Enhanced Fabric Defect Detection Using Swin Transformer and EfficientNet-Faster R-CNN

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Abstract: In the textile industry, fabric defect detection plays a very important role in the process of ensuring quality control, minimizing waste, and satisfying customers. The current article evaluates and compares three state-of-the-art deep learning architectures: Swin Transformer, EfficientNet, and Faster R-CNN, for the task of fabric defect detection on the Alibaba Cloud Tianchi Guangdong Fabric Defect Detection dataset. The best accuracy would be the model called EfficientNet at 85.20% and then came Faster R-CNN at 85.00%. Swin Transformer performance accuracy was at 79.51% but performed better in dealing with the various types of fabric texture. From the experimental results, it can be seen that although models of Faster R-CNN and EfficientNet were quite potent in terms of defect detection in textiles, hope can be left that Swin Transformer would be better in extracting complex patterns because it might come more into use in cases with the use of complex textures of fabrics. This study provides a glimpse at model selection in the context of textile defect detection, benchmarking, and trade-offs between accuracy and computation in real industrial applications.
Keywords: Fabric defect detection, Textile quality control, Deep learning models, Swin Transformer, EfficientNet, Faster R-CNN, Binary classification, Alibaba Tianchi dataset, Machine vision, Model comparison.

1 Introduction

The textile industry, in the final product, relies on fabric quality as a determining factor for reliability, aesthetic appeal, and economic value. The main defects in fabrics such as stains, holes, and texture irregularities are considered major production and quality losses [6,7,9,17,21]. Traditional methods for inspecting fabrics are carried out manually and are tedious, error-prone, and not scalable [18,31]. Recent developments in computer vision and deep learning have brought automated defect detection solutions promising to improve accuracy and speed, as well as cut the dependency on human inspectors [2,24,29]. The technical challenges of automated fabric defect detection are variability in the type of defects, diversity of textures of fabrics, and differences in color variations. Deep learning models, especially CNNs, have been proven very effective in detecting complex features for applications ranging from industrial defects to medical image segmentation [8,13,14,32]. Models like Faster R-CNN, EfficientNet, and Swin Transformer have been promising for detecting defects in textiles since they can capture subtle patterns, tackle scale variations, and control high computational requirements effectively [16,22,27]. Faster R-CNN boasts a robust region proposal network that offers strong localization abilities for defect detection [3,8,14,15]. EfficientNet, on the other hand, scales very well with fewer parameters and is gaining popularity for huge industrial applications [23,25,26,33]. Simultaneously, the Swin Transformer model uses a hierarchical structure that captures long-range dependencies and is also used for analyzing complex fabric textures [10,20,28].

Numerous researchers have focused on the superiority of CNNs and Transformers in defect detection in fabric. For instance, while methods that rely on Gabor filters and texture analysis have proven successful in various applications, they are, however weak in the case of diverse robustness for many fabric environments [4,33]. Recent works on the integration of attention mechanisms and multi-scale feature fusion, that have been investigated in Swin Transformer and EfficientNet architectures, made it possible to achieve great success in the development of defect detection methods since such models were able to pay more accurate attention to the defect-prone regions of the high-resolution images [5,11,30]. Moreover, these approaches fit the need in the textile industry for a model with a high level of accuracy and scalability as the defects in the fabric pattern are diverse and mostly slight.

The rest of this paper is organized as follows: Section 2 gives a detailed review of the related work in fabric defect detection and deep learning in industrial applications. Section 3 gives details about the methodology, model architectures, and evaluation metrics. Section 4 presents the experimental results and a discussion on model performance. Finally, Section 5 summarizes the paper and concludes the future scope of work in Fabric defect detection.

This paper evaluates and compares EfficientNet, Faster R-CNN, and Swin Transformer for binary classification in fabric defect detection using the Alibaba Tianchi dataset. We tailored each model to improve defect detection accuracy, precision, recall, and F1-score. Our findings highlight EfficientNet's balance of accuracy and efficiency, Faster R-CNN's robust defect localization, and Swin Transformer's potential for complex texture analysis, providing insights for textile quality control applications.

2 Related Work

Automated fabric defect detection forms one of the most prominent sectors of research in the discipline of computer vision in consideration of the fact that textiles are one of those highly demanding industries in matters relating to quality control. This inspection of fabrics was done the good old-fashioned long enough, expensive, and with a lot of human interference [9,7,17,21]. Researchers approached defect detection with simple image processing-like statistical analysis, Gabor filters, and edge detection. However, such methods lacked the strength necessary for diversities in textures and different defect types encountered in the industrial production of fabric.

