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Exploration of CNN Architectures for Enhanced Fabric Defect Detection

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Abstract

Detecting fabric defects is crucial to ensure quality control in the textile industry. Convolutional neural networks (CNNs), are inspired by recent advancements in deep learning. Deep learning offers notable upgrades over traditional methods. It has been proven that they are highly effective in automating and enhancing the accuracy of error detection processes. This study provides a comparative overview of four well-known CNN architectures used specifically for fabric defect detection: AlexNet, VGG16, Inception V3, and ResNet50. The analysis examined each model's architecture, performance, and suitability for detecting fabric defects, highlighting their strengths and limitations. AlexNet provides a solid foundation with moderate accuracy, whereas VGG16 offers a deeper feature extraction at the expense of computational power. Inception V3 features an optimal balance between accuracy and speed, making it highly effective for real-time applications. ResNet50 with the remaining connections achieves the highest accuracy, especially when combined with advanced techniques such as Faster R-CNN. Despite progress, challenges remain, such as detecting different fabric patterns and small defects and suggesting future research approaches in the areas of hybrid models, data augmentation, and transfer learning. This report highlights the significant impact of advances in CNNs on fabric defect detection and provides insights into potential improvements to increase accuracy and efficiency further.

Keywords

Accuracy Optimization in AI Models, AlexNet for Image Analysis, Convolution Neural Networks, Dataset Augmentation, Deep Learning Applications, Explainable Artificial Intelligence (XAI), Fabric defect detection, Future Trends in Textile Inspection, Hybrid Deep Learning Models, Inception v3, Machine Learning for Manufacturing, Quality Assurance in Textiles, Resnet 50, ResNet Architecture, VGG16.

INTRODUCTION

In the textile industry, fabric defect detection is essential for ensuring product quality and reducing waste. Traditional methods have typically depended on manual inspection or simple image processing techniques, which are both time-consuming and prone to errors. These methods raise costs and often give inconsistent results, making quality control difficult. Crucial changes have been brought to this field by the progress of deep learning techniques, primarily Convolutional Neural Networks (CNNs), which offer more digitized, accurate, and efficient solutions. CNNs can learn patterns from raw images without needing manual feature extraction, making defect detection more consistent and reliable [1].

Many convolutional neural network (CNN) architectures have been developed and trained to perform various computer vision tasks including defect detection in fabric [2]. Representative models in this field are AlexNet, VGG16, Inception V3, and ResNet [3] [4] [5] [6] [7] with respective strengths and weaknesses depending on the nature of the fabric defects and application requirements of the inspection process. As an example, AlexNet is also cited for its simple architecture and operational practicality, which is ideal for the detection of significant defects. Conversely, VGG16, with its more intricate architecture, is adept at capturing subtle details, which is particularly beneficial for detecting smaller or less apparent defects. Multi-scale strategy is used by Inception V3 to detect defects of different scales so that it can be generalized beyond fabrics. During the meantime, the use of residual connections in the ResNet allows easier training of deeper networks and allows the model to learn more complex patterns and obtain better performance in fabric defect detection.

Although promising results are achieved by these CNN architectures, the selection of the optimal CNN model for the fabric defect detection is subject to some factors such as dataset size and defect type, and the computational resources available. For example, with deeper networks like ResNet, more computational power and longer training times might be necessary, but deeper networks can achieve better accuracy for more difficult detection tasks. By way of contrast, lighter architectures such as AlexNet could provide higher efficiency for real-time tasks but could not perform as well in more difficult defect detection contexts. Therefore, a careful evaluation and comparison between these models is essential to extract the understanding of the performance and suitability of these models in different fabric defect detection environments.

This paper reviews the use of different CNN architectures in fabric defect detection, showcasing their contributions to advancements in computational intelligence and image analysis. By using these architectures, the textile industry can improve defect detection accuracy, reduce the need for manual work, simplify quality control, and quickly spot issues in real-time, helping to reduce waste and respond faster during production.

