Fabric defect detection: a hybrid CNN-LSTM approach using TGANet for improved classification and traceability

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ABSTRACT – REZUMAT

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The fashion industry is incredibly adaptable and strives to adjust to shifting fashion trends. A critical phase in the textile industry is ensuring that quality standards are met. The identification and categorisation of fabric flaws is an essential stage in the production process that keeps any defective fabric off the market. Individuals manually detected the fabric's surface flaws; however, this is time-consuming and raises issues with human error. The creation of hybrid systems based on Textile Generative Adversarial Networks (TGANet) is the result of efforts to improve the accuracy of flaw detection using image processing studies. To solve fabric pattern classification and detection issues in fabric traceability and management, Convolutional Neural Networks (CNN) and long short-term memory (LSTM) in deep learning are used to extract texture features. To enhance the feature extractor, we employ TGANet in this study. Using fabric photos to train the new CNN-LSTM, the texture features are effectively retrieved, and the fabric categories are correctly identified using classifiers that have been tuned. Multimodal datasets for textile design are used. To verify the model's robustness and generalisation, various data are used, such as training with tiny training sets and varying image sizes. The accuracy and speed of the suggested network model are 94% better than those of the traditional deep learning classification techniques.

Keywords: *deep learning, fashion industry, TGANetwork, hybrid CNN-LSTM, detection and classification, classifier*

Detectarea defectelor materialelor textile: o abordare hibridă CNN-LSTM utilizând TGANet pentru o clasificare și o trasabilitate îmbunătățite

Industria modei este incredibil de adaptabilă și se străduiește să se adapteze la tendințele modei în schimbare. O fază critică în industria textilă este asigurarea respectării standardelor de calitate. Identificarea și clasificarea defectelor materialului textil este o etapă esențială în procesul de producție, care împiedică comercializarea oricărui material defect. Persoanele au detectat manual defectele de suprafață ale materialului textil; cu toate acestea, acest lucru consumă mult timp și ridică probleme legate de eroarea umană. Crearea de sisteme hibride bazate pe rețele adversare generative pentru materiale textile (TGANet) este rezultatul eforturilor de îmbunătățire a preciziei detectării defectelor cu ajutorul studiilor de prelucrare a imaginilor. Pentru a rezolva problemele de clasificare și detectare a modelelor de materiale textile în ceea ce privește trasabilitatea și gestionarea materialelor, rețelele neuronale convoluționale (CNN) și memoria pe termen scurt lung (LSTM) în învățarea profundă sunt utilizate pentru a extrage caracteristicile texturii. Pentru a îmbunătăți extractorul de caracteristici, folosim TGANet în acest studiu. Folosind fotografii de materiale textile pentru a antrena noul CNN-LSTM, caracteristicile texturii sunt recuperate în mod eficient, iar categoriile de materiale textile sunt identificate corect folosind clasificatoare care au fost reglate. Sunt utilizate seturi de date multimodale pentru designul textil. Pentru a verifica robustețea și generalizarea modelului, sunt utilizate diverse date, cum ar fi instruirea cu seturi de instruire mici și imagini de diferite dimensiuni. Precizia și viteza modelului de rețea sugerat sunt cu 94% mai bune decât cele ale tehnicilor tradiționale de clasificare prin învățare profundă.

Cuvinte-cheie*: învățare profundă, industria modei, TGANetwork, CNN-LSTM hibrid, detectare și clasificare, clasificator*

INTRODUCTION

Defect identification and classification are essential in the fabric business because they can yield useful data for textile production quality management. Fabric flaws are traditionally examined by humans, which takes a lot of time and effort. Furthermore, the weariness brought on by prolonged effort can make this human inspection procedure ineffective. Therefore, the modern fabric business may find automated visual inspection and classification procedures desirable. Defect detection is a major problem when it comes to identifying abnormal surface areas in industrial products such as paper, textiles, aluminium plates, etc. The existence of flaws has been predicted to lower fabric prices by 45% to 65%. Since all products must be inspected for flaws, any defects must be found, fixed, or replaced to guarantee quality control in the fabric business.

Defects in fabrics are imperfections in the material that lower their quality, which lowers their usefulness and worth. It is impossible to fix or undo these flaws once they are on the market. Delivering high-quality products, therefore, requires making sure the final product is perfect. A key component of ensuring customer satisfaction and cutting manufacturing costs is quality control. During the manufacturing process, a variety of factors, including the raw material, spinning, dying, knitting, and weaving, can result in defects in the fabric. Faulty fabrics are produced as a result, which could reduce customer satisfaction. In addition to the production costs, subpar items are typically sent back to the textile mill for replacement or repair, raising the total cost. Therefore, if there are any fabric flaws, they must be found so that the producers can determine the source and take the appropriate action to address the problem [1, 2]

It is possible to get the conclusion that the majority of these studies employ a window or filter-based technique after examining these relevant works in the field of fabric defect identification. The Gabor filter analyses texture using a linear filter. Around the analysis point, it looks for any particular frequency content in the picture. The linear structure of the filter means that the flaw identification process takes too long. It records the features and converts them into a feature vector, whose dimensions continue to grow because of the filter's linearity. Redundancy of characteristics is another effect of this that lowers the recognition rate [3, 4, 5]. Deep learning, commonly referred to as Deep Neural Networks (DNN), including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), was developed to address the problem of insufficient processing power for massive amounts of unstructured data.

When compared to other current approaches, the suggested hybrid CNN-LSTM utilising deep learning and TGANet performs well in classification.

