approach was compared with well-known deep learning architectures such as VGG, DenseNet, Inception, and Xception networks

III. PROPOSED METHODOLOGY

The approach used in this work was thoughtfully created to satisfy the demands of automated fabric flaw inspection. The study uses a hybrid framework that combines feature extraction and deep learning approaches because to the intricate textural features of fabric materials and the lack of annotated faulty samples. While the learning-based component makes it possible to discover complex defect variations that are difficult to capture using traditional rule-based approaches, texture-aware feature representations enable efficient modelling of fabric patterns. Furthermore, the suggested approach places a high priority on computational efficiency, which is crucial for implementation in real-time industrial inspection settings. Benchmark fabric defect datasets are used to validate the approach, and standard evaluation metrics are used to systematically compare it with current state-of-the-art techniques. This guarantees both practical applicability and methodological correctness. As a result, the chosen research approach successfully tackles important issues with detection precision, model generalization, and practical implementation.

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

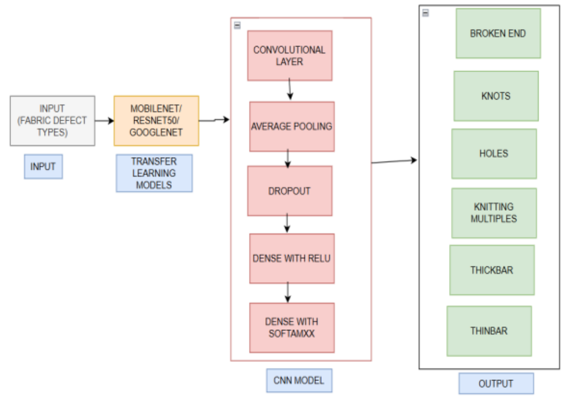

Fig. 1. Overall workflow of the proposed textile defect inspection

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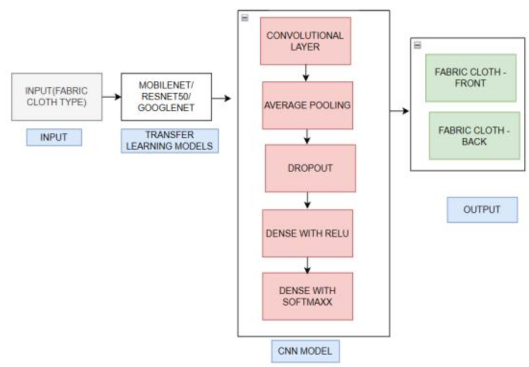

Fig.2 Overall workflow of the proposed textile surface detection

IV. DATASET AND PREPROCESSING

Preprocessing includes:

- Resizing to model input dimensions
- Normalization
- Augmentation: rotation, zoom, brightness variation, shift, flipping

Preprocessing improves feature diversity and prevents overfitting.

For checking whether the jeans cloth is front or back, we had collected 50 jeans data from the shop for both front and back. as shown in Fig 4 and Fig 5

Fig. 3. Fabric Front Surface

Fig. 4. Fabric Back Surface

Data is also collected from various sources for fabric defects. There are totally six classes. shown

