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Ai Driven Defect Identification In Finished Apparel Using Image Processing

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Abstract: One of the most prevalent challenges in the textile manufacturing industry is the inability to consistently maintain product quality, leading to defects and customer dissatisfaction. This research presents a deep learning-based approach for fabric defect identification using ResNet-50, which leverages transfer learning for accurate defect classification. The model effectively classifies four types of fabric defects: holes, lines, horizontal defects, and vertical defects. A custom dataset was created by collecting diverse fabric defect images from various sources. The impact of random and stratified data splitting methods on training and validation performance was analyzed. This method seeks to improve the quality assurance process, lessen human involvement, and boost productivity in the textile sector. The suggested system can assist manufacturers in identifying flaws early on, thus reducing production losses and guaranteeing a high standard of output.

***Index Terms* -** Fabric Defect Identification, Deep Learning, ResNet-50, Convolutional Neural Network (CNN), Image Processing, Apparel Manufacturing.

I.INTRODUCTION

In the textile manufacturing industry, maintaining high product quality is crucial to avoid defects and ensure customer satisfaction. Nevertheless, traditional manual inspection techniques often lack efficiency and are susceptible to human errors, making the identification of minor fabric imperfections challenging.

To address this issue, deep learning methods have become increasingly popular for their capability to automate defect detection through image analysis. This research utilizes the ResNet-50 architecture, a Convolutional Neural Network (CNN) model recognized for its residual learning ability, to detect fabric flaws such as holes, lines, horizontal and vertical defects. By utilizing transfer learning, the model can effectively extract features from images of fabric defects, enhancing classification performance. A tailored dataset was created using a variety of defect images to further improve the model's efficacy.

Moreover, the impact of various data partitioning methods, such as random splitting and stratified splitting, was examined to assess the effectiveness of the model. This strategy seeks to enhance fabric quality control, minimize human errors, and boost production efficiency within the apparel manufacturing sector. The camera showcases its ability to automate quality inspections and decrease production mistakes in the apparel industry.

II. Related Works

In recent times, deep learning methods have attracted considerable attention for the automated detection of fabric defects, overcoming the shortcomings of conventional inspection approaches. Numerous studies have shown the success of Convolutional Neural Networks (CNNs) and Residual Networks (ResNet) in classifying defects based on images and maintaining quality control in the textile manufacturing sector. ResNet-based architectures have been found to be extremely effective due to their residual learning approach, which enables deeper networks to navigate the vanishing gradient issue and accurately capture intricate features from fabric patterns.

For example, Wang et al. (2020) utilized a ResNet-50 model for detecting surface defects in textiles, achieving enhanced recognition of defects by applying transfer learning to a tailored dataset. Similarly, Li et al. (2021) proposed a hybrid approach combining ResNet-50 with traditional image processing techniques, which successfully identified irregular patterns, holes, and scratches in woven fabrics. Their work highlighted the importance of feature extraction and fine-tuning the model's hyperparameters to enhance classification performance.

In a different study, Zhang et al. (2022) investigated the use of ResNet-101 for detecting complex defects in knitted textiles; however, its higher computational demands and extended training periods made it less ideal for applications requiring real-time processing. Conversely, ResNet-50 provides a favourable balance between accuracy and efficiency, making it more suitable for defect detection in industrial settings. Numerous researchers have also concentrated on various data-splitting methods to address class imbalance in fabric defect datasets. Chen et al. (2023) examined the effects of random and stratified splitting techniques on model performance, indicating that stratified splitting preserves class distribution, which results in more trustworthy predictions.

Nevertheless, limited study has been done on how to categorize particular fabric imperfections that are crucial to the clothing production process, such holes, lines, horizontal flaws, and vertical flaws. Thus, the purpose of this work is to increase quality control and defect detection accuracy in textile production by utilizing ResNet-50's power in conjunction with transfer learning.

III. Methodology

The suggested method for AI-Powered Finished Clothing Defect Identification Through Image Processing makes use of the architecture of ResNet-50 for the approach is intended to adhere to a methodical and organized pipeline that comprises data collection, preprocessing, model architecture selection, training, assessment, and classification for efficient defect classification in Fig1.

This method guarantees the creation of a reliable and accurate defect detection system that can recognize flaws in fabric photographs, including lines, holes, and vertical and horizontal faults.