Breathability, temperature control, electrical information, and colour-changing material are how textiles or fabric images are categorised. The spread of coherence and the log Gabor filters lessen noise, uneven lighting, and processing flaws brought on by bogus ridges and ridge fractures in the textile photos.

Problem statement

The hybrid CNN-LSTM approach based on TGANet is utilised to enhance the fabric picture classification and detection efficiency. Coherence diffusion and log Gabor filters are applied to fabric images to extract very resilient features and noise. To improve the retrieved texture features, statistical texture transformations and texture filtering are applied. The main issues with the suggested approach include poor image quality, environmental flaws, subpar material quality, and incorrect classification. But classifying flaws according to these textural characteristics makes it difficult to identify particular flaws. Deep learning-based fabric picture classification is used to get around these flaws.

Contributions of the paper

- Combining the coherence diffusion filter with the log-Gabor filter: It reduces processing defects caused by spurious ridges and ridge fissures, as well as noise and uneven lighting in the textile images. For the filtering, a convolutional function with ReLu activation is taken into consideration.
- TGAnet: The current research proposes an enhanced TGANet to learn the reconstruction of fabric images in an unsupervised way, hence addressing the issue of the lack of defect samples. In contrast to conventional methods of detecting fabric defects, which rely on a high number of defect samples, the enhanced TGANet accepts a large number of normal fabric photos as input.
- Hybrid CNN-LSTM is used to increase the recognition accuracy level and achieve excellent performance in detection and classification compared to other existing methods.
- Deep learning algorithms are considered to make it faster and easier to analyse multiple datasets. The algorithm has led to better-quality and improved accuracy of 94 % of textile images

The structure of the paper is as follows: In the 2nd section, the literature on detection, filtering and classification is reviewed. In the 3rd section, the methodology for this experiment is explained. The experiment's results are discussed and summarised in the 4th section. The recent research is concluded in the 5th section.

LITERATURE SURVEY

Several studies have successfully employed image filters, classification and detection of textile images for highlighting defect features in fabrics.

Dataset preprocessing using filters

The most popular filters for enhancing textile qualities are the Local Binary Pattern, Gabor, and Median filters. These filters are commonly used in conjunction with other deep learning algorithms to get exceptional results for jobs involving fault identification. Utilising a variety of models, extracting GLCM and LBP features, and converting images to grayscale, an image classification technique that achieves high validation accuracy on unseen data [7]. It was possible to attain up to 70% test accuracy and 83.9% validation accuracy. A median filter for denoising and pooling operations using deep learning methods to detect fabric problems [8]. The accuracy achieved with this strategy was 90%. The sensitivity of defect identification can be increased through picture preprocessing, as these filters demonstrate.

In fabric analysis, pattern recognition techniques are essential. For pattern identification, a variety of image processing filters are available. Preprocess fabric images for classification by binarising them, filtering (smoothing with the Direct Fourier Transformation method in combination with Gaussian filtering, and compressing with the Daubechies wavelet method),

and after that, employing image processing techniques to extract pilling features (number of pilling points, area, etc.) [9].
The standard option for localising frequency and spatial data is to use Gabor filters. Since the Gabor filters only have an octave maximum bandwidth, they are not the greatest choice for those seeking broad-spectrum information with maximal spatial localisation [6]. A similar method to identify fabrics by identify the texture of wrinkles. After removing noise and converting images to LBP-like grayscale and binary formats, it extracts information such as the area-to-height, area-to-perimeter, and wrinkle width-to-length ratios. Contextual filtering, CNN filters, Gaussian, LaPlace, Gabor, and other filters are employed. However, the Log Gbor (LGF) filter is utilised because of certain loss, error, noise, complex backdrop image, poor feature extraction results, and blur defects [10].

Textile image detection

Neural networks utilised for image synthesis serve as the foundation for Generative Adversarial Networks (GANs) [11]. It is composed of a discriminator and an image-generating generator. The generator uses noise and latent space as its weights to produce images. These produced images are fed into a discriminator, which computes the error value, also known as the loss function, by comparing the produced images with actual images that are already there. The generator receives these loss functions, and it adjusts itself to create better images by responding to the loss function. The discriminator also took advantage of this mistake to improve future forecasts.
Our discriminator has an error value of 40%, for instance, if we send it an actual image and it indicates that it is 60% correct. Also, if we send the discriminator a phoney image and it indicates that there is a 70% likelihood that it is incorrect, our discriminator error is 30%, and our generator error is 70%. Both the discriminator and the generator learn from this. With each iteration, the back-propagation approach is used to alter the weights of both models. Numerous GAN variations followed, including deep convolutional GAN (DCGAN), conditional GAN (CGAN) [12, 13], and Wasserstein GAN (WGAN) [14]. Additionally, GAN is used in a variety of applications, such as data production [15, 16].
Convolutional networks were used to classify clothing designs. The task involved automatically recognising the clothing according to the newest trends in internet fashion. A deep convolutional neural network was used to achieve good results. Using two popular models, AlexNet and VGGNet [17, 18], high hand-engineered feature extraction was accomplished. The data detection function in this suggested approach is accomplished using a textile generative adversarial network.
A novel method for automated textile design pattern generation using generative models. The accuracy of state-of-the-art results in the classification of textile design patterns was improved by 2% through data cleaning and pseudo labelling [27]. Convolutional Variational Autoencoders (CVAEs) for all classes separately, and have evaluated the models using the inception score. Conditional generative adversarial network (cGAN) for fabric defect data augmentation. The image-to-image translator GAN features a conditional U-Net generator and a 6-layered PatchGAN discriminator are used in [28]. The conditional U-Network (U-Net) generator can produce highly realistic synthetic defective samples and offers the ability to control various characteristics of the generated samples.
GANs generate new images by learning features from the existing images. Features are extracted by a convolutional network, and images are generated through a deconvolutional network [29]. Different variants of GANs are available in various fields, and they have helped in many other fields, along with the field of fashion. DCGAN has been trained on all the patterns collectively up to a specific point, and the weights from the trained model have been saved. After that point, the model is trained on specific kinds of patterns, i.e., cheetah, to generate that specific kind of new pattern.

