Detection of garment manufacturing defects using CFPNet and deep belief network: an image-based approach

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ABSTRACT – REZUMAT

Detection of garment manufacturing defects using CFPNet and deep belief network: an image-based approach

The demand for high-quality items and the quickly shifting economic landscape increase the importance of ready-made garment manufacturers in providing the correct quality product. It is difficult work in the textile industry since the efficacy and efficiency of automatic flaw identification determine the quality and cost of every textile surface. In the past, the textile industry used manual human efforts to find flaws in the manufacturing of clothing. The main downsides of the manual garment fault identification technique include lack of concentration, human tiredness, and time requirements. Applications based on digital image processing and computer vision can overcome the aforementioned restrictions and shortcomings. In this article, we use intelligent algorithms like Channel-wise Feature Pyramid Network (CFPNet) based on deep learning-based techniques with Deep Belief Network (DBN) to monitor the quality and predict any occurrences of manufacturing problems in clothing. The suggested algorithm is mostly utilised in the textile industry to find flaws in clothing while estimating client needs based on the environment and the economy to react quickly and meet business objectives. The performance evaluation was used to determine the 12 kinds of garment faults, which included holes, excessive margins, stains, cracks, inappropriate stitch balancing, needle breaks, ink stains, torn clothing, drop stitches, soil content, and broken clothing. The suggested model obtains a 95.85% stain defect detection rate, a 97.33% defect-free garment recognition rate, and a 97.16% hole defect recognition rate.

Keywords: *garment industry, quality assurance, prediction classification parameter optimisation, digital image processing, deep belief network*

Detectarea defectelor de fabricație a articolelor de îmbrăcăminte utilizând CFPNet și rețeaua „Deep belief network”: o abordare bazată pe imagini

Nevoia producătorilor de articole de îmbrăcăminte de a oferi un produs de calitate corespunzătoare este sporită de cererea de articole de înaltă calitate și de peisajul economic în schimbare rapidă. Este o muncă dificilă în industria textilă, deoarece eficacitatea și eficiența identificării automate a defectelor determină calitatea și costul fiecărei suprafețe textile. În trecut, industria textilă folosea eforturile umane manuale pentru a găsi defecte în fabricarea îmbrăcămintei. Principalele dezavantaje ale tehnicii de identificare manuală a defectelor de îmbrăcăminte includ lipsa de concentrare, oboseala umană și cerințele de timp. Aplicațiile bazate pe procesarea digitală a imaginilor și viziunea computerizată pot depăși restricțiile și neajunsurile menționate mai sus. În acest articol, au fost utilizați algoritmi inteligenți precum Channel-wise Feature Pyramid Network (CFPNet) bazați pe tehnici de învățare profundă cu Deep Belief Network (DBN) pentru a monitoriza calitatea și a preconiza orice problemă de fabricație a îmbrăcămintei. Algoritmul sugerat este utilizat în cea mai mare parte în industria textilă pentru a găsi defecte în îmbrăcăminte, în timp ce estimează nevoile clienților pe baza mediului și a economiei pentru a reacționa rapid și a îndeplini obiectivele de afaceri. Evaluarea performanței a fost utilizată pentru a determina cele 12 tipuri de defecte ale articolelor de îmbrăcăminte, care au inclus găuri, margini excesive, pete, fisuri, echilibrare necorespunzătoare a cusăturilor, rupturi de ac, pete de cerneală, cusături desprinse, conținut de murdărie și îmbrăcăminte ruptă. Modelul sugerat a obținut o rată de detecție a defectelor de 95,85%, o rată de recunoaștere a articolelor de îmbrăcăminte fără defecte de 97,33% și o rată de recunoaștere a defectelor de găuri de 97,16%.

Cuvinte-cheie*: industria de îmbrăcăminte, asigurarea calității, optimizarea parametrilor de clasificare a predicțiilor, procesarea digitală a imaginilor, „Deep belief network”*

INTRODUCTION

Manufacturers must offer their clients high-quality but affordable items if they want to increase their competitive advantage and survive in today's aggressive market. This has a significant effect on quality control procedures. Human inspection has always been used to detect clothing flaws; however, this method hides the link between production process variables and product quality [1]. It is difficult to perform effective product assurance without any information discovery from the production processes at a parameter level. It is critical to identify defects in the clothes production process as early as possible to provide clients with high-quality garments at competitive costs. In these conditions, having a system in place that can identify the points where these flaws occur, how frequently they occur, what causes them, and what fixes are available will help the workers produce high-quality clothing. Moreover, this process will be greatly impacted by machinery maintenance [2]. As a result, there is a constant need in the textile sector for data processing and the finding of worthwhile and potentially useful knowledge from these data [3]. It is an inevitable fact that certain events that may occur during the production process can result in variations in product quality [4].

The present Information technology (IT) solutions have not enhanced Human Resources (HR) systems. Even though HR systems were already in place, it appears that no provision has been made for automated decision-making using modern IT trends. To address manufacturing problems related to quality, quality improvement (QI) of industrial processes and products is required [5]. Numerous textile investigations have used a variety of conventional mathematical and statistical methods to process textile data [6]. So, when a projected machinery component failure occurs, users will be informed that the relevant machine is in danger as a result. This work's main contributions are:

- To monitor the quality and predict any occurrences of manufacturing defects in garments using Channel-wise Feature Pyramid Network (CFPNet) algorithms.
- To optimize the production, predicting the customer requirements based on eco system and demand forecasting to respond rapidly and meet business demands using with Deep Belief Network (DBN).
- The following 12 default categories were chosen: hole, excessive margin, ink stain, crack, stain, ripped, drop stitch, broken end, defect-free, and incorrect stitch balance.
- The proposed work achieves a high accuracy value of 95.85%, and the BPN method provides a low accuracy value of 83.33%.