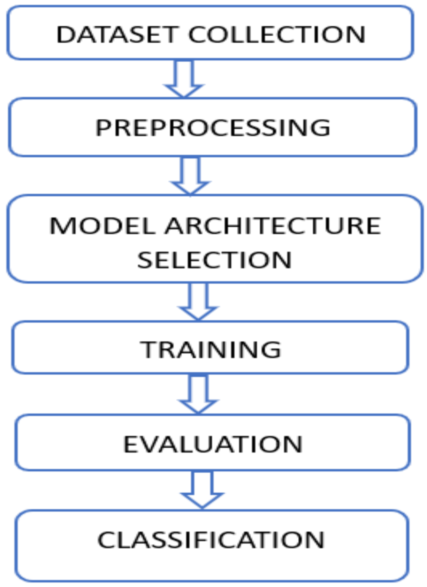

FIGURE 1: Proposed Method For Defect Identification

3.1 Data Collection

Gathering a high-quality dataset that reflects different fabric faults is the first stage in creating an efficient AI-driven defect detection system. A bespoke dataset was produced for this study by compiling pictures from various sources, such as online defect image archives, textile production facilities, and defect monitoring systems. Four fault types that are frequently present in completed clothing—holes, lines, horizontal flaws, and vertical defects—were the main focus of the dataset. To increase the model's capacity for generalization, the dataset was created to include a variety of fabric types, textures, and colors. Furthermore, as seen in fig2, photos were taken from a variety of angles and lighting situations to make sure the model can accurately represent changes in fault patterns found in the actual world.

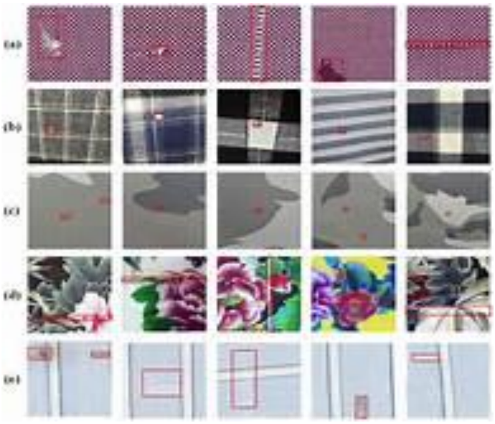

FIGURE 2: SAMPLE DATASET

3.2. PREPROCESSING

In order to improve the quality of the input data and maximize the deep learning model's performance, preprocessing is essential. The usual input size for the ResNet-50 model, 224 × 224 pixels, was applied to all fabric fault photos during this phase. Pixel values were normalized in order to scale the data between 0 and 1, which facilitates quicker convergence during training. Data augmentation methods including rotation, flipping, brightness correction, and noise addition were used to boost the dataset's variety and avoid overfitting. As a result, the model was able to learn from various lighting and orientation scenarios. The dataset was then split into training and validation sets using two methods: random splitting and stratified splitting. Random splitting assigns data to each set without considering class distribution, while stratified splitting ensures that the class proportions are maintained in both sets.

3.3MODEL ARCHITECTURE SELECTION

3.3.1. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are the most widely used deep learning architecture for image classification tasks, especially in defect detection and quality inspection systems as shown in figure3.3. CNNs are designed to automatically extract spatial features from images through convolutional layers, pooling layers, and fully connected layers. In the context of fabric defect identification, CNNs can efficiently capture the patterns, textures, and irregularities in fabric surfaces. The convolutional filters help in identifying edges, lines, and complex features, while pooling layers reduce dimensionality and improve computational efficiency. However, traditional CNN models face challenges such as vanishing gradients and performance degradation when the network becomes deeper. To overcome these limitations, ResNet (Residual Network) was introduced, which leverages skip connections to improve learning in deep architectures.