Textile image classification

Jianli and Baoqi have put forth a technique that consists of principal component analysis (PCA), NN, and grey-level co-occurrence matrix (GLCM). They employed GLCM for feature extraction and PCA to minimise the input vector's dimensionality. The high-dimensional space is represented at a low level via PCA. According to [19], these high-dimensional components are independent. To classify faults, a three-layer back-propagation neural network was employed. Fabric defect detection technology based on wavelet transform and NN [20]. To create an efficient defect system, they merged two approaches.
Artificial neural networks (ANN) are recommended for classification [21] employing supervised, reinforcement, and unsupervised learning techniques, including Multi-Layer Perceptrons, Learning Vector Quantisation, and Self-Organising Feature Maps. The MLP, LVQ, and SOFM techniques are used to classify the images into seven groups. Key depth features can be learned both intelligently and adaptively using deep learning algorithms, namely Convolutional Neural Networks (CNN). Systems for detecting fabric defects are better suited for different kinds of defects because of this capability. Every piece of input data that represents the faulty fabric image is stored in the CNN's deep structure.
CNN has also been used for positions like classifying and detecting fabric flaws. Using a modified AlexNet, [22] initially used CNN to classify defects in yarn-dyed fabrics. To classify fabric faults in a limited sample size, CNN was also used in conjunction with compressive sensing [23]. Additionally, a lot of activities involving the detection of fabric defects have been finished using CNN-based techniques. An effective unsupervised model for fabric defect identification

based on multi-scale convolutional denoising autoencoder networks [24].
LSTM has been used in several fields, such as image processing, convolution networks for classifying different materials, and anomaly detection in time series. Defect identification in fabric was found to be learning based [25, 26]. The invisible images of the fabric are categorised and segmented using LSTM-based texture classification. Labelling the trained images that are being classified is a crucial step in the texture classification process. In texture categorisation, four distinct methods are used. Co-occurrence features, greyscale differences, signed differences, and the Local Binary Pattern of microstructures, which blends a statistical and structural approach, are the methods employed. In the field of prediction, deep learning's long short-term memory (LSTM) has exceptional processing capabilities for time series data.

PROPOSED METHOD

The main reason for using CNN-LSTM instead of LSTM is that, in contrast to other LSTM-based techniques, it can anticipate the output with high accuracy. CNN typically raises the image's level of complexity. The main outcome is that it enhances the performance of movement prediction concepts and can automatically extract high-level features. The automatic captioning of images is enhanced by the integration of CNN-LSTM. The primary goal is to resolve the time-series paradigm, and it can produce a more effective sequence plan. The procedures for textile image preparation, detection, and classification. Below is the suggested block diagram.
The hybrid CNN-LSTM-based TGANet approach for textile image recognition and classification is depicted in figure 1. The acquisition and preprocessing of the dataset is the first phase. The textile images are extracted from the textile design multimodal dataset and preprocessed by applying the log Gabor and coherence diffusion filters to eliminate mistakes and noise. The detecting step then receives the preprocessed data. The suggested TGANet technique is used to identify the filtered images during the detection phase to increase accuracy and efficiency and prevent flaws. Subsequently, the photos are supplied to the classification phase, where textile images are categorised using a hybrid CNN-LSTM algorithm.

Pre-Processing

The pre-processing involves the process of data histogram, data thinning, data binarisation, data normalisation, data validation, data cleansing, data reduction and data enhancement. To solve the issues of varying clarity, grey scale, and channel count amongst various textile images, image pre-processing was standardised. That eliminates the unwanted distribution and noise in the image. It converts different forms of words to their respective root words.