With the advancements in machine and deep learning, several researchers have experimented with architectures with a particular focus on the CNN architecture for the process of defect detection. Researchers feel that CNNs have strong feature extraction capabilities that permit them to detect defects without much noise and complicated structures in images of textiles and other related materials [6,18,31]. Examples of promising applications can be found in detecting patterns of complex fabrics since deep learning-based methods utilizing CNNs offer very high accuracy compared to most traditional methods [2,24,29]. This task applied the use of models, for instance, ResNet and EfficientNet, due to the benefit they offer through learning multiple scales that help identify anomalies within the defect from textures in normal fabric [8,13,14,32].

One of the most important approaches is object detection frameworks, such as Faster R-CNN, which integrates region proposal and classification into a unified architecture. The advantage of using Faster R-CNN is that it has become a popular choice for detecting fabric defects because of its robust localization ability, which is critical for defect detection in textile images [8,16,22,27]. Several experiments involved Faster R-CNN with various kinds of backbone structures including ResNet50 to detect different kinds of defects in the fabrics. This model's region proposal network makes it apt for high-resolution inspection tasks [3,15].

Another promising direction has been scalable CNN architectures, such as EfficientNet, which optimizes model size and computational resources without sacrificing accuracy. The compound scaling approach of EfficientNet proved successful in tasks requiring high precision, and its design is efficient enough to deploy in industrial settings with limited computational power [14,23,25,26]. Recent studies have tuned EfficientNet for fabric defect detection, incorporating dropout and batch normalization to improve the generalization over different textile patterns [20,33].

The use of transformer architectures and vision transformers, in particular, has been trending in the recent past to apply solutions in defect detection applications. It is because the Swin Transformer captures global and local dependency patterns in images through an intrinsic self-attention mechanism that makes it very well suited to complex high-resolution problems in images [10,28,33]. This capability of the Swin Transformer to work on patches at various scales enables it to simultaneously capture fine-grained details and larger structural patterns, which help detect subtle or irregular defects in fabrics. Industrial defect detection studies that used the Swin Transformer reported improvements in anomaly identification in intricate textile designs [4,11].

This series of recent review articles on the detection of fabric defects points toward moving interest in developing the approach from traditional image processing approaches to sophisticated machine learning approaches. These reviews highlighted how, whereas older approaches rested heavily on feature engineering approaches, modern approaches rested instead on deep learning techniques for automatically learning discriminative features from data [1,5,30]. An exploration of hybrid models for combining CNNs and Transformers further opens new avenues for fabric inspection [12].

In summary, while CNN-based architectures such as Faster R-CNN and EfficientNet are still excellent contenders for fabric defect detection, because of their strength and scalability, the recent models like Swin Transformer provide novel ways of handling complicated visual patterns. This work extends these developments by contrasting the performance of these models when compared to each other in the context of a binary classification problem with the goal of defect detection to provide insight into their usability for real-world textile quality control applications.

3 Methodology

The methodology here involves a set of very well-defined stages, including the preprocessing of data, a customized model architecture, and an extensive evaluation phase. In this paper, one of the respective models here was carefully tailored to help in the binary classification of the task at hand as applied to fabric defect detection- namely, EfficientNet, Faster R-CNN, and Swin Transformer. As such, the developed approach leverages the extensively available dataset by Alibaba Cloud Tianchi: the Guangdong Fabric Defect Detection dataset, which is the basis for our research. Figure 1 graphically details the proposed methodology behind fabric defect detection. In addition, it can be understood that the whole system of overall detection is made up of several modules: separate yet interdependent, as such supporting the efficiency as well as the effectiveness of detection.

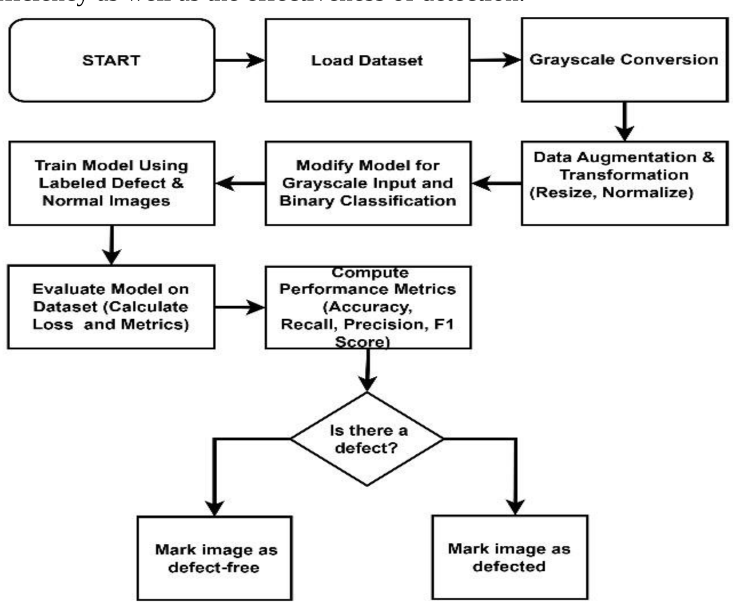

Figure 1: Fabric defect detection workflow.