The following sections of this article are arranged as follows: A review of related prior research is presented in the 2nd section, each algorithm utilized in this study is briefly described in the 3rd section, the results and discussions are presented in the 4th section, and the article is concluded in the 5th section.

LITERATURE SURVEY

A technique utilizing the auto correlation function and grey level co-occurrence matrix to detect fabric faults in yarn-dyed fabrics [7]. The Fisher criterion-based deep learning algorithm was chosen by the author [8] for the detection of deformable patterned fabric defects. This work is used to create simple, twill, periodic patterns, and more intricate jacquard warp knit fabrics. An automatic and effective fabric defect detection methodology [9]. This technique was specifically used to identify defects in woven fabrics. A support vector machine classifier for an automated fabric flaw detecting system [10]. Three steps make up this work: threshold comparison, defect image inspection, and calibration. The benefits of this work include high accuracy and success rates with short processing times [11]. A multi-channel feature matrix extraction and joint low rank decomposition-based approach for fabric flaw detection. Wavelet transform was developed [12] to discover fabric flaws to cut production costs, waste, and time in the textile sector. A defect inspection approach based on a back propagation neural network in texture images was proposed [13]. The neural network model of production cycle time prediction is designed to increase forecast accuracy and get a deeper understanding of the production process in the garment manufacturing industry [14]. A sewing defect detection method using a CNN feature map extracted from the initial layers of a pre-trained VGG-16 to detect a broken stitch from a captured image of a sewing operation [15]. To assess the effectiveness of the proposed method, experiments were conducted on a set of sewing images, including normal images, their synthetic defects, and rotated images. A deep learning algorithm on LSTM infers details about the textile using digital images [16]. The LSTM technique is utilized to identify the defects in the fabric. Even with complex designs, the imperfections are visible. The predictive power of alternative machine learning (ML) algorithms in terms of real fit satisfaction (RFS) for customers' clothing fit and to compare the predictive capacities of these algorithms [17]. As test items, skirts composed of various textiles were utilized.

Previous techniques for finding clothing flaws could never guarantee a 100% inspection rate. It is imperative to address the massive dimensionality and complexity of textile data. Certain textile studies may involve complex interactions between several variables and aspects that are challenging to interpret using conventional techniques. Owing to these serious disadvantages, attempts are being made to automate the process of detecting garment defects through the use of a Channel-wise Feature Pyramid Network (CFPNet), which is based on deep learning-based techniques with a Deep Belief Network (DBN). This will help to maintain ongoing garment quality measurement and enhance the probability of the best garments.

METHODOLOGIES

It's crucial to pinpoint the causes of variability in manufacturing to reduce production errors and enhance and sustain process performance. The primary factor harming the textile industry is substandard clothing. Two stages make up the automatic method for identifying clothing defects. Phases of detection or testing and phases of learning or training. The system is trained using photos of clothing that are free of flaws during the learning phase. Following that, feature values that serve as classifier input are calculated. Only the features of interest are taken into account during the detecting phase. By dividing a test image into smaller windows and calculating the necessary statistics for each one, defects can be detected. If a window's required statistic set differs from the original training texture, a problematic region is identified.

Image acquisition

The initial database comes from a scan of the manual on clothing defects. All typical types of flaws found in textile industries are included in the sample of garment photographs that were chosen in this manner. Twelve classes are covered by this algorithm: hairiness, tiny hole, lumpy, horizontal stripes, lumpy, soil stain, oil stain, double end, snarls, and miss. 100 photos total are included in each class; 20 are used for teaching, and 80 are used for testing. For this study, a total of 500 samples were utilized (figures 1 and 2).