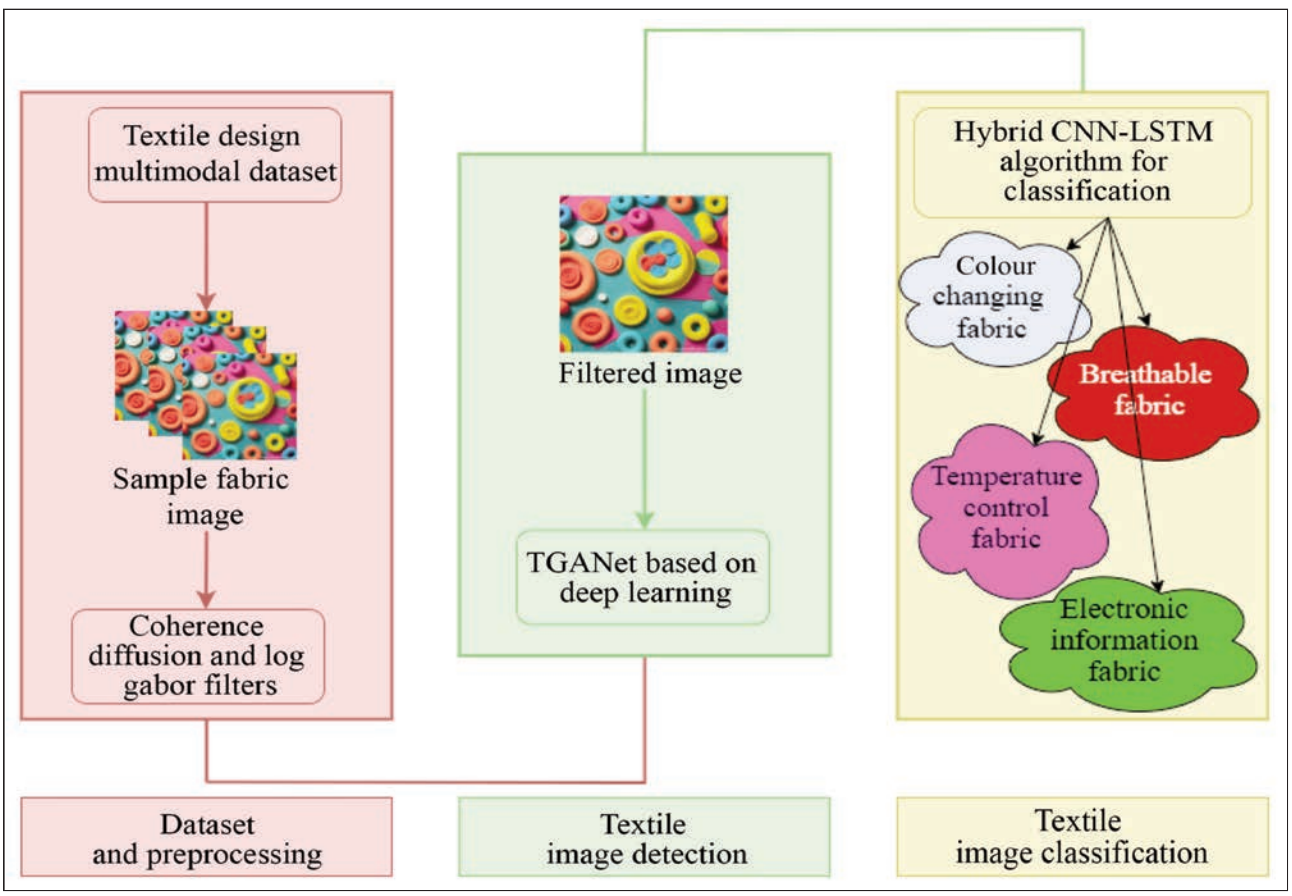

Fig. 1. Proposed block diagram

Preprocessing with filters

It is generally an edge-preserving filter. If there is any degradation in the improvement of colour saturation, the direct channel-bright method is used with certain colour factors. The general filtering equation is given below.

$$E = S(O) + \tau D \quad (1)$$

where O represents the observed image, S is the edge-preserving filtering operation, and τ is the parameter. D is the layers of the image. E is the enhanced image. Filtering is used as the template to gain the similarities between the images.

Convolutional function with the ReLu activation is considered for the filtering. Some of the filters are Prewitt, Sobel, kernel and Laplacian. All these filters are used to detect the edges along the horizontal and vertical axes.

Coherence Diffusion filter

Partial differential equations are used in the coherence diffusion filter technique, a nonlinear diffusion enhancement method, to maintain the dependence of textile image values on the gradient of neighbouring image intensities.

$$\delta t \, I = \mathrm{div}\,(D.\nabla I) \quad (2)$$

$$D = \frac{1}{1 + (||\nabla|| k)2} \quad (3)$$

where "I" denotes the image gradient, "div" denotes the divergence operator, "D" denotes the diffusion tensor, and "k" is the matching constant.

Log Gabor Filter

The log-Gabor filter helps to minimise noise and uneven lighting in the textile image, as well as processing flaws brought on by false ridges and ridge fissures. The Log-Gabor filter consists of two pieces. The following displays the angular frequency response and the radial filter frequency response.

$$G(f) = \frac{f_0}{f} \exp\left(\frac{-(\log(f/f_0))^2}{2(\log(\sigma/f_0))^2}\right) \quad (4)$$

$$G(f,\theta) = \exp\left(\frac{-(\log(f/f_0))^2}{2(\log(\sigma/f_0))^2}\right) \exp\left(\frac{-(\theta-\theta_0)^2}{2\sigma_\theta^2}\right) \quad (5)$$

Multiplying them together provides us with the log-Gabor filter:

$$G(r,\theta) = Gr(r)\cdot G\theta(\theta) \quad (6)$$

where the log-Gabor filter is constructed using the Polar coordinate (r,θ), the local centre frequency f_0, the local orientation angle θ_0, the scale bandwidth σ_f, and the angular bandwidth σ_θ the filter's response is managed by these four settings. The angular and radial components are the two parts that make up the log Gabor filter bank. To create Log-Gabor filters, some parameters are also needed, including the following: The smallest scale filter's wavelength determines the lowest frequencies that the filter wants to cover. The quantity of filter scales. How many different filter orientations can be used. The ratio of the standard deviations of the angular Gaussian spreading function to the angular spacing between filter orientations controls the angular overlap of the filter transfer functions.

Minutiae feature extraction

Feature extraction is an important part in recognition tasks, predicting performance, and it reduces the computation. All these are done by using the feature selection method. A key feature in textile image identification is the feature extraction to make it more accurate and run time to improve the accuracy. In this method, extraction is done through CNN using deep learning. The feature extraction includes the process of filtering, clustering, fusion and mapping. The extraction is normally of two types. They are knowledge-based and a deep learning-based method. The DL method performs automatic feature extraction. The extraction is done through the convolution function, that the function will refine the pixel properties, such as sharpening, deblurring, and finally enhancing the edges to strengthen the security.

