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YUCATAN -A New Yarn Quality Prediction Model Using Entropy Optimized Adaptive OTSU Thresholding and Convolutional Neural Networks

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Abstract

With the advent of the unsupervised learning architectures, intelligent manufacturing is becoming the developing direction of textile and clothing industry. Many textile enterprises are exploring the intelligent techniques to improve production efficiency and product quality on each stage of production line in the textile industry. In spinning mills, examining the yarn strength, Yarn thickness and yarn hairiness parameter are considered important for yarn quality prediction. Yarn hairiness or amounts of released fibers from the staple yarn are one of the main aspects to detect the yarn quality. Most existing approaches uses machine learning algorithm for the image acquired during the cotton knitting process in the spinning and weaving. Despite of several advantage of the machine learning models, still it slightly degrades in terms of prediction accuracy and computation cost. In order to enhance the computation performance, a novel yarn quality prediction approach using deep learning technique for all types of images in the spinning mill has proposed which is named as Yarn QUality PrediCtion using Entropy optimized Adaptive ThResholding And CNN (YUCATAN).

Initially Image pre-processing has carried out with noise filtering using improved wiener filter and skewness correction through Hough Transform. Processed image undergo feature reduction and feature extraction process using SIFT technique. Further image segmentation has been carried out employing information entropy optimized adaptive OTSU thresholding model. Feature Selection and feature vector clustering using markov random field. Finally Convolution Neural Network has been employed for selecting the appropriate properties affecting the yarn qualities such as Yarn Evenness, Yarn Strength and Yarn Mass Parameters to generate the quality index. A quality Index has been computed towards effective prediction of the yarn quality in the yarn sequence image. Experimental results of the proposed model on the yarn images outperform the existing Support Vector Machine in terms of computational time, Quality and efficiency.

Keywords: *Yarn Quality Prediction, Yarn Hairiness, Deep Learning, Image Processing, Segmentation*

1. Introduction

Cotton yarn processing is the production process from cotton fiber to cotton yarn. The process includes cleaning cotton, combing cotton, Thick yarn, Fine yarn and so on. Visual assessment is one of the fundamental methods of yarn Quality evaluation and fabric structure analysis in the Machine vision techniques[1]. In modern computer vision systems image processing and analysis algorithms are used for an automatic measurement of important yarn quality parameters, such as hairiness, thickness, density and surface defects [2]. Image analysis techniques are used for estimating the dimensions of spliced connections of yarn-ends and repetition of yarn structure which influence fabric quality[3]. The unevenness distribution of hairiness of two weft yarns can cause differences in the degree of reflection and color difference affects fabric appearance strongly.

The yarn hairness is an important index of the quality of the yarn. Hairiness is an important indicator to measure yarn quality among the many indexes of yarn quality detection[4]. Yarn hairiness can affect appearance and handle of the final textile products. Yarn hairiness is fiber head or fiber tail that exposed to yarn stem, which is caused by being not twisted completely. The basic form of hairiness is divided into two categories: one is the protruding fiber ends, another one is the looped fibers arched out the yarn stem [5]. Furthermore, the yarn with much hairiness can easily

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make the cloth pilling [6], which is influenced by friction in the post-machining process. Therefore it is necessary to measure and control yarn hairiness during its production. Although a number of approaches for yarn hairiness determination exist, the methods using image processing and analysis algorithms are still under development.

Several image-based approaches dedicated to yarn properties assessment have already been proposed. However, these methods use various kinds of thresholding approaches for yarn core and protruding fibres segmentation which often lack universality as they either are dedicated to the certain class of images provided by the certain vision system or require certain yarn orientation and experimental setting of parameters by trial and error examination. In this paper, a new model named as Entropy Optimized Adaptive OTSU Thresholding for segmentation and Convolutional Neural Networks for the generating the quality index to determine the quality of the yarn has been proposed.