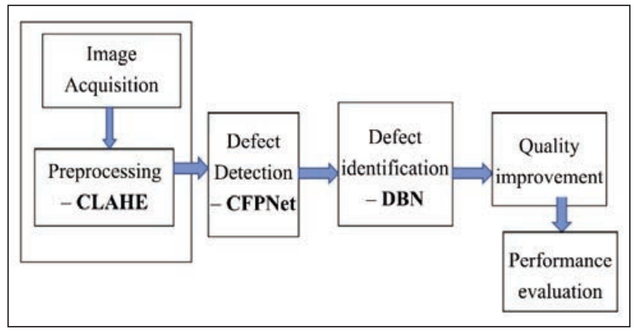

Fig. 1. Proposed framework for garment defect detection

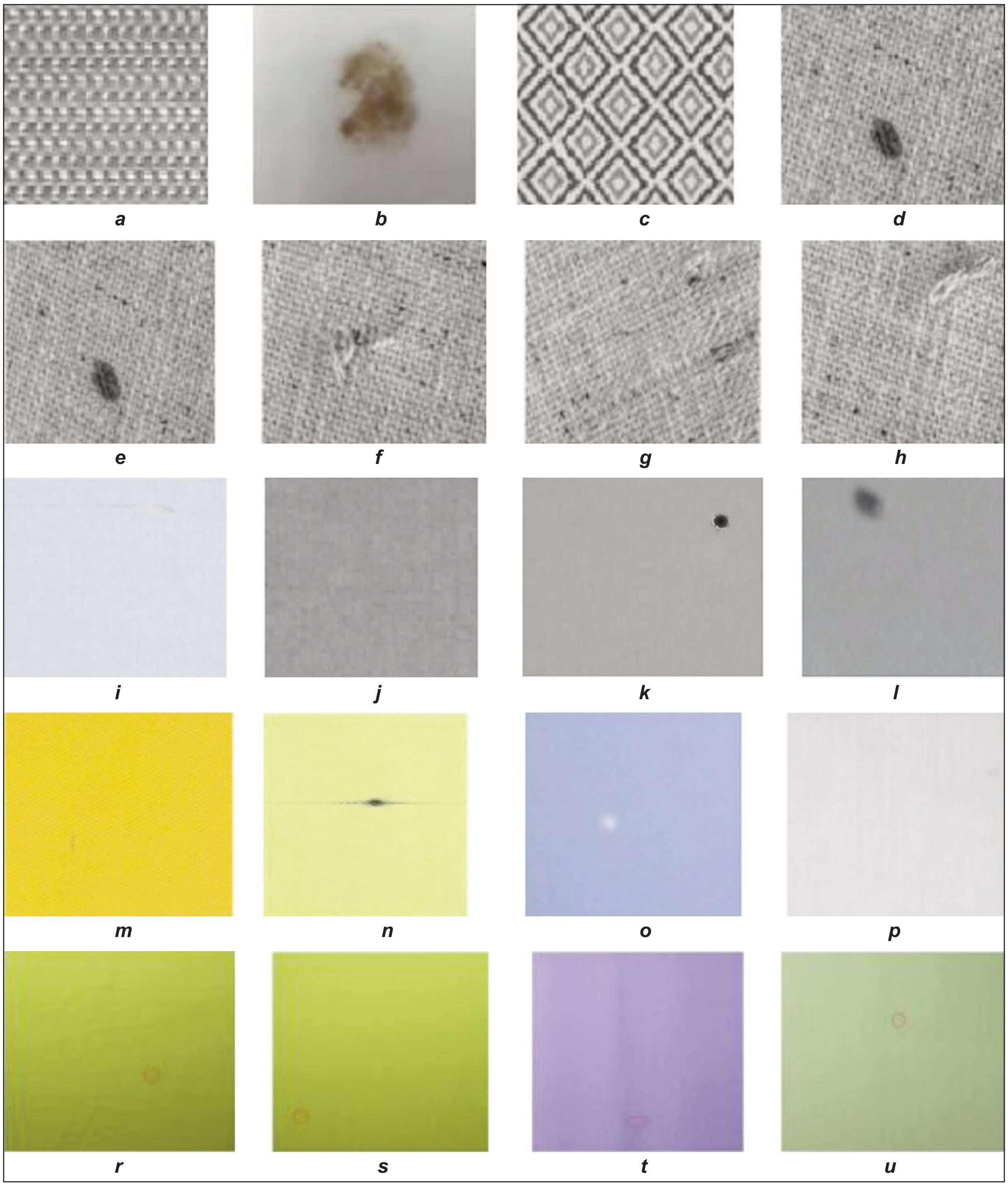

Fig. 2. Input images of: *a* – defect-free image; *b* – image with soil stain defect; *c* – defect-free image; *d* – image with oil stain defect; *e* – oilstain; *f* – double end; *g* – snarls; *h* – miss; *i* – horizontal stripes, *j* – lumpy; *k* – hole; *l* – dye spot; *m* – lumpy; *n* – horizontal stripes; *o* – fall out; *p* – hairiness; *r-u* – samples with tiny hole defects

Images of garments typically have noise following the scanning process. The clarity of the photos is impacted by this noise, which also distorts the textures and contours of the clothing. Common type of noise that affects the garment images are impulse noise, Gaussian noise and salt & pepper noise. It creates difficulties for the further garments' texture analysis and retrieval process. If noise is present, there is a chance for the misidentification of the noise as a defect. It affects the accuracy of the detection process. So, de-noising is one of the most important steps in the garment inspection process and computation. Noise is removed in this instance using contrast-limited adaptive histogram equalization. Channel-wise Feature Pyramid Network (CFPNet) is for extracting defects, and finally, the DBN algorithm is used for classification.

Contrast Limited Adaptive Histogram Equalization (CLALE)

The local contrast of an image can be improved via CLAHE (figure 3). It is an extension of histogram equalisation using both traditional and adaptive algorithms. Once the algorithm has divided each image into contextual zones, histogram equalisation is applied. This improves the visibility of the image's hidden information and evens out the distribution of the used grey values. The complete greyscale serves as the image. CLAHE is an improved version of AHE, or Adaptive Histogram Equalization, which was developed to address the shortcomings of conventional histogram equalisation.

Instead of processing the entire image, the traditional histogram, AHE method, only processes discrete data portions. (tiles). Because the contrast of each tile has been increased, the output region's histogram

