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Predicting bursting strength of single jersey 100% cotton plain knitted fabrics using different machine learning models

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Abstract

Bursting strength is an important parameter of knit fabrics. It depends on multiple factors. This study aims to determine the best machine learning model to predict bursting strength. Besides, determining the optimum GSM and yarn count to get best bursting strength using RSM (Response Surface Methodology). We tried 9 machine learning models. Among which, the XGBoost (Extreme Gradient Boosting), Random Forest and ANN models performed best having 99%, 85% and 80% R2 value, respectively. The Pearson correlation shows the most significant factors is stitch density, whereas porosity and GSM have most meaningful correlation according to scatterplot. In the same way, RSM determined the GSM and GSM square are significant for bursting strength having p-value > 0.10 (at 90% confidence level). The RSM also depicted the optimum GSM range is from 150 to 245 and yarn count is 24/1 Ne to 31/1 Ne. Again, the RSM found that the GSM, yarn count, and stitch length can influence the bursting strength significantly.

Keywords: Bursting Strength; Machine Learning; Response Surface Methodology; Random Forest; Artificial Neural Network; Extreme Gradient Boosting

1. Introduction

Knitting is one of the three basic ways that fabrics are created, along with nonwovens and weaving. The drape, flexibility, wrinkle resistance, and other carefree features of knitted fabrics set them apart from other fabric kinds. Underwear, casual wear, activity wear, and sportswear are some of the most popular end products made from knitted materials because of their softness and comfort compared to woven fabrics [1].

. In addition, knitting fabric takes very little time and effort and has low manufacturing costs. That's why you see more and more knitted garments being used in places all around the globe. Knitted materials' physical and mechanical properties are significant in many settings. One of the most important mechanical properties of knitted materials is their bursting strength. Fabric's bursting strength is the force needed to tear it away from a flat surface when applied perpendicularly. It's important that the fabric can handle the stresses of dying, finishing, and regular wear. Because of their distinct construction, knitted materials should not be subjected to the same tensile and rip strength tests as woven ones. Therefore, the bursting strength of knitted materials is used to measure their ability to withstand several axial loads without failing (Mavruz & Oğulata, 2010) [2].

There are numerous variables that influence the bursting strength of knitted materials. It is commonly known that bursting strength increases as component yarn tenacity, knitted stitch length, and knit fabric density (GSM) increase [3]. Prior to knitting processes, these three factors have established values and are accessible from the manufacturer. They are also the most influential factors on bursting strength.

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In some circumstances, it could be required to foresee a fabric's bursting strength before it is manufactured by using the properties of the yarn that was used to knit the cloth. But prior to conducting bursting strength tests, it is extremely challenging to anticipate the bursting strength of knitted materials. It is also revealed from the study that the relationship between the factors and fabric bursting strength is non-linear. Various machine learning models such as regression, neural network, because of their ability to model non-linear relationships, have been employed in the past for the prediction of bursting strength of knitted fabrics. Jamshaid et al. created intelligent models with yarn strength, yarn elongation, and fabric GSM as input variables to estimate the bursting strength of knitted materials [4]. Filipe et al. constructed an ANN-based model for forecasting the bursting strength using yarn strength, yarn evenness, yarn count, yarn elongation, yarn twist and fabric wales and courses as input variables. Using a neural network and an adaptive network-based fuzzy inference system, Ertugrul and Uçar completed a study about the prediction of bursting strength of cotton plain knitted fabrics from the fabric weight and yarn tensile properties before manufacturing [5]. Artificial neural networks were used in a study by Ünal, Üreyen, and Armakan to explore the impact of yarn characteristics on the bursting strength of plain knitted materials. Bahadir et al.used ANN model for the prediction of bursting strength of knitted fabrics. This study aims to find out the best machine learning models in terms of R^2 value. Besides, it explains different influencing factors of bursting strength using Responsive Surface Method (RSM).

2. Material and methods

2.1. Data collection

The bursting strength data was collected from NRG Knit Composite, Narayanganj, Bangladesh. For this bursting strength test Bursting Strength Tester TF142A/B by Testex was used. All the samples were single jersey knitted fabrics with different parameters such as shrinkage, English count, stitch length, GSM, fabric thickness, porosity, bursting strength (table 1). Here, the independent variable: Bursting strength and dependent variable are all rest parameters.

