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Prediction of Bursting Strength and Pilling Rating of Three Thread Fleece Fabric using Artificial Neural Network

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ABSTRACT

In this work, the bursting strength and pilling rating of polyester-cotton fiber-blended three-thread fleece fabric were predicted using an artificial neural network (ANN) back propagation (BP) model. Bursting strength and pilling were predicted from 50 three-thread fleece fabrics with different stitch lengths, grams per square meter (GSM), yarn counts, and twists per inch. All three-thread fleece fabrics have their own bursting strength and pilling rate, which were used for the prediction. To validate the two models in the training steps, training precision, and simulation precision, 40 fabrics were used for training and 10 fabrics were used for testing, and the predicted pilling property was obtained. The results show that the predicted values of bursting strength and pilling rating were closer to the experimental values, which are determined by the ANN backpropagation (BP) model. This study shows that an optimized model with BP can predict the bursting strength and pilling rating of polyester–cotton three-thread fleece fabrics with acceptable accuracy.

Key words: Three-thread fleece fabric, ANN backpropagation, Bursting strength, Pilling.

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1. INTRODUCTION

Three-thread fleece fabric is widely used as winter clothing where both strength and pilling are important. Pilling is a fabric surface property with small, tightly entangled balls of fibers that occurs as a result of friction of protruding fibers on the surface [1].

Pilling creates discomfort for the user and also deteriorates the outer look of the garment. The tendency of pilling formation is associated with the yarn properties like stitch length, twist per inch, yarn count, and yarn type [2]. Fabrics with less twist per inch in yarns show more pilling. Uncombed yarns also create excessive pilling due to their hairy surface on the yarn body [3].

Bursting strength is a key measure of knit fabric strength that indicates the durability of the garment to be produced by the fabric. Bursting strength indicates how much pressure a fabric can withstand before it breaks by air pressure. The bursting strength property of fabric can also be associated with stitch length, twist per inch, yarn count, and fabric grams per square meter (GSM). Higher GSM fabrics exhibit higher bursting strengths [4].

The impact of GSM on knit fabric pilling is negligible. A higher GSM of fabric would produce a small percentage increase in pilling. Applying heat setting and singeing can effectively improve knit fabric pilling. Recently, biopolishing is an enzymatic process used to pill resistant fabric [5]. Moreover, it is challenging to produce pill-resistant three-thread polyester cotton blended fleece fabric because of cotton and polyester blends. The resistance of knitted fabrics to pilling is dependent on the density of the fabric; that is, the stitch length. Resistance to pilling increases as the surface density of the knitted fabric increases and the stitch length decreases [6]. In the analysis of the relationship between knit structure and pilling propensities, it is found that knitted fabrics with rib structure were the most resistant to pilling, knitted fabrics with interlock structure were less resistant, and woven fabrics with plain weave were more likely to pill. Any fabric, knit or woven, is more susceptible to pilling if the number of yarns per unit length of the fabric reduces [7].

Spinning process has technological advancements such as compact and vortex spinning for the reduction of pilling and bursting strength of the fabric. Vortex yarn structure is very compact, and the outer fibers are lodged in the center of the yarns so that the outer surface fiber cannot form pills easily [8]. For efficient use of textile fibers, process machinery, and technical parameters, it is necessary for the manufacturer to produce fabrics or garments as per customer specifications, and for that, prediction of fabric or garment parameters from process variables is essential nowadays. Statistical regression can provide a predicted value as a fundamental method [9]. Predicting using advanced computational techniques like artificial neural networks (ANN) offers a promising solution for manufacturers for process optimization [10].

The main objective of artificial intelligence like ANN in textile industries is to create a system that is capable of thinking and acting like humans. Backpropagation with a variable learning rate and several linear regressions are being used in the ANN methodology. ANN is recently used in textiles for the prediction of fabric defects [11]. Developing a predictive model using ANNs can streamline the process, allowing manufacturers to anticipate how different fabric construction parameters affect both bursting and pilling performance.