The remaining of the paper is categorized as follows; related work is presented in the section 2. In section 3, proposed model named, Yarn Quality Prediction model using Entropy Optimized Adaptive OTSU Thresholding and Convolutional Neural Network 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 existing model applied to yarn image towards quality prediction using machine learning algorithms for yarn properties has been summarized and detailed as follows

2.1. Yarn Quality Prediction using Support Vector Machine

In this method, Yarn Quality Prediction has been processed using Support Vector Machine model on the properties of the cotton yarn. In this model, decision boundary construction using hyperplane helps to determine the yarn mass[7]. The diameter calculation is performed through the detection of all the edges along a set of parallel searching lines on the hyper plane. Once all edges are detected, the distance is calculated between the pairs of edges detected by all the search lines using objective function. The diameter is obtained by the average of all the calculated distances. Once calculated the diameter, the yarn mass is easily approximated through the correlation between linear mass and diameter. Further, same objective function can used to estimate the other properties of the yarn.

3. Proposed model

In this section, we define a Yarn Quality Prediction Model Using Entropy Optimized Adaptive OTSU Thresholding and Convolutional Neural Networks on various properties of the yarn to improve the fibre quality.

3.1. Type-2 Fuzzy Controller- Image Quality Assessment

Type 2 Fuzzy Controller (T2FC) is employed to solve uncertainty issues by applying patch level quality testing using different image criterions (Image Brightness, Image Region Contrast, Edge Blur Width, Noise Degree, and Image Sharpness). T2FC computes different image criterions for each yarn images. T2FC defines the Image quality value parameter as IQv and threshold for it. On estimation, if IQv value is greater than threshold the yarn quality prediction process is initiated as it considered as high quality image else pre-processing operation is initiated[8].

3.2. Image Pre-processing

In Image Pre-processing, Image Conversion, Noise removal, Feature Reduction and contrast enhancement has been carried out in parallel to increase the prediction performance of the yarn images.

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- **Gray Scale Conversion**

Principle component analysis is used to convert the color image into gray scale images. In this, PCA generates the pixel matrix with values 0 to 255 and it uses mathematical function G that receives a colorful image as input R^{3mn} and outputs a monochromatic image R^{mn}. Gray Scale representation is highly feasible ways to filter the imperfections of the image with high noise level in the background of the considered images[9]. The Gray scale of the image is given by

$$g(x,y) = H (f(x,y)) + \eta(x,y)$$

Further the image is presented in the spatial form as follows

$$g(x,y) = \int_0^T f(x-x_0(t),y-y_0(t))\, dt$$

- **Noise Removal - Improved Wiener Filter**

The Improved Wiener filter is to estimate the power spectra of the original image and the additive noise. It is proposed by optimizing the Structural Similarity Index (SSIM), which gives better performance than traditional wiener filter. In addition, we considered the noise reduction direction is a Left-to-Right direction[10]. The degradation of the image is given as follows

Mean square error: $e^2 = E\{ (f-f^c)^2\}$

Weiner filter function is given by

$$F^c(u,v) =[1/H(u,v)] [|H(u,v|^2 / (|H(u,v|^2 +S_\eta(u,v)/S_f(u,v))] G(u,v)$$

- **Skewness Correction – Hough Transformation**

Skew correction of yarn image is performed using Hough Transform to ensure the yarn axis flatly. The Hough transform[11] is realized by the use of Hough function, and Hough transform matrix is obtained. The extreme points are found in Hough transform matrix and line segments are extracted in yarn image. Meanwhile, we take the average distance between yarn stem edge and yarn axis as baseline to count the number of yarn hairiness of different length. The baseline can fit yarn stem edge to the utmost extent.

$$H(k_1f_1 + k_2f_2) = k_1 H(f_1) + k_2 H(f_2)$$

$$g(x,y) = H(f(x,y))$$

Initially finding the center pixels of yarn stem in the first column and last column by row scanning, and matching the two pixels is given as

$$g(x,y) = H(\iint f(\alpha,\beta)\, \delta(x- \alpha,y- \beta)\, d \alpha\, d \beta)$$

Linear approximation of yarn borders on the different lightening condition has parameterized as line segments is been given as

$$g(x,y) = \iint f(\alpha,\beta)\, H(\delta (x-\alpha ,y- \beta))\, d \alpha\, d \beta$$

$$g(x,y) = \iint f(\alpha,\beta)\, h(x, \alpha ,y, \beta)\, d \alpha\, d \beta$$

In this $h(x, \alpha ,y,\beta)$ is the "impulse response" or "point spread function.