Table 1 Dataset for implementing machine learning model

Sl.	Shrinkage %	Count (Ne)	Yam Diameter (cm)	Stitch Length (mm)	Stitch Density (CPCm x WPCm)	GSM	Fabric Thickness (mm)	Porosity	Bursting Strength (kg/cm2)
0	3.8	32	0.160	2.90	312	135	0.021	0.1025	4.45
1	9.2	28	0.171	2.65	288	140	0.020	0.1377	5.22
2	2.1	24	0.185	3.20	214	170	0.021	0.3232	5.02
3	8.3	30	0.166	2.80	270	140	0.022	0.0969	3.65
4	5.8	26	0.178	3.00	230	150	0.020	0.2477	4.79
5	7.5	22	0.192	3.00	347	280	0.037	0.0570	2.25
6	6.7	28	0.169	3.00	453	300	0.033	0.0321	2.69
7	2.9	28	0.172	2.75	456	280	0.028	0.0543	3.54
8	14.6	22	0.188	2.85	384	290	0.030	0.0857	2.38
9	12.9	28	0.171	2.60	194	220	0.029	0.0339	5.58
10	4.6	24	0.185	2.80	174	250	0.032	0.0568	7.51
11	4.2	28	0.171	2.75	171	210	0.031	0.0348	4.37
12	8.8	30	0.166	2.95	182	220	0.032	0.0304	5.29
13	0.8	30	0.166	2.80	175	200	0.027	0.0464	5.66
14	5.4	28	0.171	2.70	326	195	0.029	0.0397	5.42
15	5.4	26	0.178	2.70	343	215	0.030	0.0466	5.27
16	6.7	24	0.185	2.75	308	215	0.036	0.0331	5.36
17	6.3	28	0.171	2.55	358	200	0.031	0.0231	5.84
18	4.6	24	0.185	2.65	316	210	0.034	0.0360	4.36

2.2. Data Pre-processing

All the data was numerical and the level of measurement was both continuous and discrete. The dataset had no missing values. As the dataset is very small no outliers were determined. Both the training and testing set were conducted on the same dataset. Some models need feature scaling and some models do not require feature scaling. Hence, the feature scaling was done for the preferred cases.

2.3. Machine learning Models

This study was utilized different regression based, tree based and Artificial Neural Network (ANN).

2.3.1. The scaling of independent variables

In this study we used 19 samples with 8 parameters. The dataset was trained by various machine learning models including regression and tree based models. For determining the accuracy of models we used R^2 score. Although R^2 score is not a very good way to determine the model accuracy, but it is used to compare different models. Among different regression based models we used Linear, Lasso, and Ridge Regression.

The Bursting Strength Tester was used to conduct the evaluation of the bursting strength. During this study we tend to used nineteen samples with eight parameters. The dataset was trained by numerous machine learning models together with regression and tree based mostly models. For decisive the accuracy of models we used R^2 score. Though R^2 score isn't a really great way to work out the model accuracy, however it's accustomed compare totally different models. Among different regression based models we used Linear, Lasso, and Ridge Regression.

2.3.2. Feature scaling

Some models are strongly dependent on feature scaling such as K-nearest neighbour, Support Vector Machine (SVM), Artificial Neural Network (ANN). There are plenty of feature scaling option such as min-max, standard scaling, normalization etc. however, this study used standard scaling. Interestingly the tree based models such as Random Forest, XGBoost are not influenced by the feature scaling. The scaled data is presented in table 3.

Some models are powerfully keen about feature scaling like K-nearest neighbour, Support Vector Machine (SVM), Artificial Neural Network (ANN). There are lots of feature scaling choices such as min-max, standard scaling, normalization and so forth. However, this study used standard scaling. Apparently the tree primarily based models such as Random Forest, XGBoost aren't influenced by the feature scaling.

2.3.3. Artificial Neural Network (ANN)

Artificial neural network is a very powerful machine learning algorithm. For this study we used tensorflow as the library.