ANNs were also used for predicting different fabric properties for several fabric types [12]. But still now no research has been done on predicting pilling rate and bursting strength for three-thread fleece fabric. With a view to fulfilling the gap of this field of study on three-thread fleece fabric, this work was conducted in order to develop an artificial neural network-based model capable of predicting the bursting strength and pilling rating of three-thread fleece fabrics and to design and train an ANN model using experimental data to predict these fabric properties with high accuracy and also analyze the effect of hyperparameters like the number of hidden layer nodes, the number of epochs, and loss functions on model accuracy.

2. MATERIALS AND METHODS

2.1 Raw materials

The polyester-cotton blended three-thread fleece fabric where the first thread fiber type was polyester and cotton and their blend ratio was 40% polyester and 60% cotton. The second thread fiber type was 100% polyester, and the third thread fiber type was 80% cotton and 20% polyester. 50 different three-thread fleece fabrics were collected from a local garment factory in Bangladesh. The fabrics were different in terms of their parameters. Yarns and fabric parameters of those fabrics are summarized as their lowest and highest values in Table 1.

Table 1: Range of yarn and fabric parameters of 50 sets of three-thread fleece fabrics.

Fabric and yarn parameters	Value range
1st thread yarn count	30-41 Ne
2nd thread yarn count	50-75 Ne
3rd thread yarn count	10-16 Ne
1st thread yarn Twist per inch	17-22 TPI
2nd thread yarn Twist per inch	25-28 TPI
3rd thread yarn Twist per inch	10-16 TPI
Fabric GSM	215-242 g/sqm
1st thread Fabric stitch length	4.3-4.85 mm
2nd thread Fabric stitch length	3-3.9 mm
3rd thread Fabric stitch length	1.8-1.9mm
Fabric Bursting Strength	450-548 KPa
Fabric Pilling Rating	3-5

2.2 Analytical methods

The backpropagation (BP) model mainly consists of a multilayer forward neural network. There are two parts in the backpropagation model: training and testing parts. The 40 sets of data are used for training the model, and 10 sets of data are allocated for testing the model. Four physical factors—yarn count, twist, GSM, and twist—are taken as the training input vector. Therefore, the number of input nodes (m) of training is 4. The number of pills and the busting strength are used as the learning target data, and therefore the number of nodes in the output node (n) is 2, and what will be the number of nodes in the hidden layer (N) is calculated using equation no. 1 considering the constant (a) [1, 10]. To minimize the errors, the same samples with different node numbers should be trained, and the mean absolute percent error (MAPE), the root mean square error (RMSE), and the mean absolute error (MAE) are calculated as per the following equations.

$$N = \sqrt{m+n} + a \quad \text{..............} (1)$$

$$MAPE = \frac{1}{k}\sum_{i=1}^{k} abs\frac{(A(i)-B(i))}{B(i)} \quad \text{..............} (2)$$

$$RMSE = \sqrt{\sum_{i=1}^{k}\frac{(A(i)-B(i))^2}{k}} \quad \text{..............} (3)$$

$$MAE = \sum_{i=1}^{k} abs\frac{(A(i)-B(i))}{k} \quad \text{..............} (4)$$

Where *abs* denotes the absolute value, the output value of the model is denoted by *A(i)*, the experimental value is denoted by *B(i)*, and the number of samples is denoted by *k*.

2.3 Required parameters for training the model

Table 2. Setting of training parameters

Training Parameters	Settings
Transfer function of hidden layer	ReLU
Transfer function of output layer	Not Specified
Training function	Loss Function (MAE, RMSE, MAPE)
Epochs	Num_epochs = 1000
Learning rate	lr = 0.0001 for Pilling lr = 0.001 for Bursting strength
Input node	10
Hidden node	10
Output node	1

2.4 Process flowchart

Process flowchart of ANN model was developed to predict pilling rating and bursting strength. Python coding to develop an ANN model can be found as supplementary information. The process flowchart is shown in Figure 1.