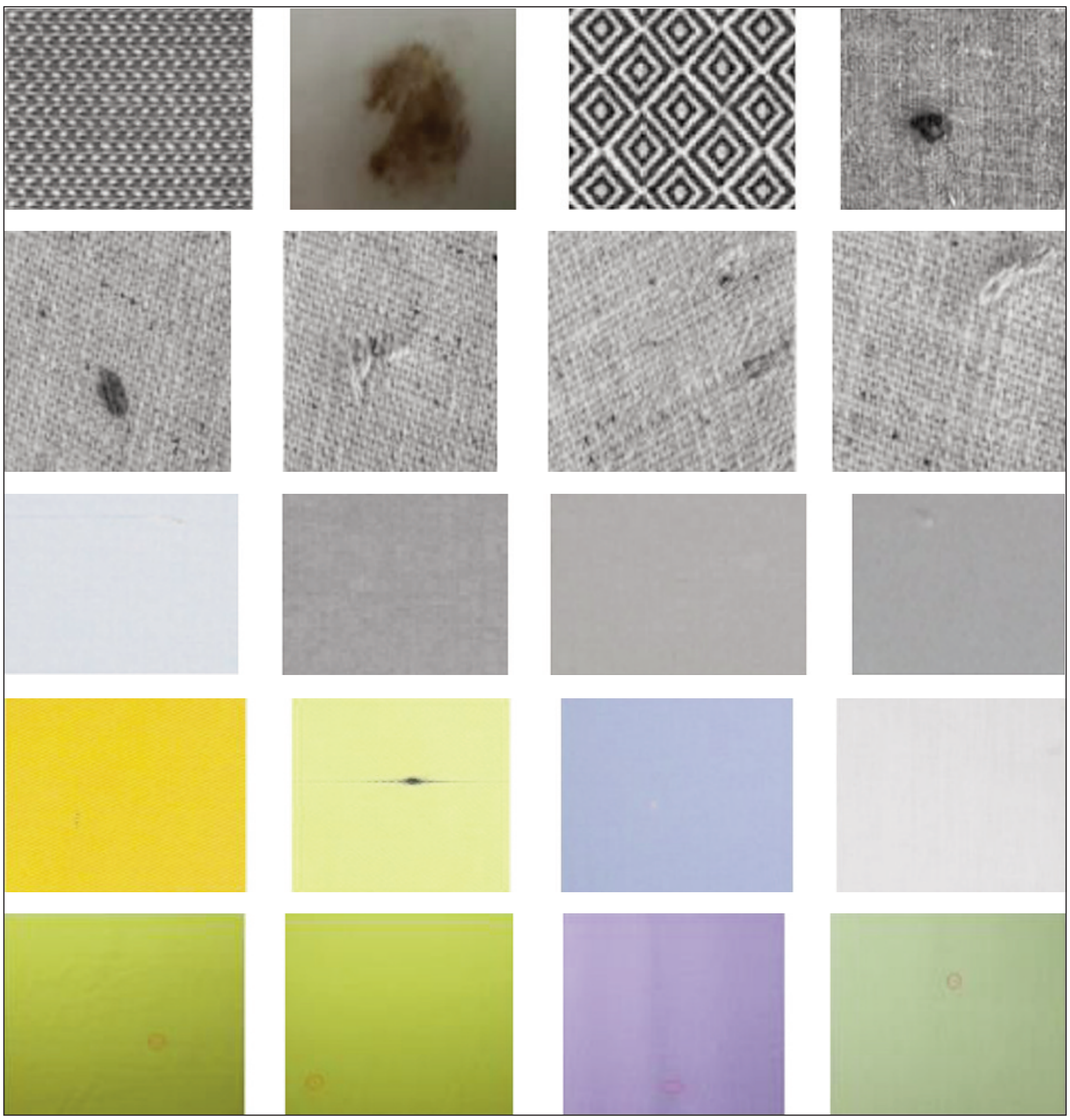

Fig. 3. CLAHE result of input images

roughly resembles the necessary histogram. Next, adjacent tiles are combined using bilinear interpolation to remove artificially created boundaries. Reducing the contrast will prevent the possible noise in the image from increasing, particularly in areas of homogeneity [16].

This algorithm's temporal complexity is $O(M \times N \times W^2 + n)$, where $M \times N$ represents the image's entire pixel count. The window size is W, and there are n bins. The AHE algorithm's temporal complexity rises with window size. So, it is important to choose the window size carefully. A small window lets in noise, whereas a large window lets in artifacts.

CLAHE was introduced to address this AHE issue. Contrast enhancement is the slope of the function that relates the input intensity to the output. According to the cumulative histogram equation 1 with histogram equalization, the mapping function $m(i)$ is proportional.

$$m(i) = (display\ range) * (cumulative\ histogram\ (i) / region\ size \quad (1)$$

Consequently, the derivative of $m(i)$ is related to the *histogram*(i). In CLAHE, the histogram is restricted, which restricts contrast enhancement. Below is a list of the CLAHE algorithm.

- Step 1: Acquire every input, such as the picture, the number of regions in the histograms showing the row and column directions, the number of bins for the histograms showing the dynamic range (also called the "dynamic range"), and the clip limit for contrast limiting. Normalized between 0 and 1.
- Step 2: Process the inputs first: Pad the image before region-based processing and, if needed, extrapolate the real clip limit from the normalized value.
- Step 3: By processing each contextual area (tile), grey level mappings are created: Extract a single region of the image using the number of bins that are provided, use the clip limit to clip the histogram, and then create a mapping (transformation function) for that region.
- Step 4: build the final CLAHE image by interpolating grey level mappings: Extraction of a group of four nearby mapping functions, processing of the portions of the image that partially encircle each mapping tile, extracting a single pixel, connecting four mappings to it, then breaking up the outcomes to get the output pixel; repeat across the picture.

Channel-Wise Feature Pyramid Network (CFPNet)

The Channel-wise Feature Pyramid Network (CFPNet) was created to collect production process parameters and determine how they relate to the final product's quality. The goal is to use the associations found to determine the proper manufacturing process settings to improve product quality.

Operating as the central nervous system of CFPNet, the channel-wise feature pyramid (CFP) module is a factorized convolution operator that splits a large kernel into smaller convolutions. Inception-v2 substitutes two 3 × 3 convolutional operators for the 5 × 5 size kernel that was employed in the original Inception module. Create a module using factorizations and multi-scale feature maps to handle a kernel size of up to 7 × 7. As with Inception-v2, swap out the 5 × 5 and 7 × 7 size kernels for two and three 3 × 3 convolution kernels, accordingly. Our real-time objectives cannot yet be met with this technique's size because of the complex procedure for saving the parameter up to 28% and 45%. To aggregate the convolution kernels into a single channel, only use the three 3 × 3 kernels. The Feature Pyramid (FP) channel was then created by asymmetrically transforming the conventional convolution [17]. Create a multiscale feature map by utilizing a skip connection to merge the recovered data from every asymmetric convolution block. Even with the same receptive field size, the FP channel can save an additional 67% of parameters as compared to the implementation of Inception-v2. Since every asymmetric convolution block has concatenating properties, reorder the filter numbers for each asymmetric block so that the input and output have the same dimension. The first and second blocks of the 3 × 3 and 5 × 5 convolutions, respectively, should be assigned N/4 if the input dimension is N. Pull out the large weighted significant features from the 7 by 7 kernel of the third block using N/2 filters.