The sequential model of tensorflow was used with 4 dense layer. As activation function we used 'relu'. For fitting the model the Adam optimizer with 0.0001 learning rate has been used. On the other hand as loss function we used mean absolute error (mae). In total 600 epochs were tried to get optimum results. The following table depicts a summary of ANN model summary.

Table 2 Summary of the ANN model

Layer (type)	Output Shape	Parameters
dense_19 (Dense)	(None, 100)	900
dense_20 (Dense)	(None, 250)	25250
dense_21 (Dense)	(None, 10)	2510
dense_22 (Dense)	(None, 1)	11

The artificial neural network algorithm for machine learning is one of the most powerful ones. Tensorflow was the library that we utilized for this particular research project. The sequential paradigm of tensorflow was applied, and there were four dense layers utilized. "relu" was the activation function that we employed. It was decided to utilize the Adam optimizer with a learning rate of 0.0001 in order to fit the model. On the other hand, we utilized the mean absolute error as our loss function (MAE). In order to find the optimal outcomes, a total of 600 epochs were tested. The following table provides an overview of the ANN model. The summary of the Artificial Neural Network (ANN) model is depicted (table 2).

Table 3 Data transformed with standard scaling

S. N	**Shrinkage%**	**Count (Ne)**	**Yam Diameter (cm)**	**Stitch Length (mm)**	**Stitch Density (CPCmxWPCm)**	**GSM**	**Fabric Thickness (mm)**	**Porosity**
0	-0.765160	1.857340	-1.736620	0.558353	0.254704	-1.537210	-1.445067	0.292781
1	0.856853	0.416954	-0.485056	-1.001751	-0.017298	-1.436842	-1.635735	0.748582
2	-1.275794	-1.023432	1.107844	2.430479	-0.855974	-0.834636	-1.445067	3.150601
3	0.586517	1.137147	-1.053949	-0.065689	-0.221301	-1.436842	-1.254398	0.220267
4	-0.164415	-0.303239	0.311394	1.182395	-0.674639	-1.236107	-1.635735	2.172960
5	0.346219	-1.743626	1.904294	1.182395	0.651375	1.373452	1.605630	-0.296393
6	0.105921	0.416954	-0.712613	1.182395	1.852721	1.774923	0.842956	-0.618821
7	-1.035496	0.416954	-0.371277	-0.377710	1.886722	1.373452	-0.110387	-0.331355
8	2.478866	-1.743626	1.449180	0.246332	1.070713	1.574188	0.270950	0.075240
9	1.968232	0.416954	-0.485056	-1.313772	-1.082643	0.169040	0.080281	-0.595513
10	-0.524862	-1.023432	1.107844	-0.065689	-1.309312	0.771246	0.652287	-0.298983
11	-0.645011	0.416954	-0.485056	-0.377710	-1.343312	-0.031695	0.461619	-0.583859
12	0.736704	1.137147	-1.053949	0.870374	-1.218645	0.169040	0.652287	-0.640834
13	-1.666279	1.137147	-1.053949	-0.065689	-1.297979	-0.232430	-0.301056	-0.433651
14	-0.284564	0.416954	-0.485056	-0.689730	0.413373	-0.332798	0.080281	-0.520409
15	-0.284564	-0.303239	0.311394	-0.689730	0.606042	0.068673	0.270950	-0.431062
16	0.105921	-1.023432	1.107844	-0.377710	0.209371	0.068673	1.414961	-0.605872
17	-0.014228	0.416954	-0.485056	-1.625793	0.776043	-0.232430	0.461619	-0.735361
18	-0.524862	-1.023432	1.107844	-1.001751	0.300038	-0.031695	1.033624	-0.568320

3. Results and discussion

The Pearson correlation show the inter parameter relations (figure 1). From the heat map it is seen that the bursting strength is highly correlated with stitch density (but negatively), which mean the increase in stitch density will decrease the bursting strength. That is pretty obvious. Among other factor the effect of stitch length, yarn count and shrinkage is significantly important. Intestinally the fabric thickness has a little influence on bursting strength and the porosity is almost non-correlated with the bursting strength of knit samples.