- **Yarn Segmentation - Information Entropy optimized Adaptive OTSU Thresholding**

Yarn Segmentation is used to divide image into sub regions by computing a global optimum among all segmentations satisfying some hard constraints imposed for object and background[12]. The division is performed using information entropy optimized adaptive OTSU

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thresholding. Thresholding is a technique for partitioning image directly into region based on intensity value and/or property of this value. It is employed to fix the threshold value in optimum and adaptive manner. The yarn image has been segmented based on the class variance

Class variance is given by

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t)$$

Where Class probabilities is given as

$$q_1(t) = \sum_{i=1}^{t} P(i) \quad \text{and} \quad q_2(t) = \sum_{i=t+1}^{I} P(i)$$

The Class probabilities of certain properties are sensitive to nonuniform background illumination and adjust threshold by experimental setting of parameters. The variation process of parameters is equivalent to generating a better initial segmentation result.

3.2. Feature Extraction

In this section, feature extraction technique named as Scale Invariant Feature Transform, It is used to extract the features based on more criterions and parameters of the yarn. It generates the key points on the segmented image. It uses the gaussian function to determine the difference of the each pixel on the segmented region[13]. Further it applies the localization to determine the various properties of the key points. The key points of SIFT is given by

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

Where $$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

Key points are detected using scale-space extreme in difference-of-Gaussian function. The gaussian function D has scales differing by a constant factor it already incorporates the σ^2 scale normalization required for scale-invariance. Image features are described differently on account of adopting different resolutions. Also the image information that reflected by spatial relationships between different scales' inner pixels are different It is given by

$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k-1)\sigma^2\nabla^2 G$$

The Smoothing of the each octave can be carried out by increasing σ which increases robustness of the feature simultaneously. Key point is selected as a feature only if it is a minimum or a maximum of these points.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

Weight magnitude of each sample point by Gaussian weighting function. Descriptor computed relative to key point's orientation achieves rotation invariance. The figure 1 represents the architecture diagram of the proposed model.

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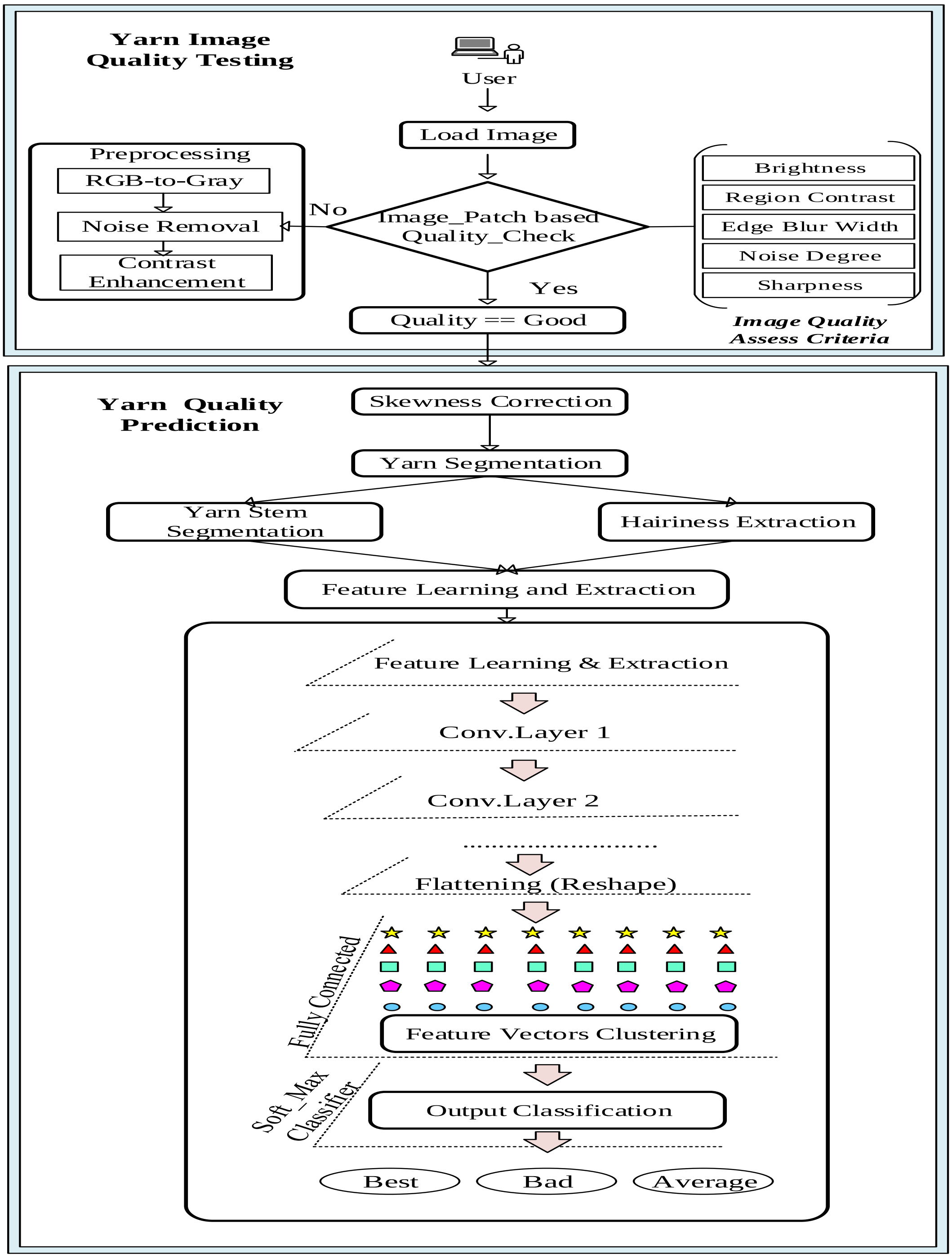

