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PREDICTION OF YARN QUALITY BY DEEP BELIEF NEURAL NETWORK

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Abstract

Many textile industries are utilizing the artificial intelligence techniques to enhance the production quality and product performance on each phases of production unit. In spinning mills, examining the yarn parameters such as unevenness, strength and mass are considered important for yarn quality prediction. In order to improve the performance of yarn quality, an innovative quality yarn prediction using Deep Belief Neural Network (DBNN) approach for yarn images are proposed. Initially pre-processing of the images is carried out using deinterlacing. Deinterlacing is a process which introduces the missing lines of encoded image sequence on spatiotemporal domain. It is employed to recognize and initialize weight to the important features and biases. It used for determination of the quality among the pair of units on heterogeneity information of the yarn. Feature extraction and feature selection is carried out by constructing the feature vector using principal component analysis. DBNN is employed for obtaining the latent and optimal features which represents the Yarn Evenness, Yarn Strength and Yarn Mass Parameters. It is considered as yarn quality determining features. The quality of the yarn is determined with respect to quality index of the features explored in deep learning processes. Experimental results obtained from the proposed model on identifying the quality of the yarn images is outperforming in terms of scalability and efficiency on comparing it against traditional deep learning architecture such as Convolution Neural Network.

Keywords: Yarn Quality, Feature Extraction, Deep Learning, Yarn Evenness, Yarn Hairiness, Deep Learning, Deinterlacing

抽象的

许多纺织行业正在利用人工智能技术来提高生产单元每个阶段的生产质量和产品性能。在纺纱厂，检查纱线参数如不匀度、强度和质量对于预测纱线质量很重要。为了提高纱线质量的性能，提出了一种使用深度置信神经网络 (DBNN) 方法对纱线图像进行质量纱线预测的创新方法。最初使用去隔行对图像进行预处理。去隔行是在时空域上引入编码图像序列的缺失行的过程。它用于识别和初始化重要特征和偏差的权重。用于判断成对单元间纱线的异质性信息的质量。通过使用主成分分析构造特征向量来进行特征提取和特征选择。 DBNN 用于获得

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代表纱线均匀度、纱线强度和纱线质量参数的潜在和最佳特征。它被认为是纱线质量的决定性特征。纱线的质量是根据深度学习过程中探索的特征的质量指数来确定的。从所提出的识别纱线图像质量的模型中获得的实验结果在与传统的深度学习架构（如卷积神经网络）进行比较时，在可扩展性和效率方面表现出色。

关键词：纱线质量、特征提取、深度学习、纱线均匀度、纱线毛羽、深度学习、去隔行

1. Introduction

Cotton yarn is generated on production process of cotton fiber processing. Cotton yarn processing includes cotton cleaning, cotton combing to thick yarn and fine yarn. Quality inspection on yarn quality is carried out manually as visual assessment [1] and it is automated through fabric structure analysis[2] through employment of machine vision techniques. Automated Yarn Quality Assessment method employs image processing and Image analysis techniques on basis of machine learning or deep learning. Quality assessment of yarn measures yarn hairiness, yarn thickness, yarn density and yarn surface defects [3]. Image analysis is to compute the dimension of sliced connection of yarn ends with respect to yarn structure and yarn repetition as those factors influence the yarn fabric quality. Further uneven distribution of two weft yarn causes strong color difference and degree of reflection in the color degree of reflection in the appearance of the fabric.

In addition, quality of the yarn depends on another important indicator of yarn which is considered as yarn hairiness [4]. Yarn hairiness is considered as fiber head or tail which twisted partially on exposing to yarn stem. Yarn hairiness is classified into two categories on appearance, one kind of appearance in form of protruding fiber end and other in form of looped fiber arched near the stem. It affects the appearance of fabric as final textile product [5] and results in cloth pilling. In order to control occurrence of the yarn hairiness during its production, machine learning and deep learning approach has been employed but still it requires strong solution to control yarn hairiness.

Despite of several deep learning approaches along various thresholding based segmentation techniques to measure the yarn quality, yarn core and protruding fibers lacks prediction due to orientation effects. In order to tackle those challenges, a deep belief neural network has been proposed in this paper. It process the yarn images with initial preprocessing techniques referred as deinterlacing, feature extraction techniques referred as principle component analysis, extracted feature processed in deep learning layers for determining optimal features related yarn properties such as hairiness, Mass and Strength . Finally those features representing properties is referred with quality index to predict the quality of yarn.

The remaining of the paper is categorized as follows; related work is presented in the section 2. In section 3, proposed model named Deep Belief Network for Yarn Quality Prediction is described. The experimental setup and experimental results are evaluated in section 4. Finally Conclusion is presented in section 5

2. Related Work

In this section, various traditional deep learning model employed to yarn image in order to measure quality of the yarn with respect to quality index to the properties of yarn has been summarized and detailed as follows

2.1. Yarn Quality Prediction using Convolution Neural Network

In this method, Yarn Quality assessment has been carried out by employing Convolution Neural Network model which composed of the multiple layer architecture. In this model, max layer and convolution layer with 2*2*2 convolution supports to identify the yarn properties such as yarn mass, evenness and hairiness [7]. The yarn mass is computed with respect to diameter computation in the image features in the softmax layer. Further, same objective function can used to estimate the other properties of the yarn in output layer.