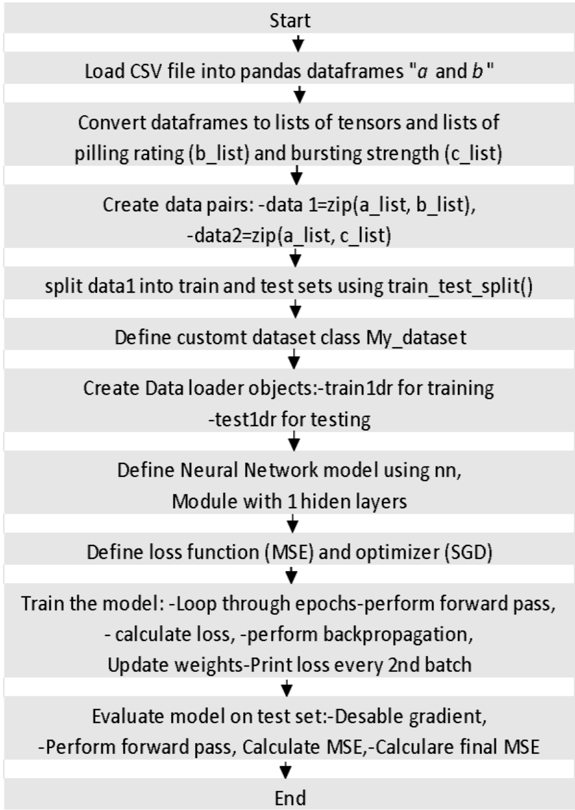

Figure 1. Process flowchart of ANN model.

3. RESULTS AND DISCUSSION

3.1 Effect of the number of hidden layer nodes

PyTorch 3.0 and Pylance were used for the development and analysis of neural network models. As per equation (1), the value range of the hidden layer node is (5, 14). Errors of different hidden layer nodes for bursting strength and errors of different hidden layer nodes for pilling rating are tabulated in Table 3 and Table 4, respectively.

Table 3. Errors of different hidden layer nodes for bursting strength

Hidden layer node	MAPE	RMSE	MAE
5	0.2146	0.2968	0.2237
6	0.8932	0.2915	0.2121
7	0.5827	0.2894	0.2135
8	0.7945	0.2883	0.2187
9	0.9565	0.2946	0.2141
10	0.5072	0.2899	0.2075
11	0.6257	0.2915	0.2016
12	0.5276	0.2903	0.1999
13	0.4849	0.2885	0.1989
14	0.4362	0.2900	0.2007

Table 4. Errors of different hidden layer nodes for Pilling Rating

Hidden layer node	MAPE	RMSE	MAE
5	0.1392	0.1591	0.3477
6	0.9251	0.1967	0.3595
7	0.6872	0.1687	0.3723
8	0.5965	0.1669	0.3525
9	0.5885	0.1557	0.3735
10	0.4188	0.1567	0.3370
11	0.4586	0.1322	0.2855
12	0.4568	0.1573	0.3576
13	0.5973	0.1516	0.4060
14	0.3682	0.1425	0.3590

It is evident that error functions of bursting strength show their minimum for MAPE at node 5, RMSE at node 8, and MAE at node 13. Similarly, error functions of pilling rating show their minimum for MAPE at node 5, RMSE at node 11, and MAE at node 11. The reason for this is the too small number of hidden layer nodes. Following the same, for nodes 11 and 12 of bursting strength and nodes 7 and 8 for pilling, the error values rose.