LITERATURE REVIEW

Background of CNN Architectures

There Visual data is studied and understood using Convolutional Neural Networks (CNNs), which are innovative deep-learning models designed specifically for this purpose. They consist of multiple layers that automatically learn features from images, including convolutional layers, pooling layers, and fully connected layers as shown in figure 1. CNNs have shown remarkable success in various image-based tasks due to their ability to capture complex patterns and hierarchical features. An outline of the basic principles of CNNs and their importance in detecting fabric defects is offered in this section. [3].

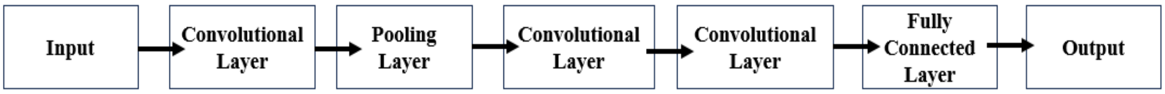

Figure 1. Basic CNN Architecture

CNNs typically consist of several key layers

- Convolutional Layers: These layers implement convolution operations to identify features within images. They use kernels to scan over the input image and detect patterns.
- Pooling Layers: The dimensionality of feature maps is decreased by pooling layers while preserving key information. Typical pooling operations, including max pooling and average pooling, are utilized.
- Fully Connected Layers: These layers use the attributes extracted by the convolutional and pooling layers to perform classification. They connect all neurons in the previous layer with each neuron in the current layer.

OVERVIEW OF CNN ARCHITECTURES

AlexNet Model

AlexNet was invented by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, and is identified as one of the primary deep learning architectures. [3] [4]. An immense, deep convolutional neural network was trained to categorize the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into 1000 classes. The top-1 and top-5 error rates of 37.5% and 17.0% were achieved on the test data, representing a significant improvement over the previous cutting-edge technology. This gives a final neural network with around 60 million parameters and 650,000 neurons. They used five convolution layers, three pooling layers with two dense layers, and a Soft-Max layer for classification as shown in figure 2. It uses non-saturating neurons and an efficient GPU for the convolution. They also applied a newly developed regularization method since one of their models did not have drop-out in the fully connected layers. An alternative of this model was also entered into the ILSVRC-2012 contest. It achieved a top-5 test error rate of 15.3%. This performance was better than the next-best entry. The second-place entry had a rate of 26.2%. AlexNet brought several features to the architecture table; these include ReLU activations and dropout.

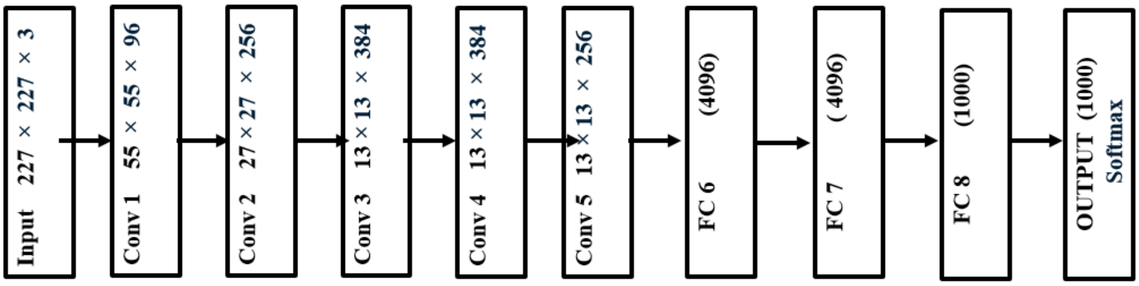

Figure 2. An AlexNet Architecture

AlexNet's innovations include:

- Instead of tanh and a batch size of 128, it uses the ReLU activation function. The SGD Momentum algorithm was used for model training.
- Dropout Regularization was used to randomly drop out some of the units during training, thus reducing the overfitting problems.
- Data augmentation techniques like Flipping, jittering, cropping, and color normalization were used to improve model performance.

VGG16 Model

The Visual Geometry Group at the University of Oxford built VGG. VGG16 can be described as a convolutional neural network whose architecture has been designed in depth and with an equal distribution of its layers. It provided a top-5 accuracy of 92.7% on the image net dataset. This dataset includes over 14 million images across 1000 classes. Unlike AlexNet, instead of large filters, VGG16 uses several 3×3 filters which leads to better performance. Because of the small size of 3×3 convolutional filters, it performs well in tasks of image classification. It was trained using Nvidia Titan Black GPUs. It is popular for its strong image classification capabilities. It handles 224x224 image inputs.