TGANet Detection

Textile Generative Adversarial Networks (TGANs) are used to enhance photos and generate images, videos, and 3D scenes. When it comes to picture production, TGANets create new images by extracting features from preexisting ones. The majority of these designs consist of a single repeating pattern. To build the entire design, the designers must first generate these patterns, which are then photoshopped. Designers can get ideas for new designs by using TGANets to generate textile patterns. It has been suggested that TGANets create new patterns to accomplish this aim. There are several TGANet variations in use, and they have aided numerous other sectors besides fashion.

Figure 2 shows the basic architecture of TGAnet. TGANet is a generative model that is mostly used for image production and has its theoretical foundation in zero-sum game theory. The authors simultaneously trained two deep learning models, a discriminative model called 'D' and a generative model called 'G',

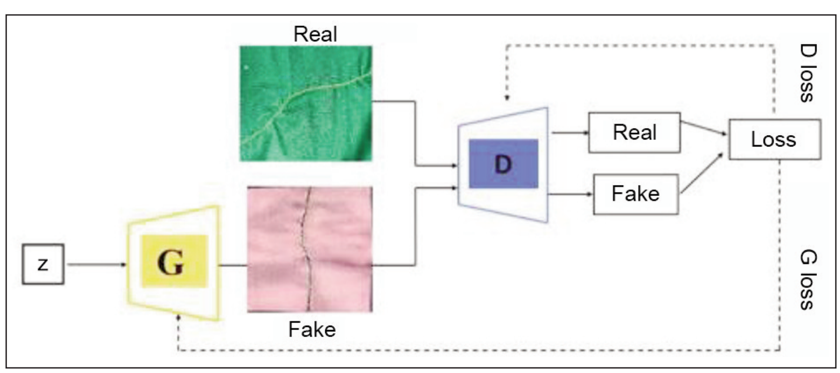

Fig. 2. Basic TGAnet architecture

using a min-max optimisation framework. The idea behind this strategy is a zero-sum game, in which the goal of one player is to maximise their gain and the goal of the other is to minimise their loss. To improve the training stability, this update involves removing the pooling layers and adding Batch Normalisation between the convolutional layers and the activation functions. Fully connected hidden layers are eliminated in favour of deeper designs. The generator employs ReLU activation for internal layers for the output, while the discriminator uses LeakyReLU throughout. These changes collectively improve training and output quality in the Textile Generative Adversarial Network.

Hybrid CNN-LSTM classification

The CNN-LSTM technique is used to improve the image's accuracy level and address less reliable image faults. The image's features are extracted using a CNN architecture-based deep learning model, and the extracted output is then fed into an LSTM input to carry out the extraction's prediction (figure 3). Complex patterns that are exceedingly difficult to learn using conventional methods can be learned via LSTM. CNN-LSTM is a multiple-layered algorithm. Time Distributed Layer, Flatten Layer, LSTM Layer, Dropout Layer, Dense Layer, and Output Layer; 1D Convolution Layer, Dropout Layer, 1D Maxpool Layer, and so forth are the layers that make up this. This can automatically extract feature information. Below is a block schematic of the Integrated CNN-LSTM.

The prediction accuracy of CNN-LSTM is higher than the single LSTM model, which reduces the training time. The hybrid CNN-LSTM, which extracts the traffic network data features and provides better intrusion detection systems. It also improves the memory utilisation, speeds up the processing and improves the robustness. In this method, the first block consists of a pooling and consensual layer, and the second block, that is the LSTM block, has a dense-based layer to increase the efficiency level. In the hybrid CNN-LSTM method, the linear layer is introduced after the CNN layer, which reduces the dimensions without any reduction in the accuracy. In this method, the first block consists of a pooling and consensual layer, and the second block, that is the LSTM block, has a dense-based layer to increase the efficiency level. It also shows the accuracy of the RMSE value:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - x_j)^2} \tag{7}$$