- Broken end
- Holes
- Knots
- Netting multiple
- Thickbar
- Thinbar

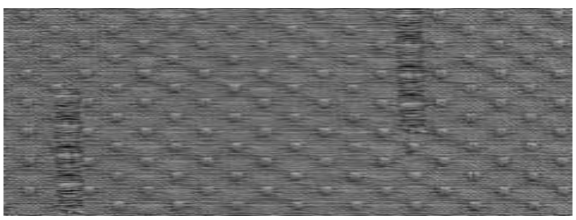

Fig. 5. Broken end

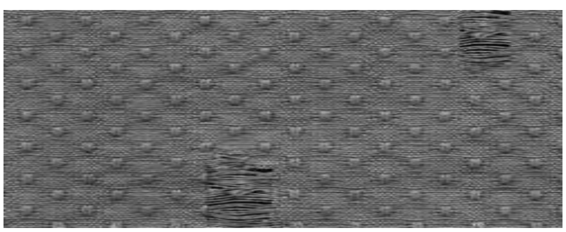

Fig. 8. Holes

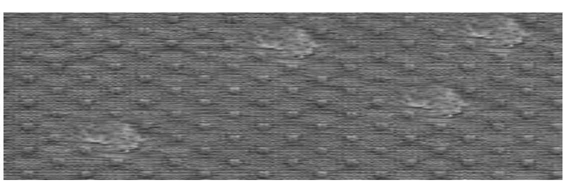

Fig. 6. Knots

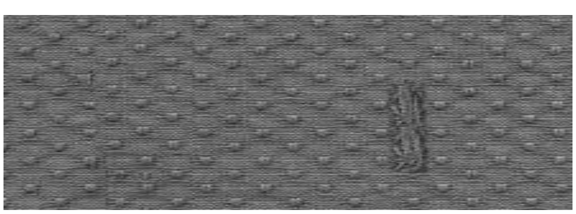

Fig. 9. Netting Multiple

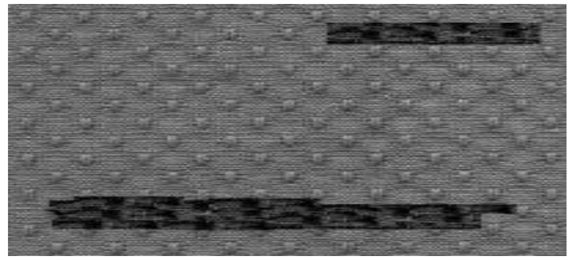

Fig. 7. ThickBar

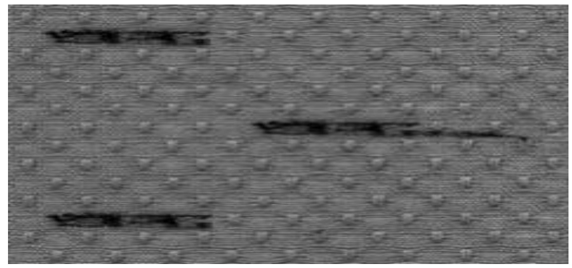

Fig. 10. Thinbar

V. EXPERIMENTATION AND RESULTS

MobileNetV2 uses linear bottlenecks, inverted residuals, and depthwise separable convolutions to provide lightweight and effective learning—perfect for edge devices. Fig. 4 displays its accuracy performance. The vanishing gradient issue is resolved by ResNet50's skip connections:

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

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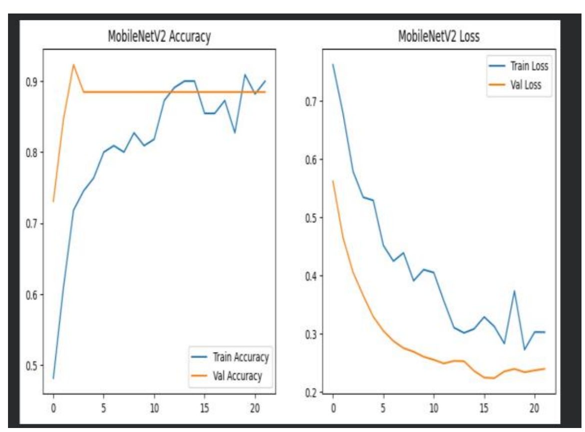

Fig. 11. Performance of MobileNetV2

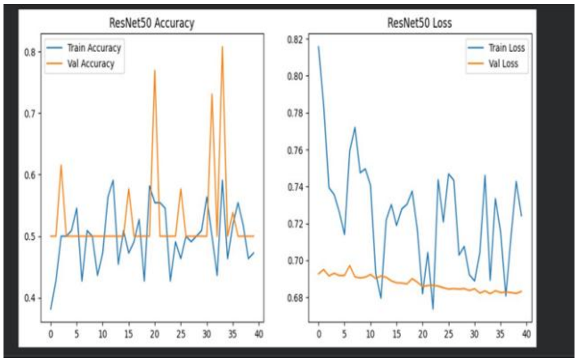

Fig. 12. Performance of ResNet50

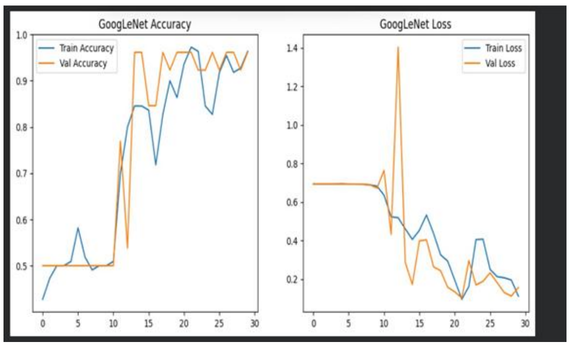

Fig. 13. Performance of GoogLeNet

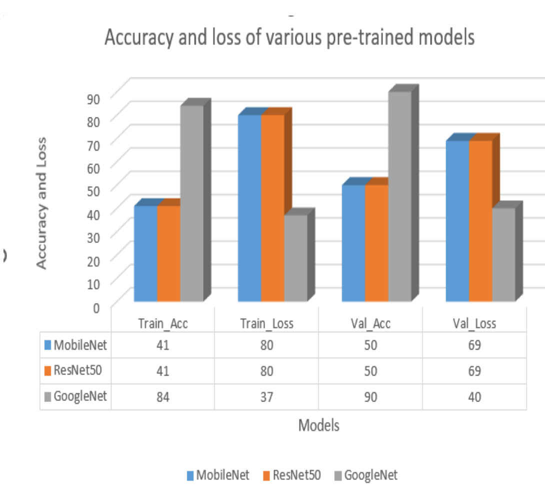

Fig. 14. Comparison of all models for Fabric cloth Surface detection and Fabric Defect Types

VI. RESULTS

Table 1 presents the performance analysis of the five CNN models that were tested. The best performance is shown by GoogLeNet, followed by MobileNetV2. Due to dataset size constraints, ResNet50 performed poorly.

Table 1. 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

From Fig.14. we find out that GoogLeNet Performs well for Fabric defect detection and Fabric SurfaceType.

VII. CONCLUSION AND FUTURE WORK

This paper shows that deep learning, specifically GoogLeNet and MobileNetV2, may greatly increase the accuracy of textile surface and defect type examination. While MobileNetV2 provides a lightweight and deployment-friendly substitute, GoogLeNet attained a validation accuracy of 90%. In upcoming research work, we can increase the dataset size for accuracy and we can perform in real-time.

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