VGG16 is a deep neural network that includes 16 layers. It has around 138 million parameters. It is a simple and uniform architecture. As shown in Figure 3, it has 13 convolutional layers and 3 fully connected layers.

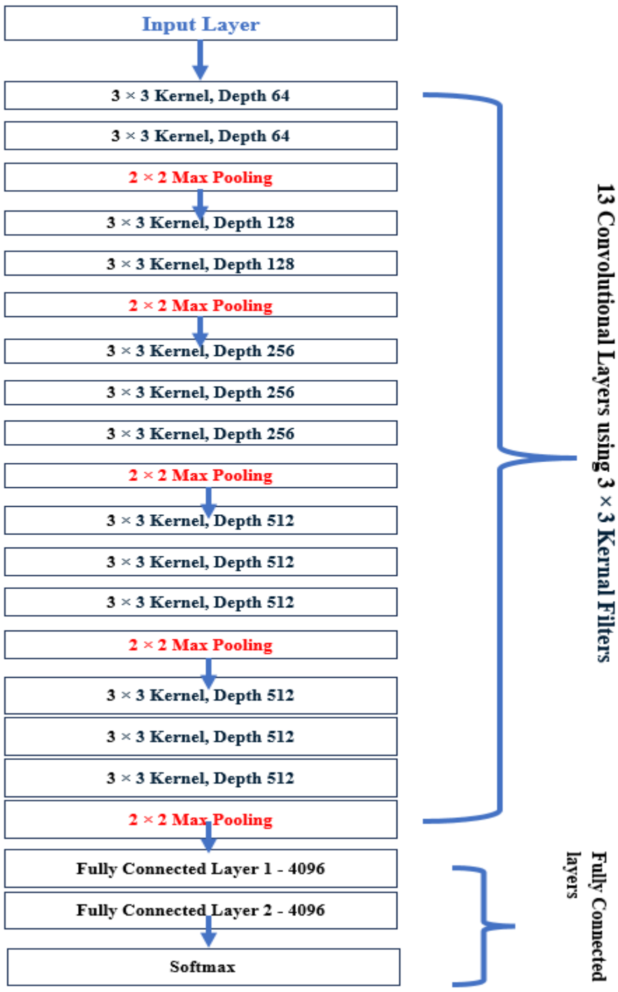

Figure 3. VGG16 Architecture

In VGG16, 64 filters of size 3×3 are used in the first and second convolutional layers, The input is transformed to 224x224x64 by the first and second convolutional layers, followed by max pooling with a stride of 2. The third and fourth layers use 128 filters of size 3×3. After max pooling with a stride of 2, the dimensions are reduced to 56x56x128. The fifth through seventh layers utilize 256 filters of size 3×3, followed by max pooling. The eighth through thirteenth layers incorporate 512 filters of size 3×3. Max pooling with a stride of 1 is then applied. The final two layers are fully connected with 4096 units each, culminating in a final softmax output layer with 1000 units. [5].

VGG16 innovations include:

- VGG-16 incorporates 13 convolutional layers and 3 fully connected layers. It is deeper than former networks such as AlexNet.
- It uses the same size 3x3 convolutional filters throughout the network. Thus, it allows the network to capture more fine-grained details.
- It uses a 3x3 uniform sequence of convolutional layers succeeded by max-pooling layers. It makes the model simpler while increasing its depth.
- VGG-16 was pre-trained on the large ImageNet dataset. It allows it to perform exceptionally well on various image recognition tasks.
- VGG-16 has been widely used as a foundation model for transfer learning in various computer vision tasks due to its performance.
- Convolutional layers are succeeded by max-pooling layers which reduce spatial attributes, output of the max-pooling layer is given as an input to fully connected layers which record high-level features of an image.

Inception models

Overfitting is avoided by Inception V1 through the use of multiple filters of different sizes at the same level, resulting in a wider model rather than a deeper one. Four types of layers are included in each Inception module: 1×1 convolution, 3×3 convolution, 5×5 convolution, and 3×3 max pooling. Various details in the image are captured by this design. The initial model was computationally expensive, with the 5×5 convolution layer being particularly costly. Efficiency was enhanced by adding a 1×1 convolutional layer before each convolutional layer, which reduced dimensions and speed up computations, as depicted in figure 4 [6].