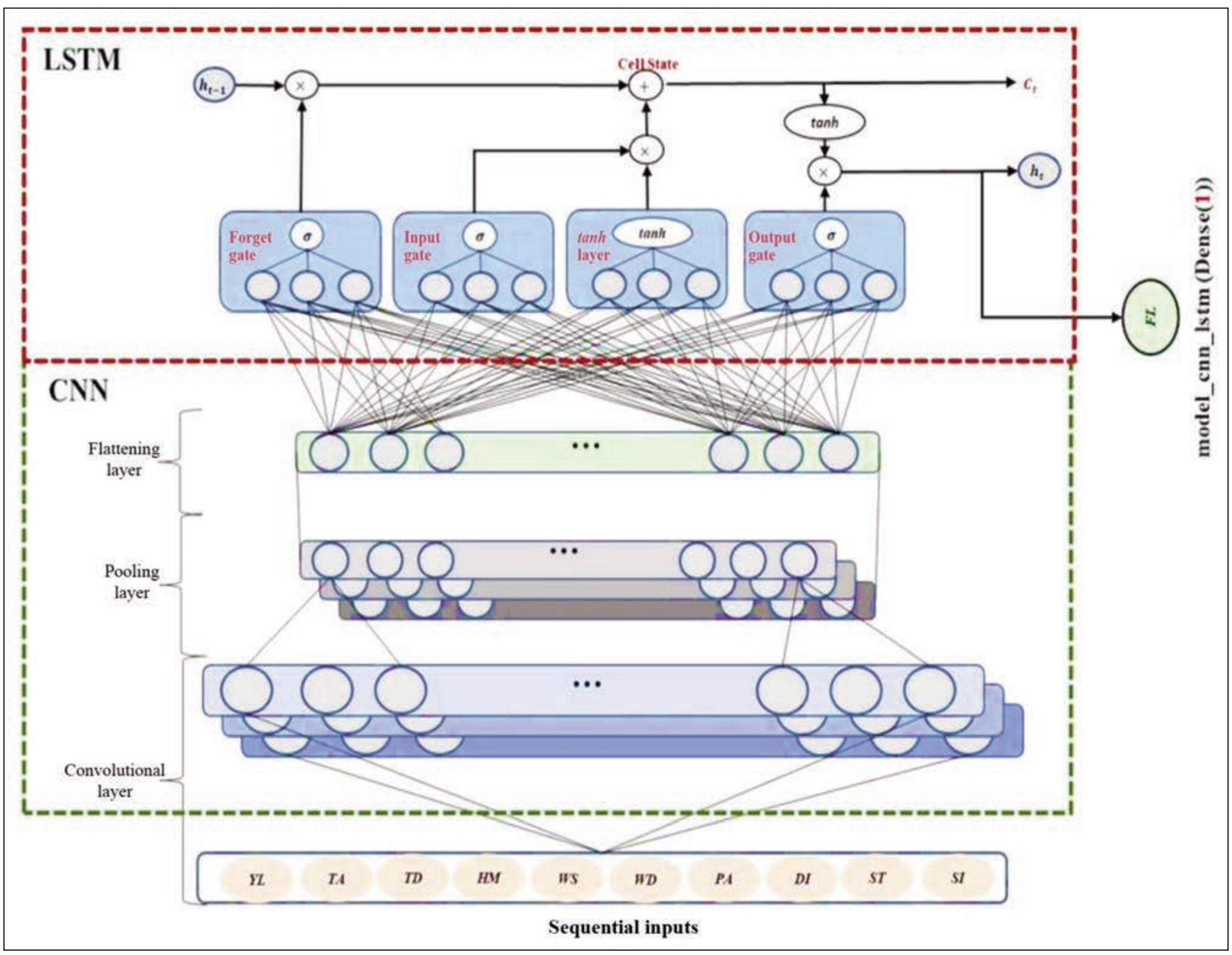

Fig. 3. The proposed hybrid CNN-LSTM architecture

where N is the number of errors. x_i is the observed value and x_j is the forecasted value. The value will be approximately equal to 1 using the deep learning method. The accuracy measurement is given below.

$$Accuracy = \frac{Message\ that\ was\ correctly\ predicted}{total\ number\ of\ predicted\ messages} \tag{8}$$

ReLU expression can be represented as,

$$ReLU(x) = f(x) = \max\ (0,\ x) \tag{9}$$

where $ReLu$ is a Rectified Linear Unit of X, will be the maximum value of x along the x-axis and 0 along the y-axis. Followed by the down-sampling layer is known as the max-pooling layer. That expresses the generalisation and convergence of the image to reduce the noise. The basic formula for the LSTM using the deep learning method is as follows:

$$h_t = \sigma\ (Wi,\ h \cdot x_t + Wh,\ h \cdot h_{t-1} + b) \tag{10}$$

whereas W represents the weight of the input and the hidden layers. b is the hidden vector bias. x is a sample of the image. CNN is used for the extraction purpose, and the LSTM is used for the classification.

Performance analysis

Different performances are used to analyse the accuracy measurements. Each of the metrics is defined by the formulas below.

Accuracy: The message was correctly predicted among the total number of predicted messages.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Sensitivity: It is the ability to translate expected positive numbers into unquestionably positive ones.

$$Sensitivity = \frac{TP}{TP + TN} \tag{12}$$

Specificity: It is a statistic used to predict the presence of true negatives.

$$Specificity = \frac{TN}{TN + TP} \tag{13}$$

where TP is the number of classifications that were true positives. To put it another way, FP stands for false positives, TN for true negatives, and FN for false negatives.

RESULT AND DISCUSSION

A textile image multimodal dataset comprising 8000 photos with categories for broken thread defects, seam puckering, and uneven stitching was used to train TGANet. We used a mini-batch training strategy to increase training efficiency and prevent loading all images into memory at once. We created a sample plot for local visual assessment for each of the 40 training batches. We produced a variety of samples with a range of faults using TGANet. The sample dataset photos are displayed in figure 4.

To eliminate noise, error, patches, clarity, and environmental flaws, the dataset samples are filtered using the log Gabor and coherence diffusion filters. Additionally, figure 5 compares photos with and without filters.

The comparison of different detection strategies is provided below. The evaluation of current techniques like GAN, DCGAN, CGAN, WGAN, Alexnet, and VGGnet. To determine the detection efficiency and degree of correctness of the identified textile images, the suggested TGAnet is contrasted with all of these current techniques.