Figure 1: Architecture Diagram of the proposed model

Multiple orientations assigned to key points from an orientation histogram. The magnitude of the each point of the endpoints on the orientation of histograms will ssignificantly improves stability of matching. It is given by

$$m(x,y)=\sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2}$$

The magnitude of the weight represents the feature weight of the pixel on the particular region. It represents the discriminating power of the endpoints on linear series of the pixel in the well defined function to eliminate the non linear illumination changes. Further it effectively collects the important key points through nearest neighbor search.

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3.3. Feature Vector Clustering

Features are extracted based on the yarn parameters have been defined in terms of the vectors. The yarn parameters are grouped under three categories such as Yarn Unevenness (3 features), Yarn Strength (5 features) and Yarn Mass (2 features). The set of feature vectors with mixed features is mapped to a set of feature vectors with only real valued components with the condition that the new set of vectors has the same proximity matrix as the original feature vectors. Feature Vector Clustering[14] is employed for determining proximity (similarity or dissimilarity) between features. Proximity of objects is generally based on their feature vectors.

The Vector computes the local average intensity and entropy of image are taken as the constraints for the clustering the key points obtained as the yarn properties. Assuming that label field is independent in each scale and the label field can be modelled in each scale. Then the joint probability distribution of label field in all scales can be expressed as criterion. The computation of the local average intensity is given as follows

$$O_{pj}(net_j) = \frac{1}{1+e^{-\lambda net_j}}$$

With constant iterations of the vector, the value of weight decreases, while the intensity of label field increases, the parameters are optimized

3.4. Convolution Neural Network

Convolution Neural Network is employed for effective prediction of yarn quality on modelling the new quality index on the clustered features. It is a multi-layered network which can create internal representations and learn different features in each layer. Each higher layer learns more and more abstract features that can be used to classify the image. Each layer finds patterns in the layer below it and it is this ability to create internal representations that are independent of outside input that gives multi-layered networks[15]. The complexity of processing using CNN is very less and accuracy of the result is high. Yarn quality index has been measured using perceptron which is step function based on a linear combination of real-valued inputs. It is given by

$$\delta_{pj} = O_{pj}(1-O_{pj})\sum_k \delta_{pk}W$$

The yarn different properties, it makes the complex to predict. The perceptron using delta rule can increase the prediction quality. The delta rule is used for calculating the gradient that is used for updating the weights. It minimizes the error. The feature vector is represented as

