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Complex Pattern Jacquard Fabrics Defect Detection Using Convolutional Neural Networks and Multispectral Imaging

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ABSTRACT Manual inspection of textiles is a long, tedious, and costly method. Technology has solved this problem by developing automatic systems for textile inspection. However, Jacquard fabrics present a challenge because patterns can be complex and seemingly random to systems. Only a few in-depth studies have been conducted on jacquard fabrics despite their important and intriguing nature. Previous studies on jacquard fabrics are of simple patterns. This paper introduces a new and novel field in fabrics defect detection. Complex-patterned jacquard fabrics are much more challenging. In this paper, novel defect detection models for jacquard-patterned fabrics are presented. Owing to the lack of available databases for jacquard fabrics, we compiled and experimented on our own novel dataset. Our dataset was collected from plain, undyed jacquard fabrics with different complex patterns. In this study, we used and tested several deep learning models with image pre-processing and convolutional neural networks (CNNs) for unsupervised detection of defects. We also used multispectral imaging, combining normal (RGB) and near-infrared (NIR) imaging to improve our system and increase its accuracy. We propose two systems: a semi-manual system using a simple CNN network for operation on separate patterns and an integrated automated system that uses state-of-the-art CNN architectures to run on the entire dataset without prior pattern specification. The images are preprocessed using contrast-limited adaptive Histogram Equalization (CLAHE) to enhance their features. We concluded that deep learning is efficient and can be used for defect detection in complex patterns. Proposed method of EfficientNet CNN gave high accuracy reaching 99% approximately. We also found that multispectral imaging is more advantageous and yields higher accuracy.

INDEX TERMS Complex patterns, convolutional neural networks, fabric defect detection, jacquard, multispectral imaging.

I. INTRODUCTION

The development of a flexible, efficient, reliable, and integrated real-time vision system for industrial applications is an essential issue in quality control processes in various industries. The textile industry is one of the most critical industries in terms of quality assurance. In the textile industry, fabric is classified as first-grade or second-grade fabric based on its quality. This classification is based on the type and frequency of the defects in the fabric. If the fabric has no major or prominent surface defects that disturb it, the fabric is considered to be of first quality. Otherwise, major defects and/or frequent minor defects reduce fabric classification to second-grade quality. If these defects are detected during production or before shipping, they can be treated or prevented to conserve production resources. Second-grade fabrics lead to major revenue losses. They can be sold for only 45%-65% of the original first-grade fabric price. Undetected fabric defects cause at least 50% of second-grade fabric production [1].

Quality control reduces or prevents the unwanted production of low-quality fabrics. Traditionally, fabric defect detection has been performed both manually and offline. Weaving machines produce fabric in the form of large rolls that are carried to inspection stations for review. Sufficient lighting

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is applied from above or under the fabrics by machines or tables, for better detection of defects. The fabric rolls are then inspected at high speeds by skilled staff. Human inspection has many shortcomings owing to tiredness, boredom, and inattentiveness, resulting in accuracies of only approximately 60%-75% [2]. Therefore, we aim to avoid human error.

Besides human error, the late detection of defects can lead to the production of more second-grade fabrics. In large factories with high production rates, manual inspection can present a bottleneck in production. The solution would be to increase the labor force, which would lead to more expenses. Fortunately, technological advances in computer science and machine vision have introduced the possibility of automatic fabric inspections. An automated visual inspection system can be used for better quality control to increase the overall quality, homogeneity, and reliability of fabrics.

The purpose of this study is to introduce an automatic inspection system for jacquard-patterned fabrics to efficiently detect defects. The rest of the paper is organized as follows: Section II provides background information about jacquard-patterned fabrics. Section III reviews previous related studies on fabric defect detection. Section IV provides a brief overview of multispectral imaging and the reasoning for its use in our study. Section V presents the proposed systems. The results are presented and discussed in section VI. Finally, Section VII concludes the paper.

II. JACQUARD FABRICS

For any woven fabric, there are interlaced threads of yarns vertically aligned that are called "weft yarns", and horizontal threads running across the fabric that are called "warp yarns". These threads are efficiently interlaced together using loom devices to create fabrics. Traditional fabrics are created using dobby looms, which can only control the warp yarns in groups. Because the loom can control only a limited number of warp groups, patterns are limited in how complex they can be.