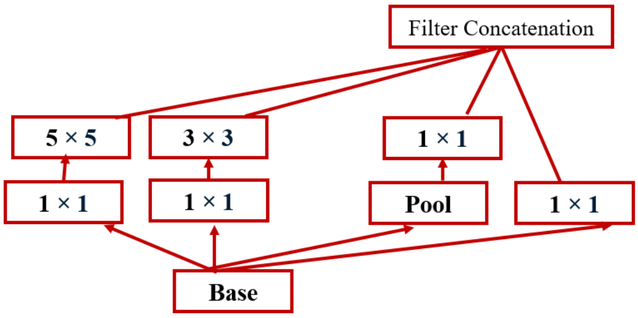

Figure 4. Inception V1 Architecture

Inception V3 was introduced in 2015. It is a more advanced and efficient version of Inception V1. The network is deeper and balances speed with accuracy. Inception V3 is used for image analysis and object detection. It is computationally less expensive. The model has 42 layers and achieves a lower error rate than previous versions. Key improvements include breaking down large convolutions into smaller ones. It uses asymmetric convolutions and adds auxiliary classifiers for regularization [8]. The model also reduces grid sizes efficiently, as shown in Figure 5. Originally part of GoogLeNet, Inception V3 is the third version of Google's Inception network for the ImageNet Recognition Challenge. The design aims to deepen the network without adding too many parameters. Inception V3 has fewer than 25 million parameters, compared to AlexNet's 60 million. It helps classify objects in computer vision. The design is often pre-trained on ImageNet and used in various applications, including life sciences research such as studying leukemia [9].

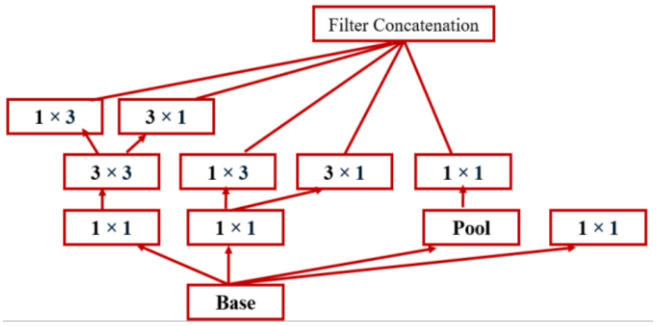

Figure 5. Inception V3 Architecture

Key innovations of Inception V3 include:

- Inception V3 uses filters of different sizes together to capture more fine details.
  It makes the model more computationally efficient by breaking down 5x5 convolutions into two 3x3 convolutions.
- It reduces the computational cost and also maintains accuracy by using asymmetric convolutions i: e., 3x1 followed by 1x3.
- Auxiliary classifiers are added during training, the model can more quickly figure out the best weights to minimize the loss function, which leads to better overall performance.
- The Root Mean Square Propagation is used to adjust learning rates based on recent gradients that improve training efficiency.

Residual Neural Networks

ResNet was first introduced in 2015. ResNet won the ImageNet competition in 2015 and made residual connections widely popular [7]. Today, this approach is commonly used in many neural networks, including Transformers (like BERT and GPT), as well as in AlphaGo Zero, AlphaStar, and AlphaFold [10] [11] [12]. It is a deep convolutional layer network. It uses residual connections where the layer output is added to its input improving training stability. It allows deeper networks. ResNet50 consists of 50 layers.

ResNet50 is a powerful image classification model. It uses residual connections to train deeper networks effectively without facing vanishing gradient issues. Its architecture includes four main parts: convolutional layers for extracting features, identity, and convolutional blocks for processing and transforming these features, and fully connected layers for making the final classification as shown in Figure 6. Convolutional layers apply batch normalization and ReLU activation, while identity blocks add the input back to the output to learn residual functions. Convolutional blocks include a 1x1 convolution to reduce the number of filters. The final classification is performed by the fully connected layers, with the output passed through a softmax function to determine class probabilities [13].