3.2 Effect of epoch number and loss function

The performance functions that come with the neural network toolbox are the MAE and RMSE. The Y-axis of the error curve of the training is mean absolute error. From the Figure, the training step of the BP neural network for bursting strength is 820. On the other side, it is seen from Figures 2 to 11 that the training step of the BP neural network for pilling rating is 990. This result indicates that the network reaches the target value using the mean absolute error function for bursting strength and using the root mean square error function for pilling rating.

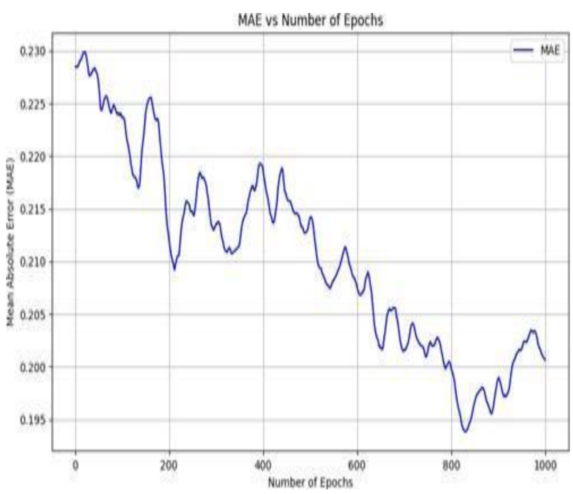

Figure 2. Training error curve (MAE) of BP Model for bursting strength.

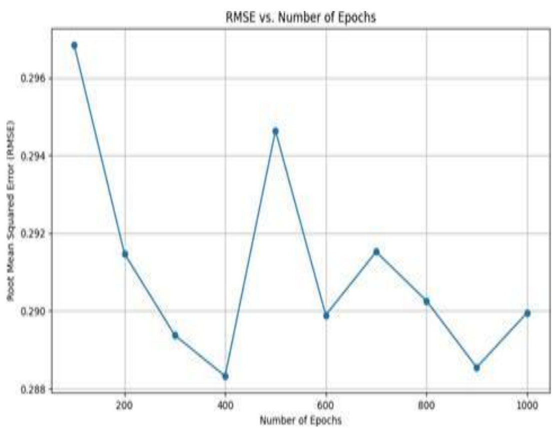

Figure 3. Training error curve (RMSE) of BP Model for bursting strength.

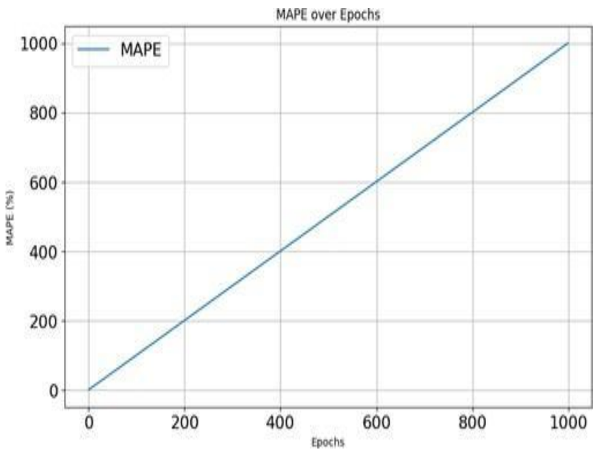

Figure 4. Training error curve (MAPE) of BP Model for bursting strength.

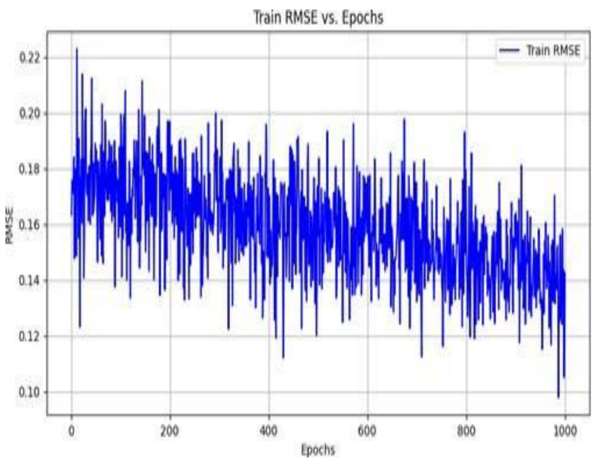

Figure 5. Training error curve (RMSE) of BP Model for Pilling Rating.