It was challenging to create complex pattern designs in fabrics hundreds of years ago. They had to be woven by hand, which was a long and painful process. In 1804, Joseph-Marie Jacquard created the Jacquard loom. This improved device could weave patterned fabrics based on predetermined designs by reading a long row of punched wooden cards. This form of "code reading" changed how patterned fabrics were created forever and was later adapted and used in computer technology. The term "jacquard" refers to the method of creating the pattern through weaving, not the specific pattern itself. A jacquard loom selectively lifts warp yarns to create a pattern. Today's jacquard looms allow control of each warp yarn individually. This allows the weaving of considerably more complex designs [3].

Jacquard fabrics are more complex than plain fabrics because they may have multiple repeated patterns in the same fabric. The Patterns in jacquard fabrics are both macro and micro. Multiple different micro patterns are present in the same fabric. Macro patterns are combinations of different

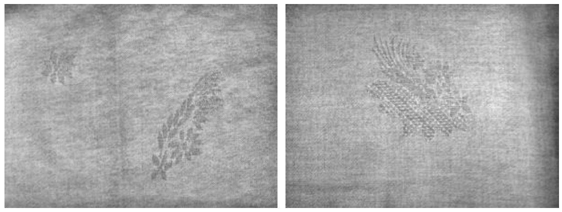

FIGURE 1. Jacquard macro pattern (P05) consisting of three different micro patterns in the same fabric.

micro patterns in a certain area, as shown in Fig.1. Jacquard fabrics have a wide array and range of complex and contrasting designs. An unlimited number of patterns and choices are allowed. We can achieve anything from stripes, paisleys, polka dots, and florals to very large complex, detailed, and difficult designs. Traditional fabrics can have patterns printed on them after they are woven. In contrast, jacquard fabrics exhibit woven patterns. This means that the pattern is created in conjugation with the cloth [4].

III. PREVIOUS WORK

Many previous studies have been conducted in the field of fabric defect detection using different methodologies and techniques. However, most of these studies were conducted on traditional fabrics. Very little research has been conducted on jacquard fabrics, despite the importance of automatic fabric inspection in such complicated fabrics. A short recap of some traditional fabric techniques is given. Then, a detailed review of jacquard fabrics is presented.

A. TRADITIONAL FABRICS

Many studies have been conducted on plain fabrics with great results and methods that achieve high accuracies. Most published papers consider fabric as a near-regular texture that may be degraded by defects of a repetitive background pattern fabric. These abnormalities can be discovered through the use of pattern and texture recognition. Hanbay *et al.* [5] presented one of the most recent and detailed reviews of traditional fabrics. The presented methods were categorized into seven categories: structural, statistical, spectral, model-based, learning, hybrid, and comparative studies. Among the reviewed methods some achieved favorable results such as cross-correlation and gray level co-occurrence in statistical approaches. Also, Gabor filters and wavelet transform in spectral approaches. However, those studies were mostly conducted on plain traditional fabrics with fewer studies conducted on patterned fabrics. However, defect detection in complex patterned fabrics, such as jacquard fabrics, requires more sophisticated methods and is much more challenging.

B. JACQUARD FABRICS

Based on our research, we categorize previous work on jacquard fabrics into two main fields: texture segmentation and defect detection. In texture segmentation, the goal is to extract the texture or pattern from the jacquard fabrics. Different methods have been used in previous studies, such as: Mumford-Shah model [6], phase-field model [7], [8], wavelet transform with K-means clustering [9], [10], multiresolution Markov random field (MRF) modeling [11], and multi-view image fusion [12].

Only a few contributions have been made to the field of jacquard fabric defect detection. This leaves the field open to new ideas. In [13], golden image subtraction (GIS) was used for defect detection in a dot-patterned jacquard. They also introduced a modified version combining GIS with wavelet transforms. However, this method was tested on a very small sample size, and the dot pattern can be considered simple because of its high periodicity. In [14], a defect detection method was introduced for a color-patterned jacquard fabric using multiple color channel analysis. This method uses neural networks for color separation, which segments the jacquard image into color channel images. Then, the color channel pattern was extracted and compared to characterize and detect defects. However, this method focuses on the colored jacquard fabric of square grids with no draw patterns.