Key innovations of Resnet include:

- ResNet uses skip connections which allow the network to learn differences from the input instead of direct mappings. Thus, deep networks are trained by reducing the vanishing gradient problem.
- The degradation problem occurs when we try to add more layers to the network. It enables the user to train networks up to 152 layers and solves degradation problems.
- Identity mapping is used through skip connections. It allows the gradients to flow directly through the network. It makes backpropagation more effective in deep layers.
- It uses 1×1 convolutions to lower the number of parameters and computational cost while preserving the network deep.
- Many neural networks were inspired by the popularity of ResNet's architecture. Thus, most deep neural networks use residual connections as a common element in their design.

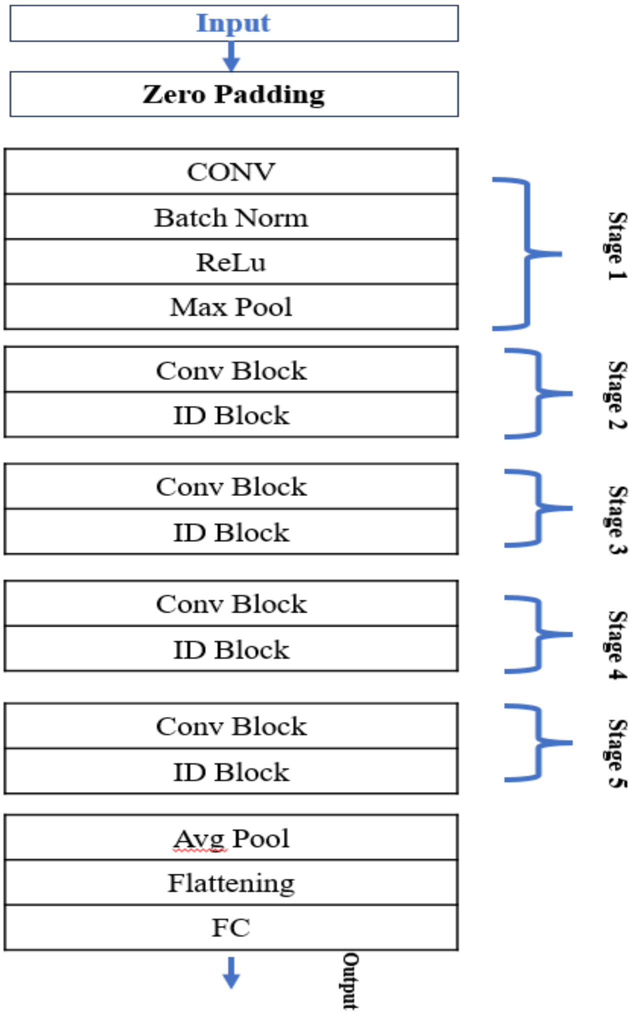

Figure 6. ResNet50 Architecture

COMPARATIVE ANALYSIS

K. K. Sudha et al. [14] tested the effectiveness of two Convolutional Neural Networks (CNNs), GoogLeNet and AlexNet, for detecting textile defects. They used 200 fabric images from the 'Cotton Incorporated database. Initially, Image preprocessing is done by converting them to grayscale followed by noise cleaning with a Wiener filter. Both networks were trained and tested on the pre-processed images. The results showed that GoogLeNet surpasses AlexNet regarding training speed, accuracy, and other parameters. GoogLeNet, with its 22 layers and advanced Inception modules, achieved 100% accuracy and faster training times where as AlexNet's achieves 90% accuracy and shows slower performance. The authors conclude that GoogLeNet is the best choice for fabric defect detection. They suggested that future work could involve developing hybrid CNN models to achieve better performance.

Syeda Rabia Arshad et al. [15] demonstrate using deep learning models, ResNet and VGG-16, for fabric defect detection. They clearly explained why automating this process is important for enhancing fabric quality and cost reduction, and they also showed how deep learning manages the drawbacks of older methods like Gabor filters and grey-level co-occurrence matrices. Their results proved that VGG-16 is more effective than ResNet. VGG-16 achieves an accuracy of 73.91% whereas ResNet's archives an accuracy of 67.59%. The researchers used diverse fabric images of the One-shot dataset, TILDA, and Kaggle fabric defect dataset for testing. They used various deep learning methods to detect the different types of fabric defects such as warp, weft, and holes. This research focuses on detecting one defect per image. If different types of defects are present in a single image, further upgrades can help to detect them.