3. Methodology

In this section, yarn quality prediction model using DBNN is defined to measure various properties of the yarn and its quality is computed with respect to quality index of yarn. Proposed architecture of the work is described in the figure 1.

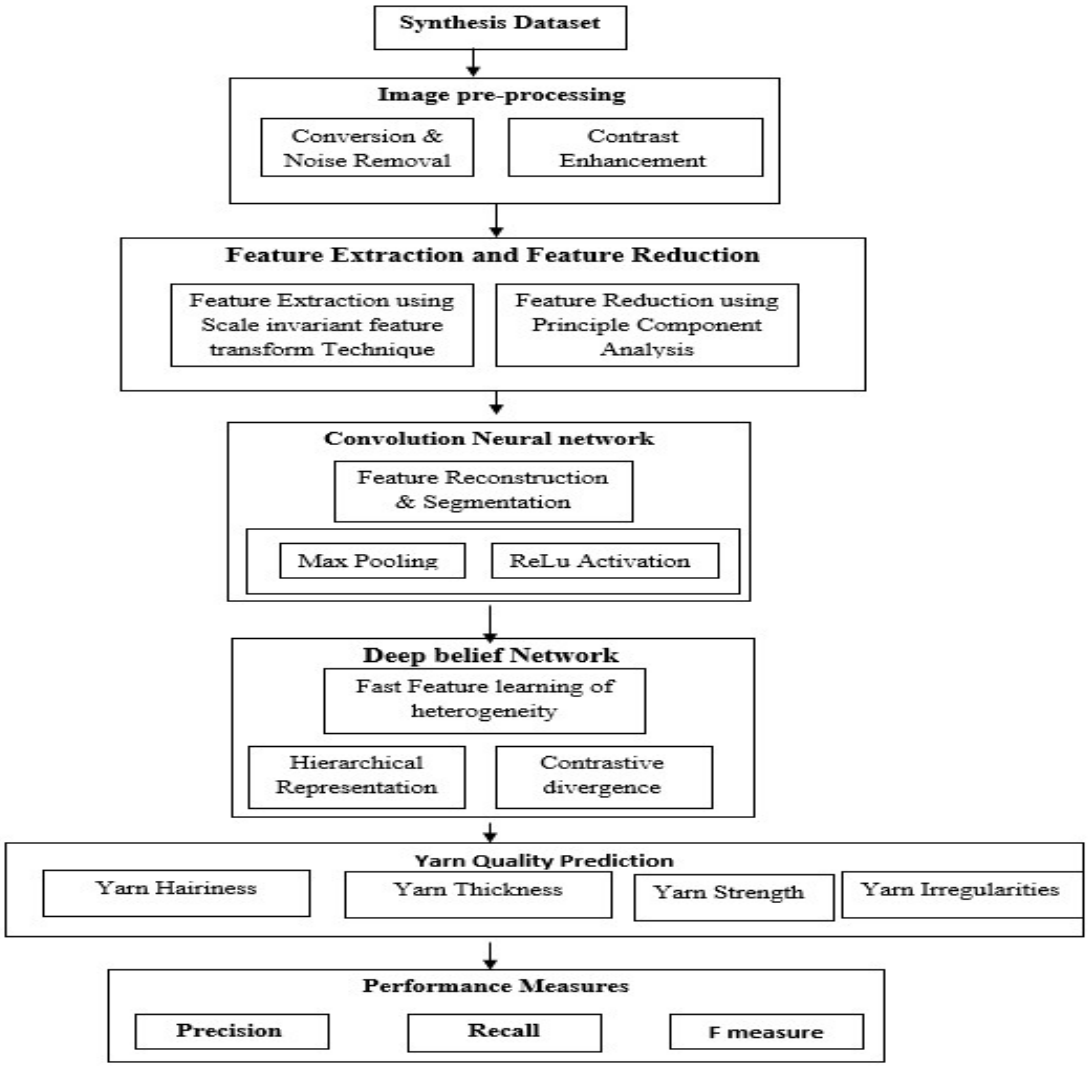


Figure 1 Architecture of Yarn Quality Prediction using Deep Belief Network

3.1.Yarn Image

The image test set used contains images extracted in the spinning mills in Coimbatore region of India. Images with resolution 768 × 576 and 528 × 522pixels, respectively) has been used to detect the quality of the yarn. The good indications for yarn quality are properties with respect to hairiness, evenness, mass and strength. The ground truth of quality index of yarn is generated for the yarn quality patches.

Generative Adversarial Net is employed to produce synthetic images for the training and testing of the yarn quality. In this process, thousand of synthesis image is generated for selecting the unreliable patterns of the images as yarn properties on robust learning. In order to completely exploit those generated images, modify a deep CNN specifically tailored for the quality prediction task. Formulate class-dependent fine-grained properties for classifying the yarn quality properties.