From this review, we can see that there has been little in-depth research on pattern jacquard fabric defect detection. The area of complex-patterned jacquard fabrics defect detection is novel. Automatic defect detection in complexly patterned jacquard fabrics is very challenging and has a long way to go. However, it is very important and appealing. This study opens the gateways for defect detection in it.

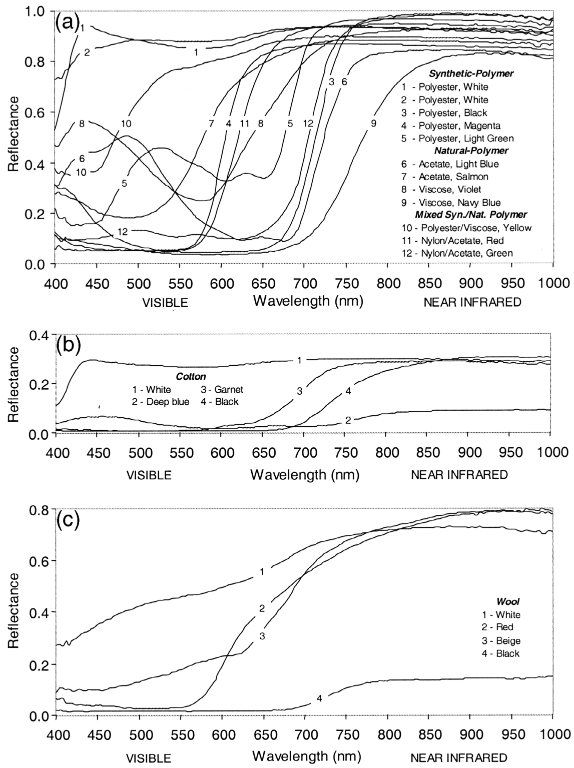

FIGURE 2. Spectral reflectance of fabrics of varied colors and compositions: (a) artificial fibers, (b) cotton and (c) wool [15].

IV. MULTISPECTRAL IMAGING

Generally, there are shortcomings in using a visual light source (VLS) to inspect patterned fabrics. The two main challenges in using VLS inspection are the lighting conditions and patterned fabric structure. For visual inspection, the lighting conditions should be uniform across the fabric. Unfortunately, this is easily affected by surrounding conditions, such as room illumination and daylight severity. Second, the pattern structures of square, line, circle, or similarly patterned fabrics can sometimes be mistaken for superstructure noise, where the texture pattern can be considered noise superimposed on the basic background. This could lead to the misdetection or under-detection of defects.

In this study, we considered the use of multispectral imaging in jacquard fabric inspection based on two properties. First, jacquard fabrics often use different yarn types for weft and warp. In addition, yarn threads can often be color-dyed to make colorful fabrics. Second, as mentioned previously, jacquard patterns are created by selecting and lifting warp yarns. Consequently, the patterns produced are naturally salient [3].

The first property was tested on traditional fabrics in [15]. The spectral reflectance of different fabric types and colors was tested. This shows that NIR imaging can provide better results, especially for colored patterns. In addition, combining different wefts and warps yarn types in jacquard fabrics can improve NIR imaging and image contrast. From Fig. 2, we can see that the spectral reflectance of different colors in an NIR image is nearly the same, with nearly uniform contrast. However, in VLS images, there could be much more contrast diversity.

The second property of saliency in jacquard fabrics makes multispectral imaging more appealing for defect detection. In jacquard fabrics, patterns are created by controlling hooks that selectively lift warp yarns as desired. This allows the creation of salient complex patterns. Fabric defect detection based on saliency has been studied previously [16], [17]. Studying the feature saliency of defects and considering them provided better results for defect detection. In [18] and [19], migrating from RGB to multispectral images improved unsupervised saliency detection. It was found that analyzing all the spectral bands of an input image in parallel can provide a higher amount of information compared to RGB images alone. This higher amount of information can allow a convolutional neural network (CNN) to find more complex features and better detect saliency.