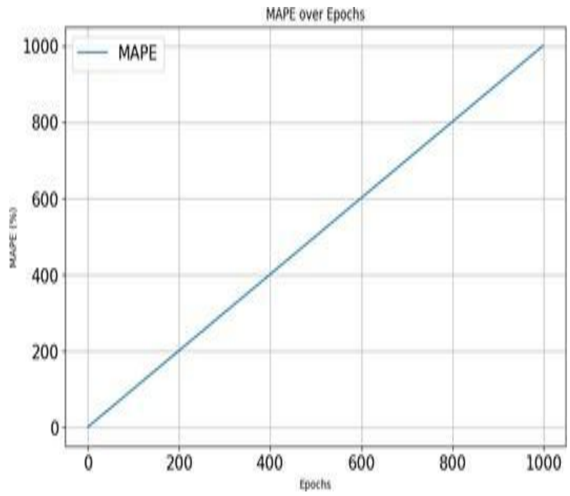

Figure 6. Training error curve (MAPE) of BP Model for Pilling Rating.

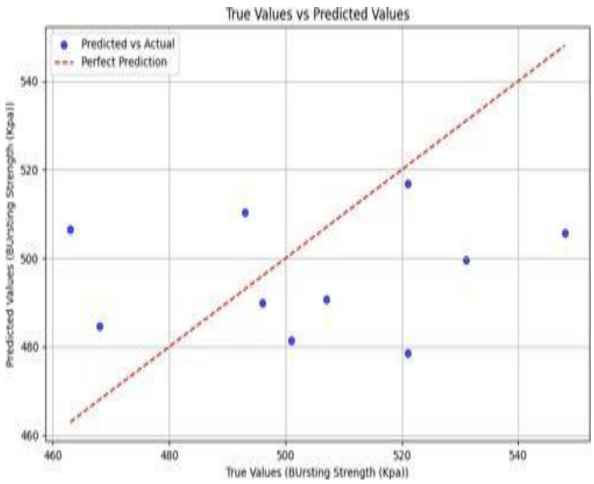

Figure 9. Correlation between actual and predicted value of bursting strength using root mean square error function.

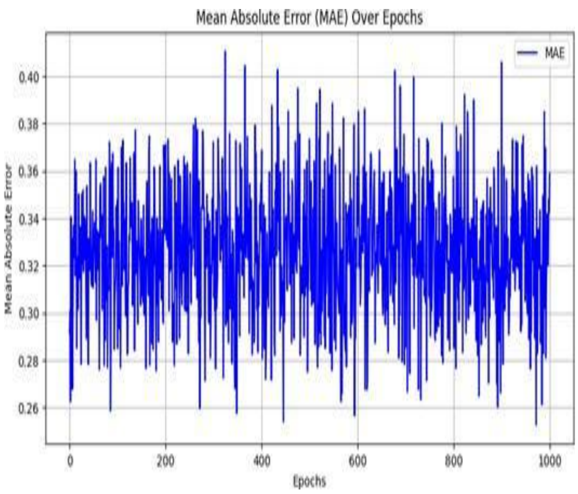

Figure 7. Training error curve (MAE) of BP Model for Pilling Rating.