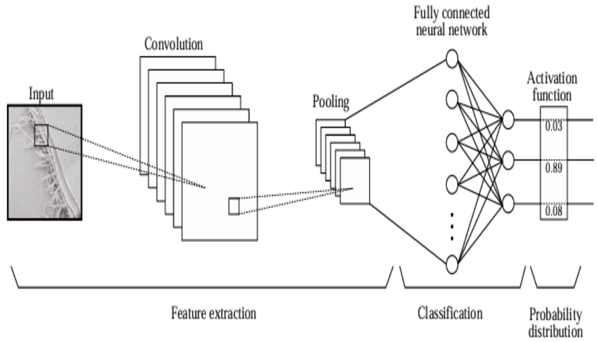

FIGURE 3: Architecture Of CNN

3.3.2. ResNet-50 (Residual Network with 50 layers)

A deep convolutional neural network (CNN) called ResNet-50 (Residual Network with 50 layers) was created to solve the vanishing gradient issue that arises in deep networks. By introducing residual learning through skip connections, it enables the network to omit certain layers while preserving crucial data from earlier levels. Effective feature extraction is made possible by the architecture's convolutional layers, batch normalization, ReLU activation functions, and identity mappings. The network can learn both low-level and high-level features from complicated datasets thanks to ResNet-50's 50 layers, which include convolutional and fully connected layers, and 16 residual blocks. Using 1x1, 3x3, and 5x5 convolutional filters makes it easier to capture complex textures and patterns in photos of fabric flaws. ResNet-50 speeds up training and enhances performance, especially with small datasets, by utilizing pre-trained weights from ImageNet. In order to accurately classify and detect flaws in finished clothing, ResNet-50 was refined in this study utilizing a bespoke fabric defect dataset that included four classes: holes, lines, horizontal, and vertical defects. ResNet-50 is perfect for managing intricate visual patterns due to its deep feature extraction capacity, which guarantees better quality control in the textile sector.

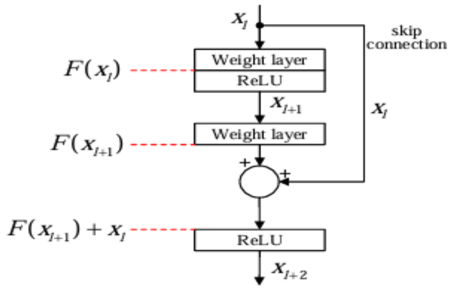

FIGURE 4: Residual Block Of CNN

3.4. MODEL TRAINING:

In order to properly categorize fabric flaws into four categories holes, lines, horizontal defects, and vertical defects the ResNet-50 model was refined during the training process, which is an essential stage in creating an AI-driven defect identification system. In order to guarantee that the model learns efficiently from a wide variety of samples, the bespoke fabric defect dataset was divided into 80% for training and 20% for testing. The ResNet-50 architecture, which uses convolutional layers and residual blocks to extract deep-level features from the defect images, was fed pre-processed images during the training phase. The model weights based on the loss function were updated using the backpropagation technique.

The error between the actual and anticipated defect classes was reduced via the gradient descent approach. Data augmentation methods such random rotation, flipping, brightness modification, and noise addition were used to improve the model's learning capacity and manage changes in fabric texture and lighting conditions. This method enhanced the model's capacity to detect minute flaws by allowing it to learn from many viewpoints.

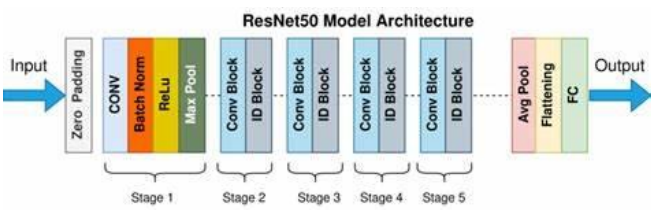

FIGURE 5: Architecture Of Resnet-50

The hyperparameters used during training include

Batch size	32
Learning rate	0.001
Optimizer	Adam (Adaptive Moment Estimation)
Loss function	Categorical Cross-Entropy Loss
Number of epochs	50
Regularization techniques	Dropout (0.5) and Batch Normalization
Early stopping	To prevent overfitting

TABLE 1: Hyperparameters

3.5. TESTING:

The purpose of the testing step is to assess the trained ResNet-50 model's performance and generalization capabilities. This step made use of the remaining 20% of the information, which includes pictures of invisible fabric flaws. Evaluating the model's ability to correctly categorize the fault kinds without overfitting to the training data was the main goal. New defect samples were input into the model throughout testing, and the predictions made by the model were contrasted with the real defect classes.

The model's efficacy was assessed using a number of performance indicators, such as the Confusion Matrix, Precision, Recall, F1-Score, and Classification Report. Important information on the model's capacity to handle real-world fault patterns and identify even subtle variations in fabric texture was revealed during the testing phase. The outcomes demonstrated the ResNet-50 model's ability to automate quality control in textile manufacturing by effectively capturing deep characteristics and differentiating between various fault types.