Yarn Samples - Spinning Method Ring Spinning

SAMPLE ID	YARN CONTENT	COMBED TYPE	COUNT
C1	COTTON	COMBED	30’S
C2	COTTON	CARDED	30’S
C3	COTTON	CARDED	32’S
C4	HOSEIRY	SEMI COMBED	40’S
C5	COTTON	CARDED	60’S
C6	COTTON	CARDED	80’S
C7	COTTON	COMBED	105’S

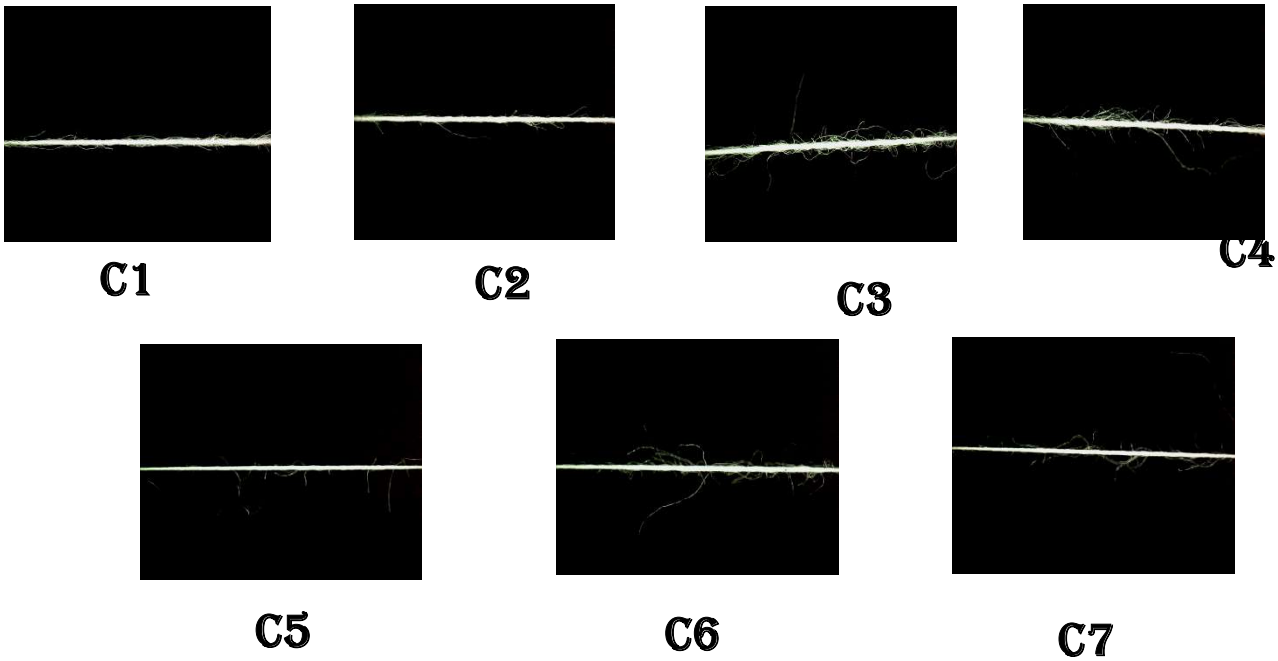
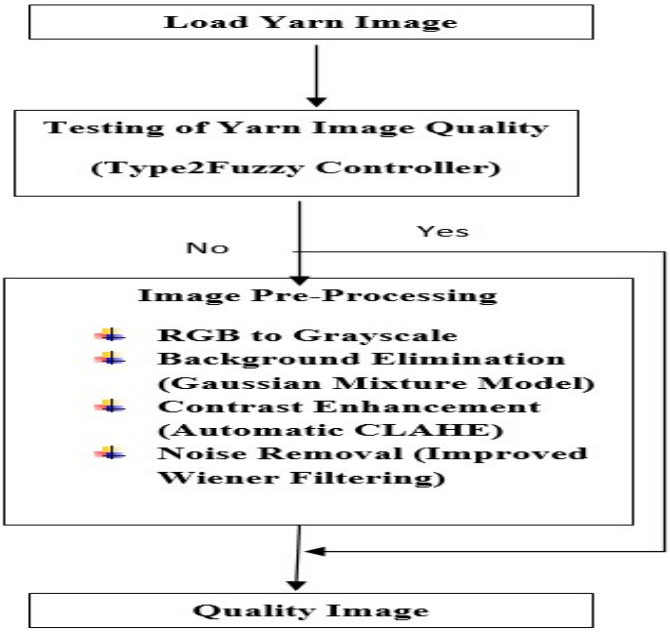


Figure 2 Steps in Image Pre-Processing



2.2. - Image Quality Assessment using Type 2 Fuzzy Controller

Initially, Image Quality of yarn image is assessed using Type 2 Fuzzy Controller. It is projected to solve uncertainty issues in the synthesis images by employing preprocessing technique to identify the image pixels in patch level using different image criterions such as Image Brightness, Image Contrast, Image Blur, Image Noise and Image Sharpness. Further employing the preprocessing, the image is quality is computed through Image quality value

parameter as IQv and its threshold to the particular parameter. On computation of condition such that if IQv value is greater than its threshold the yarn quality prediction process is initiated else it is taken for image pre-processing operation.

2.3. Image Pre-processing

Background Elimination:

- The Gaussian Mixture Model (GMM) is employed as background elimination method as it contains many advantages such as simple, fast and adaptive processing steps in comparison with histogram equalizations based background elimination methods
- The Gaussian Mixture Model formulated as follows:

$$G(x, y) = I(x, y) - B(x, y) \quad \text{----- Eq. 1}$$

Where I(x, y) represents the Input yarn image with background, B(x, y) is the Input image of background without yarns, and G(x,y) is the processed image after background elimination.