Figure 1 Heat map of Pearson correlation among different parameters

Again, the data are plotted in scattered plot (figure 2) using pair plot of Seaborn library [6]. The pair plot shows the bursting strength is linearly correlated with the porosity and GSM. But for other samples there is not significant relation. Hence we need complicated machine learning models.

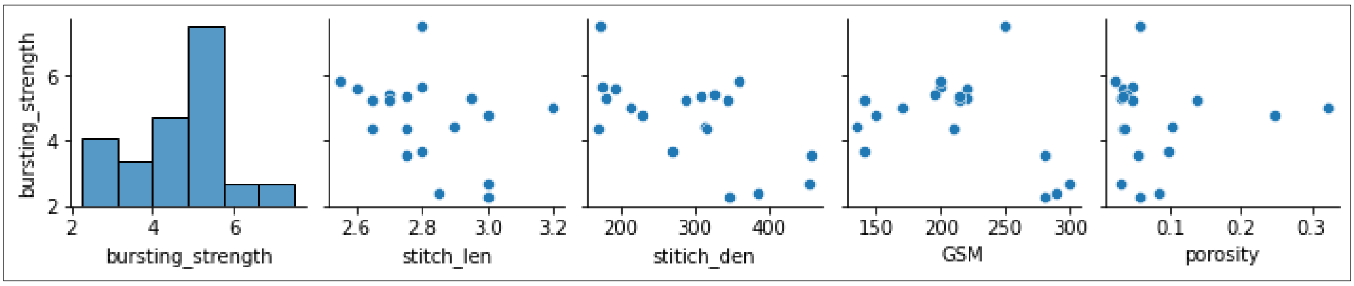


Figure 2 Pair plots of different parameters

3.1. Prediction by different Algorithms

3.1.1. Regression analysis

To ascertain the nature of the connection between two (in the case of single linear regression) or more (in the case of multiple linear regression) variables, statisticians employ a technique called regression analysis (multiple regression).

The regression is mostly employed for two functions:

- To study the magnitude and structure of the relationship between variables
- To forecast a variable based on its relationship with another variable

Both of these realizations are useful for guiding important business choices. Jan Hammond, an HBS professor says, that regression gives us information about how the relationship is built and how well the data fit that relationship. These kinds of insights can be very helpful when looking at historical trends and making predictions [7].

LASSO

Lasso regression is a regularization approach. In order to make a more accurate forecast, it is utilized instead of regression approaches. Sparse models are encouraged by the lasso technique, which means that models with fewer parameters are preferred. This particular kind of regression works particularly well for models that exhibit significant levels of multicollinearity. It is also useful in situations in which you wish to automate certain aspects of model selection, such as the process of selecting variables or eliminating parameters [8].

ANN MODEL

ANNs are abbreviation for artificial neural networks, which are computer programs that are biologically inspired and are supposed to imitate the way that the human brain processes information. ANNs obtain their knowledge by identifying the patterns and relationships included within the data. They do not learn (or are trained) by the use of programming but rather through experience. An artificial neural network (ANN) is made up of hundreds of individual units that serve as either artificial neurons or processing elements (PE). These units are connected to one another by Coefficients (weights), which make up the neural structure and are arranged in layers.

The ability to do complex computations relies on the connectivity between neurons in a network. Every PE has one output, in addition to weighted inputs and a transfer function. The behavior of a neural network is influenced not only by the learning rule, but also by the architecture of the network itself as well as the transfer functions of the neurons that make up the network. A neural network is a parameterized system because the weights may be adjusted; in this sense, the weights are the adjustable parameters. The activation of the neuron is the result of adding up all of the different inputs and weighing them. In order to generate a single output from the neuron, the activation signal must first be processed by the transfer function. A non-linear behavior is brought into the network through the transfer function [9].

KNN Model

Because of its ease of use, the K-Nearest Neighbors method in machine learning, also known as KNN, is one of the most used types of learning algorithms. KNN is a non-parametric learning algorithm that employs slow learning. It makes use of data that belong to many classes in order to make a prediction regarding the categorization of the new sample point. KNN is considered non-parametric since it does not make any assumptions about the data that is being investigated; more specifically, the model is derived from the data itself. KNN is utilized in fields such as genomics, data compression, and economic forecasting despite the fact that it is quite straightforward and performs better than more complex classification methods [10] [11].