In the Results section, we calculate the detection rate accuracy for RGB and multispectral imaging. The test results proves that multispectral imaging leads to higher accuracy.

V. CNN ARCHITECTURES

Recently, there has been a series of breakthroughs in deep learning and computer vision. Convolutional neural networks have become significantly deeper and more complex. These models have achieved state-of-the-art results for problems such as image classification and image recognition. They can solve more complex tasks and make them more robust. Several architectures exist in the field of CNNs. In the next subsection, we briefly present the architecture used in our study.

A. VGGNet

The runner-up in the ImageNet challenge (ILSVRC 2014) was VGGNet [20], as shown in Fig. 3. It showed that the network depth is a critical element for good performance. Their best network consists of 16 CONV/FC layers and has a very homogeneous architecture that only performs 3×3 convolutions and 2×2 pooling from start to end. However, the VGGNet has two major drawbacks. It has large network weights and is extremely slow to train.

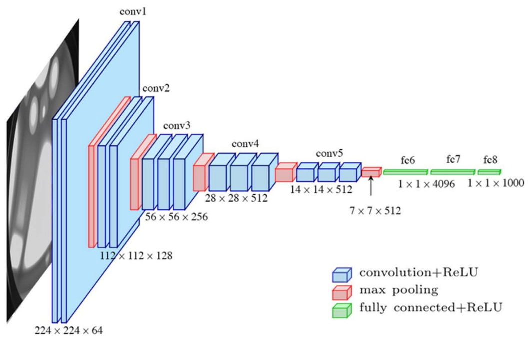

FIGURE 3. VGGNet architecture [21].

B. ResNet

Kaiming He *et al.* [22] developed a residual network, which was the winner of the ILSVRC 2015. ResNet allows training of much deeper networks by introducing residual blocks, as shown in Fig. 4. Residual blocks utilize the concept of skip connections, which allows for an alternate path for the gradient to flow through. This mitigates the vanishing gradient problem. The ResNet model is one of the most popular and successful deep learning models. ResNet skip connections have since been used in many other model architectures, such as the fully convolutional network (FCN) and U-Net.

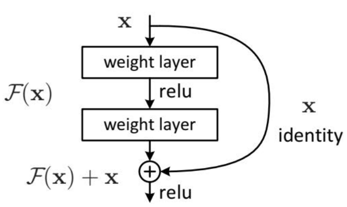

FIGURE 4. Residual block [22].

C. InceptionNet

The inception network is an important milestone in the development of convolutional neural networks (CNNs). The most popular CNNs simply stack convolution layers deeper and deeper, hoping to achieve better performance. The inception network, on the other hand, is complex and improves accuracy and speed using multiple tricks. InceptionNet has constantly improved, creating several versions.

The first inception deep convolutional architecture was introduced by Szegedy *et al.* [23] as GoogLeNet and was later named Inception-v1. Since then, the network has been refined in various ways. First, batch normalization was introduction in Inception-v2 [24]. Later, additional factorization ideas were introduced in the third version of Inception-v3 [25]. Inception-v4 [26] uses specialized "reduction blocks to change the height and width of the grid.

In addition, hybrid modules combining InceptionNet and ResNet achieve very good results. These are known as InceptionResNet v1 and v2, respectively. In this study, we used Inception-v3, as shown in Fig. 5, as it proved to be more computationally efficient, both in terms of the number of parameters generated by the network and memory cost.

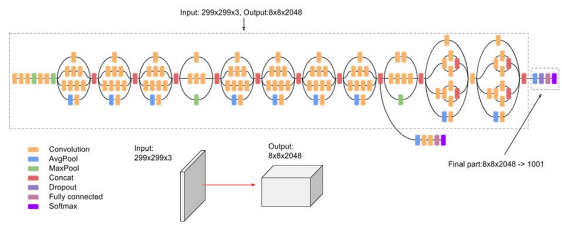

FIGURE 5. InceptionNetV3 architecture [27].

D. EfficientNet

Previously, the most common way to scale up CNNs was by one of three dimensions: image resolution (image size), depth (number of layers), or width (number of channels). The main concept of EfficientNet [28] is compound scaling. This implies scaling all three dimensions while maintaining a balance between all dimensions of the network.