Raw image of background without yarns

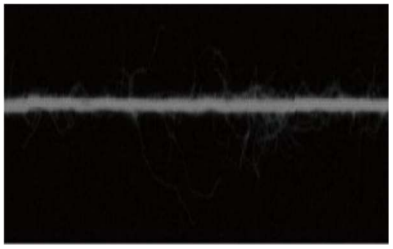
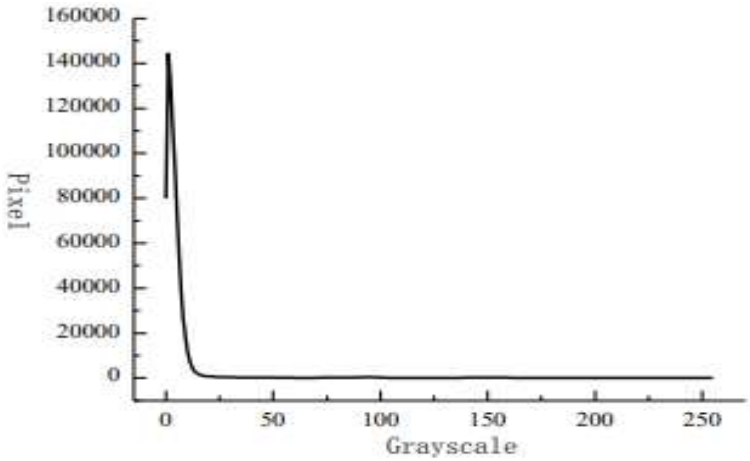


Image after background elimination



Deinterlacing

Deinterlacing of the pre-processed image is considered as Noise elimination process using edge based median filter and adaptive minimum pixel difference filter. Initially image is converted into gray scale images. Gray Scale image is generated as matrix using principal component analysis with values 0 to 255 and it uses mathematical function G representation which is highly reliable process to filter the

imperfections of the image with high noise level in the pre-processed image after background elimination process[9]. The gray scale image is represented as equation is given below

$$G(x,y) = E(I(x,y)) + D\eta(x,y) \quad \text{----- Eq 2}$$

Further the image is presented in the spatial form as follows

$$G(x,y) = \int_0^T E(x-x_0(t),y-y_0(t))\,dt \quad \text{----- Eq 3}$$

The spatial form of image computes the correlation between the pixel to identify the shape and temporal features for interpolations.

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2.4. Feature Extraction

Principal Component Analysis is a mathematical feature extraction tool which transforms a correlated Eigen value from the Eigen vector into uncorrelated Eigen value of Eigen vector called principal components. It is the combination of multiple different interpolations of the frames of missing lines using covariance and correlation matrix. In this chapter, the PCA algorithm is modelled to extracts the shape related features from the interlaced images. Implication of PCA in the DBN is to flatten the activation matrix of the activation layer to detect feature redundancy on computing the principal components of the feature vector .

Properties of the yarn feature is represented as $P_1(t), p_2(t) \ldots p_n(t)$

Where t is the time space,

Local maxima of non linear feature is

$$L = Nx,$$

where

'N is some Non Linear Feature matrix

The features of yarn are correlated for quality estimation with respect to quality factor. Yarn properties related features produced has following effectiveness in terms of

- classification quality
- Eliminate feature redundancy
- It computes the spatial and temporal features
- It discriminates the pattern efficiently.

2.5. Sparse PCA Representation

Sparse PCA is a feature analysis mathematical tool employed to determine the sparse features in the image vector. In yarn image, it represents the missing lines with respect to covariance and correlation matrix. Sparse feature containing the yarn properties effectively discriminates on quality assessments. The figure 3 represents the sparse based feature pruning of the Yarn images.

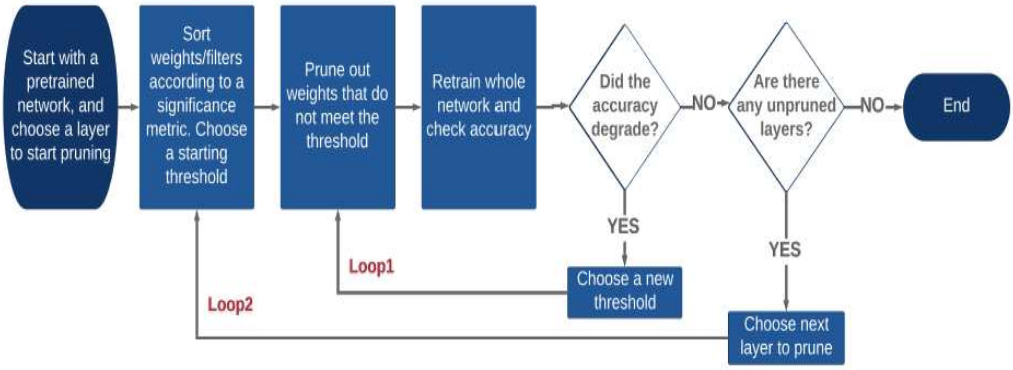


Figure 3 Pruning of the features of the interlaced frames

Sparse PCA is to analyze the results and to optimize the network layer in CNN against yarn quality factor classification. The focus in this work is to pre-trained networks of DBN with multiple iterations for effective feature retraining. Further, Sparse PCA has also been used to initialize neural networks and analyze their adversarial robustness.