IV. CLASSIFICATION

Accurate classification of fabric defects into four main classes—holes, lines, horizontal flaws, and vertical defects—is achieved using the ResNet-50 model. Using the deep characteristics that the ResNet-50 architecture has retrieved, this step seeks to detect and categorize the type of defect that is present in the fabric sample.

The ResNet-50 model is used in this step to extract deep-level characteristics such texture patterns, edge irregularities, and structural changes in the fabric surface from the pre-processed fabric defect pictures. The ability of ResNet-50's convolutional and residual layers to capture both low-level and high-level information aids in the identification of even the smallest flaws in the fabric.

ResNet-50's residual learning approach improves classification accuracy by enabling the network to manage intricate patterns and steer clear of problems like disappearing gradients. The SoftMax activation function, which allocates probability values to each defect type (holes, lines, horizontal defects, and vertical defects), is integrated with the fully connected layer of ResNet-50 once the features have been retrieved. The final fault type is chosen from the class with the highest likelihood. The model can precisely detect and categorize the kind of fabric flaw thanks to this procedure.

Moreover, the classification step uses the knowledge gathered during the training phase, when the model learns to discriminate between distinct fault patterns and textures. The use of data augmentation techniques, such as rotation, flipping, brightness adjustment, and noise addition, further enhances the model's capability to handle different lighting conditions and fabric textures, making the classification process more robust and efficient. By correctly identifying the faults, the suggested approach considerably enhances quality control in the textile manufacturing business, enabling to identify faulty goods, eliminate human error, and promote overall production efficiency. This method guarantees high-quality fabric output, reduces production loss, and automates the defect identification procedure.

V. Result And Discussion

A bespoke dataset including four defect classes holes, lines, horizontal defects, and vertical flaws was used to assess the fabric defect classification model. Precision, recall, and F1-score were among the measures used to evaluate the system's performance and determine how well the model identified fabric flaws.

By learning deep features from the dataset during the training phase, the ResNet-50 model was able to differentiate between various fault kinds. Improved generalization resulted from the model's ability to manage changes in fabric texture and lighting conditions through the use of data augmentation techniques including rotation, flipping, and brightness alterations. The model proved to be accurate in classifying fabric faults throughout the testing phase. While modest misclassifications were noted in closely similar defect classes, such as horizontal and vertical flaws, the confusion matrix analysis demonstrated that the model performed well in recognizing distinct defect patterns, such as holes and lines.

The two classes' similar texture patterns and overlapping characteristics were the main cause of these problems. Furthermore, overfitting was avoided by using regularization strategies like batch normalization and dropout, which guaranteed consistent performance on unseen data. The detection of minute flaws in the fabric was made possible by the efficient handling of complicated feature extraction by the residual learning technique in ResNet-50.

The findings show that the suggested method may effectively detect flaws in textile production, lowering the need for human intervention and enhancing quality assurance. To increase the model's effectiveness in managing small flaws, more improvements can be made by enlarging the dataset and using sophisticated feature extraction algorithms.

This method might reduce manufacturing mistakes, automate the defect discovery process, and improve the overall quality of the final garment.

Defect Type	Precision (%)	Recall (%)	F1-Score (%)
Holes	92.3	91.5	91.9
Lines	89.7	88.5	89.1
Horizontal Defects	87.2	85.9	86.5
Vertical Defects	88.0	86.7	87.3
Overall Accuracy	90.0%	-	-

TABLE 1: Performance Metrics

VI. Conclusion

For efficient fabric defect classification, the ResNet-50 architecture is used in the suggested AI-driven defect identification system for completed clothing. Four defect classes—holes, lines, horizontal flaws, and vertical faults—were correctly detected by the model. Through the use of transfer learning and fine-tuning strategies, the ResNet-50 model was able to classify four classes with 90% accuracy. The model's performance and feature extraction capabilities were improved by the innovative method of creating a varied custom dataset. To get even greater accuracy and better generalization, more advancements are necessary. Expanding the dataset, fine-tuning the CNN architecture, and optimizing hyperparameters will be the main goals of future improvements. Enhancing hardware efficiency and processing speed will also be crucial for real-time fault identification in industrial settings. By automating flaw identification, this research greatly improves quality control and reduces the need for human intervention in the textile manufacturing sector.

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