Network architecture: To create a shallow network with both light and effective properties, as shown in figure 4. Table 1 also displays the architecture's characteristics. The initial feature extractor starts with three 3 × 3 convolutions. Next, the same down sampling method was used with the ENet [18] model, which comprises a 2 × 2 max pooling, a stride 2 convolution, and a 3 × 3 convolution. The output dimensions are one-eighth the size of the input after these three downsampling repetitions. Before the first and second max pooling layers and the final 1 × 1 convolution, use skip connections to inject decreased input

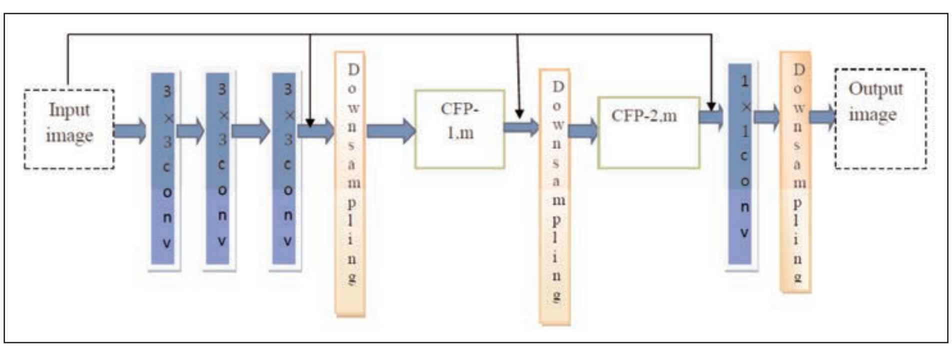

Fig. 4. Architecture of proposed CFPNet

images to provide the segmentation network additional information. Finally, pick the CFP module's repeat intervals of n = 2 and m = 6 using the dilation rates $r_{KCFP}-1$ = [2,2] and $r_{KCFP}-2$ = [4,4,8,8,16,16] for the CFP-1 and CFP-2 clusters, respectively.

The final feature map is activated using a 1 × 1 convolution after the segmentation masks are constructed using a straightforward decoder and bilinear interpolation. After each of those convolutions, the PTeLU activation function and batch normalization are performed. Because studies have already shown that, in a shallow network, PTeLU outperforms TeLU. Each feature contains or represents a key attribute or

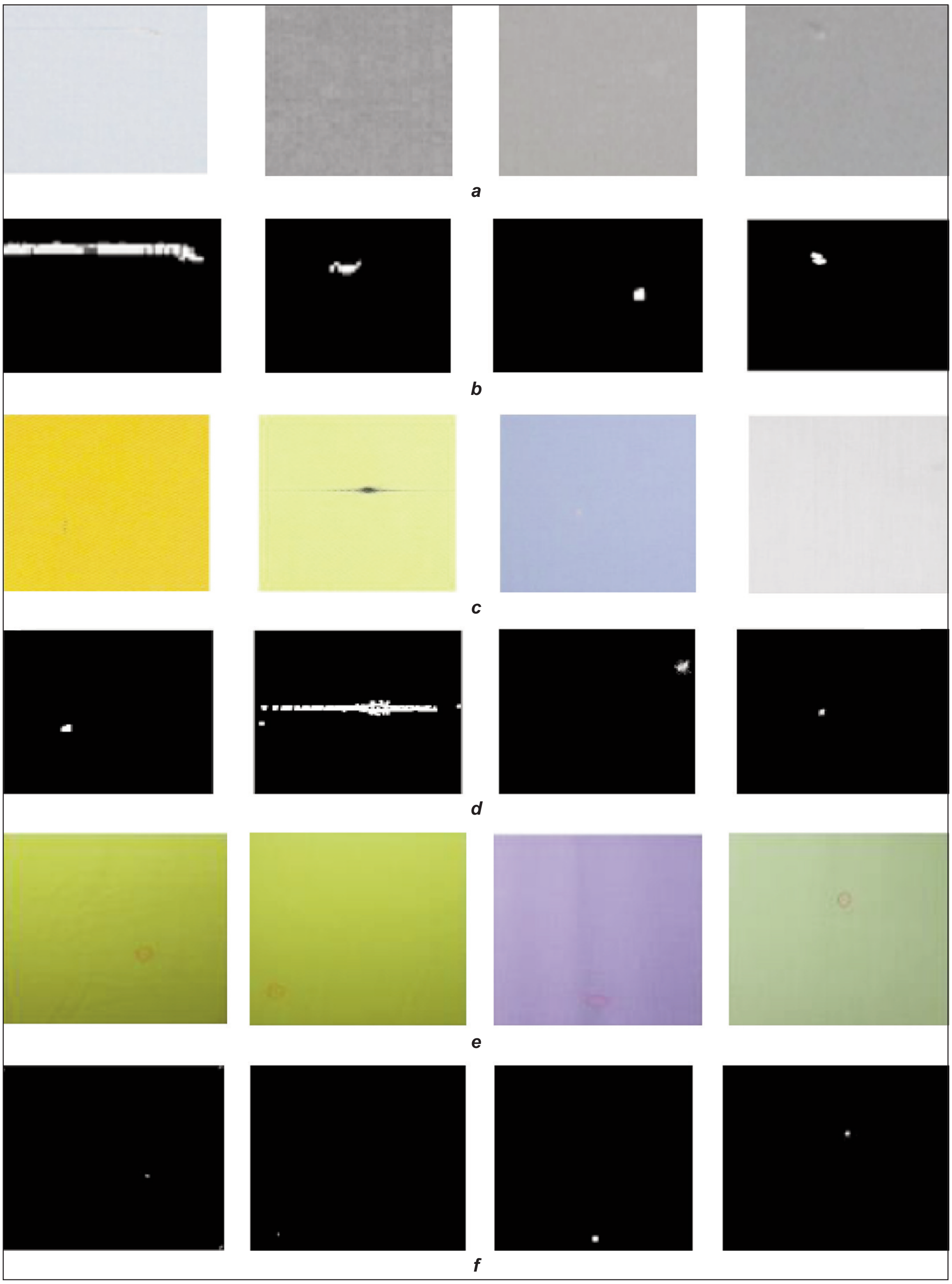

Fig. 5. Results of the proposed method: *a, c, e* – input images with defects; *b, d, f* – detection results of input images