XG Boost

Because of its easy parallelism and excellent prediction accuracy, the Gradient Boosting Machine (GBM) has been a competitive tool among artificial intelligence methods, and XGBoost is an efficient and scalable implementation of GBM. In addition, it is flexible enough to deal with the transient stability prediction because of the following benefits:

To predict the transient stability with a huge amount of data in the real power grid, the XGBoost model can automatically call multithreading parallel computing, which is faster than the standard ensemble learning. Two, XGBoost generalization capacity is enhanced by the inclusion of a regularization term, mitigating the drawback of the decision tree susceptibility to over-tuning [12].

Different Machine learning algorithms showed different accuracy score. Here, the accuracy score is not that important as the predicted values showed a little variation. The table 4 depicts the predicted and actual values of different machine learning algorithms.

Table 4 Prediction of different ML models and actual value

Linear	Lasso	Ridge	KNN	RNF	XGB	SVM	ANN	Actual
4.066595	4.276037	4.479292	4.9	4.4426	4.449111	4.62759	4.44749	4.45
5.051739	5.124415	4.96239	4.75	4.908	5.219563	4.740778	5.223712	5.22
4.95793	4.720533	4.749301	4.908571	5.0742	5.0203	5.069162	5.026378	5.02
4.378291	4.573626	4.692725	4.701429	4.165	3.650918	4.823371	3.651541	3.65
4.847189	4.790301	4.796702	4.91	4.7702	4.790272	4.996084	4.797293	4.79
3.148912	3.229617	3.486249	4.411429	2.8846	2.250544	4.208344	2.250824	2.25
2.406469	2.315842	2.471886	3.761429	3.2184	2.689622	3.609822	2.691535	2.69
3.943166	3.910831	3.667361	3.912857	3.62	3.540513	3.64	3.541172	3.54
2.600328	2.851034	2.839754	3.761429	2.6524	2.380032	3.962791	2.389793	2.38
5.771454	5.564584	5.341979	5.46	5.4488	5.579753	5.147851	5.572659	5.58
5.710956	5.945203	5.867566	5.46	5.787	7.508843	5.198254	7.513613	7.51
6.117239	6.095687	6.048221	5.46	5.0366	4.370737	5.224654	4.860562	4.37
4.713748	4.536159	4.7629	5.46	5.1644	5.290348	5.19	5.280102	5.29
6.038612	6.240232	6.196119	5.46	5.2444	5.659598	5.211414	5.660334	5.66
4.790689	4.809611	4.796857	5.131429	5.3108	5.419625	4.500998	3.92748	5.42
4.638402	4.723567	4.674558	4.707143	5.058	5.270327	4.368989	4.076725	5.27
4.764893	4.621941	4.729657	4.817143	5.3134	5.358779	4.576695	5.350548	5.36
5.396903	5.065067	4.878198	4.707143	5.2578	5.840352	4.309903	5.844918	5.84
5.306486	5.255712	5.208285	5.131429	4.6978	4.360743	4.536998	5.942488	4.36