However, the authors found that it was critical to have a good baseline network. Therefore, they also developed a new mobile-size baseline called EfficientNet using a neural architecture search. In particular, the baseline network is called Efficient-B0. Next, this baseline network was scaled using compound scaling to get Efficient B1-B7. The differences in the compound scaling are shown in Fig.6.

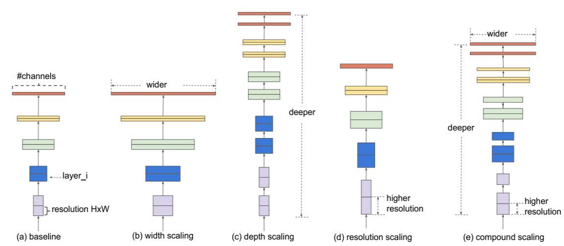

FIGURE 6. Model Scaling. (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) Proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio [28].

VI. PROPOSED SYSTEMS

In this section, we describe our imaging system, image dataset, preprocessing technique, and two detection systems. Fig. 7 shows a block diagram of the proposed systems.

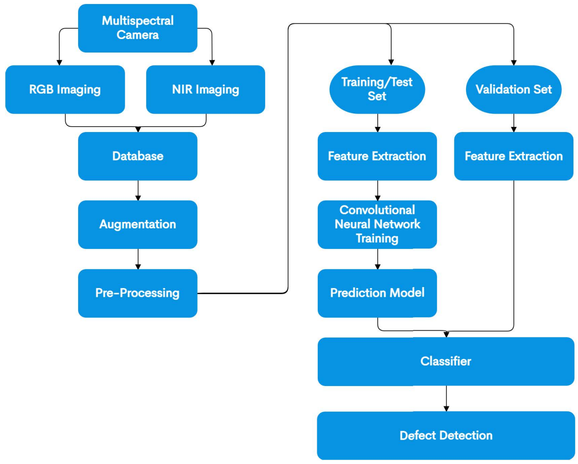

FIGURE 7. Systems block diagram.

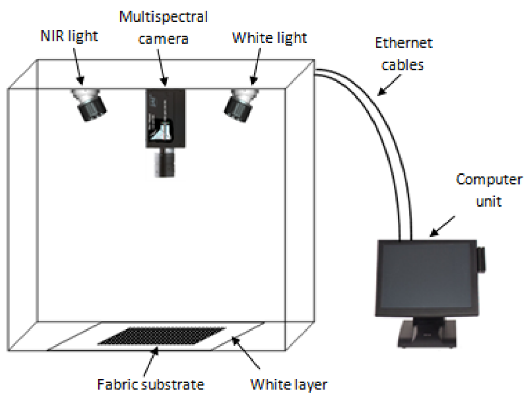

FIGURE 8. Used image acquisition system configuration [29].

A. IMAGING SYSTEM

The system used for the image capture is shown in Fig. 8. This approach was inspired by [29]. The imaging system provides proper lighting for both RGB and NIR imaging. A JAI AD-080G camera is used. The camera model is an area-scan camera. It is a multispectral 2-channel CCD camera. The camera can capture RGB and NIR images of a scene at the same time. The camera delivers 30 frames/s with a full resolution of (1024 × 768). In this camera model, the visual color spectrum is separated into a wavelength band of 400–600 nm. In addition, the NIR band ranges from 760 to 1000 nm. Two Ethernet cables transfer the captured images to a computer.

We manually collected the images used in our model training and testing. We captured a dataset consisting of 1,348 images with different unique complex jacquard macro patterns from multiple samples per pattern. Our dataset was collected from plain, undyed jacquard fabrics with different complex patterns. The dataset was further increased using data augmentation techniques to four times the original size (i.e., 5,392 images). Each fabric sample was simultaneously captured using RGB and NIR at the same time. The dataset was balanced, where half of the images were non-defective and the other half were defective samples. The database contained 10 different complex macro patterns with different defects. These defects included warp and weft defects, fabric breaks, knots, and loose picks. The samples of the dataset showing different macro patterns and sample defect types are shown in Fig. 9 and 10, respectively.