Table 1

ARCHITECTURE DETAILS OF CFPNet			
No.	Layer	Mode	Value
1	3 × 3conv	Stride 2	32
2	3 × 3conv	Stride 1	32
3	3 × 3conv	Stride 1	32
4	Down sampling		64
5-6	2 × *CFP*	$r_k = 2$	64
7	Down sampling		128
8-9	2 × *CFP*	$r_k = 4$	128
10-11	2 × *CFP*	$r_k = 8$	128
12-13	2 × *CFP*	$r_k = 16$	128
14	3 × 3conv	Stride 1	19
15	Bilinear interpolation	× 8	19

set of characteristics from the source image. Hidden neuron's j, k^{th} output in equation 2:

$$\sigma(\rho + \textstyle\sum_{i=0}^{n} W_l, \sum_{m=0}^{m} a_j + 1, k + m) \tag{2}$$

where, σ – Neural activation function, ρ – Shared bias value, W_l, m – Shared Weights ($n \times n$ array), J, k – hidden neurons and $a_{x,y}$ – Activation inputs at x, y.

The output of the convolutional layer is of size $(N - m + 1) \times (Nm + 1)$, where the $N \times N$ input neuron layer is convoluted with a $M \times M$ filter. Through the neural activation function, non-linearity was implemented. The analytic function represents a smooth approximation to the rectifier.

In the convolutional layer, $N \times N$ input neuron layer is convoluted with $M \times M$ filter, then the convolutional layer output will be of size $(N - m + 1) \times (Nm + 1)$. It applied non-linearity through neural activation function. A smooth approximation to the rectifier is the analytic function in equation 3:

$$f(x) = \ln(1 + e^x) \tag{3}$$

The sparsity in the hidden units is induced by this activation function. It has also been shown that deep neural networks can be trained more efficiently than sigmoid and logistic regression activation functions. Quality control is a crucial aspect of the textile business. Traditional human inspection might result in inaccurate findings, increased costs, and sluggish production. As a result, several researchers employed SVMs to identify flaws in clothing and fabric (including yarn, woven fabric, knit fabric, and dyeing flaws) (i.e., cutting, sewing, and accessories defects). Yet, it never yields a precise result. The most popular kind of DBN is utilized in this study for flaw identification and quality control.

Deep belief network

In increasingly complex setups, deep belief networks can replace deep feed-forward networks or even convolutional neural networks. They gain from having far higher resistance to the vanishing gradients problem and lower computational cost. Deep belief networks include significant restrictions on their weight connections, making them significantly less expressive than deep neural networks, which perform better on jobs for which sufficient input data is available. Even in their prime, deep belief networks were rarely directly applied. Instead, they were used as a pretraining phase to define and train a deep belief network that shared a similar deep neural network's general design. A suitable deep neural network is then built using its weights, modified, and then utilized. Sequentially connected, bounded Boltzmann machines make up a deep belief network. Every Boltzmann machine has an "output" layer that is trained to convergence, frozen, and then used as input by the machine in the chain following it. This process continues until the entire network is trained in equations 4 and 5 [19]:

$$oup = \begin{cases} 1 & \text{with } 1 - Bnz_{prb}(\lambda) \\ 0 & \text{with } 1 - Bnz_{prb}(\lambda) \end{cases} \tag{4}$$

$$Bnz_{prb}(\lambda) = \frac{1}{1 + e^{-\lambda / pte}} \tag{5}$$

where pte stands for the pseudo temperature parameter, which supports the probability's noise level. A representation of the stochastic system in equation 6:

$$\lim_{pte \to 0} Bnz_{prb}(\lambda) = \lim_{pte \to 0} \frac{1}{1 + e^{-\lambda / pte}} = $$

$$= \begin{cases} 0 & \text{for } \lambda < 0 \\ 1/2 & \text{for } \lambda = 0 \\ 1 & \text{for } \lambda > 0 \end{cases} \tag{6}$$

We modify the Boltzmann system depending on the Boltzmann distribution to precisely mimic the input patterns in equation 7.

The joint probability distribution is represented by the energy function given by equation 8, which is derived from the Gibbs distribution and computed using equation 9, where h_n and x_m might have values in the set [0,1], and $\xi_{n,m}$, β_m, γ_n are real valued weights.

$$\max_{\xi} \textstyle\prod_{x \in X} p(X) \tag{7}$$

$$E(x,h) = \textstyle\sum_{n=1}^{N} \sum_{m=1}^{M} \xi_{n,m} h_n x_m - \sum_{m=1}^{M} \beta_m x_m - \sum_{n=1}^{N} \gamma_n h_n \tag{8}$$

$$p(x,h) = \frac{1}{\sum_x \sum_h e^{-E(x,h)}} e^{-E(x,h)} \tag{9}$$

Deep networks are initially learned using unsupervised learning, and then supervised learning is applied to improve the model with tagged data. This method nearly always outperforms networks learned without pre-training since pre-training acts as a regularizer and aid for the supervised optimisation problem. The greatest energy that results from tying the network weights is equivalent to the energy found in the directed model, and it is upper bounded by equation 11. For the directed model, one may estimate this energy using equation 10. The derivative equals in equation 12 at equality, which is utilized to resolve the maximization problem, which is now easier to understand.

$$E(x^o,h^0) = -\left(\log p(h^0)\right) + \left(\log p\left({x^o}/{h^0}\right)\right) \quad (10)$$

$$\log p(h^0) \geq \Sigma_{\forall h^0}\, p\left({h^0}/{x^o}\right)\log p(h^0) + \log p\left({x^o}/{h^0}\right) -$$
$$- \Sigma_{\forall h^0}\, Q\left({h^0}/{x^o}\right)\log Q\left({h^0}/{x^o}\right) \quad (11)$$

$$\frac{\partial \log p(x^o)}{\partial \xi_{n,m}} = \Sigma_{\forall h^0}\, p\left({h^0}/{x^o}\right)\log p(h^0) \quad (12)$$

Figure 6 shows the outcomes of categorization and detection. When the proposed work is applied to the garment photos that have problems, the quality is improved, and the defects are accurately detected.