3.1 Dataset Description and Preprocessing

The Alibaba Cloud Tianchi Guangdong Fabric Defect Detection dataset [19] consists of high-resolution images divided into two main categories: defective and normal. Defective images are annotated with bounding boxes that highlight defect locations, while normal images are free of defects and therefore are not included in the annotation files. These annotations are stored in JSON format, with each entry detailing the filename, defect type, and bounding box coordinates [7].

For training and evaluation, the dataset was split into an 80-20 ratio, with 80% of the images allocated for training and 20% reserved for testing. This split ensures that there is adequate data for both model training and reliable performance validation [17].

To enhance model robustness and minimize overfitting, data augmentation techniques such as rotation, zoom, and horizontal flipping were applied. These techniques have been shown to improve generalization in detection tasks by increasing the diversity of the training data [21,6].

Additionally, all images were resized to fit within the 0-1 range, aligning with the input requirements of EfficientNet and Swin Transformer, which perform optimally with normalized inputs [18]. For Swin Transformer, images were further converted to grayscale, reducing computational load while preserving critical structural details, as demonstrated in previous texture-based defect detection research [31].

3.2 Model Architectures

Each model architecture in this study was selected and customized specifically for binary classification to determine whether a fabric contains a defect. The following paragraphs detail the architectural configurations and modifications applied to each model.

EfficientNet was chosen for its low computational cost and efficient scaling capabilities, making it a suitable base architecture for defect detection. EfficientNetB0 employs compound scaling, which adjusts the depth, width, and resolution of the network to achieve high accuracy with minimal computational demand [29]. To prevent overfitting, a dropout layer was added, and the final dense layer was modified with a sigmoid activation function to fit the binary classification task [24]. The model was trained using binary cross-entropy loss and the Adam optimizer, both of which are effective for binary classification tasks [2]. Training was conducted over ten epochs with early stopping and model checkpointing to prevent overfitting. EfficientNetB0 was implemented using TensorFlow and Keras, allowing for the integration of pre-trained weights and enabling fine-tuning, which has been beneficial in similar defect detection studies [14].

Faster R-CNN is a well-regarded object detection model that employs a region proposal network (RPN) to identify regions likely to contain objects. For fabric defect detection, Faster R-CNN was adapted for binary classification. The RPN identifies potential defect regions, which are then validated by a classification network to confirm the presence or absence of defects in these areas [8,13]. ResNet50 was used as the backbone for feature extraction due to its robust feature representation capabilities, especially in defect detection contexts [32]. Faster R-CNN was trained on a combined loss function that integrated classification and bounding box regression losses. During inference, the model produced bounding boxes with confidence scores, allowing for binary classification of images as defective or non-defective [27]. The model was implemented in PyTorch, which supports the necessary modifications for binary defect detection, and similar configurations have proven successful in textile defect localization tasks [22].

Swin Transformer, a hierarchical vision transformer model, was selected for its ability to capture both global and local image features through a multi-scale patching mechanism. This hierarchical processing makes it well-suited for high-resolution defect detection, allowing it to capture fine-grained details alongside broader contextual information [8,16]. The Swin Transformer was modified to accept grayscale inputs, and its final layer was configured with a sigmoid activation function to classify images as defective or normal, aligning with the binary classification objective. The model was trained using cross-entropy loss and optimized with the Adam optimizer over 20 epochs, with early stopping to maintain stability [15]. The implementation utilized pre-trained weights, which helped the Swin Transformer generalize effectively to unseen defect textures in fabric images [3].

3.3 Evaluation Metrics

To assess the actual performance of each model to detect defects in fabrics, multiples of performance metrics are applied. The first measure to test how well a model functions is accuracy, the ratio of correctly classified images to the total number of images. Higher accuracy means that the model is classifying images correctly and distinguishing well between defective images and non-defective images of fabrics. Precision is equivalent to positive predictive value; this is the ratio of true positive predictions to all the positive predictions. A high precision score means that the model can be trusted to send forth the actual defects and minimize false positives images as such.