PCA is a feature dimensionality reduction technique which can employ to remove feature redundancy between correlated features of the interlaced image set. It identifies new, spatial and temporal features which are linear combinations of all the features extracted using Eigen values in Eigen vector. Obtained spatial and temporal features are ranked on basis of the feature variations.

Input pre-processed image is represented as NxM sized matrix in PCA. In this N represents samples containing M features. Further image interpolates spatially or temporally based to obtain the highest possible feature resolution.

2.6. DBNN based Representation of the Image

In this section, a proposed DBN architecture to compute the yarn image quality automatically learns features of the extracted using sparse PCA. The proposed DBN architecture has six-stage architecture utilizes the multiple convolutions and fully connected layers for feature representations. The convolution layers and fully connected layers operations on the obtained features are followed by ReLU activation layers for better sparse representation. The DBN architecture composed of feature processing layers such as input layer, hidden layer, activation layer, fully connected layer, Soft Max layer and output layer.

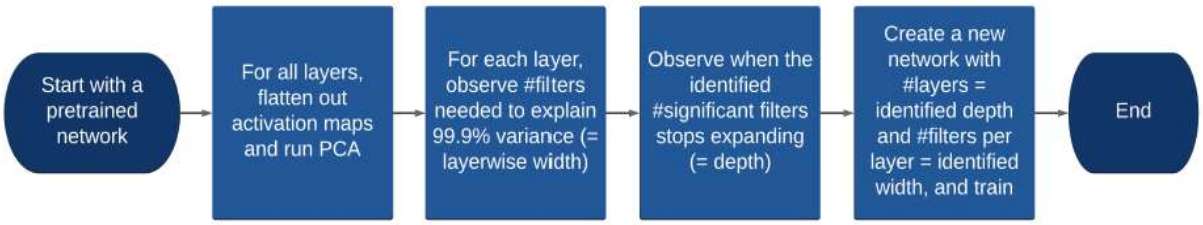


Figure 4: Layer based Architecture of DBN on predefined Network

The basic definitions and processes of every layer are represented as follows.

- **Input layer.**

The input layer explores the extracted sparse PCA features containing the yarn properties and it is constructed as feature vector. Feature vector is represented in the form of matrix for processing further in the hidden layer, deep layer and activation layer with objective function values.

- **Deep layer.**

Deep Layer in DBN's architecture is to generate several combination of feature to feature vector. It contains dense and deep feature combination hidden in the normal extraction technique. The purpose of the deep learning is to extract the different characteristics of the input data with hidden features on feature of sparse PCA in temporal and spatial form. In addition, the deep layer extracts low-level features such as edge, line and angle level, and more complicated features from the feature of sparse PCA. It is processed iteratively from the low-level feature.

- **Down-sampling layer.**

The down-sampling layer also represented as max pooling layer which produces the useful information of the hidden and deep layer features on the updating rule to eliminate on the following condition

.

$$D_v = \sum_{k=0}^{n} \frac{nx}{1!} \binom{d}{c} x^k v^{n-k} \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} \binom{n}{k} x^k v^{n-k} \frac{n(n-1)x^2}{2!} \quad \text{------ Eq.4}$$

It discovers the discriminating structure of a vector space, a locality preserving indexing computes close inputs should have similar multi-valued data.

- **Full connected layer.**

The full connected layer is a DBN layer of the perception structure. In this layer, the entire feature vector generated is fully connected with quality index of the yarn ground truth measures. It is considered as computation layer towards prediction of the yarn quality.

- **Output layer.**

According to yarn quality prediction tasks, the number of the output class parameter to features of the yarn properties been set specifically. Output layer is considered as classifier to classify the yarn features. This layer is considered as a classification layer, the output layer of the deep learning architecture represented as a classifier.

The first representation of the proposed layer is pre-processed image. The pre-processing process can be written as

$$F1 = \text{pre-process}\ (F) \quad \text{...Eq.5}$$

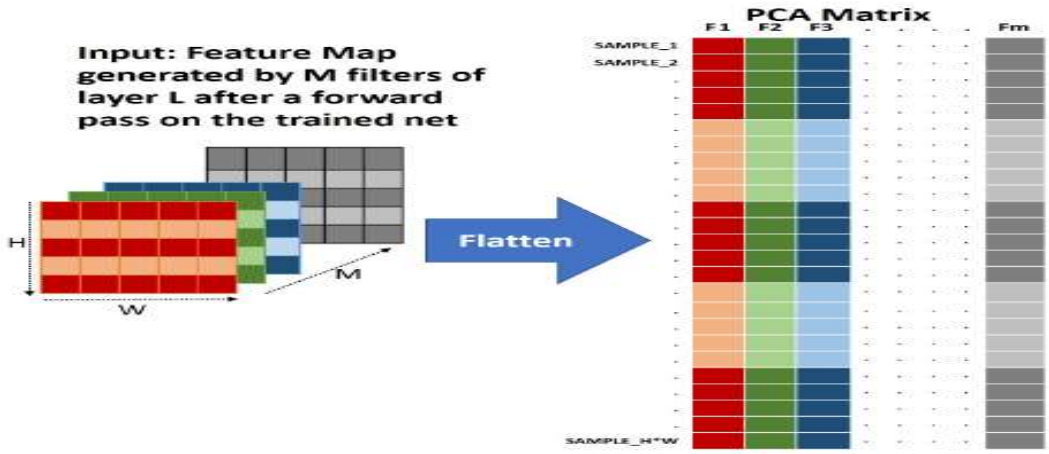


Figure 5: Feature mapping towards flattening using Sparse PCA

Pixel point in the PCA matrix corresponds to the yarn properties and the ith input patch is acted upon by the jth patch of the pixels and it acts as feature F set. The same input patch composed of features processed in the sparse PCA towards row of feature values for that input patch. The figure 2 represents the feature mapping towards flattening of the features using sparse PCA