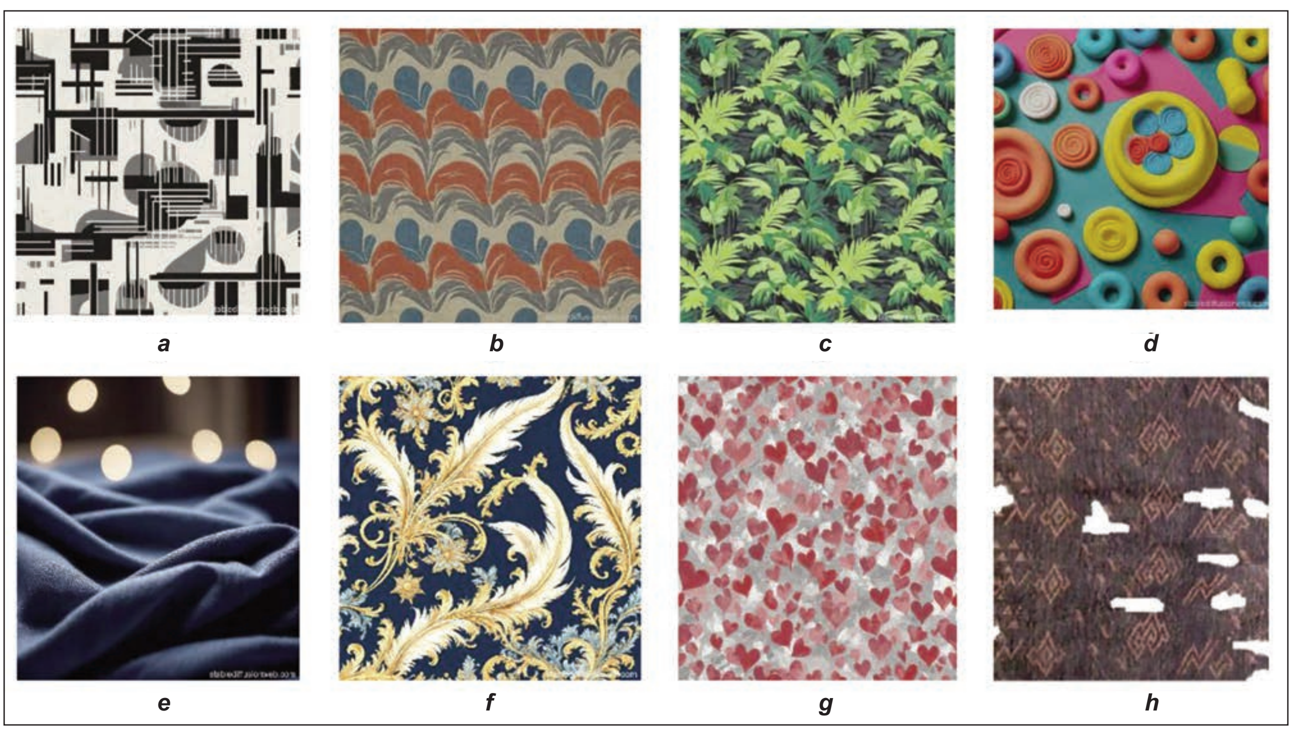

Fig. 4. Sample textile images from the dataset

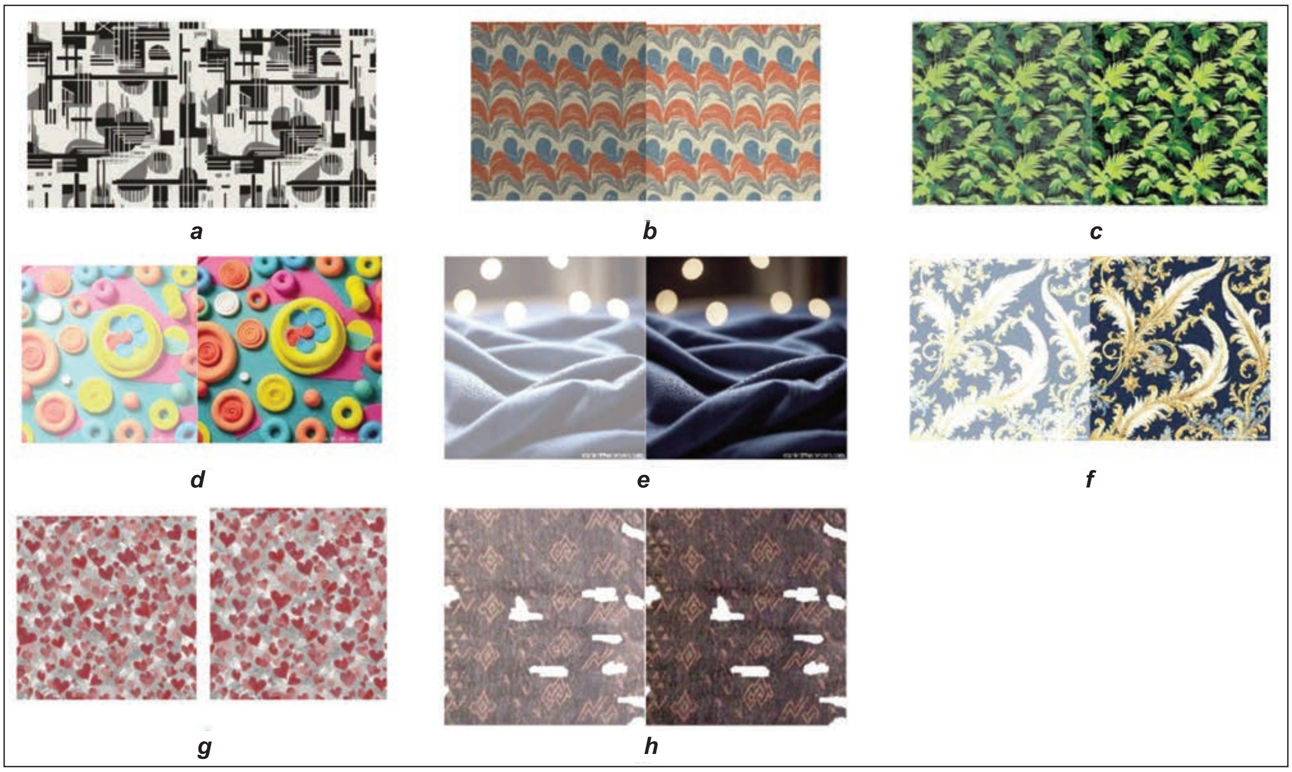

Fig. 5. Comparison of sample images vs filtered images

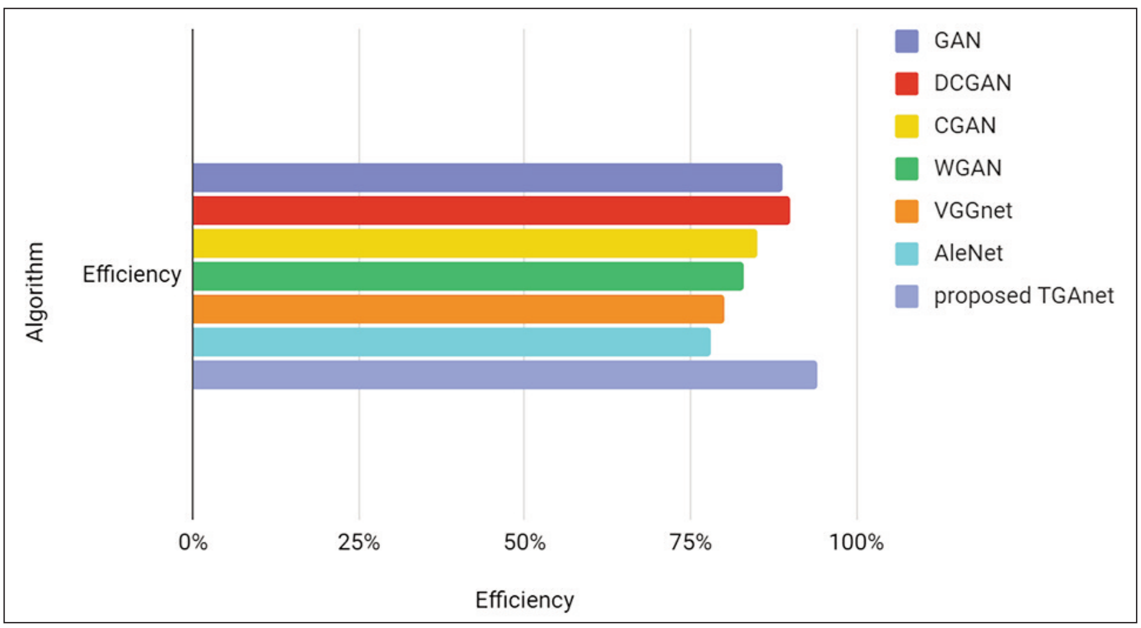

Fig. 6. Graph of detection efficiency vs algorithm

The detection efficiency level is displayed in figure 6. The detection efficiency of the GAN algorithm is 89%. 90% of the detection efficiency is provided by the DCGAN. The detection efficiency is 83% for the CGAN algorithm and 85% for the WGAN algorithm. While the Alexnet offers 78% efficiency, the VGGnet offers 80% efficiency. Additionally, the suggested TGANet algorithm offers the highest efficiency rate of all the current techniques, with a detection accuracy level of 94%.

The table below shows the classification accuracy of various existing and proposed classifiers for the textile images.

The classifiers and accuracy levels of the different classifiers used for the textile picture classifications are displayed in table 1. The accuracy of 78% was obtained using a principal component analysis method based on GLCM. The accuracy of the ANN-based deep learning approach is 68%. 79% accuracy is produced via SVM. The accuracy of the LSTM is 80%, while the accuracy of the generic CNN alone is 83%. The results of these two classifiers are better. Therefore, the suggested approach combines the CNN and LSTM hybrid forms to improve deep learning categorisation of textile photos.

The effectiveness of two distinct textile image categorisation examples is displayed in table 2. CNN produces results that are superior to those of the LSTM method when compared to the three methods mentioned above. However, the outcomes of the suggested approach are superior to those of the other three.