COMPARATIVE ANALYSIS

In this section, the suggested models are contrasted. MATLAB 2018 is used to implement the proposed task. Two CPUs and 14 GB of RAM and four CPUs

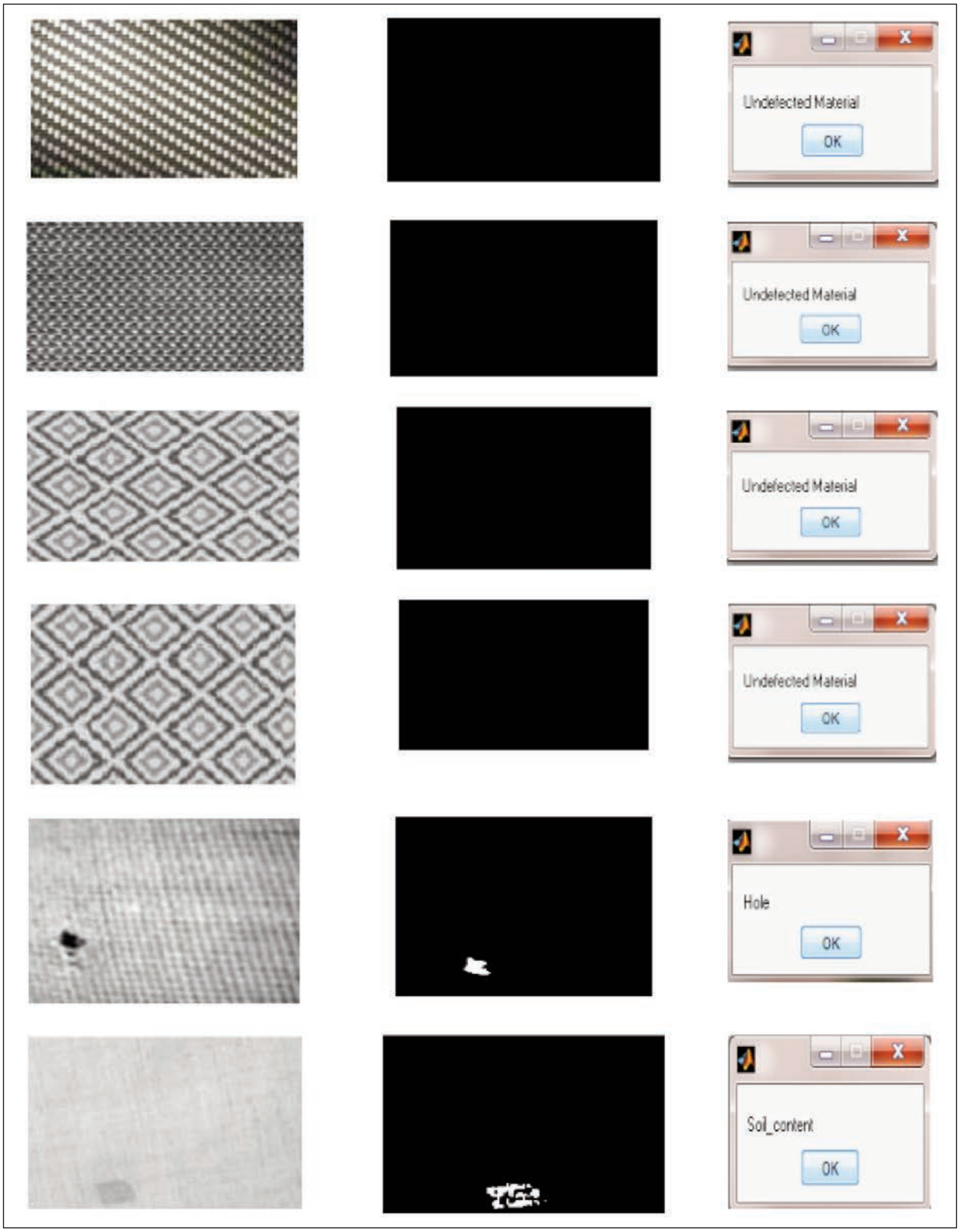

Fig. 6. Results of classification

Table 2

COMPARISON OF ENTROPY, CONTRAST AND EME VALUES WITH EXISTING METHODS				
Sl.No	**Algorithm**	**Entropy**	**Contrast**	**Effective measure of enhancement**
1	Gabor filter	6.991	0.773	52.38
2	Morphological filter	7.210	0.712	31.44
3	Histogram equalization	7.210	0.711	37.75
4	Adaptive Histogram equalization	6.181	0.771	47.52
5	Proposed	7.398	0.792	62.50

and 17 GB of RAM each were used in the computations on the Kaggle kernel. The comparison of the proposed models is followed by the presentation of the evaluations. By computing accuracy, precision, recall, f1-score, quadratic weighted kappa indices, detection rate, TPR, FPR, and confusion matrix, this paper assessed the accuracy, sensitivity, specificity, precision, recall, f1-score, and FPR applied to the DBN methodology used in this instance.