Meng An et al. [16] developed an enhanced fabric defect detection method. They combined Faster R-CNN model with a deep residual network (Resnet). It helped for better feature extraction. Additionally, they incorporated a feature pyramid network with the existing model. It gives effective multiscale integration. As a result, it allows the model to identify defects of varying sizes and shapes more effectively. Furthermore, the softmax function was used to convert model outputs into probabilities, which improves training accuracy and convergence. A hybrid model shows a 4.35% increase in average precision (AP), reaching 94.66%. Thus it demonstrates faster optimization and better detection performance. Future work will concentrate on improving the model's accuracy and enhancing its real-time detection capabilities.

Sitompul et al.[17] discuss a deep learning method for fabric defect classification with ResNet50 architecture via transfer learning; the authors implemented this in FastAI. The task is the classification of fabric images into the five classes: good, burned, frayed, ripped, and stained using an online gathered database. The system achieved 92.5% accuracy for two categories and 70.3% accuracy for all five categories during offline testing. When tested online with a smartphone camera, the 5-class model achieved 75.6% accuracy. This work demonstrates using a cyclical learning rate for the optimization of model performance, yet it concedes that more exists to be optimized into real industrial uses. Despite promising the automation of defects' classification on fabrics in manufacturing lines, the underlying work still indicates that the accuracy must be improved, along with an increase in processing speed, to become practically useful for larger-scale utilization.

Abdulkadir Seker et al. [18] illustrates an analysis of fabric defect detection through transfer learning using a pre-trained AlexNet model, and this addresses the significant challenge in textile industries. Their need involves accurate and rapid detection of fabric defects to limit the occurrence of financial losses and health issues. Seker demonstrated the superiority of transfer learning in overcoming the limitation of limited labeled data, with an image dataset of 3,725 samples composed of defective materials, out of which 936 samples were defective. Data augmentation to increase the size of datasets contributed significantly to a remarkable increase in accuracy levels for this study, from 75% when trained from scratch to the impressive 98.75% with the application of transfer learning. This development shows the practical feasibility of automated fabric defect detection systems, which will reduce dependence on manual inspection to have good prospects for improvement in quality in fabric production. Finally, it points out future directions for further research, where a much larger dataset is suggested, and pre-trained models are explored as inputs for further enhancing the technique of fabric defect detection. Overall, it narrates a very significant insight into deep learning applications and how they can be applied to the textile industry through techniques involving automation and better-quality control mechanisms.

A deep learning-based approach for detecting fabric defects was introduced by Xiang et al [19] to address common challenges in traditional methods, such as low accuracy, high costs, and difficulty in identifying smaller defects. Two models are used in their system: Inception-V1 for predicting local defects and LeNet-5 for identifying defect types on a larger scale. The detection process was improved by applying image enhancement techniques. Several well-known deep learning models—AlexNet, VGG-16, Inception-V1, Inception-V2, Inception-V3, and ResNet-50—were compared by the researchers, and it was found that Inception-V1 offered the best balance between speed and accuracy, achieving a strong 96% accuracy rate. However, the system faced challenges in determining the exact reasons behind the defects. The researchers believe that making future improvements—such as gathering better data and refining defect classification—could significantly enhance the system. This could lead to a major shift in fabric inspection within the textile industry, moving from manual checks to more efficient automated processes.