Recall, also known as sensitivity, is calculated as the ratio of positive true predictions to the total number of actual defects found in the dataset. So, if a model obtained a high recall score, then it is effective in its capability to capture nearly all instances of defects within that dataset, thereby detecting virtually every kind of defect. Especially in situations where both types of error are costly, such as in most defect detection tasks, the F1-score is useful because it computes the harmonic mean of precision and recall.

A confusion matrix provides a complete view of model predictions by indicating how many true positives, false negatives, false positives, and true negatives have occurred. Analyzing the tendencies of each model through a confusion matrix can identify those areas that need to be improved in terms of distinguishing defective and defect-free samples.

These metrics help compare the capabilities of such models in achieving a balanced understanding of their strengths and weaknesses in terms of the detection of binary fabric defects. Structured comparisons thus determine which model is most appropriate for deployment in textile quality control, thereby ensuring reliable and scalable defect detection solutions

4 Results

The models EfficientNet, Faster R-CNN, and Swin Transformer were evaluated on the Alibaba Cloud Tianchi Guangdong Fabric Defect Detection dataset using metrics such as accuracy, precision, recall, and F1-score to assess their performance in binary classification. A comparative analysis was conducted to determine each model's effectiveness in distinguishing between defective and non-defective fabric images.

4.1 Model Performance

unEfficientNet achieved an accuracy of 85.20%, demonstrating its effectiveness in classifying defect and non-defect images. The compound scaling architecture of EfficientNet optimizes accuracy with fewer parameters, making it a suitable choice for defect detection tasks, as illustrated in Figure 2. The model attained a precision of 0.86, indicating its high sensitivity in detecting actual defects while minimizing false positives. However, its recall score was slightly lower at 0.79, meaning it successfully identified a substantial portion of defective samples, though it missed some. The F1-score for EfficientNet stands at 0.82, reflecting a balanced performance in both precision and recall. This balanced F1-score makes EfficientNet appropriate for quality control scenarios where both false positives and false negatives need to be minimized. Faster R-CNN achieved an accuracy of 85.00%, comparable to EfficientNet. Its region proposal network enhances its capability to localize and classify defects,

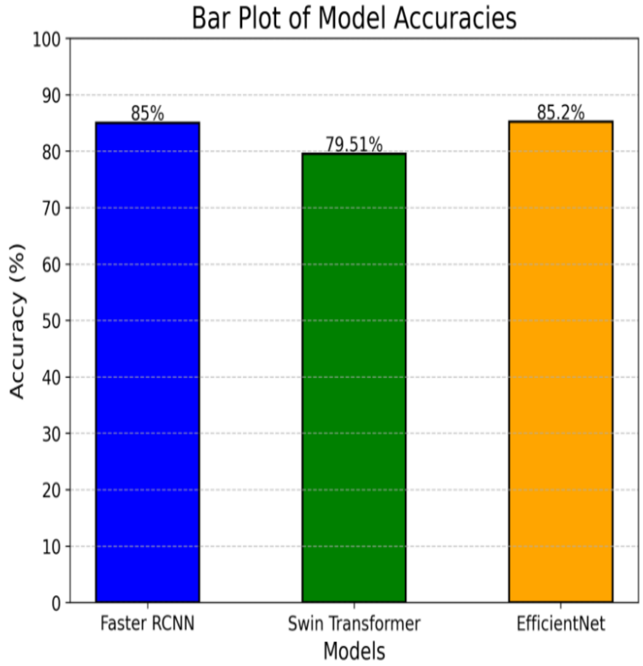

Figure 2: Bar Plot of Model Accuracies

making it highly accurate for this task. The model also achieved a high precision of 0.86, effectively reducing the number of false positives due to its fault detection capabilities. With a recall of 0.85, Faster R-CNN successfully identified nearly all defect instances in the dataset, surpassing EfficientNet in this regard. The F1-score for Faster R-CNN was 0.85, showing balanced performance in both defect identification and localization. This score makes Faster R-CNN particularly suitable for quality control applications where minimizing missed defects is critical. As shown in Figure 3, defects are marked on the segmented images using bounding boxes, providing a visual representation of the model's localization capabilities.