By gathering data on entropy, contrast, effective measure of enhancement, and average computing time, the performance of the proposed task is assessed. Table 2 summarizes performance metrics. Entropy is attained at 7.398, contrast is at 0.792, and EME is at 62.50 in the proposed work. When compared to previous enhancement techniques, the proposed work's entropy is practically identical to that of the original image. As a result, the original image's information content is kept more. Comparing this work to previous enhancement techniques, the average entropy of the suggested work is more similar to the input image.

The performance metrics are displayed in table 3. The proposed work has better precision, sensitivity, specificity, and accuracy than existing approaches, according to a comparison with existing models. When it comes to fabric inspection computation costs, AlexNet – the most popular traditional method – performs better than other conventional works. The most recent developments, GAN and CNN, which are commonly used detection methods, may identify and highlight many kinds of flaws. Evaluations are conducted in the same environment using real clothes samples. This method effectively detects impacts in garments because it applies convolutional layers in both the horizontal and vertical orientations to extract defect features. Since this model relies on the information retrieved from the flaws and the spatial domain approach, its sensitivity would not be satisfied when the defects' contours are vague and confused with the texture of regular clothing. This makes it impossible for this model to correctly represent the entire contour of the faults. Only fault types can be accurately detected by the CFPNet detection model with 97.3% accuracy.

Table 4 displays the suggested work's classification accuracy with other performance metrics. Scanned photos from a fabric guide and photographs from the classification data set were used. The following 12 default categories were chosen: hole, excessive margin, ink stain, crack, stain, ripped, drop stitch, broken end, defect free, and incorrect stitch balance. Photos of garments with holes and no imperfections are categorized more accurately than photos of other defects.

Table 5 shows that the performance metric accuracy is compared with the existing methods for defect-free garment images. The proposed work achieves a high accuracy value of 97.33%, and the image decomposition method provides a low accuracy value of 83.3%. The table compares performance metric accuracy with existing classifiers for the garments image with hole defect. The proposed work achieves a high accuracy value of 97.16%, and the artificial neural network method provides a low accuracy value of 82.33%. The comparison of performance metric accuracy with existing classifiers for the garments image with stain defect is shown in the above table. The proposed work achieves a high accuracy value of 95.85%, and the BPN method provides a low accuracy value of 83.33%. The dye spot values are also shown in the above table.

Table 3

PERFORMANCE COMPARISON TABLE OF PROPOSED AND CONVENTIONAL METHODS					
Classes	**Wavelet transform**	**AlexNet**	**Improved GAN**	**Modified CNN**	**Proposed**
Sensitivity	93.33	90	88.89	84.84	92.5
Specificity	92.85	89.58	96.22	94.12	93.7
Precision	90.32	91.52	96.48	94.73	97.23
Recall	91.2	87.75	90.68	91	93.5
F1-score	89	90	92	91	94
Accuracy	90.16	89.91	92.82	93.56	97.3

Table 4

CLASSIFICATION RESULTS OF GARMENT DEFECTS						
Types of effects	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**Recall**	**F1-score**
Defect free	97.33	78.94	98.73	95.85	92	83
Soil stain	95.85	83	98.15	91.32	91.7	91.5
Oil stain	91.32	91.5	98.20	92.2	90.8	92
Double end	92.2	92	98.73	90	98.20	83
Snarls	90	91.7	98.15	92.16	92	98.73
Miss	92.16	90.8	98.73	83	91.7	98.15
Horizontal stripes	93.33	98.20	98.15	91.5	98.73	98.20
Lumpy	94.85	98.73	83	92	98.15	98.73
Dye spot	94.32	98.15	91.5	91.7	93.33	98.15
Fall out	90.2	98.20	92	90.8	94.85	98.73
Hairiness	96	98.73	91.7	98.20	94.32	92
Tiny hole	97.16	98.15	90.8	83	93.33	91.7

Table 5

PERFORMANCE COMPARISON TABLE OF PROPOSED AND CONVENTIONAL WORK FOR THE IMAGE WITH NO DEFECT, HOLE DEFECT AND STAIN DEFECT		
Defects	**Methods**	**Accuracy**
No defect	BPN	83.3
	Modified Elman neural network	84.85
	VGG	90.32
	CNN	91.2
	Proposed	97.33
Tiny hole defect	BPN	82.33
	Modified Elman neural network	84.85
	VGG	92.32
	CNN	91.2
	Proposed	97.16
Stain defect	BPN	83.33
	odified Elman neural network	89.85
	VGG	90.32
	CNN	91.2
	Proposed	95.85
Dye spot	BPN	83
	Modified Elman neural network	87.6
	VGG	85.2
	CNN	89.7
	Proposed	94.32

CONCLUSIONS

The intelligent inspection method for identifying and categorizing garment defects was created and introduced in the current study. For the automatic inspection of apparel products, the method was primarily used and proposed in the textile industry. It was employed to make up for the shortcomings of manual inspection in detecting flaws with accuracy, consistency, and efficiency. As a result of worker exhaustion or ennui, inspection results were frequently unreliable, ambiguous, and prejudiced. To categorise garment flaws in the apparel business, a CFPNet model and DBN neural network were presented in this study. A CLAHE with an enhancement approach was first introduced. A Segmented Approach A faulty picture was created using CFPNet, and the collected photos were then input into a DBN classifier to carry out recognition operations. 12 different types of fabric defects can be categorized, including holes, excessive margins, stains, cracks, poor stitch balancing, needle breaks, ink stains, tears, drop stitches, broken ends, defect-free, and soil content images. The suggested method obtains a 95.85% stain defect detection rate, a 97.33% defect-free garment recognition rate, and a 97.16% hole defect recognition rate. The outcomes of the experiment demonstrate the viability and applicability of the strategy established in this study.

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