Table 1

COMPARISON OF CLASSIFIERS AND ACCURACY LEVELS	
Classifier	**Accuracy level**
GLCM	78
ANN	68
NN	70
SVM	79
LSTM	80
CNN	83
Proposed hybrid CNN-LSTM	**85**

Table 2

CLASSIFICATION EFFICIENCY FOR DIFFERENT CLASSIFIERS								
Sample images	**Colour changing fabric**		**Temperature control fabric**		**Electronic information fabric**		**Breathable fabric**	
	CNN	75	CNN	62	CNN	52	CNN	65
	LSTM	72	LSTM	59	LSTM	50	LSTM	60
	CNN-LSTM	78	CNN-LSTM	68	CNN-LSTM	56	CNN-LSTM	70
	CNN	68	CNN	59	CNN	50	CNN	68
	LSTM	62	LSTM	55	LSTM	53	LSTM	65
	CNN-LSTM	70	CNN-LSTM	63	CNN-LSTM	57	CNN-LSTM	73

CONCLUSION

An essential component of the production process, image-based quality control seeks to identify material irregularities. The intricacy and diversity of products, flaws, and the infrequency of flaws pose difficulties. Therefore, manual inspection is still a major component of quality control. Performance has significantly improved with supervised, data-driven techniques. By using the uniformity of defect appearance across fabrics to convey information about anomalies from one fabric to another, we get around this limitation. Deep learning detection based on TGANet is thought to increase accuracy and efficiency. The images are improved, and the noise is eliminated by applying the log Gabor and coherence diffusion filters. To categorise the photos according to specific criteria, hybrid CNN-LSTM based deep learning classifiers are employed. The future work can be performed with different filters or any other hybrid deep learning methods for the classification of textile images.

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