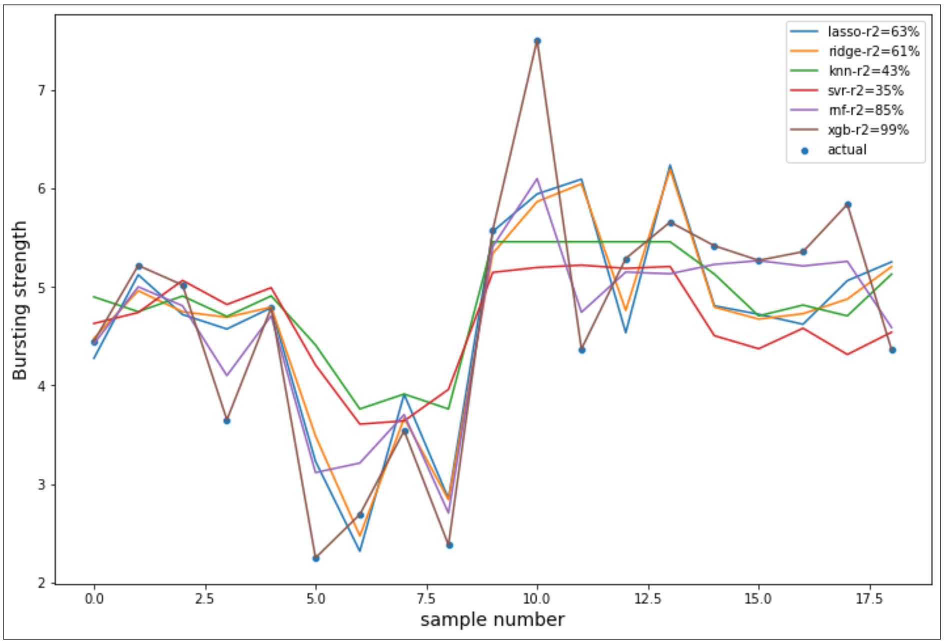


Figure 3 R2 value for different machine learning models

The R^2 value is plotted in the figure 3. It shows the highest R^2 value is achieved from XG boost algorithm. XGBoost is a tree based and very powerful algorithm. In our case the data is categorical type and hence the models worked best in this case. In the same way, another tree based model Random Forest regression shows 85% R^2 value. The second best model is ANN which shows 80% accuracy (R^2 value).

3.2. Response Surface Methodology

Response surface Method was employed using 2 factors (GSM and Count) with single replicate and 13 runs. The p-value of the coded matrix is as follow (table 5):

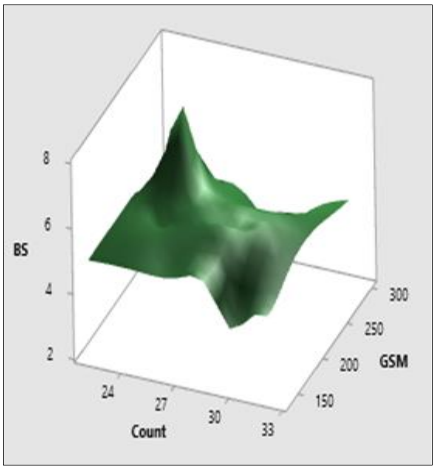
Table 5 RSM model calculated p-value

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	5.587	0.422	13.25	0.000	
Count	0.020	0.518	0.04	0.969	1.58
GSM	-0.842	0.428	-1.97	0.071	1.28
Count*Count	-0.99	1.40	-0.71	0.490	4.14
GSM*GSM	-1.993	0.679	-2.94	0.012	1.30
Count*GSM	-0.42	1.27	-0.33	0.748	4.13

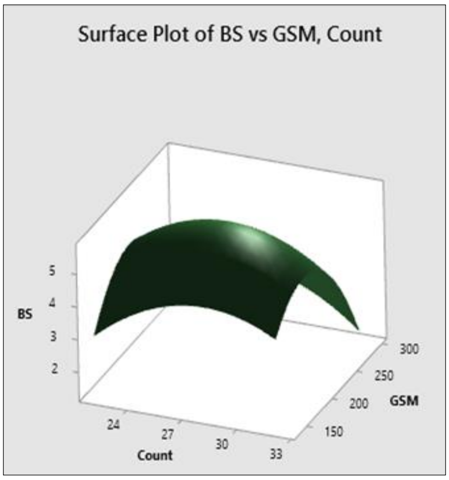
The table 5 shows that only GSM and GSM* GSM have significant p-value (less than 0.10 at 90% confidence level), hence the effect of GSM on bursting strength is significant.