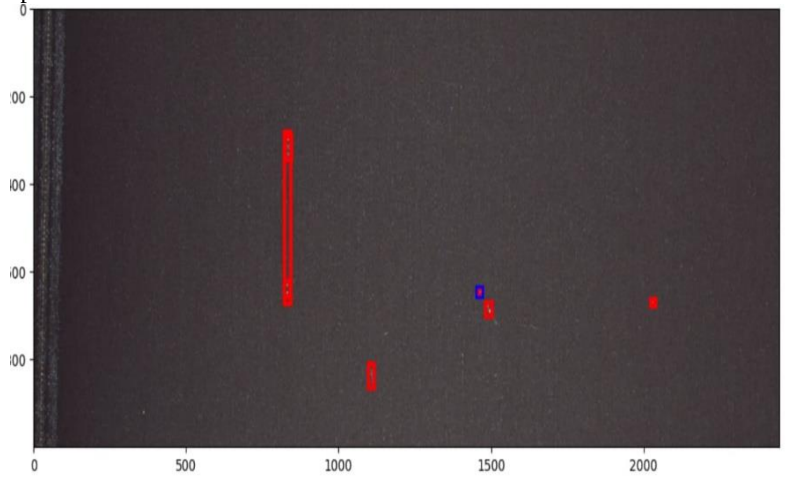

Figure 3: Defect Detection Visualization on Sample Fabric Image using Faster R-CNN model

Swin Transformer achieved an accuracy of 79.51%, which, although lower than EfficientNet and Faster R-CNN, demonstrates reasonable performance in distinguishing defective images. The model recorded a precision of 0.795, indicating a fair degree of reliability in identifying defective samples, though with a higher false-positive rate compared to the other models. Swin Transformer's recall was also 0.7952, showing consistency with its precision, though it did not reach the same effectiveness as Faster R-CNN in identifying all defect instances. The F1-score for

Swin Transformer was 0.795, reflecting a steady, yet slightly lower, performance compared to EfficientNet and Faster R-CNN. The hierarchical structure and self-attention mechanism of Swin Transformer are advantageous for capturing complex textures, yet the model may be less optimized for binary classification tasks in defect detection.Table 1 presents a summary of the performance metrics for the defect detection models, including Train Accuracy, Precision, Recall, F1-Score, and Loss.

Table 1: Performance Metrics for Defect Detection Models

Model	Train Accuracy	Precision	Recall	F1-Score	Loss
Faster R-CNN	85.00%	0.86	0.85	0.85	0.142
Swin Transformer	79.51	0.79	0.79	0.79	0.434
EfficientNet	85.20	0.86	0.79	0.82	0.435

4.2 Comparative Analysis

Results of the comparison indicate that the Faster R-CNN could recall the better result at 0.85 and F1-score, which means its model efficiency in discovering more defects with fewer false negatives. EfficientNet scored slightly higher than the other with an accuracy score of 85.20%, with a higher recall but slightly lower overall classification accuracy, so that will fit better the tasks that require balanced accuracy with full defect detection.

Although promising with a hierarchical attention mechanism, overall metrics were relatively lower than EfficientNet and Faster R-CNN. Balanced precision and recall at a slightly lower level of 0.795 mean that the Swin Transformer possibly gets overoptimized for just the binary classification of the defect. However, architecture benefits more tasks requiring more detailed extraction of features or might possibly work better in the case of complex fabric textures.

The performance metrics entail that Faster R-CNN is the most consistent model for binary detection, especially concerning recall and F1-score. That would be the ideal where the application requires every detected defect to be successfully realized. EfficientNet balances its accuracy and computational efficiency accordingly, and therefore it makes the network perfect for real-time applications of quality control. Swin Transformer lags by a bit in terms of performance but may find applications in hybrid models or tasks that require processing very intricate textures and patterns on fabrics.

5 Conclusion and Future Scope

This paper evaluates the performance of EfficientNet, Faster R-CNN, and Swin Transformer in the binary classification process regarding fabric defects based on the Alibaba Cloud Tianchi Guangdong Fabric Defect Detection dataset. Among all the models tested, Faster R-CNN showed the highest recall and F1-score, making it suitable for applications in defect detection that require high sensitivity. Of these models, EfficientNet achieved the highest overall accuracy, which balanced performance with computational efficiency, while Swin Transformer showed promise for dealing with complex textures at a slightly reduced performance level. In summary, it is found that Faster R-CNN and EfficientNet have an advantage in industrial applications where defect detection is crucial for quality.

Our future work is to extend the current model towards discrimination among various classes of defects in fabrics. This would shift the model from a simple class classification model to a multi-class detection model. Such an extension may help in more comprehensive defect analysis, which is very critical for advanced quality control. Further optimization of these models for real-time processing on edge devices and hybrid architecture may improve their applicability in the textile industry and thus support the automation of quality inspection and potentially cut costs.

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