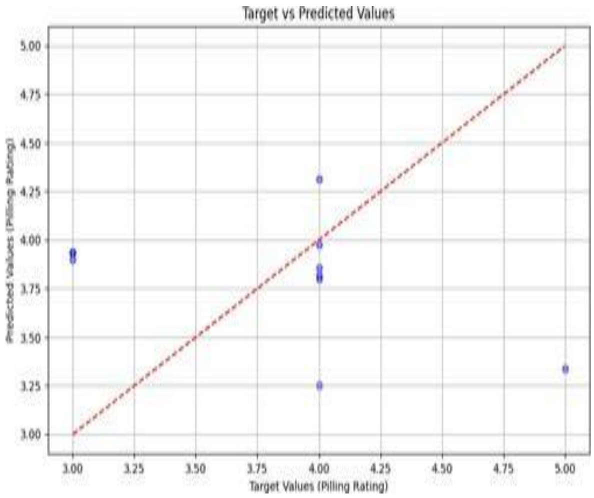

Figure 10. Correlation between actual and predicted value of pilling rating using mean absolute error function.

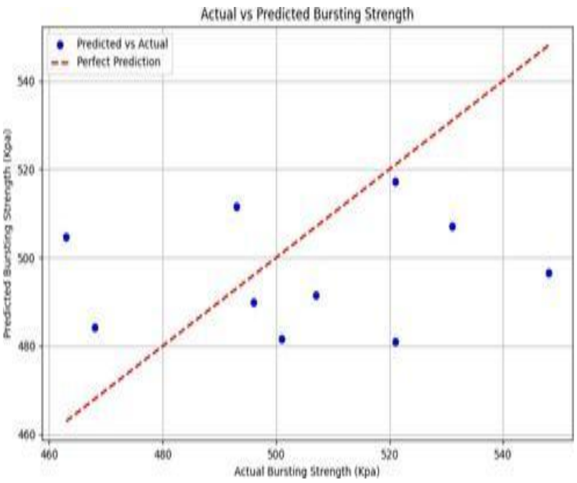

Figure 8. Correlation between actual and predicted value of bursting strength using mean absolute error function.

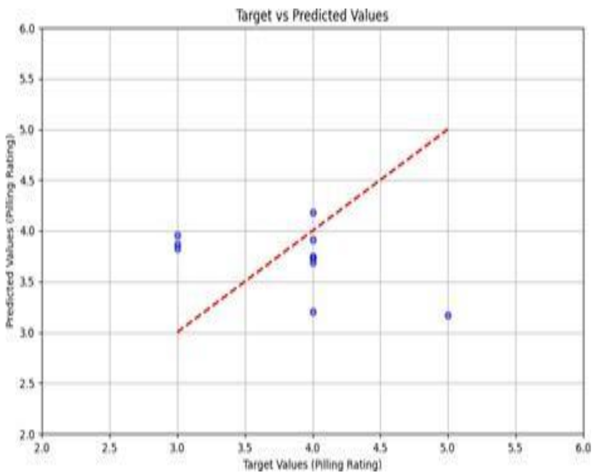

Figure 11. Correlation between actual and predicted value of pilling rating using root mean square error function.

Predicting the bursting strength of three-thread fleece fabric from the input data using the ANN Back Propagation (BP) model to determine the mean absolute error and root mean square error shows that a close predicted value was found; the MAE function as well as the RMSE function has predicted very well. Pilling of three-thread fleece fabric was also determined by an ANN back propagation (BP) model by calculating some functional measure such as MAE and RMSE error. From the graphical presentation, the RMSE function predicted a closer pilling value than the MAE function.

4. CONCLUSION

In his study, the bursting strength and pilling rating of polyester and cotton fiber blended three-thread fleece fabrics were investigated using an artificial neural network (ANN). The back propagation (BP) model predicted the bursting strength and pilling from 50 sets of three-thread fleece fabrics with respect to their four inputs (TPI, count, stitch length, and GSM) and 2 output parameters (bursting strength and pilling rate). The results show that the predicted values of bursting strength and pilling rating were closer to the experimental values. This study shows that an optimized model with BP can predict the bursting strength and pilling rating of polyester cotton fiber blended three-thread fleece fabrics with acceptable accuracy.

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