Table 1. Summary of Deep Learning-Based Fabric Defect Detection Approaches

Author(s)	Dataset	Performance Evaluation Criteria	Proposed Model and Purpose
K. K. Sudha et al. [14]	Cotton Incorporated database (200 images)	Accuracy (GoogLeNet: 100%, AlexNet: 90%)	Used GoogLeNet and AlexNet to detect textile defects, comparing their performance. GoogLeNet's 22 layers and Inception modules outperformed AlexNet in terms of speed and accuracy, achieving 100% accuracy
Syeda Rabia Arshad et al. [15]	One-shot, TILDA, Kaggle fabric defect dataset	Accuracy (VGG-16: 73.91%, ResNet: 67.59%)	Applied VGG-16 and ResNet for automating fabric defect detection. VGG-16 proved more effective, addressing challenges like warp, weft, and holes for better quality control and cost reduction.
Meng An et al. [16]	TILDA dataset and Tianchi fabric defect dataset.	Average Precision (94.66%)	Enhanced Faster R-CNN with ResNet and a Feature Pyramid Network to detect defects of varying sizes and shapes. The model showed improved accuracy, multiscale integration, and faster optimization.
Sitompul et al. [17]	Online-gathered database	Accuracy (5-class: 70.3%; 2-class: 92.5%)	Utilized ResNet50 via transfer learning to classify fabric images into five defect categories: good, burned, frayed, ripped, and stained, aiming to automate defect classification in manufacturing lines.
Abdulkadir Seker et al. [18]	Fabric dataset (3,725 samples; 936 defective)	Accuracy (98.75%)	Leveraged a pre-trained AlexNet with transfer learning to detect fabric defects. Transfer learning enabled high accuracy and efficiency with limited labeled data, reducing reliance on manual inspections.
Xiang et al. [19]	Fabric image dataset (2000 defective, and 3000 without defects, sourced from the Tianchi competition (https://tianchi.aliyun.com/competition/entrance/231666/information	Accuracy (Inception-V1: 96%)	Combined Inception-V1 for detecting local defects and LeNet-5 for classifying defect types. The method enhanced fabric inspection processes, addressing challenges like small defect detection and accuracy.

Jing et al. [20] proposed an automatic method of deep convolutional neural network-based fabric defect detection intended to enhance the accuracy and minimize the labor effort in the textile quality control process. Their approach involves breaking the images of the fabrics into patches, labels their patches and then applies transfer learning using a pre-trained CNN on those patches to identify defects. In the Results part, there are three sets of experiments: TILDA, Dark Red Fabric, and Patterned Fabric. Here, state-of-the-art techniques are surpassed by accuracy of up to 98.43%. Even though the approach requires large datasets and careful patch size selection, it's well justified in a real-time industrial inspection of fabrics. The authors have the idea of designing new architectures and introducing defect segmentation to improve performance.

VARJOVİ et al. [21] created a customized deep convolutional neural network (CNN) specifically for circular knitting fabrics, achieving an impressive classification accuracy of 97%. This performance significantly outshines established pre-trained models like InceptionV3, which only reached 78% accuracy. One of the key advantages of their simpler CNN design is its ability to prevent overfitting, allowing the network to operate effectively with fewer parameters. The research team tackled a challenging dataset containing 13,820 images, rigorously testing their model against several well-known pre-trained architectures. Their approach proved to be both efficient and practical, with a training cycle that lasted just 14 epochs and an average detection time of 15.4 milliseconds. These findings highlight the benefits of using tailored neural networks, showing that they can serve as viable alternatives to more complex models that might arise from future developments.

Chakraborty et al.[22] proposed a new ADD methodology of printed fabrics by a deep CNN. It is a required gap in the academic literature on the detection of printing defects in textiles because it is increasing day by day with the passage of time due to increased demand for quality control in fashion supply chains. The proposed CNN model successfully classified the defects using a training dataset of images collected from eight knit apparel production facilities in

Bangladesh. The two most common defects incorporated in the study were spots and misprints. Although the raw training dataset was limited, consisting of only 200 images, the dataset was augmented to 800 images through an array of augmentation techniques. Consequently, validation resulted in a 62% accuracy rate. Proceeding to the broader reality of integration of machine learning into the traditional print, it has the potential to allow real-time defect detection. As the size of datasets, architectural complexity, and print pattern diversity are improved, it is postulated that the ability of the ADD to reduce waste and improve quality in the textile industry can go really high, providing a robust basis for further work in subsequent research studies and their practical application within the industry.