$$X = (x_1, x_2, \ldots, x_n),$$

Weight of the each vector is given by

$$w_i = w_i + \Delta w_i$$

where, $\Delta w_i = -n * E'(w)/w_i$

Forward propagation of the feature vector through the neural network in order to generate the propagation's output activations is given by sigmoid (logistic) function. It is as follows

$$O(x1,x2,\ldots,xn) = \sigma (WX)$$

Where $\sigma (WX) = 1 / 1 + e^{-WX}$

Backward propagation of the propagation's output activations through the neural network using the feature vector is to generate the deltas (the difference between the input and output values)

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of all output and hidden properties. Further multiply its output delta and input activation to get the gradient of the weight.

Algorithm 1: CNN based Yarn Quality Prediction

Input: Cluster Vector

Output: Saliency Map of the Yarn Properties

Process

- Assign Standard deviation = local contrast C_k
- Assign Mean= average intensity W_{kh}
- Local threshold as $t_k = a\ \sigma_{xy} + b\ m_{xy}$

Compute Hairiness index

$$\delta_k = C_k (1-C_k)(t_k - C_k)$$

Yarn Thickness

$$\delta_h = C_k (1-O_h) \Sigma_k\ W_{kh}\ \delta_k$$

Compute Saliency Map to Yarn Properties

$$S_m = \sum_{k \in \text{next layer}} (w_{kj}\delta_k) o_j (1-o_j) o_i$$

Compute Yarn strength Y_s

$Y_s = (\delta_h - \delta_k)$

Yarn Evenness is presented as G1,G2…Gn at regular intervals

If (Y (G1)= =Y(G2))

Yarn quality index is high

Else

Yarn quality index is low (i.e Yarn has some fault properties)

4. Experimental Results

Experimental results for the proposed model is carried out using Yarn Dataset collected Kaggle repository. Among the collected data, data is categorized for training, Testing and validation. For training 1800 yarn data has been utilized whereas remaining data has been used for testing and validation. The performance of yarn quality prediction is evaluated using performance measures such as precision, Recall and F measure[16]. The performance of the proposed model has been compared with SVM algorithms. Finally experiments of CNN shows that it achieved best accuracy than SVM.

The yarn Image processed to determine the quality of the yarn using deep learning technique undergoes several processes. Initially, the input image undergoes the image conversation and noise filtering has been represented in the figure 2.

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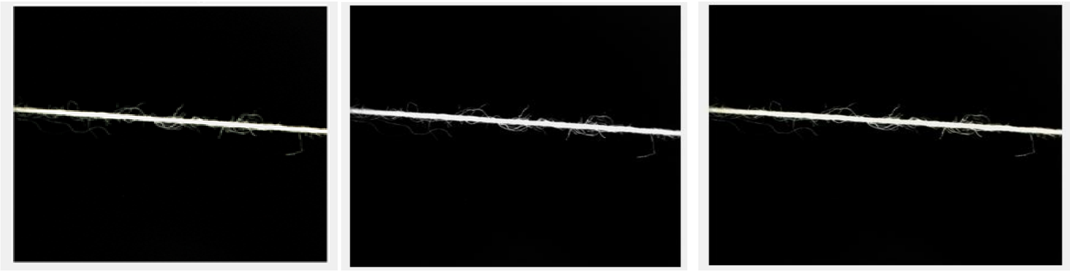

(a) Input Image (b) Gray Scale Conversation (c) Noise Filtered Image

Figure 2: Initial process of the Yarn Image

Mass irregularity of yarn stream in time is usually assumed to be random on the distribution. The pre-processed image has been segmented on basis of yarn properties using Information Entropy optimized Adaptive OTSU Thresholding on the linear distribution of the image has been presented in the figure 3.