Feature Flattening of the sparse and deep feature transformed to activation layer for connecting the multiple deep features in hidden layers. Those features are correlated in the softmax layer with error function. Layers-based architecture of DBN is the Symmetric matrix which containing the eigen value and eigen vector of the hidden features of deep layers of the architecture.

Algorithm 1: Yarn Quality Prediction using DBN

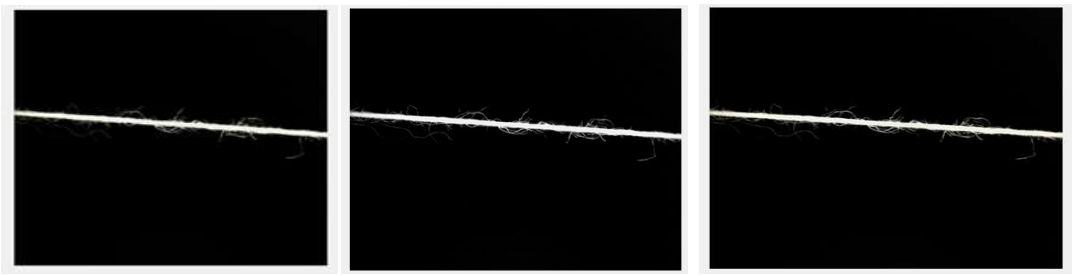
Input : Yarn Image and Quality Index
Output : Yarn quality Parameter prediction and classification
Process
Preprocess ()
Gaussian Mixture Model ()
Subtract G(x,y) with B(x,y)
Feature extraction PCA ()
Convert I(x,y) into Grayscale I(x,y)
Transform GI(x,y) into Matrix
Compute Variance V on Eigen value
Compute Correlation and Covariance on Eigen Feature vector
F(x,y) as principle feature components
Sparse PCA ()
Estimate Spatial and Temporal Feature of F(x,y)
Fs(x,y) and Ft(x,y)
Process DBNN
Input Layer ()
D I(x,y) =Fs(x,y)
Hidden Layer ()
Fs(x,y) = HI(x,y) composed of several feature combinations
Activation layer()
ReLu(Fs(x,y) on yarn properties
Output layer ()
Yarn quality recognition on the features of the properties

In the DBN, the function of the hidden layer is to share a set of hidden features generated with discriminative yarn properties for classification operations and those hidden features represented as deep features for quality

recognition. In addition, the feature maps produced by the deep layers generate the yarn features on quality factors.

4. Results and Discussion

Experimental analysis is carried out to measure the effectiveness of the yarn deep learning technique to assess the quality of input yarn images. Initially, the input yarn image undergoes preprocessing in form of gray scale conversation and noise filtering has been illustrated in the figure 6.



Input Image (b) Gray Scale Image (c) Noise Filtered Image

Figure 6: Initial process of the Yarn Image

Irregularities in the yarn mass are computed on the distribution of yarn stem. The pre-processed image is been employed to thresholding technique to segment the identifiable yarn properties using Entropy optimized Adaptive OTSU Thresholding has been illustrated in the figure 7.

Figure 7. Image segmentation of Yarn Properties using Entropy Adaptive Otsu Thresholding

The segmented image is further employed to feature extraction. It is carried out using PCA technique to generate the feature with multiple orientations. Further generated features is represented as eigen vector on estimation of the covariance and correlation with eigen value of the feature. Feature generated in spatial and temporal domain. Finally the DBN process computes the yarn image quality on the values of the yarn hairiness and strength features. The figure 8 represents the assessment of Yarn Quality using DBN.

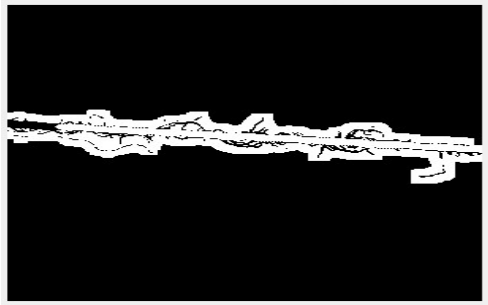


Figure 8: Yarn Quality assessment using DBN

Deep Belief Network has been incorporated to predict the yarn quality based on the adjacency map computed for the yarn properties against the hairiness and strength with quality index**.** Adjacency map determines the complex similarities of the yarn properties on the complex boundaries contained in sparse features of PCA. Further multilayer error eliminate the error on the feature learning to yield better accuracy The visualization has been employed on output layer of DBN towards identifying the discriminative features of the feature vector.