The regression equation of breaking strength will be,

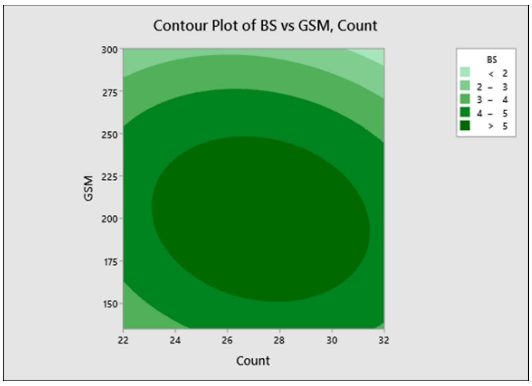
Breaking Strength = -41.1 + 2.37 Count + 0.144 GSM - 0.0397 Count*Count - 0.000293 GSM*GSM - 0.00101 Count*GSM



a) Surface plot of the overall Breaking strength



b) surface plot of the breaking strength in terms of Responsive Surface Modelling



c) Contour plot of breaking strength according to RSM

Figure 4 Different images for Surface and contour plot by RSM

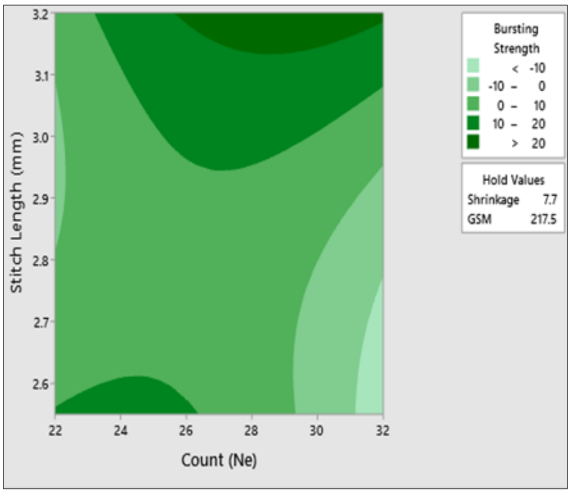


Figure 5 Contour plot of Bursting strength vs. stitch len(mm) and count (Ne)

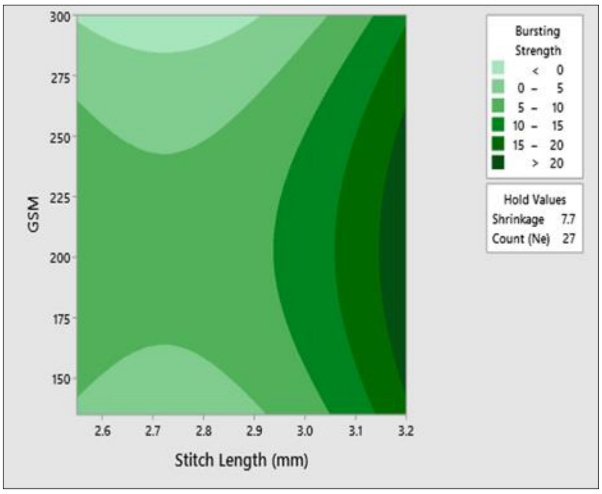


Figure 6 Contour plot of bursting strength vs. GSM, stitch length (mm)

The contour plot of the effect of yarn count and GSM on Breaking strength is depicted if the figure 4. It shows the highest breaking strength is achieved at a range of 24 to 31 and the GSM range is from 150 to 245. Beyond GSM 245 the breaking strength increased a lot.

Additionally, the contour plot of bursting strength and stitch length and count show highest Bursting strength come from 26 to 32 count and 31-32 stitch length, another pair is 22-26 Ne and 2.6 stich length (figure 5). On the contrary, the 3.2 stitch length and 150 to 250 GSM show best bursting strength (figure 6). Again from figure 7 we may assume that the data residual are normally distributed

In this study, the effects of yarn parameters, fabric quality parameters and process control parameters on the exploding strength of the plain knitted fabrics were examined with the assistance of Linear regression model, Lasso regression, ANN model, KNN model. In order to obtain reliable prediction of bursting strength of knitted fabric different quality parameters are assessed according to research of interest. All the mention models were used to analyze the scope of predicted bursting strength of the plain knitted fabrics to optimize with the actual. As independent variables yarn diameter, yarn count, stitch length, stitch density, fabric GSM and thickness, fabric porosity all of these are tried to cover the experimental design.