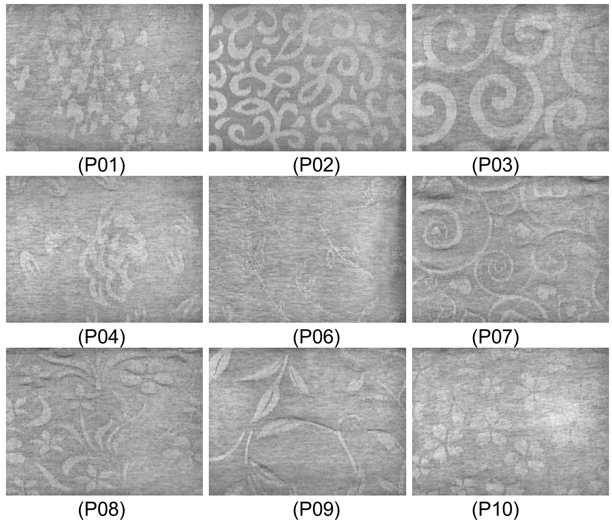

FIGURE 9. Defect free sample images of dataset different patterns.

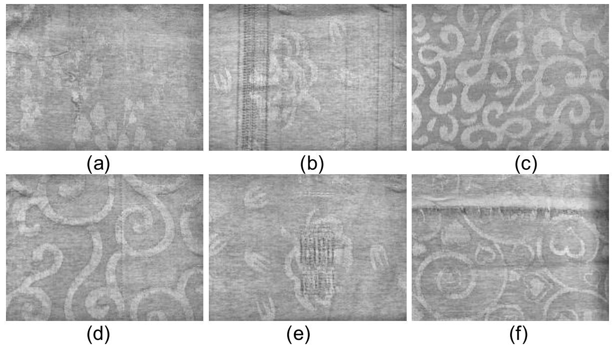

FIGURE 10. Different kinds of defective dataset different image patterns. (a) Knot, (b) Double picks, (c) Missing warp pick, (d) Broken yarn pick, (e) Ladder, (f) Breakage.

B. PRE-PROCESSING

First, the samples were resized to smaller sizes. In addition, RGB images were converted to grayscale for processing and model training. We used contrast-limited adaptive Histogram Equalization (CLAHE) [30] for image enhancement. CLAHE differs from regular AHE in its contrast limiting by clipping the histogram at a predetermined value before calculating the cumulative distribution function (CDF) to overcome the amplification of noise. The two main parameters that can be changed to control the image enhancement quality are the Clip Limit (CL) and Block Size (BS). First, the image is divided into non-overlapping contextual regions, resulting in M × N tiles. Then, the contrast-limited histogram of the contextual region is calculated using the CL value as follows:

$$N_{avg} = (N_{px} \times N_{py})/N_{gray} \tag{1}$$

where N_{avg} is the average number of pixels, N_{px} and N_{py} are the region's number of pixels in the X and Y directions, respectively, and N_{gray} is the gray level number of the contextual region. The actual clip limit can be calculated as:

$$N_{CL} = N_{clip} \times N_{avg} \tag{2}$$

where, N_{clip} is the normalized clip limit in the range of [0,1]. If the number of pixels is greater than the N_{CL}, the pixels are clipped. The part that exceeds the clip limit is better redistributed among all the histogram bins. If the redistribution causes some values to exceed the clip limit again, the process is repeated until the excess can be neglected. Fig. 11 shows the multispectral imaging for the dataset sample and the preprocessing effect

(a) (b) (c)

FIGURE 11. **Sample images of the dataset: (a) RGB, (b) NIR imaging of the same sample and (c) Enhanced sample using CLAHE.**

C. TRAINING AND TESTING

Artificial neural networks have shown promising results in different areas, such as pattern recognition and classification. In neural networks, input information is processed by groups of simple elements called neurons. Signals are transferred between neurons through the links that connect them. Each connection link has a weight (W) that represents the multiplication factor for the transmitted signal. Finally, the output is determined using an activation function that was applied to the input.

In our work, we used convolutional neural networks (CNNs) running on TensorFlow's high-level API "tf.Keras."

We experimented with different 2D CNNs, such as simple CNNs, VGGNet, ResNets, InceptionNets, and EfficientNets, to find and select the most suitable ones for defect detection in pattern jacquard fabrics.