The performance measures such as Precision, Recall, Fmeasure has be calculated with support of true positive, false positive, false negative and true negative value on the feature instance in the vector obtained using feature vector extraction. The performance analysis of accuracy is carried out on the different class samples of the feature vector obtained through Sparse PCA.

The proposed DBN is used to optimize the important pixels of the frame with similarity evaluation on another similar frame on terms of the resolution value and high resolution image is deinterlaced in the image. Further it evaluates a quality of the classifier on recognition based on the entropy value of class probability distribution in the pre-trained image classifier.

DBN is powerful and effective in that the discriminator acts as a learned loss function instead of a fixed one designed carefully for each specific task. The proposed DBN algorithm is used to optimize the significant pixels and represent the similar pixels optimally on two comparative interlaced images. Therefore, it provides the higher correlation value for given yarn images rather than the existing algorithm.

The proposed DBN technique to eliminate the distortion on the yarn images on hairiness distortion has been carried out effectively from the different frame of interlaced images. The Table describes the computed value of the CNN based for yarn quality Prediction. The performance of the proposed model has been compared with CNN algorithms. Finally experiments of DBN shows that it produces better accuracy than CNN on the training parameter described in the table 1.

Table 1: Training parameters of the Deep Belief Network

Parameter of DBN	Model Value
Learning rate	10^{-6}
Loss Function	Categorical cross entropy
Batch size	25
Max epoch	1500

DBNN has been defined to recognize the yarn quality based on the adjacency map with respect to the yarn properties such as mass, evenness, hairiness and strength. Adjacency map computes the complex similarities of the yarn properties on the complex boundaries of the hidden feature computed as feature set in deep layers. Proposed model outperforms the existing model has depicted in the figure 3 for precision measure.

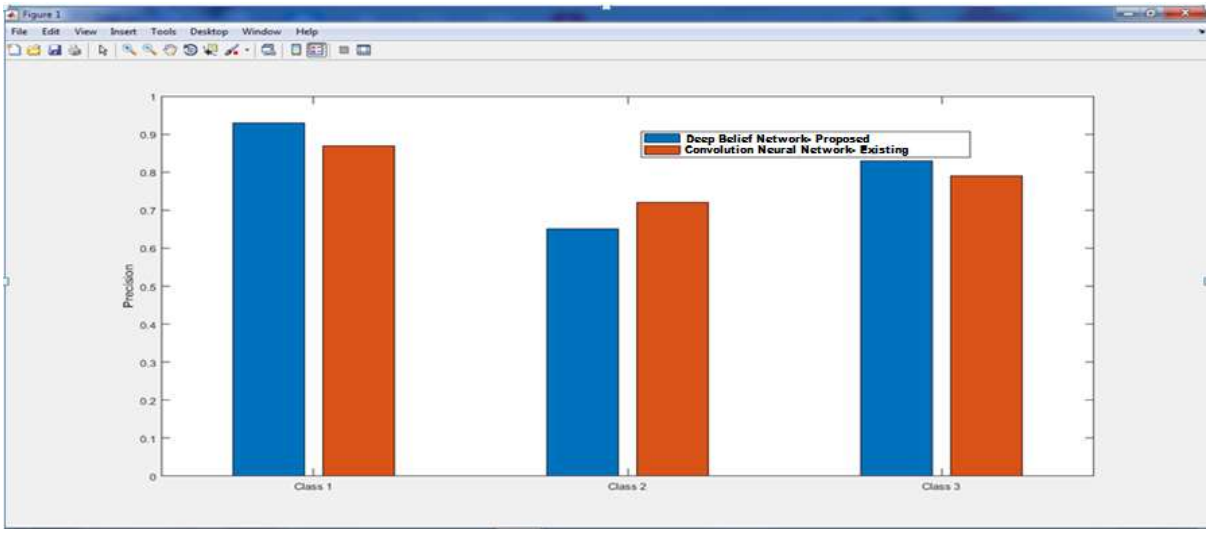


Figure 9: Performance Evaluation of Quality assessment model against Precision

The cross validation of the proposed DBN model processed with 5 fold cross validation which is represented in the Table 2. Varies yarn properties of the quality aspects has been validated and its complexity of the testing especially on yarn hairiness using layers of DBN has been reduced.

Table 2: Performance Evaluation of Yarn Quality Prediction Techniques

Class	Technique	Precision	Sensitivity	Specificity
Class 1 Feature Vector	Deep Belief Network – Proposed	0.9778	0.8912	0.9989
	Convolution Neural Network- existing model	0.9251	0.8236	0.9453
Class 2 Feature Vector	Deep Belief Network – Proposed	0.7465	0.8714	0.9871
	Convolution Neural Network- Existing model	0.7942	0.8589	0.9589
Class 3 Feature Vector	Deep Belief Network	0.9756	0.8415	0.9965
	Convolution Neural Network- Existing model	0.9436	0.8199	0.9641

On the basis of experimental results determined, the yarn quality is assessed with high quality. It yields good results on measures if true positive values of the computation of yarn feature set extracted on PCA and further it is processed in the dense layer of DBN. The comparison of the performance results computed by the DBN is effective on yarn testing compared with CNN. The performance results in terms of recall value produce the effective recognition outcomes are illustrated in the figure 4.