Figure 3: Segmented Image using Entropy Adaptive Otsu Thresholding

The segmented image undergoes the feature extraction using SIFT technique yields feature on multiple orientations. Further these features taken to feature vector clustering to ease the labelling on the obtained key points. The proximity of the objects is computed using nearest neighbour search in clustering. Finally the CNN process predicts the yarn quality on the values of the yarn hairiness and strength. The figure 4 represents the Yarn Quality

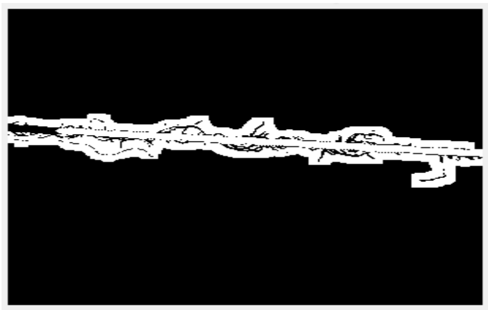

Figure 4: Yarn Quality Prediction using CNN

Convolution Neutral Network has been employed to predict the yarn quality based on the saliency map determined for the yarn properties against the hairiness and strength**.** Saliency map determines the complex similarities of the yarn properties on the complex boundaries. Further delta rule and perceptron eliminate the error on the multi layer process of CNN to yield better accuracy than machine learning models. The visualization has been employed on output layer of CNN towards identifying the discriminative features of the vector.

The performance measures named Precision, Recall, Fmeasure has be computed using true positive, false positive, false negative and true negative value on the feature instance obtained using feature vector clustering. The analysis is carried out on the different class samples of the feature

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vector obtained. In that proposed model outperforms the existing model has been computed and depicted in the figure 5 for precision measure.

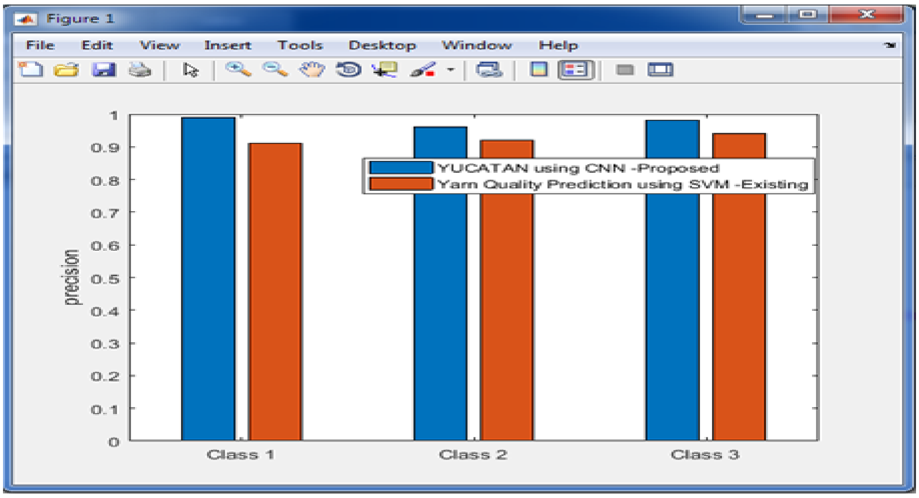

Figure 5: Performance Evaluation of Prediction model on Precision

The validation of the proposed model has been carried in 10 fold and the Performance of the prediction model has been tabulated in Table 1. The different yarn properties reduces the complexity of the testing especially yarn hairiness detection along provides the quality of the yarn approximately.

Table 1: Performance Evaluation of Autonomous Segmentation Techniques

Class	**Technique**	**Precision**	**Recall**	**F measure**
Class 1 Feature Vector	YUCATAN Model – Proposed model	0.9978	0.9412	0.9989
	SVM- Existing Model	0.9851	0.9336	0.9853
Class 2 Feature Vector	YUCATAN Model – Proposed model	0.9965	0.9514	0.9971
	SVM- Existing Model	0.9842	0.9389	0.9889
Class 3 Feature Vector	YUCATAN Model – Proposed model	0.9956	0.9615	0.9965
	SVM- Existing Model	0.9836	0.9399	0.9841

On the basis of preliminary results obtained, the yarn quality can be assumed easily. It yield better results of true positive values of the computation of feature set. The comparison of the results provided by the CNN is best suitable for yarn testing. The performance results on recall value produce the excellent results have been depicted in the figure 6.