Jun-Feng Jing et al.[23] describes a novel approach for fabric defect detection based on deep convolutional neural network (DCNN) trained on local regions of fabric images. The method is very robust in nature achieving an average value of 97.31% when tested on three different fabric datasets. When the model is pretrained with MNIST dataset, the value increases to 98.43%. The method consists of cutting fabric samples to patches, applying transfer learning and scanning for defects through the whole image. The results show that the proposed method is most effective on TILDA fabric and patterned fabric, while common stains, holes and scratches are also detected. The method has been reported to be more effective and faster than the normal techniques and other deep learning architectures such as LeNet, alexnet and vgg16. In summary, it is trustworthy, efficient and rapid in terms of fabric defect detection.

Vishwath et al. [24] proposed a novel technique to improve the accuracy of the textile industry's fabric defect detection by implementing a novel combination between the ResNet-50 and Vision Transformer (ViT) models. This dual approach is advantageous as it allows capturing both small and larger details in fabric images. Moreover, using imaging techniques such as Fourier transforms and notch filter enhances the image quality even further. A recognition accuracy of 98.5% is recorded which is better than ResNet-50 (93.4%) and ViT (96.5%) when the models are each used singularly on the MVTec AD dataset. The system exhibits good resistance to overfitting especially with small datasets and can be utilized under various manufacturing environments. It is useful since it automates the process allowing for reduction in time and costs which would otherwise have been incurred if the manual approach was employed. This therefore increases productivity and the overall quality of inspection.

Table 2. Summary of Deep Learning-Based Fabric Defect Detection Approaches

Author(s)	Dataset	Performance Evaluation Criteria	Proposed Model and Purpose
Jing et al. [20]	TILDA, Dark Red Fabric, and Patterned Fabric datasets	Accuracy (up to 98.43%)	Used a Deep CNN with transfer learning to detect defects by segmenting fabric images into patches. The approach aimed to improve textile quality control accuracy and reduce manual inspection efforts.
VARJOVİ et al. [21]	Circular knitting fabric dataset (13,820 images)	Accuracy (Customized CNN: 97%)	Designed a customized deep CNN specifically for circular knitting fabrics. It avoided overfitting and achieved efficient defect detection with fewer parameters and high accuracy.
Chakraborty et al. [22]	Dataset of printed fabrics (200 images augmented to 800)	Accuracy (62%)	Proposed a deep CNN to classify printing defects in textiles, addressing spots and misprints. This work focused on improving quality control in the fashion industry supply chain.
Jun-Feng Jing et al.[23]	TILDA, dark red fabric, patterned fabrics (box, dot, star)	Accuracy, real-time performance, robustness, defect detection accuracy	Deep Convolutional Neural Network (DCNN), pretrained on MNIST, Develop a fabric defect detection method using DCNN trained on local fabric patches to improve defect detection accuracy and efficiency.
Vishwath et al. [24]	MVTech AD	Accuracy: 98.5% Validation Performance Comparison with ResNet-50 and ViT	Hybrid model combining ResNet-50 and Vision Transformer (ViT), with Fourier Transform and Notch Filter preprocessing, To develop an automated fabric defect detection system that improves accuracy and efficiency in textile industry quality control.

CONCLUSION AND FUTURE SCOPE

The implementation of deep learning models in the textile sector to detect fabric defects has the potential to bring about a revolution to the entire manual inspection system. There are several models such as AlexNet, VGG-16, Inception V3, and ResNet50 which have successfully and rapidly detected the defects in the fabrics. However, from the lot, Inception-V has the maximum importance owing to its efficiency and expediency. Although the application of methods such as image enhancement has improved the detection process, the remaining tasks include the identification of minute defects and the attempt to detect different types of defects from a single image.

In the future, researchers will focus on integrating hybrid architectures or using larger datasets to increase fabric defect detection accuracy and speed. Moreover, ResNet with transformers would act as an advanced architecture that would improve the operational efficiency and its dynamics in real life. These systems can be self-sufficient in the sense that they might evolve to a point where they can detect many forms of defects from one image and be incorporated into manufacturing systems that improve their productivity and productivity. In addition, explainable artificial intelligence increases the credibility and trust in the use of artificial intelligence for decision-making by enabling the users to understand how AI-managed decisions occur. As well, automated methods enable businesses to crowd-source dataset training without having to remotely supervise the process. Then, incorporating all these aspects will enable low-cost micro-enterprises to apply this technology thus transforming the operations of industries with quality control technology in fabric that is more effective than manual inspections.

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