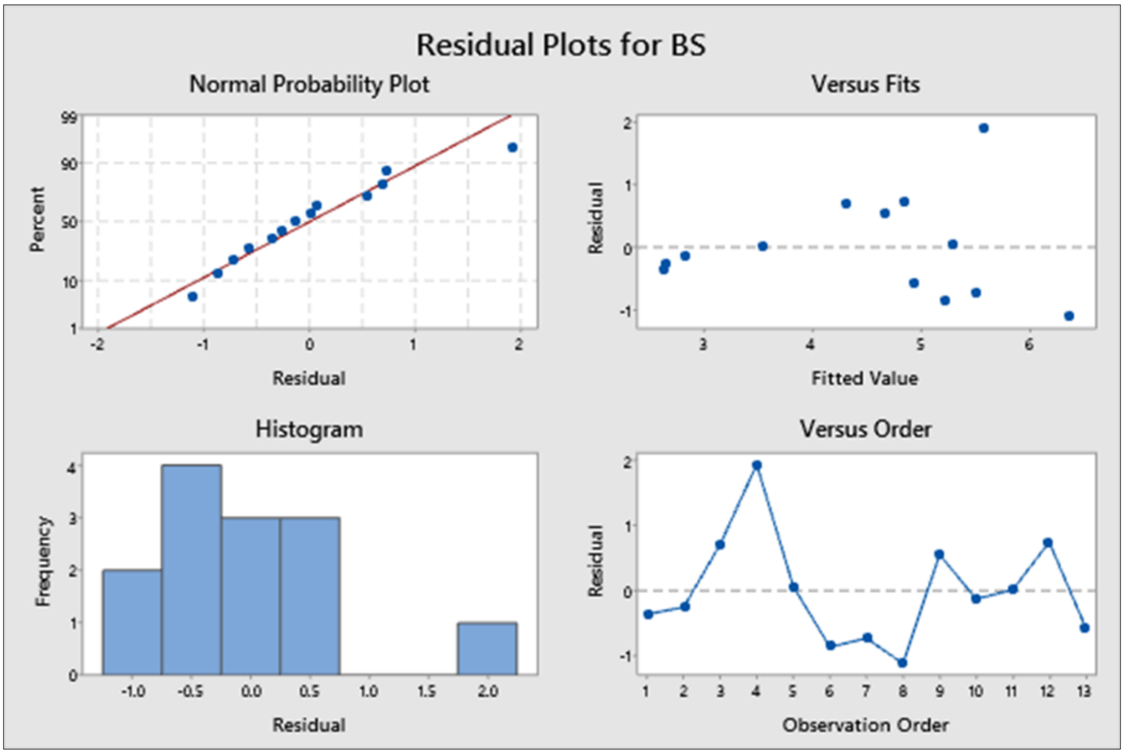


Figure 7 Residual plot of breaking strength of knit fabrics

4. Conclusion

In this study, the results of yarn parameters, fabric quality parameters and process control parameters on the exploding strength of the plain knitted fabrics were examined with the help of different machine learning models such as linear regression model, lasso regression, ANN, XGBoost, random forest and KNN model. In order to acquire reliable prediction of detonating strength of knit totally different quality parameters are assessed consistent with analysis of interest. All the mention models were accustomed analyze the scope of foretold bursting strength of the plain knitted fabrics to optimize with the actual. As freelance variables yarn diameter, yarn count, stitch length, stitch density, GSM, fabric thickness and porosity all of these are tried to cover the experimental design. For analyzing statistical relation Response Surface Methodology (RSM) were used. Extreme Gradient Boosting (XGBoost) model presents a transient stability prediction method which constructed on the interrelated quality parameters under the specific conditions. This method is developed on the interrelated quality parameters while taking into account the specific situations. Nevertheless, it appears to have the best results compared to the other models. This study presents a prediction model constructed based on different Machine Learning algorithms among them the Random Forest model exhibit best accuracy. The greater influential quality parameter is the GSM which is directly dominate the fabric strength of the plain knitted fabric. The GSM is the most important quality indicator since it dictates the fabric strength and hence the resilience of plain knitted fabrics. However, Satisfactory consequences for the prediction of the bursting strength of the plain knitted fabric have been achieved as an end result of this study.

Compliance with ethical standards

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Disclosure of conflict of interest

We declare that we have no conflict of interest to be mentioned.

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