We propose two systems. The first system is a simple CNN model for a semi-manual system that operates on separate patterns. The second system is an unsupervised system that operates on the entire dataset, uses state-of-the-art architectures, and compares them. The two systems are presented, and the advantages and disadvantages of using each system are discussed.

VII. RESULTS AND DISCUSSION

The precision, recall, and accuracy performance metrics were calculated for each system. These metrics were calculated using the following equation:

$$Precision(P) = TP/(FP + TP) \tag{3}$$

$$Recall(R) = TP/(FN + TP) \tag{4}$$

$$Accuracy = (TP + TN)/N \tag{5}$$

where, True Positive (TP) is the number of correctly labeled defective samples, True Negative (TN) is the number of correctly labeled defect-free samples, False Positive (FP) is the number of wrongly labeled defect-free samples, False Negative (FN) is the number of wrongly labeled defective samples, and N is the total number of samples. Precision measures the percentage of correctly detected defect samples for all defect detections. Recall measures the percentage of correctly detected defective samples in all defective samples. Accuracy measures the number of correct predictions that our system had in all samples.

The models were trained and tested on the database that we created. First, a semi-manual system that has 10 models is presented. System performance was studied for different patterns. In addition, a performance comparison between RGB and multispectral imaging is performed.

Second, an automatic system that operates on the entire dataset without manually selecting the target pattern is presented. A comparison between different state-of-the-art architectural models was performed.

A. SEMI-MANUAL SYSTEM

The first proposed system utilizes a simple CNN that consists of Conv2D, activation, and max-pooling layers, as shown in Fig. 12. This simple CNN is sufficient for implementing semi-manual models that operate on separate patterns. In this system, the operator selects the pattern and then the system loads the corresponding model.

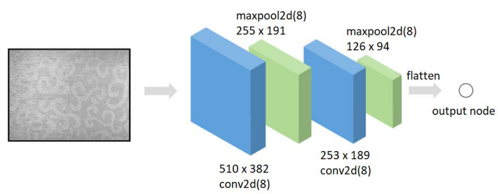

FIGURE 12. **Simple CNN architecture.**

Although this system is semi-manual and not very sophisticated, it is very simple and, therefore, faster. First, the advantage of multispectral imaging was tested using this simple CNN model across 10 different patterns. The CNN was modeled on our dataset, where 3,774 images (70%) were used for training and 1618 images (30%) for testing. In the testing phase, the CNN classified the input image into a defect or defect-free fabric.

A comparison between RGB and multispectral imaging is presented in Tables 1 and 2, respectively. Table 1 presents the test results for the defect detection using visual RGB imaging. Table 2 lists the test results for multispectral imaging.

Multispectral imaging provides better performance and higher accuracy. The detection results across separate patterns were satisfactory, with an average accuracy of 95%.

However, this system is semi-manual and requires changing the models when operating on different patterns. Simple CNN models could not achieve good accuracies on the entire dataset when the pattern was not determined by the operator, reaching a maximum accuracy of 65%. This led us to examine state-of-the-art architectures in deep learning and devise a

TABLE 1. Visual inspection by RGB.

Database Macro Patterns	Performance Metrics		
	Precision	*Recall*	*Accuracy*
01	92.2	98.81	95.24
02	100	57.14	78.57
03	82.26	91.07	85.19
04	92.23	99.56	95.58
05	90.0	98.44	93.75
06	77.65	97.06	84.56
07	100	68.52	88.67
08	88.64	82.98	86.39
09	81.28	94.68	86.44
10	79.17	95	85.0
Average Performance	**88.343**	**88.326**	**87.939**

TABLE 2. Multispectral imaging.

Database Macro Patterns	Performance Metrics		
	Precision	*Recall*	*Accuracy*
01	96.51	98.81	97.62
02	100	96.43	98.21
03	93.23	99.1	95.83
04	94.21	96.27	95.13
05	95.6	93.36	94.53
06	94.2	95.59	94.85
07	98.88	82.41	93.33
08	94.43	94.68	94.63
09	92.96	98.4	95.48
10	93.83	95	94.34
Average Performance	**95.385**	**95.005**	**95.395**

fully automated defect detection system using modern CNN architectures.