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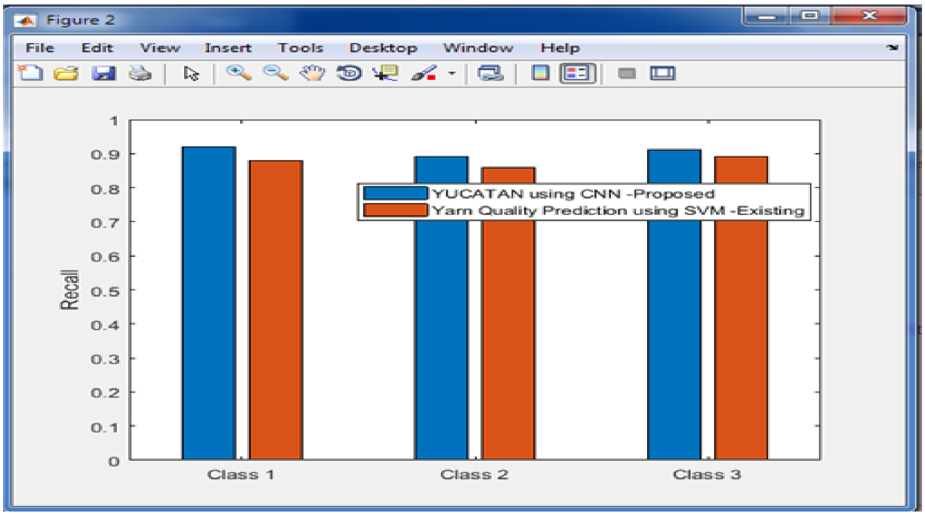

Figure 6: Performance Evaluation of Prediction model on Recall

It is noteworthy that the accuracy values are high in the proposed model on predicting the quality of the yarn. Figure 7 provides the performance outcome of the f measure value on yarn quality prediction.

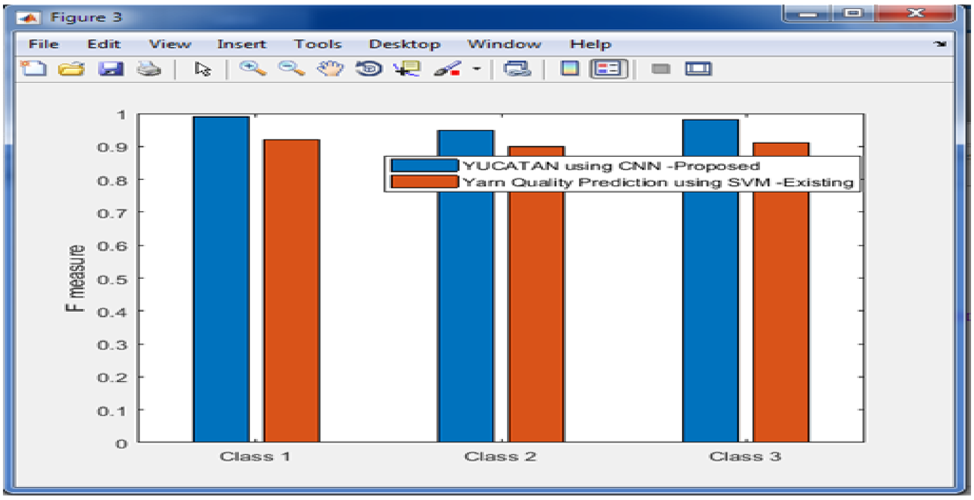

Figure 7: Performance Evaluation of Prediction model on F measure

Finally, proposed model achieves accuracy of nearly 99% on f measure against the different machine learning approaches. The proposed based on the deep learning architecture can be used as yarn testing model to textile industry.

5. Conclusion

In this work, design and implementation of YUCATAN has been carried out on inclusion of entropy optimized adaptive Otsu thresholding and Convolution Neural Network towards yarn quality testing. The proposed model uses the segmentation for yarn core extraction on various properties. The extracted core of the yarn undergone the SIFT process to yield the features. Those features have been clustered as vector. Further vector has undergone prediction using CNN architecture to determine the yarn quality on aspects of the yarn strength and yarn hairiness. Finally experimental results have proved that proposed model produces the better accuracy against state of art approaches.

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