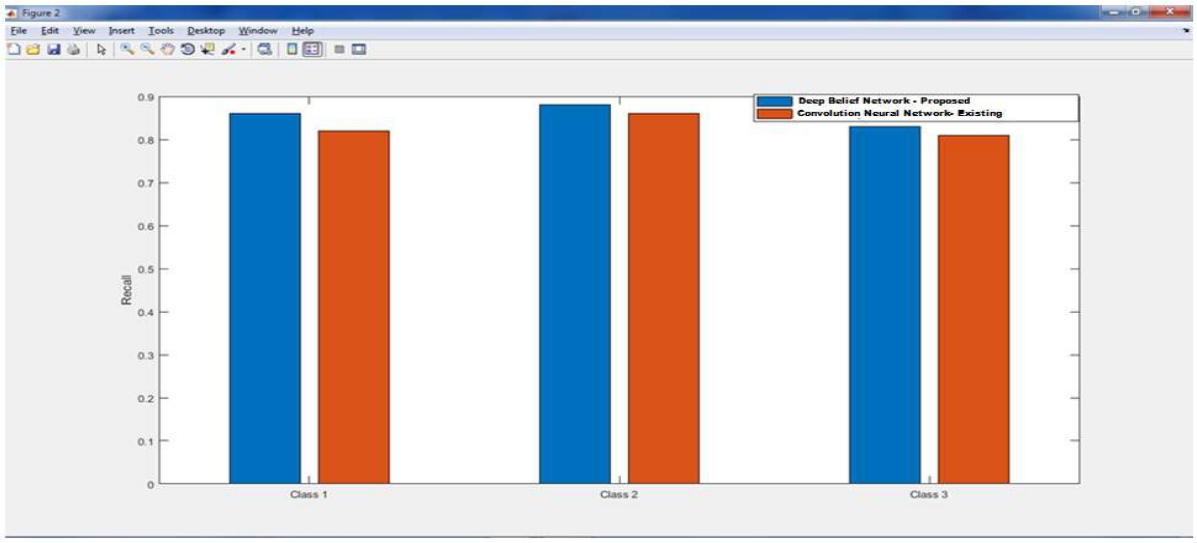


Figure 10: Performance Evaluation of Prediction model on Recall/ Sensitivity

The specificity values of the DNM architecture produces best results on predicting the quality of the yarn image. Figure 5 illustrates the performance results of the f measure value on yarn quality prediction.

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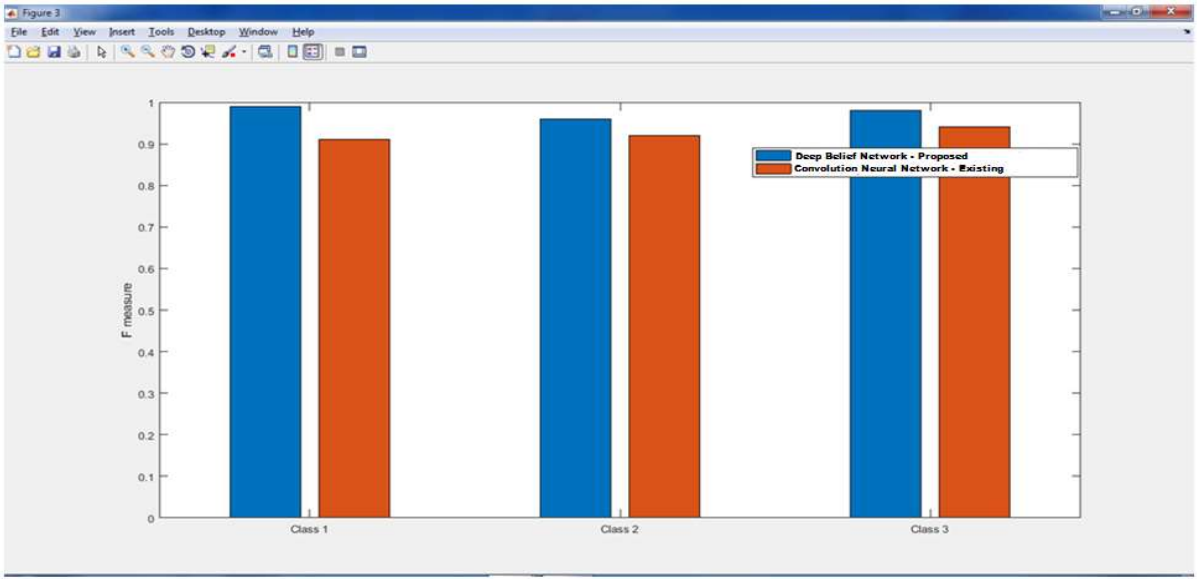

Figure 11: Performance Evaluation of Prediction model on F measure/ Specificity

Finally, proposed DBM model achieves performance accuracy nearly 99% on comparing against the different machine learning approaches.

5. Conclusions

In this proposed work, design and experiment of DBNN has been conducted to determine the yarn quality on inclusion of deinterlacing and feature extraction using PCA. The proposed DBN model uses the deinterlacing for yarn properties extraction toward effective quality assessment. The feature of core of the yarn determined using PCA. It is designed to use minimal amounts of pre-processing of the feature to predict the correct interlaced frame of the images.. Further feature vector has undergone recognition of yarn quality on the aspects of performance related factors such as yarn strength and yarn hairiness. Finally experimental results provide the performance results of the proposed model with better accuracy.

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