B. AUTOMATIC SYSTEM

We experimented with different state-of-the-art CNN architectures to achieve the highest accuracy for the dataset. We tested four different models, which were briefly presented in Section VI. All architectures were implemented from scratch and then trained and tested on our dataset. The models used our dataset, where 3,774 images (70%) were used for training and 1618 images (30%) for testing. The architectures had different sizes and numbers of parameters. The largest of these is VGG16 with approximately 138 million parameters, followed by ResNet50 with a much lower number of parameters at approximately 25.6 million. InceptionV3 had approximately 23.8 million parameters. The smallest of these is EfficientNetB3 at approximately 12.3 million parameters. Training was performed for 100 epochs, and a batch size of 4. Fig. 13 presents the accuracy and loss for training and validation for different architectures.

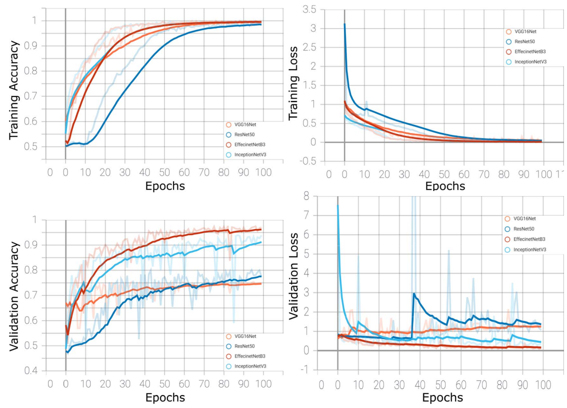

FIGURE 13. System performance.

Table 3 shows a comparison of the precision, recall, and accuracy of the four network architectures.

TABLE 3. Architectures performance comparison.

CNN	Performance Metrics			
	VGG16	*ResNet 50*	*InceptionV3*	*EffecinetNetB3*
Precision	87.04	92.98	97.23	**98.86**
Recall	80.87	93.98	99.65	**99.42**
Accuracy	84.92	93.66	98.46	**99.17**

From the results, we can see that very high accuracies were achievable, especially with EfficientNet. This shows that CNNs with multispectral imaging are very good for defect detection in jacquard fabrics, and they can overcome the difficult challenge of complex patterns. In addition, this shows that advancements in the field of CNN architectures are meaningful and steadily improving. EfficientNets achieve higher accuracies with a smaller network size and fewer parameters.

C. COMPARISON

As previously mentioned, the study of defect detection for complex-patterned jacquard fabrics is novel and no previous studies have been done on it. In our research we implemented and tested, on our database, several techniques that are well established in defect detection of traditional fabrics. Two methods that had good results were wavelet transform [31] and gray level co-occurrence (GLCM) [32].

Table 4 shows a comparison of their results with the proposed approach of using EfficientNet CNN.

From the results, we conclude that the proposed method, of using EfficientNet CNN with multispectral imaging for fault detection for complex-patterned jacquard fabrics, provides the best results with highest accuracy.

TABLE 4. Different methods performance comparison.

Performance Metrics	*Wavelet [31]*	*GLCM [32]*	*Proposed Method*
Precision	69.68	96.7	**98.86**
Recall	97.47	88.39	**99.42**
Accuracy	78.26	92.8	**99.17**

VIII. CONCLUSION

In this study, unsupervised complex-patterned jacquard fabric defect detection systems were introduced. A new and extensive image database was collected and tested. The images were preprocessed using CLAHE to enhance their features. These systems use Convolutional Neural Networks (CNNs) to detect defective fabrics. Test results for single RGB and multispectral imaging are provided. We concluded that deep learning is efficient and can be used for defect detection in complex patterns. EfficientNet CNN gave high accuracy reaching 99% approximately. We also found that multispectral imaging is more advantageous and yields a higher accuracy. These systems exhibit high detection rates. Much work and research can still be conducted in the field of jacquard fabrics.

Further investigations will be conducted in the future to further improve the performance and precisely locate the defect area. Specifically locating the defect area is much more challenging and can be further explored in future work.

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